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THE COST OF JOB LOSS IN CARBON-INTENSIVE SECTORS: EVIDENCE FROM GERMANY

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Abstract / Résumé

The Cost of Job Loss in Carbon-Intensive Sectors: Evidence from Germany

The green transformation of the economy is expected to lead to a sharp reduction in employment in carbon-intensive industries. For designing policies to support displaced workers, it is crucial to better understand the cost of job loss, whether there are specific effects of being displaced from a carbon-intensive sector and which workers are most at risk. By using German administrative labour market data and focusing on mass layoff events, we estimate the cost of involuntary job displacement for workers in high carbon-intensity sectors and compare it with the displacement costs for workers in low carbon-intensity sectors. We find that displaced workers from high carbon-intensity sectors have, on average, higher earnings losses and face stronger difficulties in finding a new job and recovering their earnings. Our results indicate that this is mainly due to human capital specificity, the regional clustering of carbon-intensive activities and higher wage premia in carbon-intensive firms. Workers displaced in high carbon-intensity sectors are older, face higher local labour market concentration and have fewer outside options for finding jobs with similar skill requirements. They have a higher probability to switch occupations and sectors, move to occupations that are more different in terms of skill requirements compared to the pre-displacement job, and are more likely to change workplace districts after displacement. Women, older workers and those with vocational degrees as well as workers in East Germany, experience particularly high costs in case they are displaced from high carbon-intensity sectors.

JEL codes : J24, J31, J42, J63, J64, J65, Q52

Key words: Job loss effect, labour displacement, labour reallocation, human capital specificity, labour market concentration, green transition, carbon-intensive sectors, difference-in-differences

This Working Paper relates to the 2023 OECD Economic Survey of Germany.

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Le coût de la perte d'emploi dans les secteurs à forte intensité de carbone : données empiriques tirées de l'exemple de l'Allemagne

La transformation écologique de l'économie devrait entraîner une forte diminution de l'emploi dans les secteurs à forte intensité de carbone. Pour concevoir des politiques publiques à même d'aider les travailleurs perdant leur emploi, il est indispensable de mieux appréhender le coût de cette perte, de savoir si la perte d'un emploi dans un secteur à forte intensité de carbone à des conséquences spécifiques et quels sont les travailleurs qui courent le plus de risques. En utilisant des données administratives relatives au marché du travail en Allemagne et en nous intéressant en priorité aux phénomènes de licenciements massifs, nous avons estimé le coût de la perte involontaire d'un emploi dans les secteurs à forte intensité de carbone et nous l'avons comparé avec le coût d'une perte d'emploi dans les secteurs à faible intensité de carbone. La conclusion est qu'en moyenne, les travailleurs des secteurs à forte intensité de carbone qui perdent leur emploi subissent des pertes de revenu plus importantes et rencontrent des difficultés plus grandes pour retrouver un travail et un même niveau de salaire. Selon nos résultats, cette situation s'explique principalement par la spécificité du capital humain accumulé, la forte concentration régionale des activités à forte intensité de carbone, et des avantages salariaux des entreprises plus importantes (firm wage premia). Dans ces secteurs, les travailleurs perdant leur emploi sont plus âgés, ils font face à une concentration locale des employeurs plus forte et ils ont moins de possibilités de retrouver ailleurs un emploi nécessitant les mêmes qualifications. Les pertes d'avantages salariaux (firm wage premia) qu'ils subissent sont plus importantes, la probabilité qu'ils changent de profession et de secteur d'activité est plus grande, comme celle d'évoluer vers des professions très différentes en termes de qualifications, et ils sont plus susceptibles de devoir changer de zone géographique après leur perte d'emploi. Les coûts de la perte d'emploi dans les secteurs à forte intensité de carbone sont particulièrement élevés pour les femmes, les travailleurs âgés et les diplômés de filières professionnelles ainsi que pour les travailleurs situés à l'est de l'Allemagne.

Ce Document de travail a trait à l'Étude économique de l'OCDE d'Allemagne 2023.

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The Cost of Job Loss in Carbon-Intensive Sectors: Evidence from Germany

Cesar Barreto, Robert Grundke and Zeev Krill[1]

Introduction

Recent empirical research suggests that although carbon emission abatement will have only a limited net impact on aggregate employment, it will require a considerable reallocation of labour and capital between sectors (Procopio, 2022) (Bickmann et al., forthcoming[1]) (Lawrence, 2023[2]). Workers will have to move from polluting, carbon-intensive sectors to newly created jobs in other sectors and firms. These transitions can entail significant adjustments costs for workers, as the recent literature on structural adjustments due to trade or technological change suggests (Grundke and Arnold, 2022[3]; Autor et al., 2014[4]; Hummels, Munch and Xiang, 2018[5]; Autor, Dorn and Hanson, 2015[6]). However, so far, little is known about individual-level adjustment costs for workers displaced in carbon-intensive industries, which will strongly reduce employment during the green transition (Hanson, 2023[7]).

This study contributes to the literature by using German administrative labour market data coupled with data on mass layoffs to investigate the adjustment costs for workers displaced in carbon-intensive industries. We define High Carbon Intensity (hereinafter HCI) sectors as the top two deciles of the carbon intensity distribution across German economic sectors, accounting for 81% of total CO2 emissions during the sample period 1993-2020. All remaining sectors are classified as low-carbon intensity (LCI) sectors. In Germany, carbon emissions have been reduced by 43% since 1990 and employment in HCI sectors has strongly declined (Figure 1). From 1993 and 2019, the share of workers in HCI sectors has fallen by a third, from about 9.7% of all workers in 1993 to about 6.4% in 2019. These job losses are related to 2704 mass-layoff events in HCI sectors during the same time period, with 878 mass-layoff events in East and 1826 in West-Germany.

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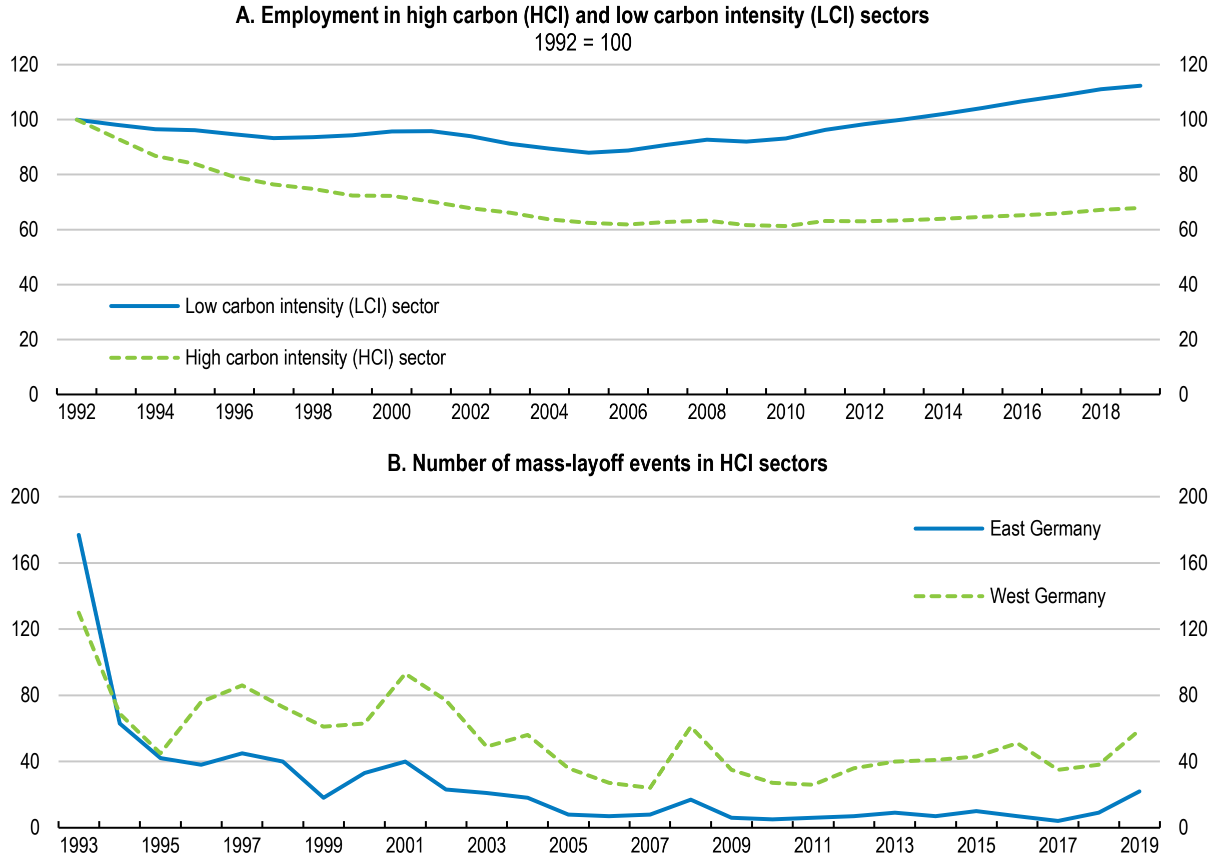
Figure 1. Germany has already experienced significant employment losses in high carbon-intensity sectors

Employment trends and mass-layoff events in high carbon-intensity (HCI) and low-carbon intensity sectors (LCI) in Germany (1992=100)



Note: Total employment is the sum of full-time and part-time employment. High carbon-intensity sectors are defined as the top two deciles of the carbon intensity distribution, while all remaining sectors are classified as low carbon intensity sectors. Mass layoff events include plant closures.

Figure 11 in the annexes shows that the decline in employment in the high carbon-intensity sectors occurred in both East and West Germany.

To investigate the adjustment costs for workers displaced in high carbon intensity sectors, we estimate the effects of job displacement on labour market outcomes, such as employment status, hourly wages and job transitions, and compare them with displacement effects for workers displaced in low carbon intensity sectors. Job displacement effects are estimated by comparing displaced and non-displaced workers before and after a mass layoff event, whereby we use a two-step matching procedure to pair each displaced worker with a non-displaced worker with similar individual characteristics and pre-displacement trends in outcomes (Jacobson, Lalonde and Sullivan, 1993[8]). Restricting the analysis to displacements during mass layoff events allows identifying the causal effects of involuntary job separations, as mass layoffs can be assumed to be exogenous to individual characteristics of the worker (Jacobson, Lalonde and Sullivan, 1993[8]), (Schmieder, von Wachter and Heining, 2022[9]). Mass layoff events are classified as a drop in employment of at least 30% among establishments with at least 50 employees. About 2% of establishments with more than 50 employees experienced a mass layoff event each year during our sample period (1993-2020), with broadly similar magnitude for both high- and low-carbon intensity sectors.

We find that displaced workers from high-carbon intensity sectors experience (on average) higher and more persistent earning losses compared to other displaced workers. Five years after the job separation, displaced workers from HCI sectors have 23% lower earnings compared to individuals with similar characteristics who haven't been displaced, while the loss for workers in other industries is only about 17%. In contrast, earnings of workers in HCI sectors who remained employed after a mass layoff event are broadly stable. The larger job loss effect is driven by a sharp decline in daily wages for displaced workers in the HCI sectors compared to displaced workers in LCI sectors, while the employment gap is less substantial. Moreover, we find that workers displaced in HCI sectors have a higher probability of switching occupations and sectors, move to occupations that are more different in terms of skill requirements compared to the pre-displacement job, and are more likely to change workplace districts after displacement.

Our results indicate that human capital specificity, the regional clustering of carbon-intensive activities and higher wage premia in carbon-intensive firms are key for explaining the difference in adjustment costs between HCI and LCI sectors. By using an Oaxaca-Blinder decomposition method, we show that about two-thirds of the differences in displacement costs between HCI and LCI sectors can be explained by composition effects. Displaced workers in the HCI sector are older, more concentrated in certain occupations (e.g., with higher routine manual task content), face higher local labour market concentration and monopsony power of employers, have fewer outside options for finding jobs with similar skill requirements and work in firms with higher wage premiums. On average, these characteristics lead to higher earning losses after displacement. Finally, we show that types of workers that are in general more vulnerable when faced with involuntary displacement – older, low-skilled and female workers, as well as those in East Germany – have an even higher displacement cost in case they are displaced from the HCI sectors. Our main findings remain robust to changing the threshold for defining High Carbon Intensity sectors, using a stricter definition of a mass layoff event (including only plant closure events), including only men in the sample or separating the sample into East- and West-Germany.

A large and growing literature has documented the high economic, social and health costs that workers face when they are displaced from stable jobs. Losing a job entails a lasting and significant reduction in employment and earnings, as first shown by Jacobson et al. (1993[8]). Likewise, it is associated with poorer overall self-rated health and more depressive symptoms (Burgard, Brand and House, 2007[10]) as well as higher mortality (Daniel and Von Wachter, 2009[11]) (Browning and Heinesen, 2012[12]) (Bloemen, Hochguertel and Zweerink, 2015[13]). Displacement costs vary with the business cycle (Schmieder, von Wachter and Heining, 2022[9]), between countries (Bertheau et al., 2022[14]) and according to local labour market conditions (Arntz, Ivanov and Pohlan, 2022[15]; Caldwell and Danieli, 2020[16]). Women, routine-intensive and older workers, as well as those with migration backgrounds, experience more significant earnings losses following a mass layoff (Illing, Schmieder and Trenkle, 2022[17]) (Blien, Dauth and Roth, 2021[18]) (Illing and Koch, 2021[19]) (Borgbjerg, 2023[20]).

However, despite the high risk of significant job losses due to the green transition, so far, only one other study has investigated the cost of job loss for workers in carbon-intensive sectors compared to workers in other sectors. Rud et al. (2022[21]) focused on the closing of coal mines in the UK and find that coal mining workers have on average significantly higher displacement costs compared to other manufacturing workers. However, they cannot explain why this is the case. We contribute to the literature by focusing on a broader set of carbon-intensive sectors and identifying several explanations for why displacement costs are higher in carbon-intensive sectors. By using time-varying measures of occupational task-content we construct an individual-level index of job opportunities in local labour markets, which have skill requirements similar to the pre-displacement job (Macaluso, 2023[22]). Our results indicate that fewer outside options of jobs with similar skill requirements are a main factor for higher displacement costs in carbon-intensive sectors. Displaced HCI workers have to move to other occupations with different skill requirements, which reduces their wages due to imperfect portability of occupation specific human capital (Kambourov and Manovskii, 2009[23]). This complements previous literature that finds that the capacity of local labour markets to absorb displaced workers plays an important role to explain adjustment costs for workers due to rising import competition (Yi, Mueller and Stegmaier, 2023[24]). Moreover, by using an Herfindahl-Hirschman index (HHI) of local labour market concentration we show that higher monopsony power in local labour markets is another key factor for explaining lower outside options and wages of workers displaced from carbon-intensive activities compared to other displaced workers (Dodini et al., 2023[25]; Bachmann et al., 2022[26]).

This study adds to the literature on adjustment costs during the green transition by providing causally identified estimates of displacement costs for workers displaced in carbon-intensive industries in Germany over the last three decades. Hanson (2023[7]) showed that in the US, regions that were highly specialized in fossil-fuel-intensive industries saw persistent declines in employment and wage rates due to a loss of agglomeration effects and labour market opportunities since the 1990s. Although our study differs from Hanson (2023) by estimating individual-level displacement effects, our findings that workers in East Germany – where outside job opportunities are more limited – suffered from more significant job loss effects also point to the importance of agglomeration effects. However, we show that other factors such as human capital specificity play an even more important role. In another important study, Walker (2013[27]) studied the transition costs associated with reallocating workers from newly regulated industries to other sectors in the US economy. He found that the average worker in the newly regulated sectors experienced a discounted value earnings loss equivalent to 20% of their pre-regulatory earnings. As almost all the estimated earnings losses were driven by workers separated from their firms, this estimate is in the same ballpark to our estimate of 23% of earnings losses for workers displaced in carbon-intensive industries after five years. However, instead of looking at the effects of changes in one specific polluting standard, our paper investigates transition costs for displaced workers in the full range of high-carbon intensity sectors and sheds light on the mechanisms underlying the displacement effects.

In the German context, Haywood et al. (2021[28]) have used a stochastic general equilibrium labour market model and calculated the lifetime welfare costs of losing a job in an archetypical carbon-intensive industry in Germany – coal mining. Although our study differs from theirs by causally identifying displacement costs and investigating the underlying mechanisms as well as covering the whole range of carbon-intensive industries, we also find that displacement costs are mostly due to lower wages in alternative employment. As our set of carbon-intensive sectors strongly overlaps with energy-intensive sectors in Germany, our results also relate to the on-going debate on the potential employment decline and adjustment costs caused by higher energy prices (Moll, Schularick and Zachmann, 2023[29])) (OECD, 2023[30]). More generally, understanding and addressing adjustment costs for workers displaced in carbon-intensive sectors is key for the public acceptability of climate policies. In particular, the geographical concentration of HCI jobs might undermine the political acceptability of climate policies (Vona, 2018[31]). This is because a minority of strongly negatively affected but better organized voters, who risk losing their job in HCI sectors due to stricter climate policies, might prevail in the political process against a weakly organized majority which does not directly feel the positive benefits of climate policies in their daily lives. Thus, it is key to know more about adjustment costs for workers displaced in carbon-intensive sectors to be able to mitigate these costs and support the affected regions.

Our study is also related to the growing literature on green and brown occupations and skills (Popp et al., 2020[32]) (Vona et al., 2018[33]) (Consoli et al., 2016[34]) (Causa, Soldani and Nguyen, 2023[35]). However, our study focuses on the sectoral perspective instead of the occupation perspective for two main reasons. First, the employment decline in high-emission sectors is expected to affect all workers employed in these sectors, not only those in "brown" occupations. Our analysis allows to quantify displacement costs for all workers displaced from high-carbon intensity sectors, while controlling for occupations or their task content. Second, occupations and their task-content are linked to production processes, and thus workers in high-emission sectors also accumulate sector-specific skills. Reallocating away from brown to green sectors could, hence, implies a higher cost of job loss due to human capital specificity even for workers who continue working in the same narrowly defined occupation category (Sullivan, 2010[36]). Moreover, brown occupations are usually defined in the literature as those prevalent in high-emission sectors (Vona et al., 2018[33]).

The paper proceeds as follows: first, we present the data sources and explain how we define the high-carbon intensity sectors. Then, we describe the methods used to estimate the costs of involuntary job displacement and present the main results regarding the different job loss effects for workers in the HCI and LCI sectors. The following section decomposes these differences according to observable and unobservable characteristics using a Oaxaca-Blinder method. Then, we investigate heterogeneity in displacement effects to identify groups of HCI workers who are particularly vulnerable to job loss. The last section summarizes the main findings.

Data sources and definitions

German administrative data

Our analysis is based on a detailed worker-level data set, which we obtain by drawing a random 10% sample from the Integrated Employment Biographies (IEB v16) dataset collected by the German Institute for Employment Research (IAB), which is an employer-employee administrative dataset based on German Social Security records. The dataset is based on employers' reports on employees' daily earnings, education, occupation and tenure and provides detailed information on workers' primary employment relationships (i.e., the employment relationship in which the worker earns the highest wage), receipt of unemployment benefits, and individual characteristics such as sex, age, migrant status, and place of residency. It does not cover civil servants, military personnel or the self-employed, who comprise about 20% of the German workforce. Our analysis focuses on the period of 1992-2020 to include East Germany in the sample.

Using unique establishment identifiers, we link our worker-level data set to establishment-level information from the Establishment History Panel (BHP), which contains information on the universe of establishments in Germany as of June 30 each year. We obtain information on time-consistent industry classification and establishment size as well as on mass-layoffs from the BHP. Then, based on Dauth and Eppelsheimer (2020[37]), we construct a yearly worker-level panel as of June 30 each year. If workers were omitted from the database and did not return in later years, they are dropped out of the sample upon exit. If workers left the database only temporarily, we assigned them zero earnings, zero employment, and missing wages for the missing spells. Because wages are censored at the social security contribution ceiling in the IEB database, we impute top-coded wages following Dustmann et al. (2009[38]) and Gartner et al. (2005[39]):

First, we deflated daily wages using the yearly CPI. Then, we ran individual wage equations separately by year, East and West Germany and three education groups to predict missing wage data. All regressions control for gender, age, tenure, average log wages for each worker over time, and average wages within each plant each year. In addition, we corrected the education variable following Fitzenberger et al. (2006[40]) and excluded spells with missing industry classification and sectors without carbon intensity data ("Activities of households as employers" (T) and "Activities of extraterritorial organizations and bodies" (U) from ISIC rev.4).

We complement the database with the following constructed variables:

- **AKM worker and establishment fixed effects.** To measure establishment wage premiums, which are a main determinant for the job loss effect (Bertheau et al., 2022[14]; Lachowska, Mas and Woodbury, 2020[41]), we estimated two-way AKM fixed effects for the period 1992-2020 based on Abowd et al. (1999[42]) and Card et al. (2013[43]). For the estimation, we follow the job displacement literature and exclude post-displacement occupations from treated and control workers, such that their estimated fixed effects are measured pre-displacement and their transitions do not contribute to the estimation of establishment fixed effects[2].
- **Occupational tasks.** We included information on task content (i.e., routine manual, routine cognitive, non-routine manual, non-routine analytical and non-routine interactive tasks) by 2-digit occupation codes (KldB 88) from the German Qualification and Career Surveys (GQCS) (Arntz, Ivanov and Pohlan, 2022[15]); (Spitz-Oener, 2006[44]). We use information from the waves 1991, 1999, 2006 and 2012 to calculate measures for time-varying task content of occupations. In each wave, we restrict the sample to workers in working age (15-65), working at least 10 hours a week and exclude observations from the public sector and the self-employed. Afterwards, following (Spitz-Oener, 2006[44]), (Antonczyk, Fitzenberger and Leuschner, 2009[45]) and (Rohrbach-Schmidt and Tiemann, 2013[46]) we calculate task intensities i.e. occupation shares (using survey weights) of routine manual, routine cognitive, non-routine manual, non-routine analytic and non-routine interactive tasks. In the analysis, we assign workers the most recent task content from the corresponding GQCS wave. Occupations were grouped at the 2-digit level for having sufficient statistical power and to limit attenuation biases that occur due to an insufficient number of observations per occupation category (Arntz, Ivanov and Pohlan, 2022[15]).
- **Skill distance between occupations.** We calculated skill distances between occupations, as in (Gathmann and Schoenberg, 2010[47]). For this, we characterize each 2-digit occupation in the skill space as a 22-dimensional task vector based on task information from the BIBB survey. Afterwards, we calculate the the angular separation between each occupation vector. The measure ranges from 0 to 1, with 0 implying no skill distance between occupations as the vectors point in the same direction and 1 implying that vectors are orthogonal i.e., the distance is the highest. As with occupational tasks, skill distances are re-calculated every wave of the BIBB and thus vary over time.
- **Labour market concentration.** We calculated a standard measure of local labour market concentration (the Herfindahl-Hirschman Index (HHI)), which measures the monopsony power of employers in the local labour market for each 2-digit occupation. Computing the index by occupation accounts for the fact that after a job loss, immediate re-employment opportunities are restricted to a similar occupation. We defined a local labour market using 223 commuting zones, as calculated by the Federal Institute for Research on Building, Urban Affairs and Spatial

[2] To check the role of limited mobility bias for our results on firm wage premia, we also ran the analysis using the estimated fixed effects from Bellman et al. (2019), which are estimated on the universe of employment biographies. We find little differences when using these fixed effects (results available upon request). As the estimated fixed effects from Bellman et al. (2019) are only available for subperiods until 2017 and are normalized differently in each sub-period, we decided to use our estimated AKM fixed effects from the 10% sample in the analysis.

Development (BBSR). Following previous works by the (Satoshi et al., 2022[48]), we defined high labour market concentration in cases where the HHI is larger than 0.15. Note that we use 2-digit occupations for consistency with the occupational task information and because 2-digit occupations allow capturing a larger set of possible re-employment opportunities with similar skill requirements (Gathmann and Schönberg, 2010[49]).

Defining the carbon-intensive sectors

For defining the set of high- carbon intensity (HCI) sectors, we compute average carbon intensity from 2000-2016 by sector (2-digit ISIC Rev.4)[3]. This is done by dividing tons of CO_2 emissions in each year and sector– extracted from the World Input-Output Database Environmental Accounts (Joint Research Centre (European Commission), 2019[50]) – by value added (in constant prices) in the same year and sector, using OECD data, and then average over the period 2000-2016. Sectoral carbon intensity is consequently defined as CO_2 emissions per unit of value added. Based on average carbon intensity from 2000-2016, we define the ten sectors (out of 54 considered sectors in the ISIC rev4 classification) in the top two deciles as High Carbon-Intensity sectors (HCI sectors) and the remaining sectors as Low Carbon-Intensity Sectors (LCI sectors) (Figure 2).

The set of carbon-intensive sectors encompass energy supply, as well as transport services (water, air and land), mining and manufacturing of energy-intensive products (basic metals, non-metallic mineral products, refined petroleum products, chemical- and paper products). The HCI sectors account for 81.4% of total emissions during this period. The set of HCI sectors does not change when using greenhouse gas (GHG) emissions instead of carbon emissions and is stable over time when ranking sectors by emission intensity for each year[4]. Our regression results are robust to changes in the threshold for defining HCI sectors.

[3] We link the time-consistent Classification of Economic Activities 08 (WZ 2008) to the 2-digit ISIC Rev. 4 to identify carbon-intensive sectors in the administrative labour market data.

[4] Table 5 in the annexes shows the development of sectoral carbon intensity over time for sectors in the top deciles of the distribution. There was a decreasing trend in carbon intensity in many sectors. Still, the HCI sectors are relatively more carbon-intensive than the remaining sectors during the sample period.

Figure 2. The high-carbon intensity (HCI) sectors

Distribution of average CO2 intensity (2000-2016)

Note: The red bars indicate the sectors in the top two deciles of the distribution (HCI sectors).
Source: Authors´ calculations based on WIOD Environmental Accounts and OECD Stat.

Employment in HCI sectors accounted for 6.4% of the workforce in 2019 (Table 1). Figure 3 shows how the share of workers employed in HCI sectors differs across local labour market regions and how it has changed from 1993 until 2019. Two patterns stand out. First, the share of workers in HCI sectors in all regions has decreased over time, consistent with the strong reduction of carbon emissions since 1990. In 2019, no local labor market in Germany had more than 15% of employees employed in the HCI sectors. Second, clusters of carbon-intensive activity exist in Eastern and Western Germany, and employment in HCI sectors has declined in all of these clusters since 1993.

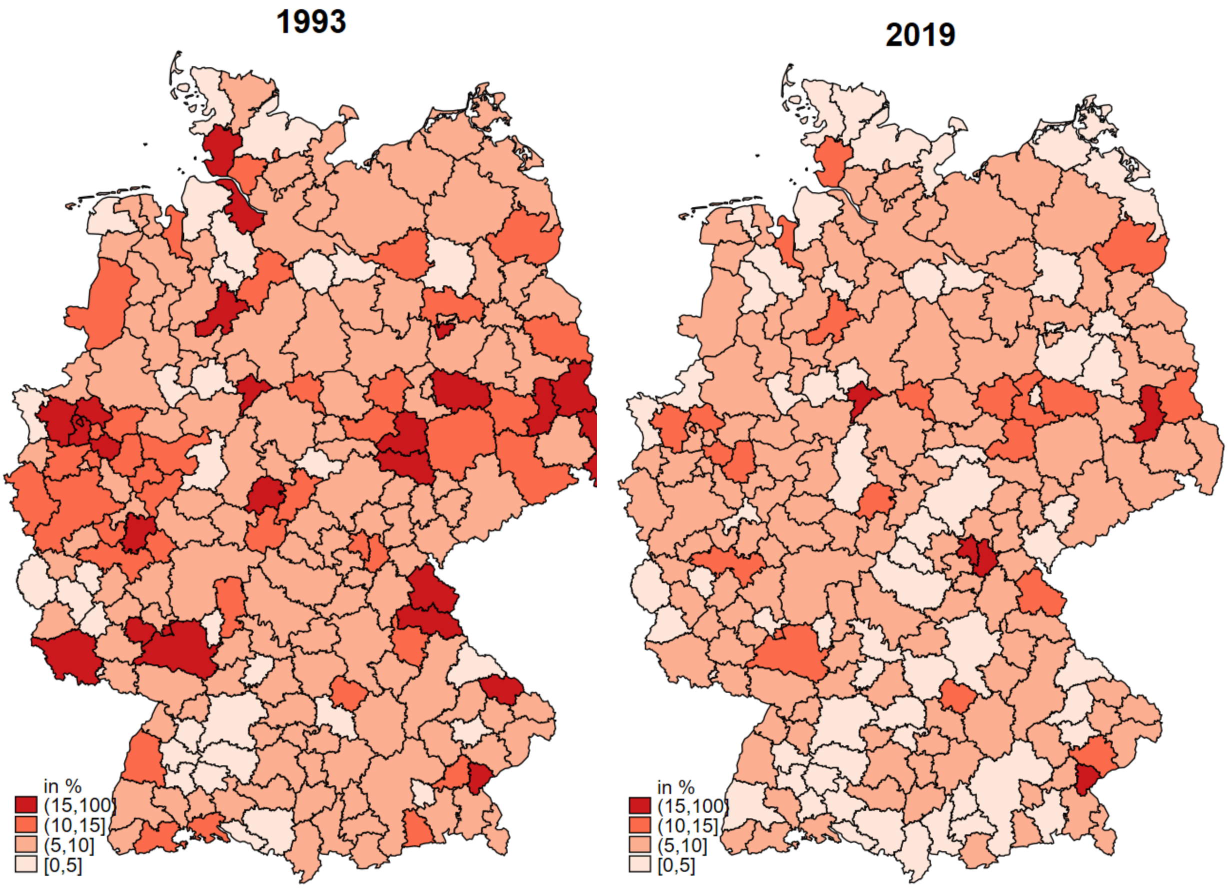
Table 1. Employment in the HCI sectors, 2019

Sector	Carbon-intensity (in tons per million EUR of value added)	GHG-intensity (in tons per million EUR of value added)	Employment share (in %), 2019
High-carbon-intensity sectors, simple average	**2973**	**2552**	**6.4**
Electricity, gas, steam and air conditioning supply	7769	6904	0.69
Water transport	6557	3860	0.05
Air transport	4250	3097	0.20
Manufacture of basic metals	2956	2170	0.87
Manufacture of coke and refined petroleum products	2635	4070	0.07
Manufacture of other non-metallic mineral products	2284	2174	0.64
Mining and quarrying	1544	1471	0.20
Manufacture of paper and paper products	716	677	0.38
Manufacture of chemicals and chemical products	627	696	1.03
Land transport and transport via pipelines	391	400	2.27
Low-carbon intensity sectors (all others sectors, simple average**)**	**86**	**191**	**93.6**

Note: Carbon intensity is calculated by dividing total emissions (in tonnes) by the sectoral value added (EUR million). The table shows the average carbon-intensity in 2000-2016. GHG intensity is calculated for the years 2009-2019.
Source: The OECD Environment Database, World Input-Output Database Environmental Accounts (WIOD).

Figure 3. Employment losses in high-carbon intensity sectors have been heterogenous across regions

Share of HCI workers in total employment (by labour market region)



Note: Both full-time and part-time workers are included. 223 labour market regions as constructed by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).

Table 2 shows sample means of worker characteristics for HCI and LCI sectors and pooled across all years. The characteristics differ substantially. On average, workers in HCI sectors earn 19% more, are two years older and have 1.5 years more tenure. In addition, fewer women and part-time employees work in the HCI sector. Moreover, university graduates are underrepresented in the HCI sectors and workers in the HCI sectors perform considerably more routine-manual and less non-routine tasks (notably fewer non-routine interactive tasks). Finally, establishments in the HCI are larger and pay higher establishment wage premiums (as measured by the AKM establishment FE). The task content differences align with (Consoli et al., 2016[34]), who found that brown occupations, which are over-represented in carbon intensive sectors, use lower levels of cognitive and interpersonal skills than green occupations, which are under-represented in carbon intensive sectors.

Table 2. Workers charactaristics, by sector

Variable	LCI sectors	HCI sectors	Difference (HCI vs. LCI)
Daily wage, imputed, EUR	101.61	120.27	18.65***
	(-74.08)	(-77.48)	(-0.03)
Age	41.35	42.54	1.19***
	(-11.08)	(-10.6)	(0)
Job tenure, years	6.63	8.18	1.55***
	(-7.08)	(-7.87)	(0)
Women, share in total	0.46	0.19	-0.27***
	(-0.5)	(-0.39)	(0)
German nationality, share in total	0.92	0.91	-0.01***
	(-0.27)	(-0.28)	(0)
Full-time job, share in total	0.79	0.94	0.15***
	(-0.41)	(-0.25)	(0)
Part-time job, share in total	0.21	0.06	-0.15***
	(-0.41)	(-0.25)	(0)
No vocational training, share in total	0.09	0.11	0.02***
	(-0.28)	(-0.31)	(0)
Vocational training, share in total	0.75	0.79	0.03***
	(-0.43)	(-0.41)	(0)
University degree, share in total	0.16	0.11	-0.05***
	(-0.37)	(-0.31)	(0)
Log est. Size	4.4	5.41	1.00***
	(-2.17)	(-2.18)	(0)
AKM Worker Fixed Effect	0.05	0.11	0.06***
	(-0.36)	(-0.31)	(0)
AKM Est. Fixed Effect	0.19	0.27	0.09***
	(-0.29)	(-0.26)	(0)
East Germany, share in total	0.2	0.19	-0.01***
	(-0.4)	(-0.39)	(0)
Urban area, share in total	0.72	0.73	0.01***
	(-0.45)	(-0.44)	(0)
Occ. share of ROUTINE MANUAL tasks	17.6	28.64	11.04***
	(-17.57)	(-20.88)	(-0.01)
Occ. share of ROUTINE COGNITIVE tasks	11.28	11.6	0.32***
	(-11.28)	(-10.95)	(-0.01)
Occ. share of NON-ROUTINE MANUAL tasks	19.79	21.03	1.24***
	(-15.85)	(-16.2)	(-0.01)
Occ. share of NON-ROUTINE ANALYTICAL tasks	25.38	20.89	-4.49***
	(-21.13)	(-19.7)	(-0.01)
Occ. share of NON-ROUTINE INTERACTIVE tasks	25.94	17.83	-8.11***
	(-17.58)	(-15.03)	(-0.01)
Observations	67,832,401	5,501,954	73,357,661

Note: Sample means over period 1992-2020. AKM Fixed Effects demeaned with the respective economy-wide average. Standard errors in parenthesis. * p<0.05, ** p<0.01, *** p<0.005.

Estimating the costs of involuntary job displacement

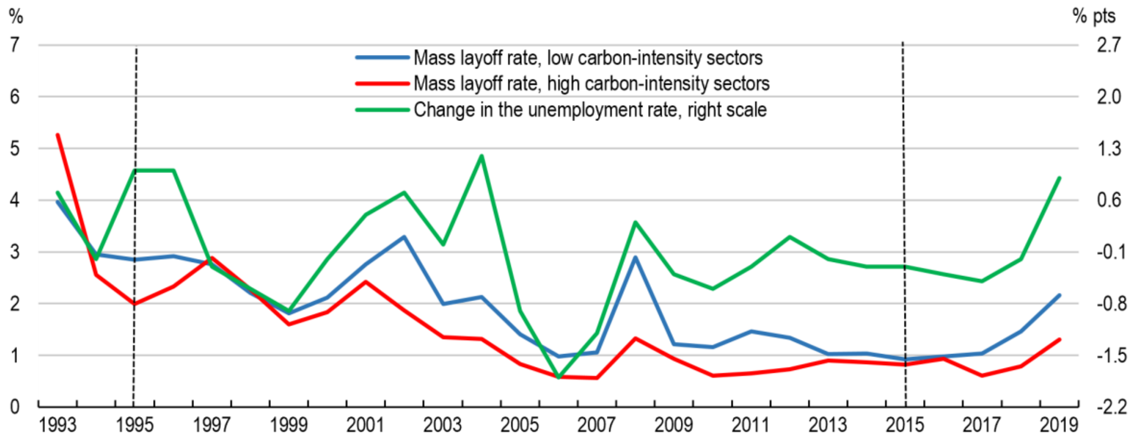
Identifying the causal effect of job displacement on the earnings losses of workers is challenging due to potential selection bias or reversed causality arising from the fact that workers lose their jobs because of their individual characteristics. For example, firms may fire workers because their performance has deteriorated or because the skill needs of the firm have changed. To address these endogeneity issues and make sure that job displacement is independent of individual characteristics, we follow the literature and investigate the labour market effects of being displaced during a mass layoff event. Mass layoff events can be assumed to be plausibly exogenous and independent of individual characteristics as the firing decision is taken for a large part of the workforce at the same time (Jacobson, Lalonde and Sullivan, 1993[8]) (Schmieder, von Wachter and Heining, 2022[9]) (Bertheau et al., 2022[14]). To estimate the clean treatment effect of job displacement, we would ideally compare labour market outcomes of the same worker in two occasions: in the event where he is losing his job, and in the event where he stays in his job. Since this is not possible, we compare each worker displaced in a mass layoff to a non-displaced worker with very similar observable individual and job characteristics by applying a two-step matching algorithm described below.

Defining mass layoff events

We follow the standard definition in the mass layoff literature (Schmieder, von Wachter and Heining, 2022[9]) and define a mass layoff event as a drop in employment from year c to year c+1 of at least 30% among all establishments with at least 50 employees. This definition includes plant closures. Moreover, we impose the restriction that no more than 20% of employees move to a single successor establishment following the mass layoff event to ensure that we capture actual displacement events rather than restructuring events, where a large part of the workforce is transferred to another firm (Hethey-Maier and Schmieder, 2013[51]). We consider mass layoff events in the baseline years $c \epsilon \{1995, \ldots, 2015\}$ to be able to observe each worker at least four years before and five years after displacement.

Figure 4 shows trends in the mass-layoff rate, according to our definition, after the German reunification (1992-2019) for HCI and LCI sectors. The share of mass layoff events is slightly higher in the LCI sectors through most years, but there are many mass-layoff events also in the HCI sector. In both sectors, mass layoffs are strongly correlated with the business cycle conditions (i.e., change in the unemployment rate). Mass layoffs are also dispersed across all regions in Germany. In total, we consider 36 749 mass-layoff events, of which 6 493 are complete plant closures.

Figure 4. Mass layoff rate by year and sector



Note: Mass layoff rate refers to the share of establishments above 50 employees where a mass layoff occurred. Vertical lines refer to the baseline years 1995 and 2015 respectively, indicating the period between which the workers in our sample are displaced.

Making displaced and non-displaced workers comparable

We construct our regression sample in two steps: First, we chose a selection of workers who fulfill our main baseline restrictions at time c. We focus on full-time employees as the German data do not provide information on hours worked. In addition, selected workers are 20-55 years old to limit the influence of early retirement during our analysis period. Excluding workers close to retirement allows to compare the results with other German studies that used the same restriction. In addition, it limits potential biases that could arise due to the heterogeneity of retirement age across time and due to data limitations on income, as we don't have data on retirement benefits in our database. Finally, we consider workers with at least two years of tenure with their main employer and in establishments with at least 50 employees in the year before displacement. Identical sample restrictions are applied for the group of potential control workers. Second, we use a two-step procedure with exact and Propensity-Score-Matching (PSM) to assign an appropriate control group to our group of displaced workers.

We define treated workers as involuntary displaced workers from an establishment where a mass layoff or a plant closure occurred between c and c+1. Each treated unit is treated only once, consistent with the idea that once a worker is displaced the first time during a mass-layoff event, it represents a permanent shock to its labour market trajectory. Moreover, treated workers are not allowed to be recalled by their original employer in the five years following displacement. Potential control workers are not displaced between c and c+1, they are allowed to be coworkers of displaced workers and may separate from their employer in subsequent years or may have been displaced before time c-2, but not because of a mass layoff event. These definitions allow us to avoid "forbidden comparisons" of treated units with units that were already treated in earlier periods (Callaway and Sant'Anna, 2021[52]) as well as an overestimation of displacement effects which could arise when restricting the control group to remain employed after c+1 (Krolikowski, 2018[53]).

Despite these restrictions, displaced and non-displaced workers may still differ according to many other observable and unobservable characteristics. To causally identify effects of job displacement, it is necessary to control for these pre-treatment differences. Therefore, we apply a two-step matching procedure to pair each treated worker with a single (similar) control unit based on observable characteristics. The procedure achieves balance in terms of observed characteristics, but importantly also in terms of untargeted moments such as permanent unobserved heterogeneity measured by AKM worker and firm fixed effects (Table 3). To investigate the differences in displacement effects between HCI and LCI sectors, we separate our sample in potential treated and control workers from LCI and HCI sectors.

The matching procedure is executed as follows. First, in each sample of HCI and LCI workers, we use exact matching to partition workers into cells defined by baseline year, 1-digit industries (ISIC rev4), and gender. The sample separation and exact matching implies that displaced workers in carbon-intensive sectors are only allowed to be matched to workers who also work in carbon-intensive sectors, have the same gender, work in the same 1-digit industry and are in the same baseline year. In the second step, we estimate a propensity score separately for each cell by using a *probit* model of job displacement on observable characteristics. As observable characteristics, we include (measured at time c): age, job tenure, dummies for education (no vocational training, vocational training and university degree), two-digit occupations (KldB 1988), German citizenship, and dummies for whether the establishment is located in East Germany and whether it is in an urban area. We also include the first and second lag of log wages to control for pre-trends in outcomes as well as establishment size with the second lag to ensure this variable is not affected by the mass layoff event. Based on the estimated propensity scores, we apply nearest neighbor matching 1:1 without replacement to assign a similar control worker to each displaced worker within each cell[5]. The two-step matching algorithm yields a highly comparable group of treated and control

[5] We use one-to-one matching as increasing the number of untreated units matched to a single treated unit typically increases the bias in the estimated treatment effect (Austin 2011).

workers (Table 3). All standardized differences are below a value of 0.1, which indicates that the observable characteristics are well-balanced (Austin, 2011[54]). In addition, the AKM worker and establishment Fixed Effects are also well-balanced, although they were not directly targeted in the matching procedure, which indicates that, on average, unobserved heterogeneity is also balanced between treated and control units in our sample. The earning trends are identical before the mass layoff, further corroborating the absence of pre-displacement differences between treated and matched control workers.

Table 3. Balance table for displaced and non-displaced workers in HCI/LCI sectors

Variable	HCI sample			LCI sample		
	Non-displaced	Displaced	Std. Diff	Non-displaced	Displaced	Std. Diff
Log wage (c-1)	4.67	4.67	-0.01	4.6	4.6	0
	(-0.4)	(-0.4)		(-0.48)	(-0.47)	
Log wage (c-2)	4.66	4.66	-0.01	4.58	4.59	0
	(-0.41)	(-0.41)		(-0.48)	(-0.47)	
Age	41.68	41.68	0	40.95	40.86	-0.01
	(-8.03)	(-8.15)		(-8.5)	(-8.44)	
Job tenure, years	8.47	8.52	0.01	7.46	7.45	0
	(-6.27)	(-6.37)		(-5.47)	(-5.61)	
Log est. size (c-2)	5.99	6.07	0.04	5.44	5.5	0.04
	(-1.52)	(-1.37)		(-1.25)	(-1.2)	
Experience, years	15.69	15.74	0	15.19	15.11	-0.01
	(-8.61)	(-8.55)		(-8.12)	(-8.03)	
No voc. Training, share in total	0.14	0.15	0.01	0.1	0.1	0
	(-0.35)	(-0.35)		(-0.3)	(-0.3)	
Voc. training, share in total	0.75	0.75	-0.01	0.76	0.77	0.01
	(-0.43)	(-0.43)		(-0.43)	(-0.42)	
University degree, share in total	0.11	0.11	0	0.14	0.13	-0.02
	(-0.31)	(-0.31)		(-0.35)	(-0.34)	
East Germany, share in total	0.32	0.32	0	0.3	0.3	0.01
	(-0.46)	(-0.47)		(-0.46)	(-0.46)	
German, share in total	0.91	0.91	-0.01	0.92	0.92	-0.01
	(-0.29)	(-0.29)		(-0.27)	(-0.27)	
Urban area, share in total	0.7	0.71	0.01	0.73	0.72	-0.01
	(-0.46)	(-0.45)		(-0.45)	(-0.45)	
Occ. share of ROUTINE MANUAL tasks	34.71	34.55	0	24.74	24.94	0.01
	(-23.46)	(-23.31)		(-21.52)	(-21.54)	
Occ. share of ROUTINE COGNITIVE tasks	12.61	12.46	-0.01	12.84	12.84	0
	(-11.84)	(-11.58)		(-12.15)	(-12.15)	
Occ. share of NON-ROUTINE MANUAL tasks	22.17	22.56	0.02	19.98	20.09	0.01
	(-16.73)	(-16.9)		(-15.07)	(-15.14)	
Occ. share of NON-ROUTINE ANALYTICAL tasks	12.14	12.07	0	16.33	16.26	0
	(-15.3)	(-15.12)		(-17.84)	(-17.83)	
Occ. share of NON-ROUTINE INTERACTIVE tasks	18.36	18.36	0	26.11	25.87	-0.01
	(-16.8)	(-16.84)		(-20.21)	(-20.17)	
AKM Worker FE	0.1	0.08	-0.05	0.09	0.08	-0.02
	(-0.26)	(-0.26)		(-0.3)	(-0.3)	
AKM Firm FE	0.3	0.31	0.05	0.23	0.23	0.02
	(-0.18)	(-0.18)		(-0.21)	(-0.22)	
Observations	8,333	8,333		73,963	73,963	

Note: Sample means of displaced workers and matched controls. Characteristics are measured at baseline year t=c, except where specified. Standard errors in brackets.

Calculating the cost of job displacement

We rely on an event study design, comparing outcomes of displaced and non-displaced workers before and after displacement separately for the HCI and LCI sectors, using the equation below:

$$y_{itc} = \alpha_i + \lambda_t + \sum_{k=-4}^{5} \gamma_k 1\{t = c + 1 + k\} + \sum_{k=-4}^{5} \theta_k 1\{t = c + 1 + k\} \times Displaced_i + X'_{it}\beta + r_{itc} \quad (1)$$

Where y_{itc} is the outcome of worker *i* belonging to cohort *c of* displaced workers and matched controls at time *t*. The coefficients of interest θ_k capture the change in outcome of displaced workers relative to the evolution of outcome of non-displaced workers in the same sector (HCI vs. LCI), where k indexes event time such that k=0 is the first post-displacement year and -1 the baseline year. The worker fixed effect α_i controls for time-invariant unobserved worker heterogeneity, λ_t is a calendar year fixed effect and X'_{it} contains age squared. Following Schmieder et al. (2022[9]), we control for year-relative-to-baseline fixed effects γ_k to account for hump-shaped earnings profiles among treated workers due to the tenure restriction. Finally, r_{itc} is the idiosyncratic error term. Standard errors are clustered at the worker level.

The cost of job displacement in the HCI and LCI sectors

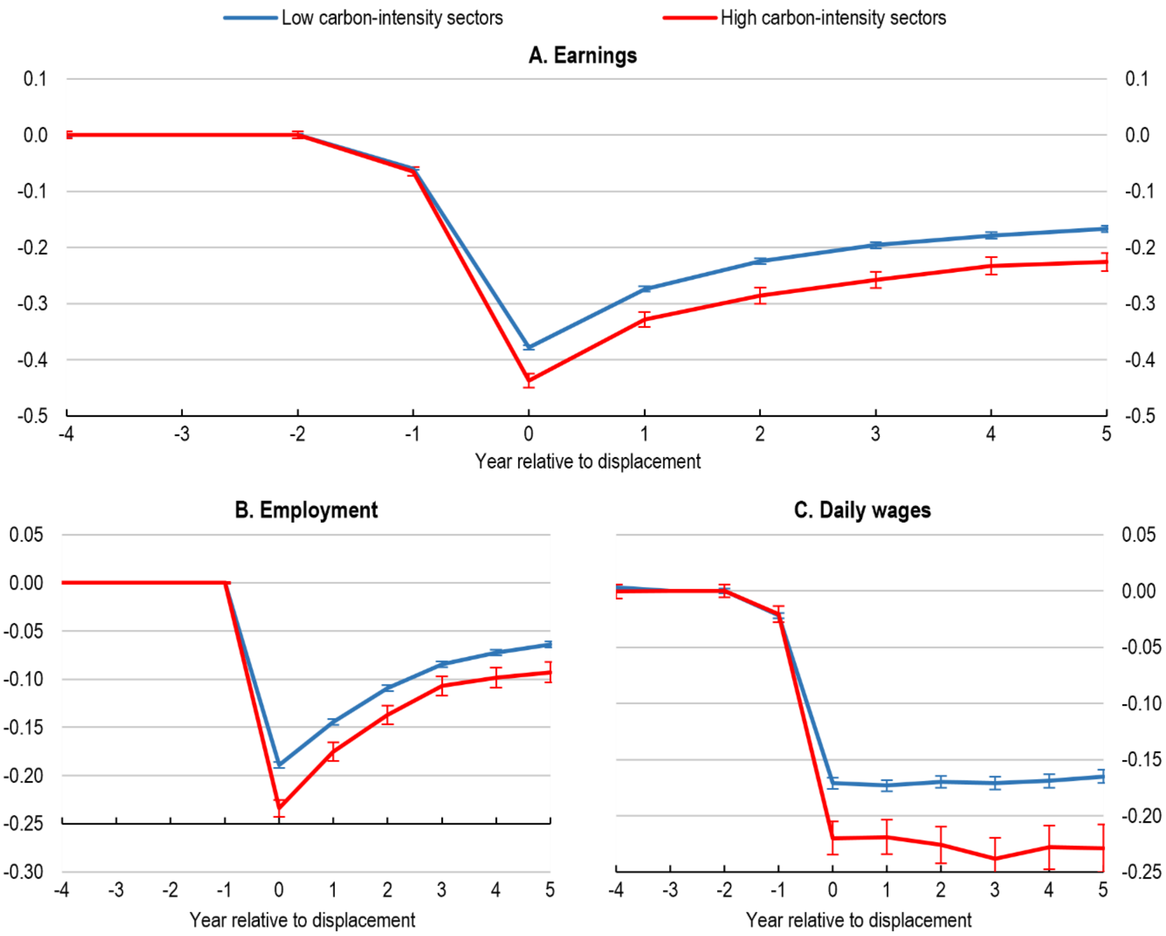
Earnings losses

We find that involuntary job losses entail a lasting and significant reduction in employment and earnings for workers in all industries. However, workers from high carbon intensity (HCI) sectors experience (on average) more elevated and more persistent earnings losses compared to displaced workers from LCI sectors (Figure 5, Panel A). Workers displaced from HCI sectors earned 43% less than their pre-displacement earnings trend in the first year following displacement (t=0), compared to 38% for workers displaced from LCI sectors. This earnings gap after displacement is persistent and amounts to 6.3 percentage points after five years. In contrast, the earnings of HCI workers that kept working in the mass-layoff establishments did not deteriorate (Figure 12 in the annexes)[6].

Earnings losses after job loss can occur due to workers' employment losses or lower wages at re-employment. Workers displaced from the HCI sector face substantially higher daily wage losses (-21.6 vs -16.9 log points in t=0) while also experiencing larger drops in the employment probability (-24% vs -19% in t=0). After five years, both groups' employment probability recovers sharply, while daily wages remain consistently below the pre-displacement level (Figure 5, Panels B & C). This indicates that, in the medium term, larger earnings losses of HCI workers are driven by persistently lower re-employment wages compared to workers displaced in LCI sectors. The fact that in HCI and LCI sectors daily wages drop already before the layoff is due to a statistical effect related to the reporting of the job separations in the data: separations refer to 30 June each year, while the yearly earnings variable reports total earnings, from all employment spells, in a given year. Thus, yearly earnings at time t-1 already reflect part of the post-displacement earnings losses (in case they were displaced after June of that year).

[6] To assess what happened to HCI workers that remained in the mass-layoff establishments, we performed a descriptive exercise by calculating the mean earnings trajectory before and after the event separately for those displaced and those who stayed in the mass-layoff establishment. Figure 12 in the annexes shows that the earnings of stayers in the mass-layoff establishment do not deteriorate but improve.

Figure 5. Displaced high carbon intensity workers suffer lasting and significant reductions in earnings



Note: Panels A, B and C show the effect of job loss on earnings relative to pre-displacement average, employment probability and log daily wages respectively. Vertical bars correspond to 95% confidence intervals based on standard errors clustered at the worker level.

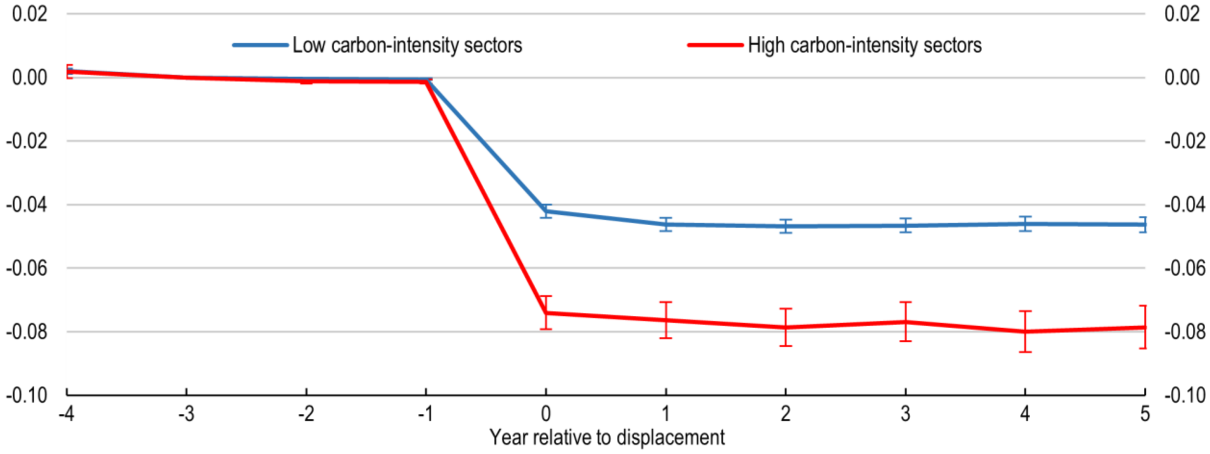
The effect on employer-specific wage premiums

The job loss literature highlights that a substantial portion of wage losses after displacement are explained by the loss of employer-specific wage premiums, with evidence for Germany (Fackler and Weigt, 2019[55]) (Schmieder, von Wachter and Heining, 2022[9]) as well as for other European countries (Bertheau et al., 2022[14]). Thus, following (Lachowska, Mas and Woodbury, 2020[41]), we estimate the event-study regression (1) using the AKM employer fixed effect as the outcome variable. We find that, on average, losses in firm-specific wage premiums are substantially higher for displaced HCI workers than for displaced LCI workers (Figure 6), while workers in HCI sectors enjoy higher firm wage premiums before displacement (Table 3 above).

Higher firm wage premia in HCI sectors may reflect productivity differences, rents, or compensating differentials for hazardous working conditions in these sectors (Card et al., 2018[56]; Sorkin, 2018[57]; Hirsch and Mueller, 2018[58]). As we do not observe firm productivity nor non-pecuniary working conditions, we cannot effectively disentangle between these explanations. However, note that high firm wage premia in HCI sectors is consistent with the history of industrial relations in these sectors. In Germany, some of the biggest and most powerful unions - such as the German Metalworkers´ Union (IG Metall) and the Mining, Chemicals, Energy Industrial Union (IG BCE) – are operating in the HCI sectors (Jäger, Noy and Schoefer, 2022[59]).

Figure 6. Displaced high carbon intensity workers suffer a more significant reduction in the establishment wage premiums

Change in the average establishment-specific wage premiums due to displacement (in percentage points)

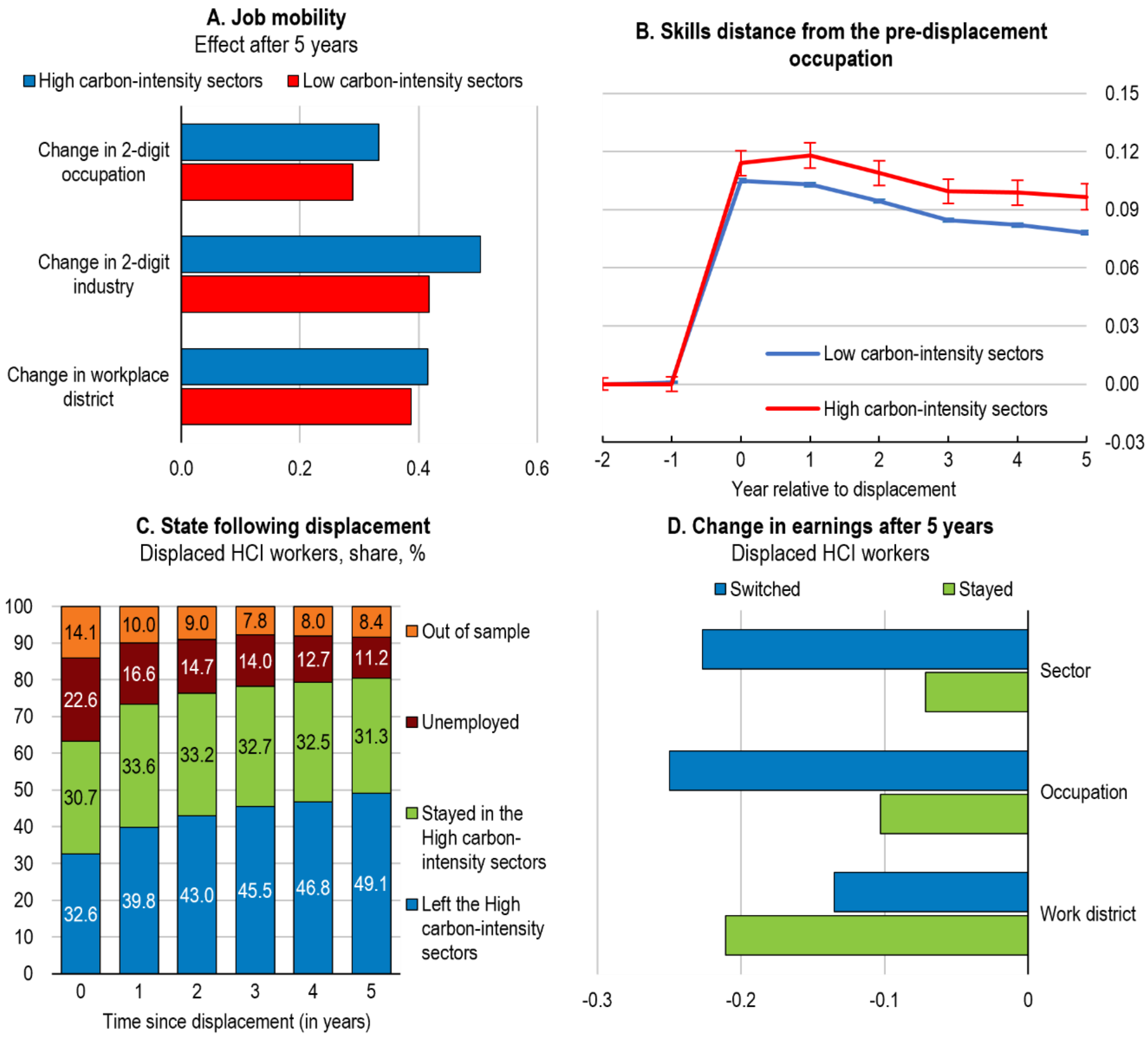


Note: Figure 6 shows the effect of job loss on AKM establishment wage premia. Vertical bars correspond to 95% confidence intervals based on standard errors clustered at the worker level. The establishment wage premiums are calculated by estimating two-way AKM fixed effects for the period 1992-2020, as in Abowd et al. (1999[18]) and Card et al. (2013[19]).

Occupational, sectoral and regional mobility after displacement

By estimating the event study equation (1) using change in 2-digit occupation, workplace district or 2-digit ISIC industry as the outcome variables, we find that displaced workers from HCI sectors are more likely to move occupation, sector and workplace district after displacement compared to workers displaced from LCI sectors (Figure 7, Panel A). These effects are conditional on re-employment, as otherwise, the occupation, region and sector are not defined after displacement. Furthermore, by using a measure for skill distance between occupations as the outcome variable, we find that if displaced workers in HCI sectors succeed in moving to another occupation, the distance between the required skill set of the new and the old job is larger than for workers in LCI sectors (Panel B). We also find that switching to employment in the LCI sector following displacement is common among workers displaced in HCI sectors (Panel C). Five years after displacement, about 49% of workers displaced in HCI sectors found jobs in the LCI sectors. However, 31% are still employed in HCI sectors.

Figure 7. Displaced high carbon intensity workers are more likely to switch occupation, sector and workplace district after displacement



Note: Panel A shows the effect of job loss on the probability to change 2-digit occupations, 2-digit sectors and workplace district at event time k=5. Panel B shows the effect of job loss on the skill distance from the pre-displacement occupation. Skill distance was measured as task distance according to (Gathmann and Schönberg, 2010[49]). It equals zero for occupations which use identical skill sets and unity for occupations that are completely different in their skill sets. Panel C shows the distribution of displaced HCI workers across different labour market states. Panel D shows the effect of job loss at k=5 among sectoral, occupational and regional switchers and stayers. Panel D refers to the sample of HCI workers. A worker is a switcher if the first post-displacement sector/occupation/region differs from the pre-displacement value at k=-1.

Switching costs

The documented sectoral, occupational, and regional mobility could influence the cost of job loss of HCI workers for various reasons. Changes in occupations and sectors following displacement could strongly increase the magnitude of earnings losses owing to the loss of specific human capital (Nedelkoska, Neffke and Wiederhold, 2015[60]); (Kambourov and Manovskii, 2009[23]) (Gathmann and Schönberg, 2010[49]). In contrast, switching workplace district could allow workers to access a larger set of re-employment opportunities and potentially mitigate their cost of job loss (Caldwell and Danieli, 2020[16]) (Duan et al., 2020[61]).

To analyze the effects for HCI workers who moved occupation, region and sector after displacement, we ran the event study regression separately for *switchers* and *stayers*. The estimated effects should be interpreted cautiously as we divide the sample conditional on post-displacement outcomes, which might bias the coefficients due to endogeneity issues. Nonetheless, the correlation can indicate whether switchers experience different displacement outcomes relative to stayers. Displacement costs for workers displaced in HCI sectors that switched occupations or economic sectors are higher than for displaced HCI workers who found a new job in the same occupation or economic sector (Figure 7, Panel D). This is consistent with Walker (2013[27]), who found that those who switch sectors face the highest earnings losses after displacement. The effect for those who switched work district, however, goes in the opposite direction. Workers who moved districts have, on average, lower earnings losses relative to stayers, hinting at the importance of regional mobility for mitigating displacement costs.

Explaining the gap in displacement costs between HCI and LCI sectors

In the previous section, we have estimated average displacement effects for workers in HCI and LCI sectors, which differ significantly. A natural follow-up question is to what extent these differences can be explained by composition effects, i.e., by differences in observable worker and job characteristics between the displaced workers in HCI and LCI sectors. Although our matching procedure ensures that we account for differences between displaced and non-displaced workers in the estimation of displacement effects, compositional differences remain between displaced workers from the HCI sector and the LCI sector (Table 3). For example, displaced workers in the HCI sector are older, less educated, and concentrated in specific occupations and regions. These compositional differences could explain why a systematically different cost of job loss is observed for those displaced from the HCI sector.

To analyse the role of the different observable worker and job characteristics for explaining the gap in displacement costs between HCI and LCI sectors, we estimate an Oaxaca-Blinder decomposition based on the matched differences-in-differences design on the pooled sample of all workers, in which each displaced worker (D) has a matched non-displaced control worker (ND). An estimate of the individual treatment effect on outcome y for displaced worker *i* with baseline year *c* is given by the difference in mean outcomes between the displaced workers and their matched controls (ND) in the periods before and after the treatment, i.e.:

$$\Delta y_{ic} = \left(\bar{y}^{D}_{i,after} - \bar{y}^{D}_{i,before}\right) - \left(\bar{y}^{ND}_{i,after} - \bar{y}^{ND}_{i,before}\right) \tag{2}$$

Where $\bar{y}^{h}_{i,after}$ indicates the average outcome for $h \in \{D, ND\}$ after job displacement (0 to 3 years) and $\bar{y}^{h}_{i,before}$ the corresponding average outcome before job displacement (-4 to -2 years).[7] The individual level treatment effect Δy_{ic} allows us to write separate linear models for displaced workers from HCI and LCI sectors:

$$\Delta y^{k}_{ic} = X^{k}_{ic}\beta^{k} + \vartheta^{k}_{ic} \tag{3}$$

Where $X^{k}_{ic}, k \in \{HCI, LCI\}$ is a vector of worker, job, firm and regional characteristics measured before displacement and ϑ^{k}_{ic} is an error term. Based on (3) and using the LCI displaced workers as the reference group, the mean difference in the displacement effect between HCI and LCI sectors (e.g., the observed earnings gap between workers displaced in HCI and LCI sectors) can be written as:

$$\Delta\bar{y}^{HCI}_{ic} - \Delta\bar{y}^{LCI}_{ic} = \left(\bar{X}^{HCI}_{ic} - \bar{X}^{LCI}_{ic}\right)\beta^{LCI} + \bar{X}^{HCI}_{ic}\left(\beta^{HCI} - \beta^{LCI}\right) \tag{4}$$

[7] Following the existing literature, we use a slightly shorter post-displacement period of three years for the decomposition compared to the estimation of displacement effects, which includes five years (Illing, Schmieder and Trenkle, 2022[17]). This avoids selecting the sample conditional on being employed for five years after displacement.

The first component of the decomposition measures the "explained" part i.e., how much of the difference in displacement effects between HCI and LCI workers are explained by differences in observable characteristics of these two groups. The explained part also allows quantifying the contribution of each characteristic in explaining the gap in the displacement effect. The second part of the decomposition represents the "unexplained" part, measuring the part of the overall gap in displacement effects that is due to structural differences between groups concerning the effects of observable characteristics on outcomes (differences in coefficients;) or due to potentially omitted (unobserved) variables.

The Oaxaca-Blinder decomposition is sensitive to the choice of the reference group. In our baseline results, we use the coefficients of the workers displaced in LCI sectors as the reference group coefficients, as workers displaced from LCI sectors represent most displaced workers in our sample (88%), while LCI workers account for over 90% of all workers. Thus, their coefficients approximate how a given characteristic affects the cost of job loss in Germany for the majority of workers. Nonetheless, to ensure that our results are not driven by the selection of a particular reference coefficient, we also estimated a pooled Oaxaca-Blinder decomposition, which uses coefficients from a pooled model including a group dummy, and a Gelbach (2016) decomposition[8]. Results remain robust in both cases (Figure 13).

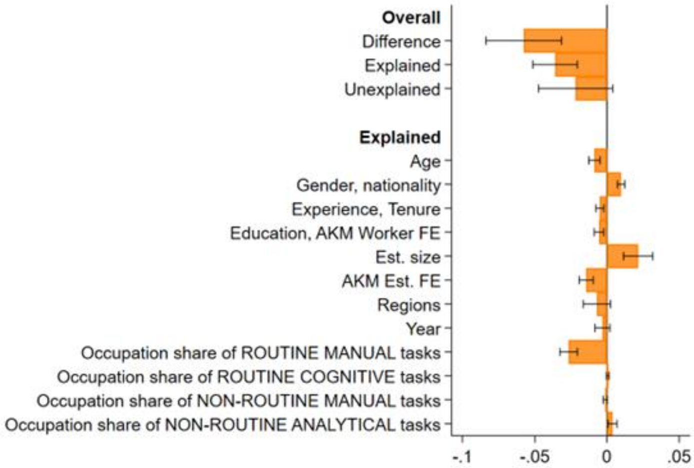
Decomposition Results

Figure 8 shows the decomposition results for the difference in earnings losses between HCI and LCI sectors. Overall, about two-thirds of the gap can be explained by differences in observable worker, job, or firm characteristics. A significant part of the earnings gap is explained by the occupational structure in carbon-intensive sectors. The higher concentration of routine-manual tasks among HCI displaced workers is the most relevant explanatory factor for the earnings gap, explaining around 42% of the gap. This is in line with other studies showing that employees with high routine-manual task component in their pre-displacement occupation experience higher earning losses after displacement (Blien, Dauth and Roth, 2021[18]; Arntz, Ivanov and Pohlan, 2022[15]; Helm, Kügler and Schönberg, 2023[62]; Athey et al., 2023[63]). The underlying mechanism refers to the well-documented general decline in routine occupations due to technological change and offshoring, which in turn implies that displaced workers' face scarcer job opportunities in their local labor markets (Hummels, Munch and Xiang, 2018[5]; Autor, Levy and Murnane, 2003[64]; Autor, Dorn and Hanson, 2015[6]). Workers faced with a shrinking number of jobs with similar skill requirements may be forced to experience longer job searches and be more likely to switch to occupations with different skill requirements, where they cannot fully use their accumulated specific human capital and thus earn lower wages (Kambourov and Manovskii, 2009[23]; Huckfeldt, 2022[65]). As shown in the previous section, HCI workers indeed have a lower re-employment probability, are more likely to switch occupations and, conditional on switching, move to occupations with more different skill requirements compared to the pre-displacement job and face larger earning losses.

[8] Instead of using LCI displaced as the reference group, we estimate a pooled Oaxaca-Blinder decomposition, which uses coefficients from a pooled model over both HCI and LCI displaced as the reference category (including a group dummy in the regression to purge the estimates from any HCI-specific effect, following Fortin (2008[70])). In addition, we estimate a Gelbach (2016[71]) decomposition, which, applying the omitted variables formula, decomposes the difference in coefficients (not means) into the contribution of each explanatory variable. We find that both quantitatively and qualitatively, both decomposition methods yield similar results to our baseline decomposition in terms of the contributions of the explanatory variables (Figure 13).

Figure 8. Two-thirds of the gap in the job loss effect could be explained by workers' and establishments' characteristics

Oaxaca-Blinder Decomposition of Earnings



Note: Figure shows the contribution of observable and unobservable characteristics to the difference in displacement effects between HCI and LCI sectors. Bars indicate 95% confidence intervals based on standard errors clustered at the district level. Some of the explanatory variables are grouped to ease reading the chart.

To shed further light on the occupational structure and human capital specificity in high-carbon intensive sectors, Table 4 shows the occupations in which the share of HCI displaced workers (out of all HCI displaced workers) is higher than the share of LCI displaced workers (out of all LCI displaced workers), meaning these are occupations in which displaced workers in the HCI sample are overrepresented relative to displaced workers in the LCI sample. We also present the main task type for the occupation and the average skill distance between the respective occupation and the available set of occupations in the local labor market[9]. Displaced HCI workers are overrepresented in 23 out of 83 2-digit occupations in the data. Miners, chemical and ceramics workers as well as machinists are examples of occupations overrepresented among displaced HCI workers. In line with the decomposition results, occupations where displaced HCI workers are overrepresented employ predominantly routine-manual tasks: out of the 23 occupations, 17 have mainly routine-manual tasks.

[9] The skill distance to the available set of occupations in the local labour market is calculated in the spirit of Macaluso (2023), by weighting pairwise skill distances with the employment share of workers from destination occupation *o* in the local labor market *r*. This weighting of skill distances gives a larger weight to distances to destination jobs that are plentiful in the displaced workers' local labour market. As the measure varies by local labour market for a given occupation depending on the local job mix, Table 3 shows the average skill distance across all local labour markets.

Table 4. Occupations, task content and skill distance among HCI displaced workers

Occupation (2-digit KldB 88)	Share of HCI displaced from this occupation	Share of LCI displaced from this occupation	Overrepresentation in HCI sample (difference between the first two columns)	Main task	Skill distance across regions	Median skill distance across regions	Skill distance above median
Miners	0.080	0.000	0.080	routine-manual	0.556	0.435	Yes
Surface transport occupations	0.097	0.028	0.069	non-routine manual	0.428	0.435	No
Chemical workers	0.051	0.008	0.043	routine-manual	0.415	0.435	No
Paper makers	0.036	0.004	0.032	routine-manual	0.444	0.435	Yes
Machinists and related occupations	0.048	0.017	0.031	routine-manual	0.455	0.435	Yes
Locksmiths	0.064	0.038	0.026	routine-manual	0.468	0.435	Yes
Ceramics workers	0.024	0.001	0.023	routine-manual	0.525	0.435	Yes
Building material makers	0.019	0.000	0.019	routine-manual	0.528	0.435	Yes
Glass makers	0.019	0.001	0.019	routine-manual	0.435	0.435	Yes
Moulders, Mould casters	0.017	0.001	0.016	routine-manual	0.427	0.435	No
Water and Air transport occupations	0.016	0.001	0.015	routine-manual	0.356	0.435	No
Electricians	0.047	0.036	0.011	non-routine manual	0.429	0.435	No
Metal producers, Rollers	0.011	0.001	0.011	routine-manual	0.441	0.435	Yes
Technicians	0.059	0.051	0.008	non-routine analytic	0.277	0.435	No
Chemists, Physicists, Mathematicians	0.006	0.002	0.005	non-routine analytic	0.354	0.435	No
Mineral, Oil, Natural gas quarries	0.003	0.000	0.003	routine-manual	0.637	0.435	Yes
Stone preparers	0.002	0.000	0.002	routine-manual	0.504	0.435	Yes
Mineral preparers	0.002	0.000	0.002	routine-manual	0.623	0.435	Yes
Technical specialists	0.012	0.010	0.002	non-routine analytic	0.344	0.435	No
Smiths	0.003	0.001	0.002	routine-manual	0.454	0.435	Yes
Attending on guests occupations	0.005	0.004	0.001	non-routine manual	0.438	0.435	Yes
Printer	0.007	0.007	0.000	routine-manual	0.403	0.435	No
Metal surface workers, Metal heat-treating-plant operators, Metal couting workers	0.002	0.002	0.000	routine-manual	0.413	0.435	No

Note: Share of HCI (LCI) displaced workers refers to the proportion of workers displaced from HCI (LCI) sectors that are displaced from this occupation. Overrepresentation in the HCI sample measures, for a given occupation, the difference in the shares of workers displaced from that occupation between the HCI and the LCI sample.
Source: IEB, GQCS.

Among the 23 occupations which are overrepresented among HCI displaced workers, 13 occupations show an above-median skill distance to other occupations in the local labour market (Table 4). The incomplete portability of specific human capital, which the HCI workers accumulated in their pre-displacement job, might be an important explanation for why the HCI displaced workers earn lower daily wages in their new job compared to displaced workers in LCI sectors (Kambourov and Manovskii, 2009[23]; Macaluso, 2023[22]; Yi, Mueller and Stegmaier, 2023[24]). To test this hypothesis, we include the measure of skill distance to other occupations in the same local labour market in the Oaxaca-Blinder Decomposition, while omitting the task-content measure and adding further control variables.[10] The results show that the skill distance measure (called "Skill remoteness" in the figure) contributes to explain a major part of the differences in job displacement costs between HCI and LCI sectors (Figure 9), which is mainly driven by lower wages (Appendix Figure 14). Displaced workers from HCI sectors face on average fewer outside options of jobs with similar skill requirements in their local labour markets compared to workers displaced in LCI sectors, which reduces their wages in re-employment after displacement due to imperfect portability of occupation specific human capital. This result complements earlier findings in the literature that the capacity of local labour markets to absorb displaced workers plays an important role to explain adjustment costs for workers (Yi, Mueller and Stegmaier, 2023[24]). Nevertheless, there is significant heterogeneity within occupations overrepresented among workers displaced from HCI sectors, as "Technicians", "Chemists, Physicists, Mathematicians" and "Water and Air transport occupations" show much smaller skill distances than other occupations (Table 4). This suggests that there is substantial heterogeneity in displacement effects also within the carbon-intensive sectors, depending on the pre-displacement occupation.

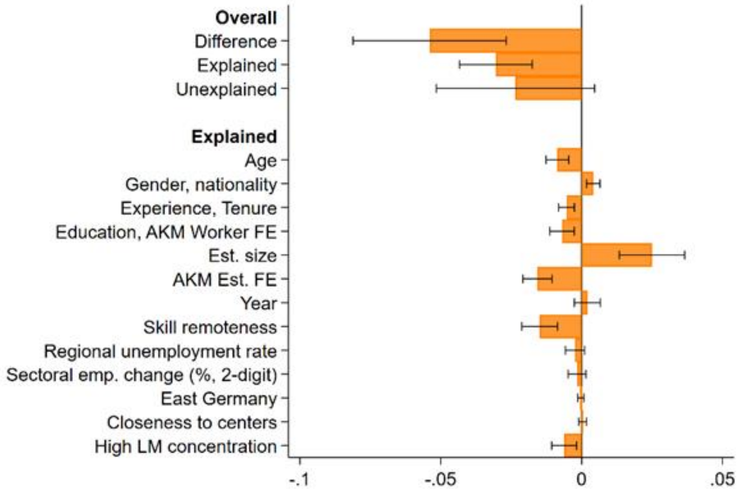
Higher displacement costs for workers displaced in HCI sectors might also be related to differences in monopsony power in local labour markets, as workers that face more concentrated labour demand receive lower wage offers (Dodini et al., 2023[25]). We test this hypothesis by additionally including a measure of local labour market concentration, which measures the concentration of labour demand among employers that displaced workers in a given two-digit occupation face in their local labour market. In the decomposition results, the significant contribution of labour market concentration indicates that the pre-displacement labour market concentration is higher for workers displaced from HCI sectors and earnings losses are on average higher for workers displaced in more concentrated labour markets (Figure 9). The results are similar for using daily wages or the employment probability as outcome variable, indicating that higher monopsony power affects post-displacement earnings both trough lower wages and reduced employment probabilities (Figure 14). The fact that the effect of the dummy for East-Germany becomes insignificant when adding the regional unemployment rate to the specification indicates that higher displacement costs for displaced HCI workers in East-Germany are also related to the amount of other unemployed workers in local labour markets in East Germany.[11]

[10] For a future version of the paper, we will re-run our regression results to present Appendix tables where we add control variables one by one. We were not able to rerun regressions due to technical issues at the IAB in Nürnberg caused by floods, preventing us from rerunning regressions on the micro data so far.

[11] Additional results will be presented in a future version of the paper and are available from the authors upon request.

Figure 9. Human capital specificity and local labour market concentration play an important role in explaining differences in displacement costs

Oaxaca-Blinder Decomposition of Earnings (with augmented control variables)



Note: Figure shows the contribution of observable and unobservable characteristics to the difference in displacement effects between HCI and LCI sectors. Bars indicate 95% confidence intervals based on standard errors clustered at the district level. Some of the explanatory variables are grouped to ease reading the chart.

Differences in worker characteristics such as age, education, experience, gender, and nationality are also relevant for explaining the difference in displacement effects between HCI and LCI sectors, although each of them they play a smaller role relative to the occupational characteristics. For example, older workers have, on average, higher displacement costs – probably due to the loss of accumulated job-specific experience or age discrimination in the labour market – and represent a larger share of workers in HCI sectors (Salvanes, Willage and Willen, 2022[66]). This explains about 1 p.p. of the higher earning losses for workers displaced in HCI sectors (which is about 15% of the overall difference of displacement effects between the HCI and LCI sectors). The lower concentration of women in HCI sectors reduces the difference in displacement costs between HCI and LCI sectors, as women have on average higher earnings losses after displacement (Illing, Schmieder and Trenkle, 2022[17]).

Differences in establishment characteristics also significantly contribute to explain larger displacement costs in HCI sectors. Establishment wage premiums account for 25% of the earnings gap, as workers displaced in HCI sectors are concentrated in establishments with higher establishment premiums, which are lost at separation, in line with the previous event study estimates and the empirical literature (Figure 6) (Fackler and Weigt, 2019[55]) (Bertheau et al., 2022[14]) (Schmieder, von Wachter and Heining, 2022[9]). In Germany, some of the biggest and most powerful unions are operating in the HCI sectors and this could be explanatory of high wage premia (Jäger, Noy and Schoefer, 2022[59]). Wage premia could also reflect compensating differentials in HCI sectors, or firm-specific productivity (Card et al., 2018[56]; Sorkin, 2018[57]). Due to data limitations, we are unable to disentangle these different channels, which are left for future research. In contrast to the firm wage premium, establishment size differences reduce the explained earnings gap, as workers displaced in HCI sectors used to work for larger establishments and being displaced from larger establishments is associated with a lower cost of job loss conditional on firm wage premia. The positive effect of establishment size on post-displacement earnings could reflect that large firms are associated with hard-to-observe attributes, which have a positive effect on post-displacement earnings, such as better training provision, co-workers networks and technology adoption (Arellano-Bover, 2022[67])

We also investigate the contribution of business cycle conditions to explain the gap in displacement costs between HCI and LCI sectors. If HCI workers would have been displaced disproportionally more often in recession years, which has been found to lead to higher displacement costs, this may explain the gap in displacement costs between HCI and LCI sectors (Schmieder, von Wachter and Heining, 2022[9]). The fact that the year dummies are insignificant indicates that this does not significantly drive the observed difference in displacement costs. To further check, whether our local skill distance and labour market concentration variables might capture general differences in local labour market conditions, we also add the local unemployment rate in each of the 223 local labour markets. Including this variable does not affect the results for skill distance and labour market concentration and its contribution is not significantly different from zero (Figure 9, Figure 14). The dummy for East-Germany is insignificant as well indicating that our local labour market specific variables already capture differences between East and West Germany that matter for displacement cost differences between HCI and LCI sectors.

Identifying vulnerable workers from the HCI sector

Earnings effects of job displacement are extremely heterogeneous across workers, regions and firms (Athey et al., 2023[63]; Gulyas and Krzysztof, 2020[68]). Investigating the heterogeneity in displacement effects for a given set of observable characteristics can help improving the targeting of support towards workers particularly vulnerable to job loss in HCI sectors. To identify vulnerable groups of HCI workers, we rely on the matched difference-in-difference approach described above. After pooling displaced workers from HCI and LCI sectors, while still matching them only with control workers from the same sector as described above, we regress the individual level treatment effect Δy_{ic}^{DID} (the earning loss) on a sector dummy (HCI/LCI), control variables representing the (pre-displacement) worker, job and establishment characteristics (X_{ic}) and an interaction variable:

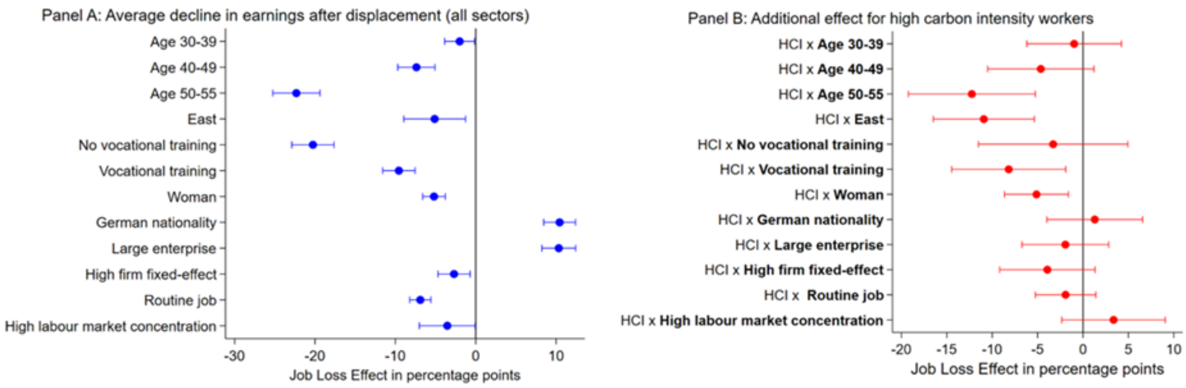
$$\Delta y_{ic}^{DID} = \beta_0 + \beta_1 HCI_{ic} + \beta_2 X_{ic} + \beta_3 (HCI_{ic} \times X_{ic}) + \epsilon_{ic} \quad (5)$$

The interaction ($\beta_3 (HCI_{ic} \times X_{ic})$) measures whether workers with a given characteristic who are displaced from the HCI sector experience an additional displacement effect, i.e. if they are particularly vulnerable to job loss relative to their LCI counterparts. The base effect represents the effect for LCI workers, which we interpret as the economy-wide average effect. Note that, as X_{ic} controls for observable characteristics, these effects control for worker composition. Thus, this additional displacement effect for workers displaced in HCI sectors corresponds to the term on the right-hand side in equation (4). Panel A of Figure 10 shows the base effects, which we interpret as the economy-wide average. Older, low-skilled (as measured by not having obtained a VET or university degree) and female workers as well as workers in jobs with high-routine task content experience steeper earning losses due to involuntary job displacement on average. Workers who work in East Germany or in highly concentrated labour markets also suffer from higher displacement costs, indicating that regional labour market conditions, affecting workers outside options, play an important role in explaining displacement costs. This is in line with the finding that switching to another local labour market after displacement is associated with a lower earnings loss (Figure 7, Panel D). Moreover, German nationals and workers in large firms show lower displacement costs on average, in line with previous literature (Illing and Koch, 2021[19]; Arellano-Bover, 2022[67]).

Figure 10, Panel B shows the coefficients for the interaction effects, which gauge the additional impact on earnings losses when workers are displaced from the HCI sectors. Workers above 50 years old, women, workers with vocational training and those in East Germany are found to have even higher earning losses if they are displaced from the High Carbon Intensity sector. The additional effects for age and vocational training might be explained by strong human capital specificity in HCI sectors, which makes it harder to use the acquired skills in other jobs after displacement. The higher displacement costs for workers displaced from HCI sectors in the East might be related to the higher amount of other unemployed workers in local labour markets in East Germany, as the effect of the dummy for East-Germany becomes insignificant when adding the regional unemployment rate to the specification.[12]

Figure 10. Older, low-skilled, and female workers as well as those in East Germany experience steeper earning losses due to involuntary displacement

Earnings Losses after Displacement by Pre-Displacement Characteristics



Note: Point estimates refer to changes in relative earnings in case of involuntary displacement. Horizontal bars indicate the estimated 95% confidence interval based on standard errors clustered at the district level. The base groups are the age group 20-29 years, having an academic degree, being male, from West Germany, without the German nationality, in an establishment with less than 250 employees, in a non-routine occupation and below the sample median AKM worker and firm FE. High labour market concentration is defined as an HHI larger than 0.15 in the corresponding labour market. A routine job is defined as an occupation with main occupation task component as routine-manual or routine-cognitive.

Robustness checks

Excluding the energy sector: The German industry classification does not allow to distinguish between renewable and brown energy generation. Thus, we re-estimate our findings excluding the energy sector altogether (Figure 15 in the annexes). Excluding the energy sector does not impact our main findings. It marginally increases the earnings gap after 5 years with respect to LCI sector from 5.9 percentage points (baseline estimate) to 6.1 percentage points.

Men only: we replicated the main event study estimates for men only, as patterns for women following involuntary job losses could be significantly different to those of men (Illing, Schmieder and Trenkle, 2022[17]). Excluding women from the sample does not affect the higher losses we document for workers displaced from the HCI sector; it even makes the patterns more pronounced (Figure 16). The reason relates to a composition effect: women are significantly more likely to work in the LCI sector and at the same time have higher average cost of job loss. Thus, in our baseline estimates, they mechanically increment the losses for LCI workers and reduce the gap with respect to the HCI sector. Results for other outcomes (e.g., job mobility, skill-distance, decomposition) are also robust and more pronounced for the sample of men and available upon request.

Plant closures and mass-layoff events. In our baseline estimates we pool workers displaced from both mass-layoff and plant closure events. Even though we control for pre-displacement trends, one can still argue that workers displaced in mass-layoff events could still be affected by selection biases, as

[12] For a future version of the paper, we will re-run our regression results with the same set of control variables as for the Oaxaca-Blinder Decomposition in Figure 9. We were not able to rerun regressions due to technical issues at the IAB in Nürnberg caused by floods, preventing us from rerunning regressions on the micro data so far.

establishments could decide to lay off workers with low abilities or bad matches. If this negative selection was more present among establishments in HCI sectors, this would bias our estimates towards finding larger losses for HCI workers. Therefore, we restrict the sample to workers displaced from plant closure events, defined as events where 90% or more of the workforce is laid off. Consequently, these displaced workers are less likely to be negatively selected. Figure 17 in the annexes shows the resulting earnings losses by type of event. In both cases, we observe higher losses for workers displaced from the HCI sector. The earnings gap after five years is 4.9 percentage points for closure events relative to 6.5 percentage points for mass-layoff events.

East and West Germany. Our observation period starts shortly after German reunification and covers a time when East Germany underwent major economic reforms. This could lead to different displacement effects for workers in East Germany. Reassuringly, our results hold for estimations on the sub-samples of East and West Germany, as shown in Figure 18 in the annexes. Nonetheless, the gap between HCI and LCI workers is more pronounced in the East, as already indicated in Figure 10.

Alternative earnings, wage and employment measures: to corroborate that our earnings results are not driven by the earnings and employment measures selection, we re-estimate the event study using alternative measures (Figure 19). First, we use (log) earnings and yearly labour earnings (in 2015 euros). The first has the advantage of excluding any missing earnings information from the unemployment/non-employment spells (recall that earnings are imputed to 0 in these spells). The latter allows checking if the change in earnings of HCI displaced is bigger also in absolute terms. In both cases, we find that the earnings loss of HCI workers is higher than that of their LCI counterparts. Second, we use another measure for employment on the extensive margin, namely the number of days in employment each year. We also provide estimates for the number of days in full-time and part-time employment. The higher and more persistent employment losses in HCI sectors remain unaltered. In addition, as the data does not have information on hourly wages, we calculate the wage effects using daily wages conditional on full-time employment. This further reassures that HCI workers experience higher wage losses after job loss and that the stagnation of wages is mainly because of the decline in wages (and less due to employment).

Concluding remarks

The green transformation of production will entail substantive changes in the labour market. Workers will have to move from polluting, carbon-intensive sectors to newly created jobs in other sectors and firms. By using German administrative labour market data coupled with data on mass-layoffs, this study investigates the adjustment costs for workers displaced in carbon-intensive industries in the last three decades. The cost of involuntary job loss is high for all workers in the economy. Still, displaced workers from high-carbon-intensity sectors have (on average) even higher and more persistent earnings and employment losses. Our results indicate that this is mainly due to human capital specificity, the regional clustering of carbon-intensive activities and higher wage premia in carbon-intensive firms. Displaced workers in the HCI sector are older, with a high proportion of men, face higher local labour market concentration and fewer outside options of jobs with similar skill requirements. On average, these characteristics lead to higher earning losses after displacement. In addition, vulnerable groups of workers such as those older than 50, women, workers with vocational training and those in East Germany, who experience steeper earning losses after displacement overall, have even higher earning losses in case of being displaced from the High Carbon Intensity sector.

The significant size of displacement costs for workers in HCI sectors emphasizes the importance of targeted support for particularly vulnerable workers. This entails the need for vocational education and training as well as adult learning courses to help displaced workers from HCI sectors to move into well-paid occupations with different skill requirements in expanding sectors and firms. Moreover, those new opportunities are often found outside one's local labour market, which suggest the need to support regional mobility. In our sample, displaced workers that were more mobile and moved to a new job outside their local labour market had lower displacement costs, indicating that policies to support the regional mobility of workers are key to mitigate the adjustment costs due to the green transition. However, due to negative agglomeration effects and the decline in consumer demand, mass transition of employees to other regions would also enlarge the hardship for the stayers (Hanson, 2023[7]). A primary challenge for policymakers is, therefore, to find the right balance between support policies that target individuals and those trying to address region-level development challenges.

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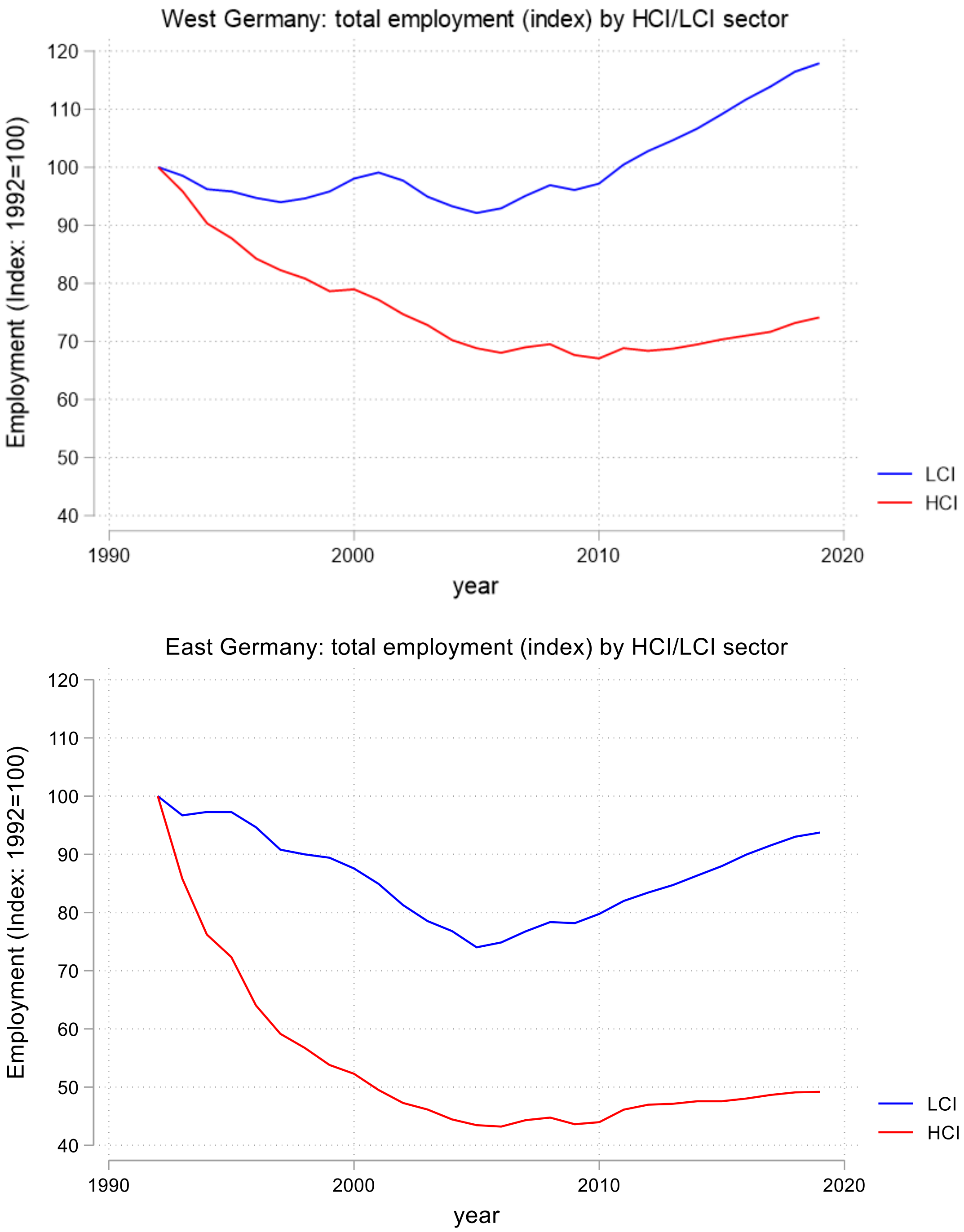
Annexes

Table 5. CO2 Intensity by sector and year

Industry	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Electricity, gas, steam and air conditioning supply	7624	8061	7884	8483	7497	7608	9098	8491	8279	6812	7043	8552	7365	7841	7727	7296	6408	**7769**
Water transport	15991	12731	10245	12645	9041	7914	9122	6155	2899	1762	2838	2268	2774	2567	3862	4179	4473	**6557**
Air transport	4390	6950	9401	8412	6273	5001	4165	3661	2107	2487	1709	1976	2517	2312	4108	3188	3595	**4250**
Manufacture of basic metals	4059	3543	3344	3799	4074	4021	3980	3981	2189	1982	2590	2216	2038	2037	2046	2084	2277	**2956**
Manufacture of coke and refined petroleum products	1315	810	1293	1600	1682	1695	1126	2058	1928	3012	2066	4748	6852	3988	3296	4070	3248	**2635**
Manufacture of other non-metallic mineral products	2384	2257	2303	2413	2427	2314	2185	2342	2324	2492	2314	2189	2174	2160	2080	2191	2276	**2284**
Mining and quarrying	1627	2133	1533	2417	2386	2452	2226	2198	1358	1260	1119	1428	777	920	857	773	783	**1544**
Manufacture of paper and paper products	752	756	748	748	734	799	698	767	828	813	768	705	617	664	638	620	514	**716**
Manufacture of chemicals and chemical products	641	602	594	659	588	630	568	627	615	678	631	686	715	687	621	593	525	**627**
Land transport and transport via pipelines	484	508	458	485	476	428	390	351	311	355	362	354	345	353	312	331	342	**391**
Crop and animal production, hunting and related service activities	134	126	117	81	60	79	78	59	456	474	481	531	525	523	459	576	572	**314**
Warehousing and support activities for transportation	555	553	463	409	361	334	316	271	217	218	218	219	213	221	220	227	223	**308**

Figure 11. Employment Trends by East/West and HCI/LCI



Note: Total employment is the sum of the full-time and part-time employment.

Figure 12. Mean Earnings for Stayers and Leavers from Mass-Layoff Events in HCI sector

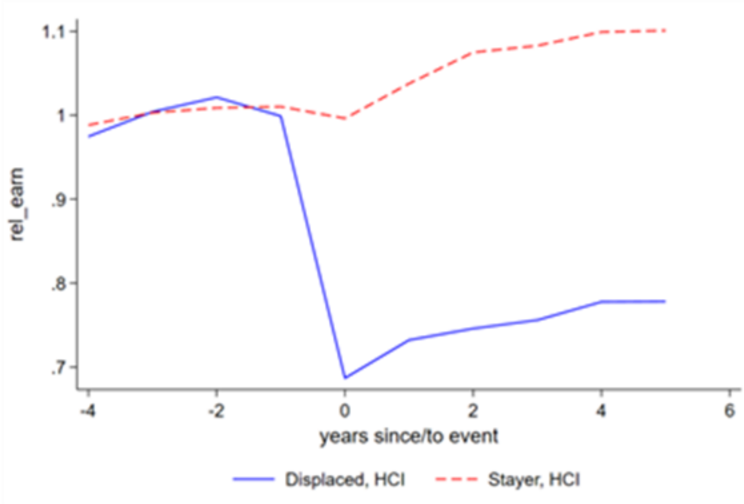
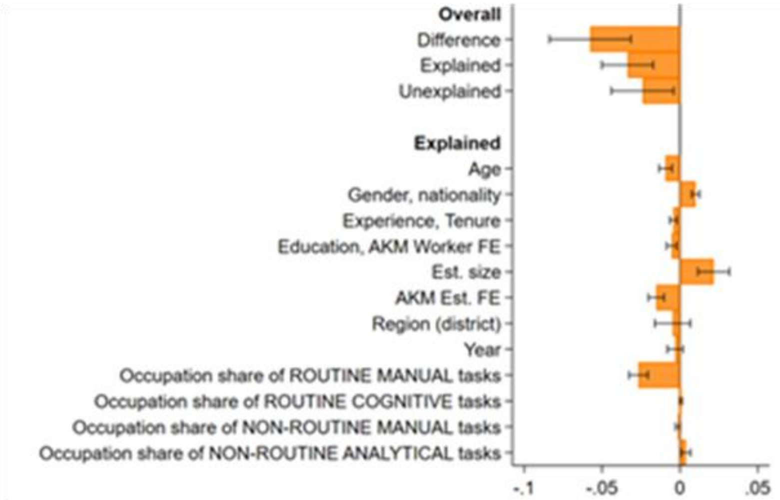


Figure 13. Alternative decomposition techniques

Pooled Oaxaca-Blinder Decomposition



Gelbach Decomposition

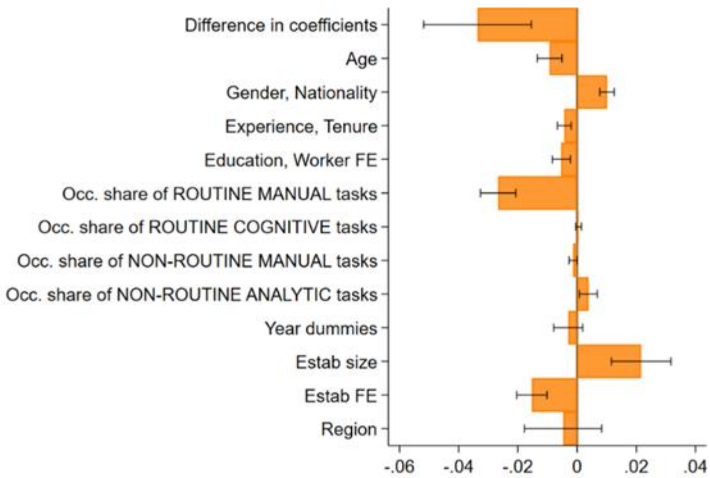
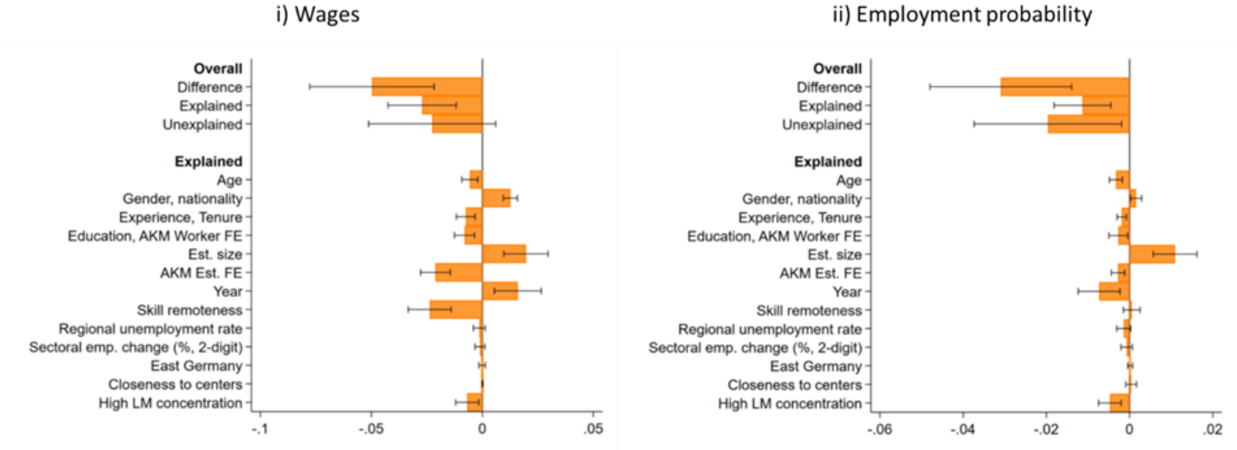


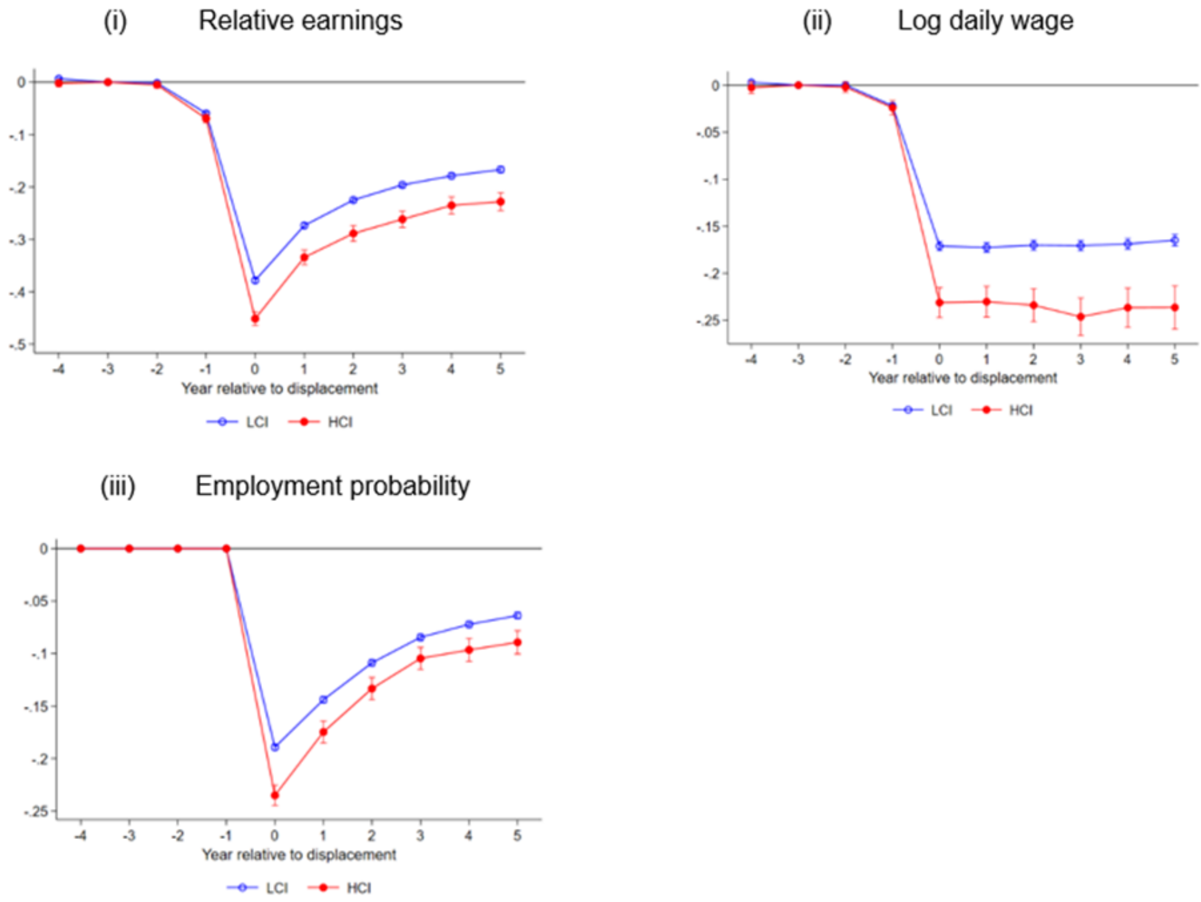
Figure 14. Human capital specificity and local labour market concentration play an important role in explaining differences in displacement costs

Oaxaca-Blinder Decomposition by different outcome variables (with augmented control variables)



Note: Figure shows the contribution of observable and unobservable characteristics to the difference in displacement effects between HCI and LCI sectors. Bars indicate 95% confidence intervals based on standard errors clustered at the district level. Some of the explanatory variables are grouped to ease reading the chart.

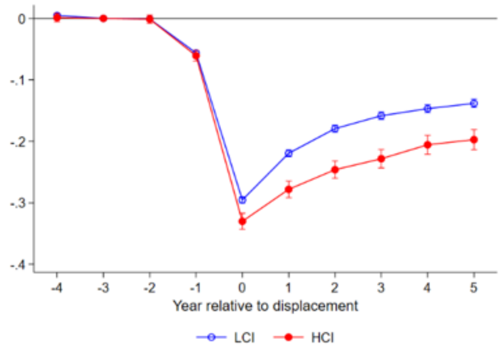
Figure 15. Event study estimates excluding the energy sector



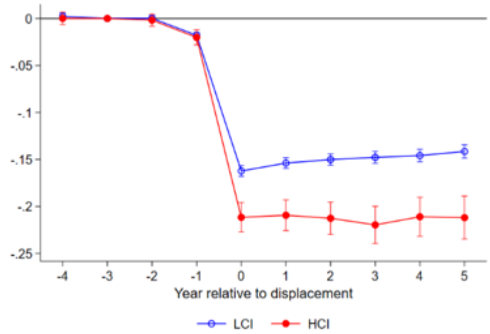
Note: Event study estimates from eq. (1). Estimates are relative to t = -3, where 0 is the first year of displacement. Vertical bars indicate 95% CI based on SEs clustered at the worker level.

Figure 16. Event study estimates for men only

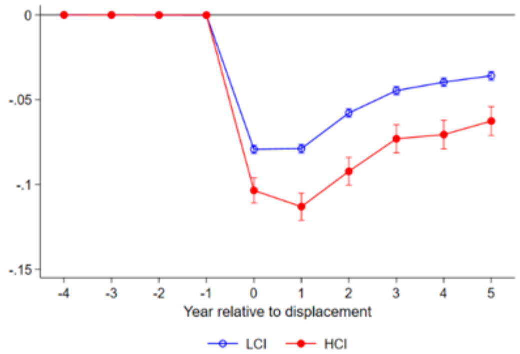
(i) Relative earnings



(ii) Log daily wage



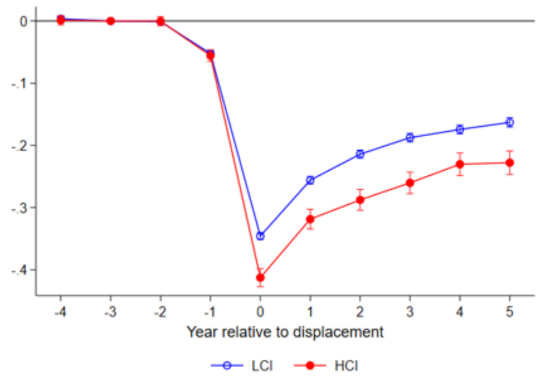
(iii) Employment probability



Note: Event study estimates from eq. (1). Estimates are relative to t = -3, where 0 is the first year of displacement. Vertical bars indicate 95% CI based on SEs clustered at the worker level.

Figure 17. Event study estimates for plant closure and mass-layoff events

(i) Relative earnings – mass layoff events



(ii) Relative earnings – plant closures

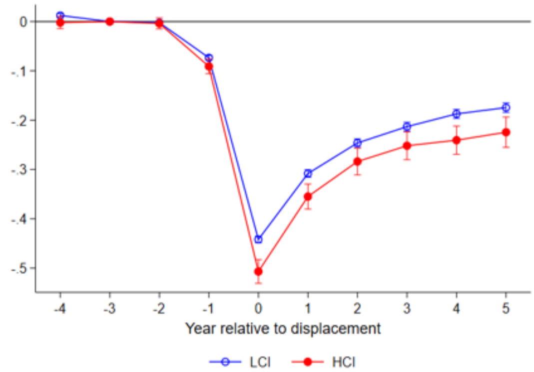
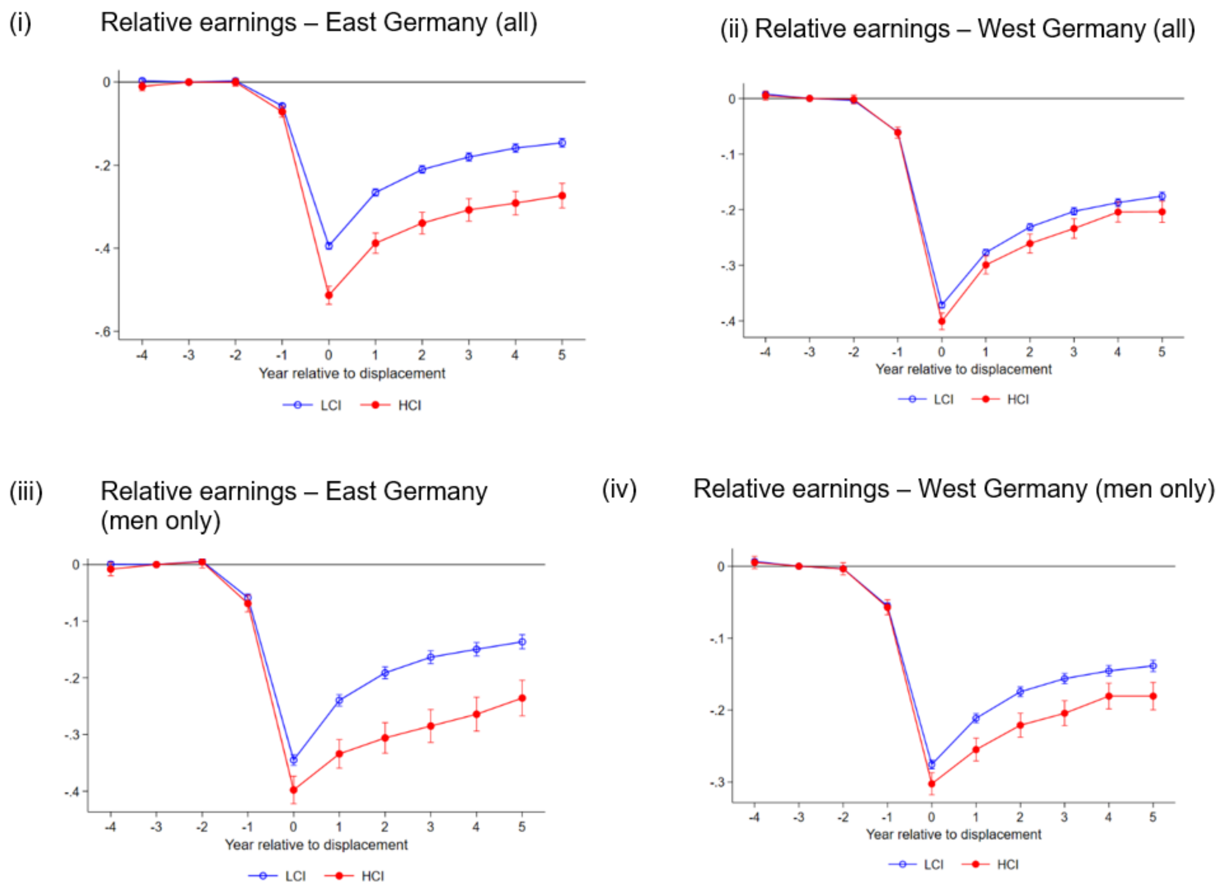
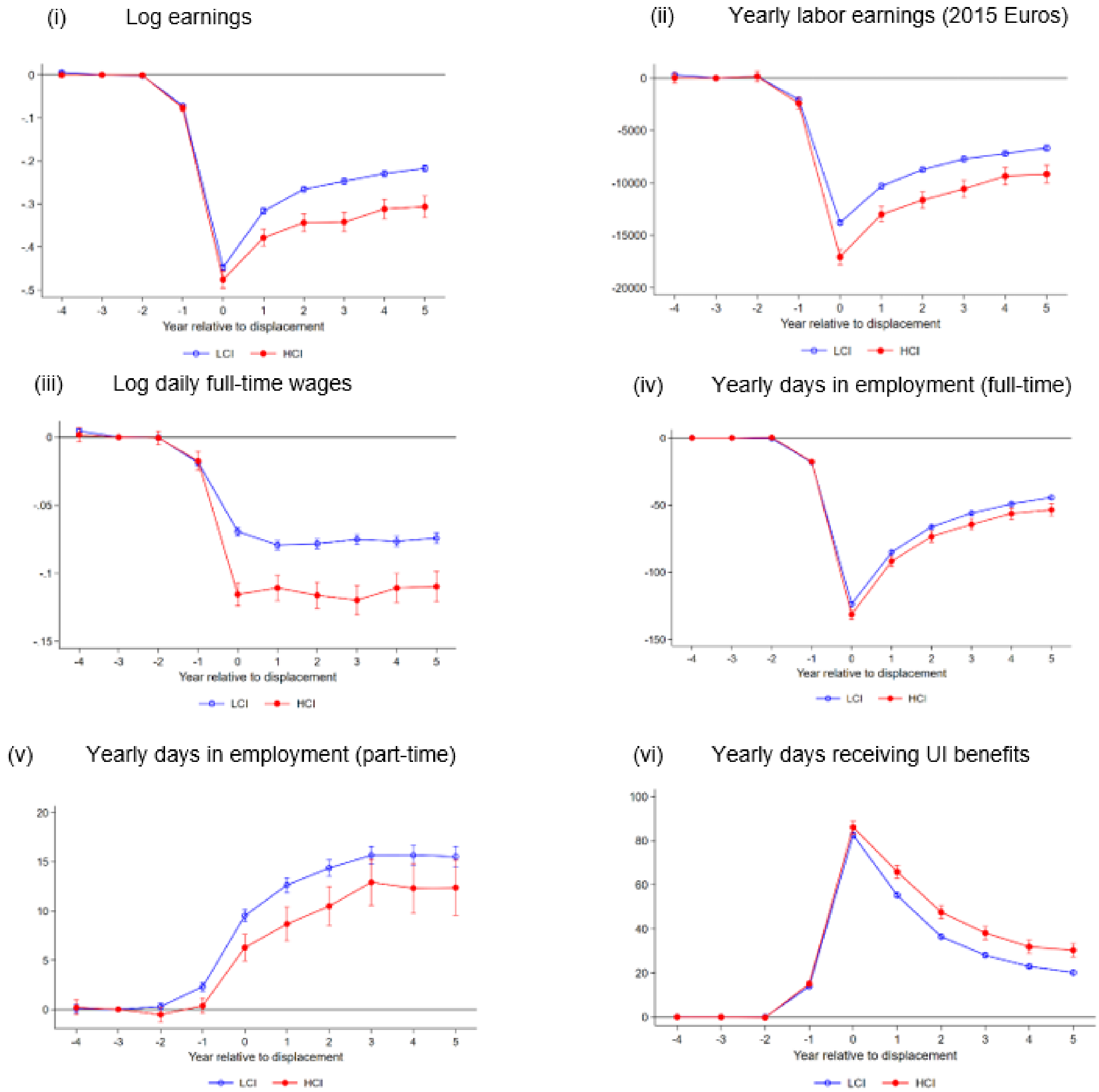


Figure 18. Event study estimates for East and West Germany



Note: Note: Event study estimates from eq. (1). Estimates are relative to t = -3, where 0 is the first year of displacement. Vertical bars indicate 95% CI based on SEs clustered at the worker level

Figure 19. Event study estimates for alternative earnings and employment measures



Note: Note: Event study estimates from eq. (1). Estimates are relative to t = -3, where 0 is the first year of displacement. Vertical bars indicate 95% CI based on SEs clustered at the worker level.