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Manufacturing Work Beyond Manufacturing Industries: A Reassessment of Structural Change

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Manufacturing Work Beyond Manufacturing Industries: A Reassessment of Structural Change*

Dominik Boddin† & Thilo Kroeger‡

October 22, 2025

Abstract

This paper studies the labor market impact of structural change by distinguishing between industry- and occupation-based measures of manufacturing and service employment. Using German data from 1975–2019, we find that 67% of manufacturing jobs lost in manufacturing industries are offset by new manufacturing jobs in service industries. Linking these aggregate patterns to worker-level outcomes, we show that the severity of displacement costs depends on the occupation–sector characteristics of the next job. Workers who retain manufacturing occupations in the service sector experience employment trajectories comparable to those remaining in manufacturing, indicating that structural change is less disruptive than commonly perceived.

JEL-classification: E24, J21, J24, J31, J63, L23.
Keywords: Employment Structure, Structural Change, Displacements, Layoffs, Occupations, Manufacturing decline, Germany.

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The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Deutsche Bundesbank or the Eurosystem.

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1 Introduction

Structural change is seen as one of the most pressing challenges for labor markets in many industrialized economies. Concerns about rapidly shrinking manufacturing employment, triggered not least by increasing trade exposure and skill-biased technical change, are omnipresent.[1]

We show, using administrative data for Germany, that structural change and the associated loss of jobs in manufacturing are less serious than has generally been perceived. Manufacturing jobs that disappear from the manufacturing sector reappear in the service sector in large numbers. These jobs offer an alternative employment option and strongly mitigate the employment decline in the manufacturing sector. A switch to the service sector after being displaced is associated with only a moderate income loss as long as the workers retain their initial manufacturing occupation. The income loss is in a similar range to that of workers who remain employed in the manufacturing sector without changing their occupations after being displaced. Our findings come out of investigating two different concepts of manufacturing and service employment: According to the industry classification of firms or establishments (hereafter "industry-based") and according to the occupation and hence the tasks of the workers (hereafter "occupation-based").

Discussions on structural change and the identification of manufacturing and service employment have predominantly relied on the industry classification of firms or establishments (the industry-based approach).[2] In this approach, the industry classification of a specific firm, often determined by its primary output, dictates whether it falls within the manufacturing or service sector. Consequently, all workers within that firm are collectively categorized as either manufacturing or service employees, irrespective of their actual occupation and the tasks they perform.

Accordingly, in the context of the industry-based approach, an assessment of the labor market consequences of structural change does not permit any statements to be made about the number of specific jobs in the economy as a whole. Instead, a shrinking number of manufacturing jobs means that there are fewer jobs in firms that mainly produce manufacturing goods. However, the loss of a job in a firm, industry or sector

[1] See, for instance, studies attributing international trade as a driving force, such as Pierce and Schott (2016), Autor et al. (2013), or Dauth et al. (2014). Digitalization is explored by Autor et al. (2003), Frey and Osborne (2017), and robotization by Acemoglu and Restrepo (2020) and Dauth et al. (2021b).

[2] For example, studies such as Pierce and Schott (2016) utilize the U.S. Census Bureau's Longitudinal Business Database, categorizing establishments based on 4-digit SIC or 6-digit NAICS industries. Similarly, Autor et al. (2013) use employment data by industry from the County Business Patterns, and Acemoglu and Restrepo (2020) enhance this data with information on wages and employment from the NBER-CES dataset for all workers in the manufacturing sector. Dauth et al. (2014) and Dauth et al. (2021b) measure manufacturing employment across a spectrum of 222 unique industries, encompassing 101 specific to manufacturing using administrative data from the German Institute of Employment Research (IAB).

does not mean that the job is generally lost in the economy as a whole. We show that jobs with the same job description appear in the service sector.

The occupation-based approach measures employment at the worker level and thus accounts for the occupational distribution and shifts at the intensive margin, i.e., changes in the workforce composition within the manufacturing or service sector. Occupations are based on the actual tasks a worker performs.[3] In the context of this paper this implies that an occupation is labeled as 'manufacturing' if workers in that occupation by nature of their tasks can directly be involved in the production of physical goods. This concept emphasizes that workers can perform the same tasks in either sector—one can drive a truck in any industry, be an office clerk or even produce a hard-drive in any industry.[4]

We document that both service occupations and, in particular, manufacturing occupations are found in large numbers in establishments for which the industry categorization (service or manufacturing) is opposite to the categorization of the worker's occupation. In 2019, the count of workers with manufacturing occupations in the manufacturing sector was only approximately 1.25 times higher than the count of workers with manufacturing occupations in the service sector.

In 1975, the service sector employed approximately 24.7% of all workers with manufacturing occupations. By 2019, this figure had risen to 42%. Also the total number of manufacturing jobs within the service sector increased by a factor of 1.6 during this period, so that workers with manufacturing occupations are increasingly finding work in service industries. We document that about 67.5% of manufacturing jobs that were lost in the German manufacturing sector between 1975 and 2019 are offset by new manufacturing jobs in the service sector.

We explicitly show that workers switch from the manufacturing to the service sector in significant numbers. Approximately half of these workers retain a manufacturing occupation. This pattern of movement is increasing over time and occurs for all manufacturing occupations.

Building on these aggregate findings, we turn to the worker-level and examine how affected workers fare along dimensions such as wages, assessing whether the service sector provides an adequate employment alternative.

In particular, we track workers in manufacturing occupations who are displaced by ex-

[3]The ILO, for instance, emphasizes that "the basis of any classification of occupations should be the trade, profession, or type of work performed by an individual, irrespective of the branch of economic activity to which he or she is attached [...]." Source: https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/

[4]See also Duernecker and Herrendorf (2022), who adopt the same approach. As an illustrative case in point, consider IBM Corporation's evolution: Originally a conventional hardware manufacturer, IBM progressively transitioned towards providing customer services from the 1990s onward (see Ahamed et al., 2013). In 1990, IBM's service segment comprised approximately 16% of total revenues, surging to 63% by 2017 (Spohrer, 2017). Ultimately, IBM underwent reclassification as a service firm upon meeting a specific threshold.

ogenous mass layoffs over time. A substantial share of these workers finds reemployment in the service sector while retaining their original occupation. To assess this alternative employment option, we match a set of laid-off workers to non-laid-off counterparts with the same initial occupation and industry, and compare their subsequent wage and employment trajectories using a difference-in-differences framework, akin to studies by Goldschmidt and Schmieder (2017), Schmieder et al. (2023) or Helm et al. (2023). To capture heterogeneity across post-layoff occupation–sector combinations, we develop a novel procedure that jointly matches sets of workers across multiple treatment states based on post-layoff employment probabilities. This approach results in matched sets of five workers (four treatments plus one control) and allows for direct comparison of treatment effects across several occupation–sector transitions, overcoming the limitations of pairwise matching in conventional designs.

The average impact of switching to the service sector reflects a decline of about 5.9% in wages when workers retain a manufacturing occupation. The magnitude of the drop in wages is about twice as large as for workers who find new employment in a manufacturing occupation-sector combination. However, this is only the case when the average pay level or establishment quality (proxied for by AKM establishment fixed effects) is not taken into account. Both the difference in costs of job loss between sector of employment and level of wage decrease almost disappears once establishment quality is controlled for. Overall, the modest income losses underscore that the service sector indeed serves as a viable employment alternative for workers with manufacturing occupations. Our analysis underscores that the loss of occupation-specific human capital is the most significant factor contributing to adverse employment outcomes following involuntary job loss during structural change.

Related Literature. This paper contributes to the growing body of research on structural change, offering a new perspective by focusing on workers' occupations rather than the industry classification of establishments. Limited recent work, such as Duernecker and Herrendorf (2022), has examined shifts in employment across occupations during structural transformation in various countries. However, most existing studies still rely on industry-based measures of structural change. For instance, Fort et al. (2018) and Ding et al. (2022) find that around 75% of the decline in U.S. manufacturing employment occurs within existing firms, while 38% of non-manufacturing employment growth originates from new non-manufacturing establishments within manufacturing firms. Similarly, Bernard et al. (2017) show that firm-level industry reclassifications drive aggregate employment changes in Denmark. To our knowledge, our paper is the first attempt to reassess the labor market impacts of structural change by focusing on workers' occupations.

Our paper also connects to the broader literature on firm employment structures and responses to economic shocks (e.g., Caliendo et al., 2015; Caliendo et al., 2020).[5] While these studies explore firms' performance and adjustment mechanisms, our focus lies on changes in labor composition within firms and sectors, emphasizing potential shortcomings in conventional measurement approaches to structural change.

Further, we extend the literature on occupational specificity of human capital and worker mobility across sectors. In line with Kambourov and Manovskii (2009), we emphasize the role of occupations in shaping employment dynamics and revisit how occupational transitions influence workers' earnings after job loss. Gathmann and Schönberg (2010) provide complementary evidence from a task-based perspective, showing that task-specific human capital accounts for more than half of wage growth—supporting our finding that workers predominantly move between related occupations with similar task structures.[6] Similarly, Moscarini and Thomsson (2007) highlight the importance of measuring workers' occupational activities, showing that roughly one-third of U.S. job-to-job switches involve no occupational change, and that many occupation changes occur without employer switches. Recently, Macaluso (2025) studied the role of skill-remoteness, highlighting that reemployment opportunities in local labor markets depend strongly on local occupational closeness to the existing skill-set. Our results for Germany align with these findings, reinforcing the central role of occupations in shaping labor market outcomes.

Our study complements research on worker displacement and adjustment costs. Jacobson et al. (1993) and Couch and Placzek (2010) document immediate post-displacement earnings losses exceeding 30%, with persistent long-term losses of 15–25% among displaced workers in Pennsylvania and Connecticut. Ashournia (2018) reports similar adjustment costs in Denmark of 10-15%. In the German context, we find comparable short-term costs when workers change both occupation and sector, but substantially lower costs when they retain either their initial occupation or sector—underscoring the mitigating role of occupational continuity.

For Germany specifically, several studies have examined related adjustment mechanisms. Schmieder et al. (2023) analyze job losses over business cycles and find persistent effects during recessions.[7] Gathmann et al. (2020) study spatial spillovers from large layoffs at "systemic" firms, while Helm (2019) explores spillovers from trade shocks,

[5]This literature encompasses: (a) reasons for structural change using industry-based classifications; (b) task-based employment changes (Grossman and Rossi-Hansberg, 2008); (c) job polarization (Bárány and Siegel, 2018; Goos and Manning, 2007; Goos et al., 2014); (d) skill-biased workforce changes (Spitz-Oener, 2006); (e) firm reorganization responding to trade shocks (Davidson et al., 2017; Caliendo and Rossi-Hansberg, 2012); and (f) occupational effects of trade (Traiberman, 2019; Helm, 2019; Dauth et al., 2021a).

[6]In contrast, Neal (1995) posits industry-specific human capital's significance, though data limitations prevented controlling for occupational changes.

[7]Davis and von Wachter (2011) present similar findings for the United States.

showing that high-tech industry clusters benefit disproportionately from export opportunities. Dauth et al. (2021a) investigate adjustments to globalization, and Blien et al. (2021) differentiate structural shifts by routine task intensity.

Most closely related to our work, Helm et al. (2023) examine the displacement effects of structural change on workers in the manufacturing sector, arguing that medium-skilled, well-paid workers are often pushed into lower-wage service occupations. Their focus on workers' relative pay (low-paid vs. high-paid) complements our emphasis on occupations and work contents in cross-sector transitions.

Moscarini and Thomsson (2007) underscore, like our work, the importance of measuring workers' activities, specifically occupations. They find approximately one-third of U.S. job-to-job switches involve no occupational change, with significant occupation switches occurring without employer changes. We observe similar patterns in Germany, emphasizing occupations' crucial role in determining labor returns.

The paper proceeds as follows: After describing the data in Section 2, Section 3 compares structural change measured by the industry-based approach versus the occupation-based approach, presenting new stylized facts on manufacturing employment decline in Germany. Then, in Section 4, we first examine the growing trend of workers in manufacturing occupations finding employment in service sectors and then present our methodology to analyze the heterogeneous costs of job loss for displaced manufacturing workers depending on their next job's occupation-sector combination as well as results alongside several robustness exercises. In Section 5, we provide a discussion on the underlying mechanisms of our findings, as well as implications for economic policy and areas of future research. Section 6 concludes.

2 Data

We rely on two detailed datasets based on social security records provided by the Institute for Employment Research (IAB) of the German Federal Employment Office, covering the period 1975 to 2019. The first is the Establishment History Panel (BHP), a detailed establishment-level dataset. The second is the Sample of Integrated Labour Market Biographies (SIAB), a longitudinal linked employer-employee dataset.[8]

These data are based on official administrative records: employers are required by law to submit reports for all employees subject to social security contributions to the responsible Federal Employment Agency ('Bundesagentur für Arbeit') at least once a year. This ensures that the data are highly reliable and not prone to misreporting.

The BHP provides comprehensive information on establishments' labor structure,

[8]For further details, refer to Antoni et al. (2019) for the SIAB and Schmucker et al. (2018) for the BHP. Comprehensive data documentation is provided in Appendix Section A.1.

occupational mix, education levels, demographics, wage structure, and industry classification. The BHP contains information on aggregate numbers by workers' occupations per establishment in a classification, which distinguishes twelve occupational groups divided into manufacturing and services (based on Blossfeld (1987) and Stops (2016)). The BHP contains the establishment's industry classification in the slightly adjusted German equivalent (WZ93) of the European NACE classification based on economic activity.

The SIAB integrates individual employee data with establishment information from the BHP, including detailed individual worker information on occupations, hierarchy levels, tenure, daily wages, schooling, and more. The SIAB data contain the worker's occupation at 5-digit level according to the "Classification of Occupations" (KldB), which can be distinguished into manufacturing and service occupations. Occupations are categorized as manufacturing if they are concerned with producing or transforming physical goods and as service if they are concerned with the provision of services, i.e., they generate or handle value-added that is intangible in nature. In Appendix Section A.1.4 we describe the occupation classification as well as how we distinguish between manufacturing and service occupations in more detail. Finally, the SIAB also contains the establishment's industry classification from the BHP.

For our purpose, one feature of both datasets is of central importance: The combined information about the occupation of the worker in addition to the industry classification of the establishment. This allows us to assess structural change by defining it as a shift in occupations and to compare this measurement to the commonly used establishment-based classifications.

3 Revisiting structural change

In this section, we compare the industry-based and occupation-based approaches to measuring manufacturing and service employment. We demonstrate substantial differences between these two measurements. In the subsequent analyses, our focus will be on West Germany, leveraging the extensive data available from 1975 to 2019.[9]

3.1 Establishment vs. occupation-based measurements

Figure 1 illustrates the evolution of industry-based and occupation-based manufacturing employment shares in Germany from 1975 to 2019. Both measurements reveal a notable decline in the share of manufacturing employment over the 45-year period. Based

[9]For simplicity, we refer to "West Germany" as "Germany" throughout the analyses. Data for East Germany are accessible from 1991 onward. The findings remain qualitatively consistent whether we concentrate solely on East Germany or consider West and East Germany together. Results are available upon request.

on the industry of the establishment, the manufacturing share in employment declines from 46.6% in 1975 to 22.8% in 2019, representing a decrease from 7.5 million workers to 6.3 million. The occupation-based measurement demonstrates a decrease from 45.4% to 27.6% during the same time-frame, corresponding to a decline from 7.3 million workers to 6.9 million.

While manufacturing employment shares decline for both metrics, there is a notable difference in magnitude. The industry-based measure shows a decrease of 23.8 percentage points from 1975 to 2019, while the occupation-based approach shows a decline of 17.8 percentage points. The discrepancy between the two measurements widens over time, peaking at 4.8 percentage points in 2019, indicative of a trend where manufacturing workers increasingly become employed in the service sector.

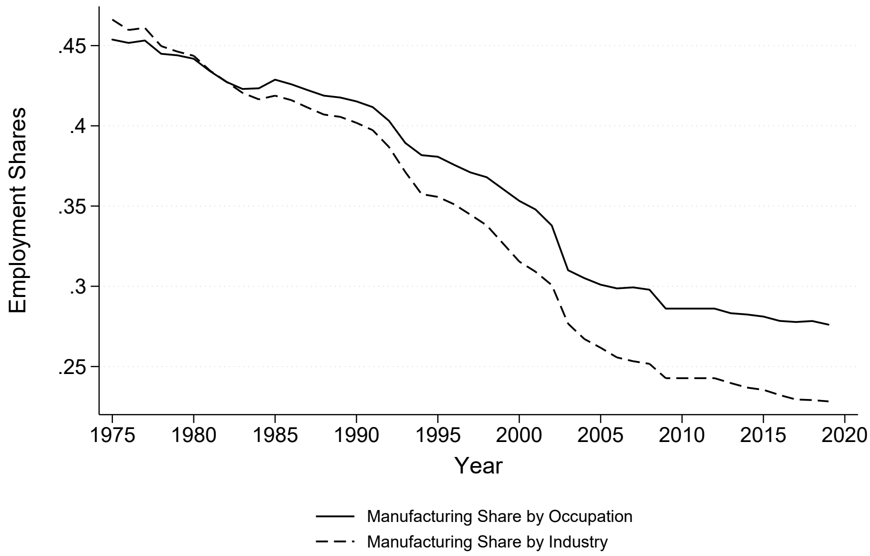


Figure 1: Manufacturing employment shares according to establishment- and occupation-based accounting methods
The graph depicts the shares in total employment for Germany either by the industry-based approach (dashed line) or the occupation-based approach (solid line). Datasource: BHP 1975-2019.

The absolute impact of this disparity shows how industry-based definitions consistently underestimate the number of manufacturing workers. On average, the number of workers in manufacturing occupations exceeded those in manufacturing establishments by 851,000, peaking at approximately 1.8 million workers in 2018—equivalent to around 4% of Germany's total workforce (see Appendix Figure A.1).

Figure 2 shows the between sector shift on manufacturing occupations outlined by the proportion of manufacturing jobs within the manufacturing sector. This share is declining from around 75% in 1975 to approximately 56% in 2019. This confirms that manufacturing workers are increasingly finding employment in service establishments.

Overall, employing the conventional industry-based approach risks overestimating structural change when the interest lies on the impact on individuals. The number of existing manufacturing jobs is consistently undervalued, leading to an exaggerated perception of the decline in manufacturing employment.

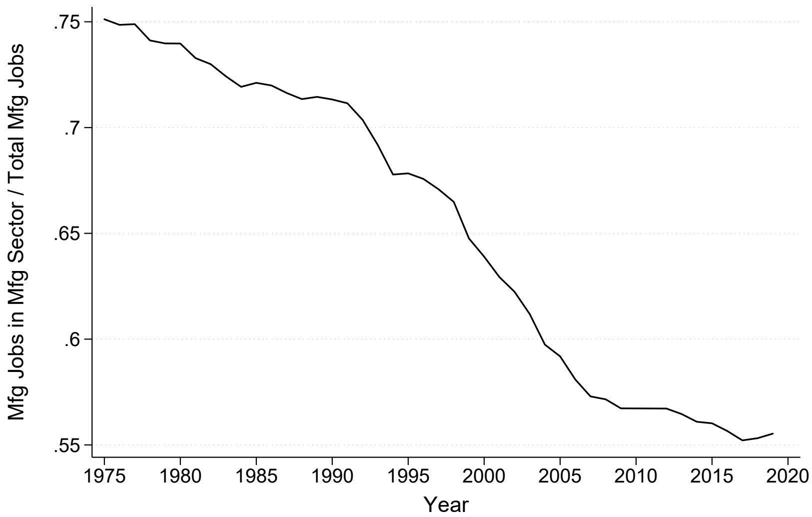


Figure 2: Share of manufacturing jobs in the manufacturing sector
The figure shows the share of manufacturing workers employed in the manufacturing sector relative to the total number of manufacturing workers in Germany. Datasource: BHP 1975-2019, Federal Statistical Office Germany.

Figure 3 shows this more clearly. The number of manufacturing jobs within the manufacturing sector declined by approximately 1.5 million (from 5.5 million to 4 million), while the number of manufacturing jobs in the service sector increased from 1.8 million to 2.9 million. Consequently, the net reduction in manufacturing jobs amounted to about 500,000 by 2019—notably lower than the frequently cited loss of approximately 1.5 million jobs in manufacturing sector employment. Around 67.5% of the manufacturing jobs lost in the manufacturing sector between 1975 and 2019 are counterbalanced by new manufacturing jobs in the service sector.

Appendix Table A.3 shows that the service sector is not merely an alternative for a select few occupations but serves as an employment option across nearly all manufacturing occupations. The share of manufacturing workers employed in the service sector increased for almost all manufacturing occupations between 1975 and 2019. On average across all two-digit manufacturing occupations, the share employed in services rose from approximately 24% in 1975 to 38% in 2019.

These aggregate patterns could in principle reflect sample composition changes rather than genuine within-establishment adjustments. However, Appendix Section A.3.3 demonstrates that our findings are not driven by (i) establishments entering or exiting the sample with different occupational compositions, (ii) establishments switching industry classifications, or (iii) workers changing occupations within establishments. En-

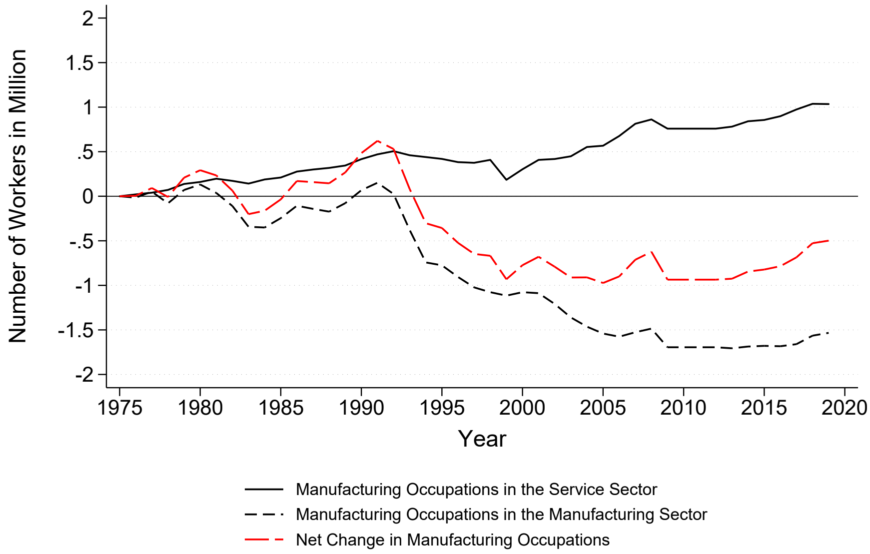


Figure 3: Manufacturing jobs in the service and manufacturing sector and net change across both sectors

The figure shows the total number of manufacturing jobs in the service and manufacturing sector (indexed to 1975=0), and the net change in manufacturing jobs across both sectors. The dashed black line and the solid black line illustrate the overall decrease and increase in manufacturing jobs compared to 1975, both in the manufacturing sector and the service sector, respectively. Additionally, the long-dashed red line portrays the net change in manufacturing occupations.
West Germany. Datasource: BHP 1975-2019.

try and exit dynamics show parallel trends across establishment cohorts, while industry reclassifications affect less than 0.02% of establishments annually—negligible compared to the documented employment shifts. Unlike Bernard et al. (2017), who find firm-level reclassifications explain 42% of manufacturing job losses in Denmark, reclassifications play virtually no role in Germany, likely reflecting our establishment-level rather than firm-level measurement. Our results therefore reflect genuine within-establishment changes in occupational composition—the intensive rather than extensive margin of adjustment.

3.2 Transition of manufacturing workers across sectors

Manufacturing workers actively transition from the manufacturing to the service sector. Figure 4 illustrates the movement of workers who originally held manufacturing occupations in the manufacturing sector and underwent changes in either their occupation or sector. Notably, there is a growing share of workers moving into manufacturing jobs within the service sector over time (grey bars). At the onset of the sample period, on average 36.1% of workers leaving a manufacturing job in the manufacturing sector secure new positions with manufacturing occupations in the service sector. By 2000-2019, this share has risen to 46.1%, reaching a peak of 60.1% in 2004.

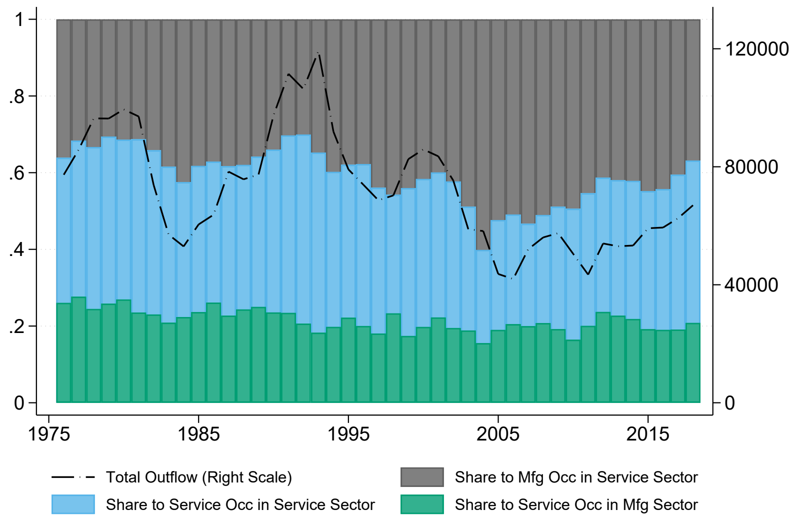


Figure 4: Outflow of manufacturing jobs from the manufacturing sector by destination
The figure shows the annual count of workers leaving manufacturing occupations in the manufacturing sector (right axis) and the breakdown by new occupation-sector combination (percentage shares, left axis). Datasource: SIAB 7519, 1975-2019.

The total influx into manufacturing jobs within the service sector also exhibits a sustained upward trend over time, rising from about 37,000-57,000 jobs annually in the 1970s-1980s to up to 82,000 jobs per year during the 2010s (see Appendix Figure A.8 for details). This observation suggests that barriers to cross-sector job transitions are sufficiently low, such that workers with manufacturing occupations transition out of manufacturing industries into service industries without switching occupation.

4 The service sector as an alternative employment option

The preceding sections demonstrated the tendency to exaggerate structural change when employment measurements rely on the establishment's industry classification rather than workers' occupations, and the service sector's capacity to absorb a substantial portion of jobs for workers with manufacturing occupations. However, for workers negatively affected by structural change, the crucial question is how wages and income are affected when workers are forced to switch sectors or occupations. While the manufacturing sector in Germany is characterized by well-paying jobs largely covered by collective bargaining agreements, the service sector is generally lower-paying and more heterogeneous in union coverage (e.g., Jäger et al., 2022). In this section, we examine the consequences for displaced manufacturing workers, first comparing wages for all workers who switch sectors before turning to causal displacement analyses. The displacement analyses serves to investigate the heterogeneity of detrimental effects when workers are losing employment in the manufacturing sector.

4.1 Wage differences across sectors

Before examining causal displacement effects, we establish baseline wage differences between sectors for workers with manufacturing occupations. Following Dube and Kaplan (2010), we estimate wage differences for workers who switch employers between sectors while maintaining their manufacturing occupation:

$$\ln(\text{wage})_{i(j)t} = \alpha_i + \gamma \text{Service}_{jt} + X'_{it}\beta + \epsilon_{it}, \tag{1}$$

where $\text{wage}_{i(j)t}$ is the wage of person i employed at establishment j at year t (in 2015 constant euros). Service_{jt} is a dummy indicating that establishment j belongs to the service sector. We are interested in the sign and size of coefficient γ, which measures the wage premium (or penalty for that matter) of the service sector over the manufacturing sector. The inclusion of person fixed effects (α_i) implies that the coefficient γ is identified through workers, who at least once changed employment between the two sectors, manufacturing and services. X_{it} includes time-variant personal characteristics such as age, age squared, and education indicators.

The results, presented in Table 1, show that working in the service sector is associated with approximately 14% lower wages on average for workers with manufacturing occupations who switch employers. This estimate includes both voluntary and involuntary switches and therefore does not necessarily represent the a causal effect of displacement. Rather, it provides important context for interpreting our subsequent causal analysis of displacement effects.

This wage gap varies considerably across occupations. In Appendix Section 4.1, Table A.4 differentiates by 47 two-digit occupations: 35 show significant negative wage premia in services (ranging up to -18.6%), while 7 show significant positive premia. These descriptive patterns suggest that the service sector generally pays lower wages for manufacturing occupations, though this does not necessarily reflect what happens to workers involuntarily displaced from manufacturing establishments. The following sections examine the causal effects of displacement, allowing us to determine whether the wage penalties faced by displaced workers who transition to the service sector are larger or comparable to those experienced by workers who remain in manufacturing establishments.

Table 1: Wage penalty of working in the service sector for workers with manufacturing occupation

	(1) coefficient	(2) std. error
Service (γ)	-.14***	(.0015)
Age	.128***	(.0002)
Age^2	-.001***	(.0000)
Years of schooling	.003***	(.0001)
College	.268***	(.0036)
Number of observations	7,909,374	
Number of groups	720,449	
R^2 (within)	0.41	
R^2 (between)	0.30	

Notes: The table reports the estimation results of Equation (1). The inclusion of worker fixed effects leads to identification of coefficient γ through workers who at least once switched employers between the manufacturing and the service sector but did not switch their occupation. Standard errors are clustered at the worker level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Datasource: SIAB 7519, 1975-2019.

4.2 Identifying displacement effects through mass layoffs

To investigate the causal effects of transitioning between sectors on workers' outcomes, we focus on mass layoffs in manufacturing establishments that impact workers with manufacturing occupations (cf., for instance, Jacobson et al., 1993; Schmieder et al., 2023; Gathmann et al., 2020). We rely on mass layoffs because alternative approaches usually cannot distinguish between voluntary and involuntary job changes. Following standard assumptions in the displacement literature, we treat mass layoffs as exogenous shocks to workers. The simultaneous dismissal of many workers within an establishment indicates that these events are driven by establishment- or market-level factors rather than individual worker characteristics.

4.2.1 Mass layoff definition and sample construction

We define a displaced worker as any full-time employed individual with at least two years tenure who is permanently displaced from an establishment during a mass layoff event. We define mass layoffs following the German Employment Protection Act: From one year to the next, a mass layoff occurs when establishments with 21–60 employees dismiss ≥5 employees; establishments with 60–500 employees reduce employment by ≥10% or ≥25 employees; or establishments with >500 employees dismiss ≥30 employees.[10]

We focus on workers employed at least two years before the layoff because labor mo-

[10]We follow the thresholds defined in the German Employment Protection Act, as it has implications on how employment relationships can be terminated. Section A.6.4 in the appendix considers a more common definition used in the literature requiring establishments with >50 employees to shrink by >30%; results remain largely unchanged.

bility in Germany declines sharply after a few years of tenure.[11] German labor regulations make layoffs increasingly difficult with tenure, irrespective of worker productivity. Both aspects render the layoff event less likely to be endogenous for the worker. Consequently, our findings can be viewed as a lower bound estimate for the costs of transitioning sectors, as voluntary switches due to improved job opportunities are likely not encompassed.

4.2.2 Layoff occurrence and job switches of displaced workers

We first present statistics on layoffs and the movement of affected workers into new employment, categorized by occupation and sector. Figure 5 illustrates the total annual number of manufacturing establishments with mass layoffs in our data (dashed-dotted line, right scale), the corresponding annual count of laid-off workers (gray bars, left scale), and the annual count of laid-off workers with manufacturing occupations (blue bars, left scale). Layoff events remain relatively stable over time, affecting approximately 2% of manufacturing establishments annually. On average, around 10,000 workers are impacted by mass layoff events each year.[12] Manufacturing workers (by occupation) consistently comprise 50–60% of displaced workers.

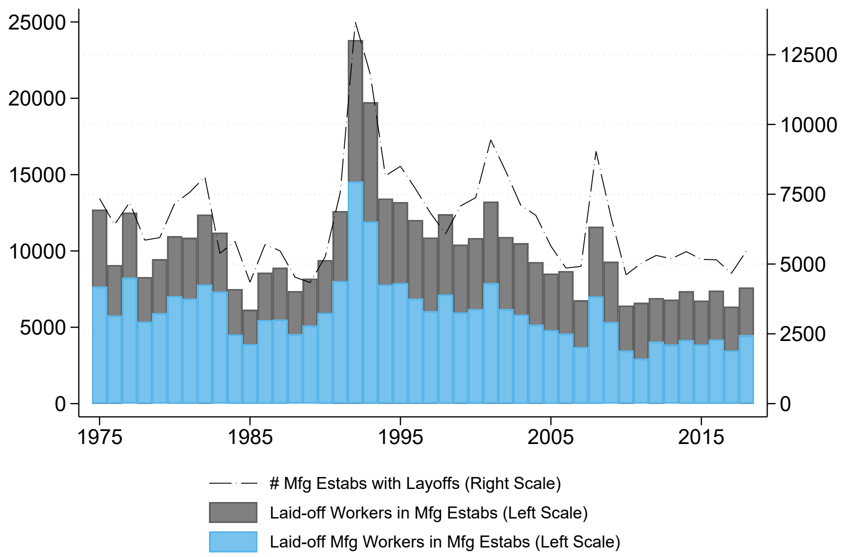


Figure 5: Layoffs and laid-off workers in the manufacturing sector
The figure shows the yearly number of layoff events observed in the dataset (right scale) and the number of laid-off workers in total and with a manufacturing occupation in the year of the layoff (left scale). Datasource: SIAB 7519, 1975-2019.

About 70% of laid-off manufacturing workers secure new employment in a manufac-

[11] Refer to Schmieder et al. (2023) for additional rationale.

[12] The underlying SIAB data may not provide individual-level information for all laid-off workers but consistently includes aggregated establishment employment, allowing identification of layoff events. This explains why the number of laid-off workers is approximately only twice the number of layoff events.

turing occupation within the manufacturing sector. Figure 6 shows the distribution of the remaining 30% who transition elsewhere. The share transitioning to manufacturing occupations in the service sector increased from around 35% in the late 1970s to over 60% in the early 2000s. On average, 46% transition to manufacturing occupations in services, 22% to service occupations in manufacturing, and 32% to service occupations in services.

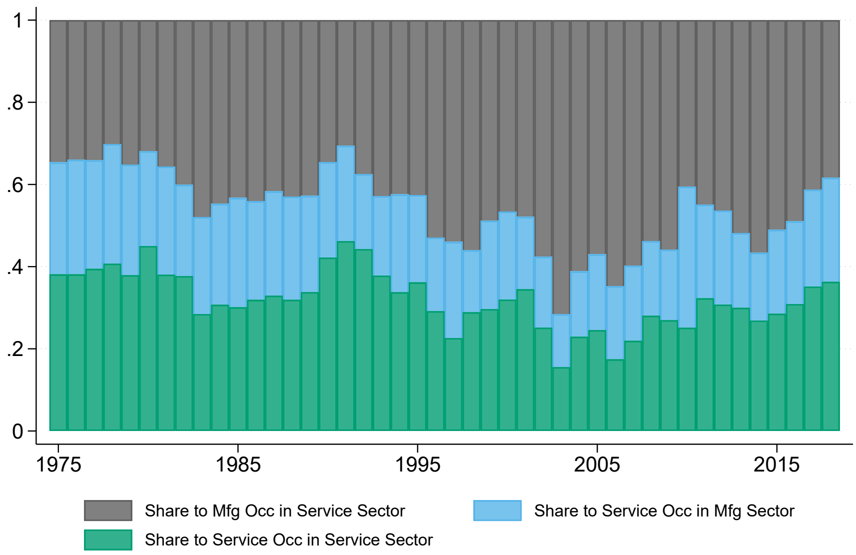


Figure 6: Laid-off manufacturing workers of manufacturing establishments and next year's occupation-sector combination

The figure shows, for laid-off workers with manufacturing occupations in the manufacturing sector, their occupation-sector combination in the year following the layoff if they leave the sector or switch to a service occupation. On average, this is the case for 30% of all laid-off workers with production occupations in the manufacturing sector. Datasource: SIAB 7519, 1975-2019.

4.2.3 Worker characteristics by occupation-sector combination after displacement

One concern for identification of the treatment effects is selection into the new job after layoff. Observable characteristics may differ between workers finding new employment across occupation-sector combinations, raising selection concerns. Table 2 presents worker characteristics in the year before layoff, categorized by subsequent destination. While differences exist, they are modest, suggesting reasonably similar workers find jobs across the four destination types. Nevertheless, we address potential self-selection through our four-way matching difference-in-differences procedure which we introduce next.

In summary, mass layoffs are common, with rising frequency during crises and restructuring periods. A noteworthy proportion of affected manufacturing workers fails to secure new employment where both occupation and sector remain unchanged. Crucially, a substantial share of these workers becomes employed in the service sector while holding a manufacturing occupation, and this trend has been rising.

Table 2: Worker characteristics in year pre-layoff by movement type

	(1) Mfg occ. in mfg sector	(2) Mfg occ. in service sector	(3) Service occ. in mfg sector	(4) Service occ. in service sector
log wage	4.35	4.11	4.41	4.04
	(0.51)	(0.66)	(0.63)	(0.66)
yearly income	31655.76	25951.98	36855.26	24880.96
	(21013.40)	(16142.41)	(33739.29)	(21046.14)
age	37.89	31.97	39.53	31.55
	(11.76)	(11.25)	(11.93)	(11.10)
college	0.03	0.04	0.07	0.05
	(0.17)	(0.20)	(0.25)	(0.21)
years in education	9.39	9.71	10.03	9.78
	(1.71)	(2.03)	(2.33)	(2.24)
tenure	6.70	2.75	6.67	2.44
	(6.40)	(2.95)	(6.16)	(2.14)
female	0.26	0.27	0.45	0.56
	(0.44)	(0.45)	(0.50)	(0.50)
Skill level $\{1 = \text{low}, 2 = \text{medium}, 3 = \text{high}\}$	1.60	1.74	1.67	1.59
	(0.69)	(0.66)	(0.72)	(0.66)
AKM person effect	4.36	4.35	4.38	4.27
	(0.39)	(0.38)	(0.40)	(0.34)
AKM firm effect	0.15	0.14	0.21	0.14
	(0.23)	(0.22)	(0.23)	(0.22)
N	28325	3478	15762	5222

Notes: The table reports worker characteristics in the year immediately before layoff, broken down by the new occupation and sector combination after layoff, $\mathcal{M}_\iota$. College and female are indicators equal to 1 if worker attended university or is female. Tenure is measured in years with the employer before layoff. Skill levels are reported according to Blossfeld (1987) skill categories. AKM effects are Abowd et al. (1999) person and establishment fixed effects. Standard deviations in parentheses. Datasource: SIAB 7519, 1975-2019.

4.3 Methodology and main results of fourfold treatment

4.3.1 Constructing quintuplets of matched displaced workers and control workers

In contrast to the conventional approach of comparing one affected worker with one control worker, our scenario involves a unique situation where treatment varies across four new occupation-sector combinations. Our aim is not only to contrast laid-off workers with non-laid-off control workers but also to compare the four distinct types of laid-off workers in new occupation-sector combinations with each other. If one were not concerned about self-selection biases arising from sorting into the new occupation-sector group based on observable or unobservable characteristics, it would be possible to follow the established literature by matching each treated worker with a non-laid-off control worker and then comparing the estimated treatment effects across new occupation-sector groups. However, our previous findings indicate that workers' pre-layoff characteristics differ modestly across the four occupation-sector combinations of the next job after a layoff.

Therefore, to enable a meaningful comparison of treatment effects across these new occupation-sector combinations, we construct matched groups of five workers (quintuplets): one non-laid-off control worker and four displaced workers, one for each element of $\mathcal{M}$, where $\mathcal{M}$ represents the set of possible post-layoff employment types:

$$\mathcal{M} = \begin{cases} \text{manufacturing occupation in manufacturing sector} \\ \text{manufacturing occupation in service sector} \\ \text{service occupation in manufacturing sector} \\ \text{service occupation in service sector} \end{cases}$$

We identify workers displaced during mass layoff events as the treated group, limited to those with manufacturing occupations at the time of layoff. There are four types of treatment according to the the occupation–sector combination of the next job a worker obtains. Workers who remain at establishments experiencing layoffs are excluded from the analysis. We form the control group by selection from the set of workers who, although not laid-off, exhibit a comparable likelihood of facing layoffs within narrowly defined occupation-industry categories each year. This control group comprises individuals with similar characteristics who were employed in the same 3-digit occupation and 2-digit industry during the year preceding the layoff event but were not affected by mass layoffs and were employed by establishments that had not experienced mass layoffs in any prior years.

Matching procedure. The matching with multiple treatments proceeds as follows:[13] (i) We begin by selecting the treatment group with the fewest observations at any 3-digit occupation and 2-digit industry level combination, denoted as $\mathcal{M}_{\min\{|\iota|\}}$. In our case, this usually corresponds to the switch to a service occupation in the manufacturing sector. (ii) We narrow down the matching sample to this group of treated workers in the year prior to the layoff and include potential non-laid-off control workers. (iii) We estimate propensity scores and select treatment-control pairs of workers based on the nearest-neighbor principle by year, where each potential control worker can only function as a control once. (iv) We then restrict the matching sample to $\mathcal{M}_{\min\{|\iota|\}}$ and workers of one of the remaining treatment groups in $\mathcal{M}$ with the same treatment year. (v) We repeat steps (iii) to (iv) for all remaining treatment groups, resulting in matched groups of five workers—one worker of each type of movement post-layoff plus one non-laid-off

[13] The conventional matching approach and their application to layoffs is, for example, applied in Davis and von Wachter (2011), Schmieder et al. (2023), or Goldschmidt and Schmieder (2017).

control worker. (vi) Finally, we expand the estimation sample to include the panel of full employment biographies for all workers identified in the treatment-control and treatment-treatment group matches from the previous procedure.

This matching strategy addresses two selection problems simultaneously: selection into displacement by relying on mass layoffs to identify treatment and selection into specific post-displacement destinations by selecting matched quintuplets. Within each quintuplet, all five workers hold the same 3-digit manufacturing occupation in the same 2-digit industry in year $t^* - 1$, the year preceding the layoff, mitigating selection bias on observables through the propensity score matching. The procedure also mitigates concerns of unequal weights in difference-in-differences estimation with staggered treatment (e.g., Goodman-Bacon, 2021 or Callaway and Sant'Anna, 2021): For each point in time where a treatment takes place, our procedure compares worker outcomes within complete sets of control and treated workers. In effect, our strategy yields a stacked panel of groups of treated and control individuals per treatment event with equal weights within quintuplets, similar to the procedure suggested by Callaway and Sant'Anna (2021).[14]

Matching quality. The matching procedure achieves good balance on observables. Appendix Table A.5 presents complete summary statistics by treatment group in year $t^* - 1$, demonstrating that observable characteristics are remarkably similar between treated and matched control workers, even for variables not directly considered in the matching process. Mean differences between groups are small relative to standard deviations, with most standardized differences below 0.10. Workers transitioning to manufacturing occupations in services are very similar to those remaining in manufacturing, with nearly identical log wages and comparable yearly incomes. Workers switching to service occupations show somewhat different characteristics but remain well-balanced across the matched quintuplets.

4.3.2 Estimating equation

We adopt a difference-in-differences event study design coupled with the propensity score matching described above. Over a period spanning five years before to ten years after the layoff, we estimate Equations (2) and (3) using the employment histories of the matched worker quintuplets.

Equation (2) estimates time-averaged treatment effects (static difference-in-differences), while Equation (3) estimates time-varying treatment effects (dynamic

[14] Appendix Section A.5.1 provides additional details on the matching algorithm and matching quality. Appendix Section A.6.1 reports results from conventional pairwise matching as a robustness check, where we estimate four separate regressions for each occupation-sector combination. Estimated layoff effects are smaller under single-treatment matching, suggesting our quintuplet approach provides more conservative estimates by better controlling for selection into specific destination job profiles.

difference-in-differences). Our evaluation encompasses four outcome variables, denoted as y_{ijt} for worker i at establishment j in year t: log daily wage in the primary job, yearly accumulated income (daily wages multiplied by days worked, summed across all jobs), days in employment, and number of different employers as a proxy for job volatility.

$$
\begin{aligned}
y_{ijt} = & \sum_{\iota=1}^{4} \gamma_\iota \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t \geq t^* \wedge t \leq t^* + 10\} + \beta \mathbb{1}\{t \geq t^* \wedge t \leq t^* + 10\} \\
& + \alpha_i + \theta_t + X_{it}'\xi \\
& + \sum_{\iota=1}^{4} \lambda_\iota^- \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t < t^* - 5\} + \lambda_{\text{control}}^- \mathbb{1}\{t < t^* - 5\} \\
& + \sum_{\iota=1}^{4} \lambda_\iota^+ \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t > t^* + 10\} + \lambda_{\text{control}}^+ \mathbb{1}\{t > t^* + 10\} + \epsilon_{it}
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
y_{ijt} = & \sum_{\kappa=-5 \backslash =-1}^{10} \sum_{\iota=1}^{4} \gamma_{\kappa\iota} \mathbb{1}\{t = t^* + \kappa\} \times \mathbb{1}\{i \in \mathcal{M}_\iota\} + \sum_{\kappa=-5 \backslash =-1}^{10} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} \\
& + \alpha_i + \theta_t + X_{it}'\xi \\
& + \sum_{\iota=1}^{4} \lambda_\iota^- \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t < t^* - 5\} + \lambda_{\text{control}}^- \mathbb{1}\{t < t^* - 5\} \\
& + \sum_{\iota=1}^{4} \lambda_\iota^+ \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t > t^* + 10\} + \lambda_{\text{control}}^+ \mathbb{1}\{t > t^* + 10\} + \epsilon_{it}
\end{aligned}
\tag{3}
$$

The variable t^* indicates the layoff year, and $\mathcal{M}_\iota$ represents the ι^{th} post-layoff occupation-sector combination. The estimation includes worker fixed effects (α_i), year fixed effects (θ_t), and time-varying worker characteristics (X_{it}'), e.g., such as a cubic age polynomial. We bin years outside the estimation window ($t < t^* - 5$ and $t > t^* + 10$) to avoid contamination from these endpoints; estimated coefficients λ^+ and λ^- are not reported as they do not capture treatment effects (Goodman-Bacon, 2021). Standard errors are clustered at the worker level throughout.

The coefficients γ_ι and $\gamma_{\kappa\iota}$ measure the treatment effect for workers in destination ι—averaged over the post-displacement period relative to the pre-treatment average and for each event year κ relative to the year the layoff occurs, respectively—relative to matched control workers. The average treatment effect on the treated (ATT) for destination ι at event time κ is thus given by:

$$\hat{\gamma}_{\kappa\iota}^{\text{ATT}} = \frac{1}{N_\iota} \sum_{ij \in \mathcal{M}_\iota} \left[(y_{ij,t^*+\kappa} - y_{ij,t^*-1}) - \big(y_{\text{control(ij)},t^*+\kappa} - y_{\text{control(ij)},t^*-1}\big) \right]$$

where $y_{\text{control(ij)},t}$ denotes the outcome for the matched control worker of worker ij. Since we match the same control worker to each quadruple of treated workers across the four destinations, differences $\hat{\gamma}_{\kappa\iota}^{\text{ATT}} - \hat{\gamma}_{\kappa\iota'}^{\text{ATT}}$ can be directly interpreted as the causal difference in the effect of transitioning to destination ι versus ι' for workers with identical pre-layoff characteristics. This enables us to assess not only whether displaced workers experience adverse outcomes relative to non-displaced controls, but also whether the service sector provides comparable outcomes to the manufacturing sector for workers retaining their occupations.[15]

4.3.3 Displacement effects by post-displacement job type

Table 3 presents results from the static difference-in-differences specification (Equation 2), while Figure 7 shows the dynamic event study estimates (Equation 3). We compare treatment effects across the four post-layoff occupation-sector combinations for wages, yearly income, days employed, and number of employers.

Wages. Column (1) of Table 3 shows negative treatment effects across all four transitions, with substantial variation by destination. Workers securing new employment in a manufacturing occupation within the manufacturing sector experience a modest average wage reduction of 2.2%. Those transitioning to service occupations within manufacturing face a 4.6% decline, while workers retaining manufacturing occupations but moving to service establishments experience a 5.9% reduction. The largest decline—29.9%—occurs for workers switching both occupation and sector to services.

Figure 7 reveals these wage effects persist over time with little evidence of convergence in the ten years following displacement. Parallel pre-trends validate our identification strategy. Critically, the wage penalties for workers retaining manufacturing occupations are modest regardless of sector: the 5.9% decline for those moving to services is only modestly larger than the 2.2% for those remaining in manufacturing. Both penalties are substantially smaller than the 14% average wage gap between sectors documented in Section 4.1, suggesting occupational human capital provides significant protection. Additionally, our focus on exogenous mass layoffs likely provides an upper bound on wage penalties—voluntary switches presumably incur smaller costs.

[15] Although the choice of which job to pursue post-layoff is endogenous, the matching procedure ensures comparability based on observable characteristics.

Table 3: Results: Difference-in-difference with multiple group matching

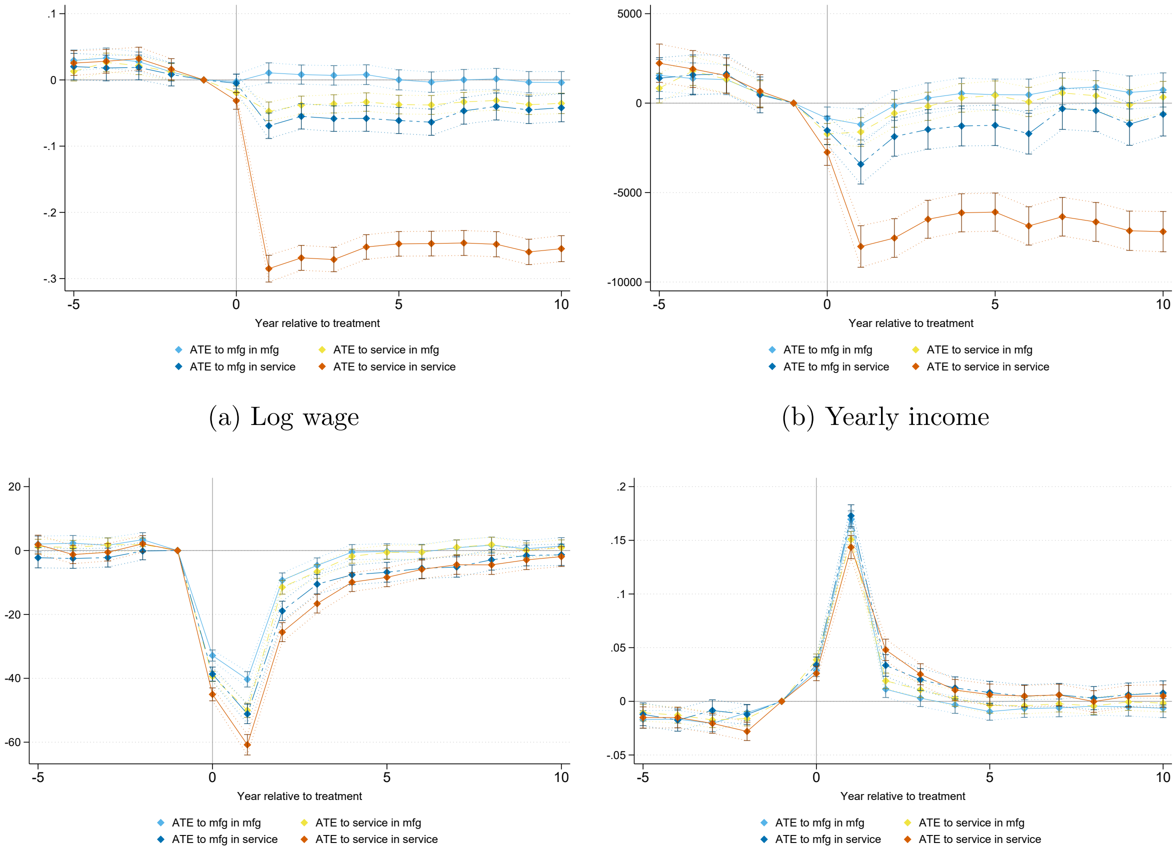
	(1) log(wage)	(2) Yearly income	(3) Number of days worked	(4) Number of employers
$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$				
	-0.022***	-876.37***	-2.13***	0.020***
	(0.002)	(137.21)	(0.38)	(0.001)
$\gamma_{\text{service occupation at manufacturing establishment}}$				
	-0.046***	-589.61***	-0.95***	0.021***
	(0.002)	(126.82)	(0.35)	(0.001)
$\gamma_{\text{manufacturing occupation at service establishment}}$				
	-0.059***	-2247.04***	-3.78***	0.034***
	(0.003)	(176.71)	(0.49)	(0.002)
$\gamma_{\text{service occupation at service establishment}}$				
	-0.299***	-9487.70***	-3.15***	0.030***
	(0.042)	(166.32)	(0.46)	(0.002)
N	718,116	720,447	720,447	720,447
R^2	0.46	0.17	0.01	0.06

Notes: The table reports regression results of the difference-in-difference terms γ_ι of Equation (2). Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Data: SIAB 7519, 1975-2019.

These effects are also smaller than displacement effects in related studies. Schmieder et al. (2023) find mass layoffs reduce annual earnings by approximately 15% for at least 15 years, while Helm et al. (2023) report wage declines of 9-11.8% following displacement. Our smaller estimates partly reflect sample composition: we condition on eventual reemployment in one of four occupation-sector combinations, whereas these studies include long-term unemployment.

Income and employment stability. Patterns in yearly income (column 2) mirror those for wages. Workers transitioning to manufacturing occupations within manufacturing experience income declines of approximately 876 euros annually, compared to 590 euros for service occupations in manufacturing and 2,247 euros for manufacturing occupations in services. Again, workers switching both occupation and sector face the largest losses (9,488 euros).

Days employed (column 3) reflect job search duration following displacement. Effects are concentrated immediately post-layoff and converge thereafter. Workers securing employment in the manufacturing sector—regardless of occupation—exhibit the shortest search periods. Those transitioning to manufacturing occupations in services or service occupations in services experience longer durations, with the latter group presumably searching for positions similar to their previous roles before settling for less desirable



(a) Log wage

(b) Yearly income

(c) Days employed

(d) Number of employers

Figure 7: Regression results of coefficient γ_k from Equation (3)

The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. The sample is restricted to only laid-off workers. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB 7519, 1975-2019.

alternatives.

Job volatility, measured by average number of employers (column 4), shows modest increases across all groups. Workers in manufacturing sector employment exhibit slightly more stable trajectories, but effects across all four destinations are small and similar in magnitude.

Sector versus occupation switches. Based on this analysis, comparing transitions where only one characteristic changes reveals that switching sectors while retaining a manufacturing occupation produces similar wage effects to switching occupations while remaining in manufacturing. The sector switch yields slightly larger losses (5.9% vs. 4.6%), although the difference is modest.[16] This finding indicates that occupational human capital matters substantially: workers who retain their occupation face manageable

[16]This aligns with Moscarini and Thomsson (2007), who emphasize the comparable importance of occupation and industry for post-displacement outcomes.

penalties regardless of whether they transition to the service sector.

4.4 Disentangling sector- and occupation-specific human capital

Recent literature emphasizes that job-specific human capital comprises both occupation-specific and industry-specific components. Card et al. (2024) show that industry accounts for approximately one-third of variation in establishment wage premia in the United States, highlighting the importance of considering sector-specific wage losses during structural change. To distinguish between sector- and occupation-specific displacement effects more explicitly, we estimate a modified specification that separately identifies losses from switching sectors, switching occupations, and switching both simultaneously.

Using the same matched sample as before, we estimate:

$$
\begin{aligned}
y_{ijt} =& \beta \mathbb{1}\{t \geq t^*\} + \gamma \mathbb{1}\{\text{sector switch}\} \times \mathbb{1}\{t \geq t^*\} \\
&+ \delta \mathbb{1}\{\text{occupation switch}\} \times \mathbb{1}\{t \geq t^*\} \\
&+ \mu \mathbb{1}\{\text{sector switch}\} \times \mathbb{1}\{\text{occupation switch}\} \times \mathbb{1}\{t \geq t^*\} \\
&+ \alpha_i + \theta_t + X_{it}'\xi + \Lambda^- + \Lambda^+ + \epsilon_{it}
\end{aligned}
\tag{4}
$$

where γ captures the effect of switching sectors (loss of sector-specific human capital), δ captures the effect of switching occupations (loss of occupation-specific human capital), and μ captures the additional effect when both switches occur simultaneously.[17]

Table 4 presents results. The loss of occupation-specific human capital generates larger wage and income penalties than the loss of sector-specific human capital. Workers forced to switch from manufacturing to service occupations experience a 6.8% wage reduction (2,200 euros annual income loss), approximately twice the 3.1% wage penalty (1,016 euros income loss) for switching sectors while retaining their occupation. The combined loss of both occupation- and sector-specific knowledge produces substantially larger effects: an approximate 30% wage reduction and 10,324 euros annual income loss.[18] This magnitude aligns closely with the treatment effect for workers switching to service occupations in the service sector identified in Table 3.

These findings explicitly demonstrate that occupational human capital is more valuable than sectoral human capital for displaced manufacturing workers. Workers who retain their manufacturing occupations face manageable wage penalties even when tran-

[17] Terms Λ^+ and Λ^- abbreviate the third and fourth lines of Equations 2 and 3, i.e., $\Lambda^- = \sum_{\iota=1}^{4} \lambda_\iota^- \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t < t^* - 5\} + \lambda_{\text{control}}^- \mathbb{1}\{t < t^* - 5\}$ and $\Lambda^+ = \sum_{\iota=1}^{4} \lambda_\iota^+ \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t > t^* + 10\} + \lambda_{\text{control}}^+ \mathbb{1}\{t > t^* + 10\}$. These terms collect any additional time varying changes that no longer are ATTs as discussed in Goodman-Bacon (2021).

[18] Calculated as $\gamma + \delta + \mu = -0.031 + (-0.068) + (-0.208) = -0.307$ for wages.

sitioning to the service sector, suggesting that service sector employment represents a viable alternative for maintaining human capital returns during structural change.

Table 4: Disentangling sector and occupation switches

	(1) log(wage)	(2) Yearly income	(3) Days worked	(4) Number of employers
Sector switch (γ)				
	-0.031***	-1,015.97***	-2.28***	0.016***
	(0.002)	(115.97)	(0.313)	(0.001)
Occupation switch (δ)				
	-0.068***	-2,200.03***	2.55***	-0.001
	(0.002)	(143.29)	(0.387)	(0.001)
Both switches (μ)				
	-0.208***	-7,124.41***	-2.05***	-0.003*
	(0.003)	(194.71)	(0.526)	(0.002)
N	883,921	886,633	886,633	886,633
R^2	0.44	0.16	0.01	0.03

Notes: The table reports estimates from Equation 4. Standard errors clustered at the worker level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Datasource: SIAB 7519, 1975-2019.

4.5 Robustness

We verify our findings across alternative specifications, sample restrictions, and time periods. Table 5 summarizes results for log wages; effects are in comparable quantitative ranges and confirm our main findings. The ranking of treatment effects across occupation-sector combinations remains stable for all robustness exercises: workers retaining manufacturing occupations consistently face smaller penalties than those switching occupations, regardless of sector. While we focus on wage effects in the main text for brevity, the appendix reports results for three additional outcomes—yearly income, days employed, and number of employers—across all robustness checks. These alternative outcomes also show consistent patterns. Full details appear in Appendix Section A.6.

Pairwise matching. As an alternative to our quintuplet matching approach, we implement conventional pairwise matching where each treated worker is matched to one control worker separately for each of the four treatment types. This approach follows the standard literature but does not control for selection into specific post-displacement destinations. Results (row 2 of Table 5) show qualitatively similar patterns with slightly smaller effect magnitudes—approximately half the size of our main estimates. The smaller effects likely reflect selection bias: workers transitioning to less favorable destinations may differ systematically from those in more favorable destinations, and pairwise matching cannot control for these differences across treatment types. Our quintuplet approach therefore provides more conservative estimates. Complete results appear in Appendix Section A.6.1.

Event study without controls. We estimate an event study using only displaced workers without matched controls, exploiting variation in layoff timing for identification.[19] This specification does not rely on matching assumptions but compares treated workers at different points in time. Results (row 3 of Table 5) show smaller effects than our main specification. This reflects the staggered design: post-treatment observations include comparisons to workers displaced in earlier years who have already experienced wage declines, attenuating estimated effects (see Sun and Abraham, 2021 and Callaway and Sant'Anna, 2021). Our main specification, which compares to never-displaced matched controls, therefore provides more conservative estimates of displacement costs. Importantly, the ranking of treatment effects across next job destinations remains identical across both specifications, confirming our core findings. See Appendix Section A.6.2 for details.

Men only. We restrict the analysis to male workers to assess whether gender differences affect our findings. Since our matching procedure conditions on gender, we simply restrict the estimation sample to matched quintuplets of male workers and re-estimate our main specifications. Results are quantitatively very similar to our main specification, with effects falling within nearly identical ranges across all four occupation-sector combinations (row 4 of Table 5). This suggests our findings are not driven by gender composition. Full results appear in Appendix Section A.6.3.

Large layoffs only. Following common practice in the displacement literature, we restrict our sample to large layoff events affecting more than 30% of employees at establishments with at least 50 full-time workers. This more stringent definition captures more severe displacement shocks. Results (row 5 of Table 5) show slightly larger effects, particularly for workers remaining in manufacturing occupations (-3.5% vs. -2.2% in the main specification), likely reflecting that larger layoffs generate more adverse labor market conditions. However, the relative ranking of treatment effects remains unchanged, and the key finding that occupational switches generate larger penalties than sectoral switches holds. See Appendix Section A.6.4.

Establishment wage premia and the mechanism of wage losses. Following the argument of Helm et al. (2023), we augment our specification with AKM establishment

[19] This design in itself is able to identify causal estimates as discussed in a series of recent papers (Athey and Imbens, 2021; Borusyak et al., 2024; Sun and Abraham, 2021).

fixed-effects (Abowd et al., 1999) to assess whether wage losses reflect transitions to lower-quality establishments or genuine skill depreciation. Results reveal that establishment quality differences account for the majority of observed wage penalties. Complete analysis appears in Appendix Section A.6.5.

Critically, workers who retain manufacturing occupations while transitioning to the service sector experience no significant wage loss once establishment quality is controlled for—the coefficient falls from -5.9% ($p<0.01$) to -0.5% ($p>0.10$). This finding demonstrates that the service sector contains establishments of comparable quality to manufacturing, and that workers who retain their occupational skills can access these high-quality service sector jobs without experiencing skill depreciation. The modest wage penalty in our main specification reflects that displaced workers, on average, transition to service establishments with lower wage premia rather than losing occupation-specific human capital. This may be an indication of a larger share of low-quality establishments in services (e.g., due to the lack of collective bargaining agreements). In contrast, workers who switch occupations continue to face substantial penalties (-2.3% for service occupations in manufacturing, -17.0% for service occupations in services) even after controlling for establishment quality, confirming that occupational switches involve genuine human capital losses beyond establishment selection. These patterns strongly support our core finding: for workers who keep manufacturing occupations after leaving a manufacturing establishment, the service sector can provide viable employment alternatives if job vacancies at comparable establishments are available.

Time period heterogeneity. Following Schmieder et al. (2023), we assess whether treatment effects vary with macroeconomic conditions by estimating effects separately for four decade-long periods: 1975–1985, 1985–1995, 1995–2005, and 2005–2015 (rows 7–10 of Table 5). While effect magnitudes vary across decades—e.g., the penalty for workers switching both occupation and sector varies between 21.8% and 31.2%—the fundamental ranking of treatment effects remains consistent throughout the entire 40-year observation period. Across all four decades, workers retaining manufacturing occupations consistently face the smallest penalties, while dual switchers consistently experience the largest losses. The intermediate penalties for workers who switch either occupation or sector fall between these extremes in all periods. Moreover, the magnitudes of treatment effects remain broadly similar across periods: workers retaining manufacturing occupations experience wage losses between 0% and 2.4%, those switching sectors face penalties of 3.6–7.0%, occupational switchers lose 1.0–6.6%, and dual switchers experience losses of 21.8–31.2%. This stability in both ranking and magnitude across four decades of substantial economic transformation—including the German reunification, European integration, and the global financial crisis—demonstrates that our findings reflect fundamental differences in the portability of occupation- versus sector-specific human capital rather than period-specific economic conditions. Detailed period-specific results and dynamic estimates appear in Appendix Section A.6.6.

Table 5: Summary of robustness checks

Specification	Log wage effects Mfg occ. Mfg sector	 Mfg occ. Service sector	 Service occ. Mfg sector	 Service occ. Service sector
Alternative specifications				
Main specification	-0.022***	-0.059***	-0.046***	-0.299***
	(0.002)	(0.003)	(0.002)	(0.042)
Pairwise matching	-0.012***	-0.036***	-0.029***	-0.234***
	(0.001)	(0.003)	(0.003)	(0.003)
Event study (no controls)	-0.001	-0.008***	-0.024***	-0.251***
	(0.001)	(0.002)	(0.002)	(0.002)
Men only	-0.017***	-0.053***	-0.030***	-0.266***
	(0.003)	(0.003)	(0.002)	(0.003)
Large layoffs only	-0.035***	-0.062***	-0.050***	-0.299***
	(0.004)	(0.008)	(0.004)	(0.008)
Controlling for AKM establishment effects	-0.009***	-0.005	-0.023***	-0.170***
	(0.002)	(0.003)	(0.002)	(0.003)
Time period heterogeneity				
1975–1985	-0.000	-0.036***	-0.036***	-0.218***
	(0.005)	(0.007)	(0.005)	(0.006)
1985–1995	-0.022***	-0.041***	-0.066***	-0.309***
	(0.005)	(0.006)	(0.004)	(0.005)
1995–2005	-0.024***	-0.050***	-0.036***	-0.312***
	(0.004)	(0.006)	(0.004)	(0.006)
2005–2015	-0.002	-0.070***	-0.010**	-0.249***
	(0.005)	(0.007)	(0.004)	(0.007)

Notes: The table reports static difference-in-differences estimates of average treatment effects on log wages. "Mfg occ." = manufacturing occupation; "Service occ." = service occupation; "Mfg sector" = manufacturing sector. Time period estimates are for layoffs occurring in the specified period. Standard errors clustered at worker level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Complete results with additional outcomes in Appendix Section A.6

5 Discussion

5.1 Reinterpreting structural change through an occupational lens

The conventional narrative of structural change emphasizes a dramatic shift from manufacturing to services, with manufacturing employment in Germany declining from 40% of total employment in 1975 to 20% in 2019 when measured by establishments' industry classification. Our analysis demonstrates that this narrative fundamentally mischaracterizes the nature of labor market transformation when workers' actual occupations are considered.

Measuring employment by occupation rather than establishment's industry reveals that structural change has been substantially more gradual. Approximately two-thirds of manufacturing jobs lost in manufacturing establishments between 1975 and 2019 were replaced by new manufacturing jobs in service establishments. By 2019, service sector establishments employed nearly as many workers in manufacturing occupations as manufacturing establishments themselves—the ratio declined from 3:1 in 1975 to 1.25:1 in 2019. This reallocation represents not the displacement of manufacturing work but rather its reorganization across establishment types.

The occupational perspective also reveals substantial heterogeneity masked by industry-based measures. Both manufacturing and service occupations are prevalent across establishment types: in 2019, 30% of workers in service establishments held manufacturing occupations, while 25% of workers in manufacturing establishments held service occupations. Moreover, 40–60% of workers newly employed in manufacturing occupations at service establishments previously held manufacturing occupations at manufacturing establishments, indicating substantial occupational continuity across the sectoral divide.

Our establishment-level analysis likely underestimates the extent to which manufacturing work has reorganized across industry classifications. Large firms often contain multiple establishments classified separately based on each unit's primary activity. A manufacturing firm expanding service operations (e.g., maintenance, logistics, customer support) may establish separate service-classified establishments while retaining manufacturing-classified production facilities. At the firm level, such restructuring would show even greater blurring of the manufacturing-service boundary than our establishment data reveal. While firm-level analyses capture different dynamics, as Bernard et al. (2017) show for Denmark, they would likely find an even larger share of manufacturing occupations in service-classified units, suggesting our findings represent a conservative estimate of cross-sectoral integration.

5.2 The mechanism: Establishment quality versus occupation-specific human capital

Our displacement analysis reveals the mechanism underlying moderate sectoral transition costs. Workers who retain manufacturing occupations while moving from manufacturing to service establishments experience virtually no wage penalty once establishment quality is controlled for. The coefficient falls from -5.9% to -0.5% (statistically insignificant) when including AKM establishment fixed effects. This 92% reduction in the ATT suggests that the modest sectoral penalty in our baseline estimates stems almost entirely from displaced workers sorting into lower-quality service establishments rather than from depreciation of occupation-specific skills.

This finding has three important implications. First, it confirms that the service sector contains establishments of comparable quality to manufacturing—high-wage-premium service establishments exist and are accessible to manufacturing workers who retain their occupational skills. Second, it demonstrates that occupation-specific human capital is portable across sectors: manufacturing skills transfer seamlessly to service contexts when establishment quality is held constant. Third, it explains why sectoral transitions involve moderate costs compared to occupational switches: the challenge is not skill incompatibility but rather access to high-quality establishments.

In contrast, occupational switches involve genuine human capital depreciation even after controlling for establishment quality. Workers switching from manufacturing to service occupations face 17.0% wage losses (vs. 29.9% baseline), indicating that approximately 60% of their penalty reflects establishment sorting but 40% stems from occupation-specific skill losses. This asymmetry—sectoral transitions involve minimal skill depreciation while occupational transitions involve substantial losses—underscores that occupation-specific human capital dominates sector-specific human capital in determining worker outcomes.

These results complement well the recent literature on the importance of establishment wage premia for the costs of job loss during mass layoffs. Helm et al. (2023), for instance, also show that a large fraction of the wage loss for displaced workers from manufacturing industries—particularly low-wage workers in their case—comes from moving to lower-premium service establishments, not from loss of transferable skills. Similar conclusions can be drawn from Fackler et al. (2021), who argue that lost firm rents rather than lost skills explain most of the observed wage decline after employer's bankruptcy.

5.3 Temporal stability and economic significance

Our findings remain remarkably stable across four decades (1975–2015) encompassing German reunification, European integration, and the global financial crisis. While effect magnitudes fluctuate—dual-switcher penalties range from 21.8% to 31.2% across periods—the fundamental ranking persists: workers retaining manufacturing occupations consistently face the smallest penalties (0–2.4%), sectoral switchers experience moderate losses (3.6–7.0%), and occupational switchers face substantially larger penalties. This temporal consistency in relative effects suggests our results reflect fundamental labor market structures rather than transitory conditions.

Our results are nevertheless also largely consistent with those of Schmieder et al. (2023), who document variation in the magnitude of post-displacement earnings losses over the business cycle. They attribute cyclical amplifications of wage losses primarily to changes in firm-wage premia. We also find sector switches to carry largest costs in the period of 1995-2005 (see results in Table A.15), the most volatile time window we can examine. As demonstrated, sector switches do come with large depreciation in firm wage premia in our case, therefore corroborating the results of Schmieder et al. (2023).

5.4 Implications for labor market policy

Our findings carry important implications for labor market policy design. First, policies targeting "manufacturing workers" should distinguish between those at risk of occupational displacement (requiring retraining) and those experiencing sectoral displacement while retaining occupations (requiring job search assistance to access high-quality service establishments). Current policies often conflate these groups despite their vastly different needs and adjustment costs. Evidence from vocational training systems further reinforces this distinction: Eckardt (2023) shows that workers lacking training in their current occupation face an average 14% wage penalty, which increases with the occupational distance between the trained job and the current job. This highlights the substantial costs of occupational mismatch and the critical role of retraining in mitigating such losses.

Second, the portability of manufacturing occupations across sectors suggests that fears about "deindustrialization" may be overstated when occupation rather than establishment industry is the relevant unit of analysis. Manufacturing work persists in the economy; its organizational locus has shifted toward service establishments. This reframing has implications for industrial policy: supporting manufacturing occupations may require different interventions than supporting manufacturing establishments.

Third, the critical role of establishment quality in determining transition costs implies that policies facilitating access to high-wage-premium establishments, whether through improved matching technologies, expanded professional networks, or reduced search frictions, may substantially reduce sectoral adjustment costs. Likewise, increasing the share of such establishments in services would also mechanically facilitate matching—for instance, by a revival of collective bargaining also in services. In contrast, occupational transitions require genuine skill development through retraining programs.

5.5 Directions for future research

Our analysis opens several avenues for future investigation. First, our focus on mass layoffs captures involuntary transitions; voluntary moves to service sector opportunities likely involve different selection patterns and potentially even transition gains. Analyzing voluntary sectoral mobility would provide a complete picture of adjustment costs and opportunities.

Second, extending this occupational lens to other dimensions of labor market analysis—trade exposure, automation, skill-biased technical change—could reveal whether effects attributed to industry shocks actually reflect occupational reallocation.

Third, generalizing our results for other countries, such as those at different stages of structural change or with differing labor market institutions, based on a harmonized approach (as in Bertheau et al., 2023) could yield additional insights relevant for labor market policies that address the labor market effects of structural change.

Finally, understanding which specific manufacturing occupations are most portable to service contexts, and which service establishments most readily absorb manufacturing workers, could inform more targeted policy interventions and provide actionable guidance for displaced workers. Understanding why displaced workers disproportionately sort into lower-quality service establishments also merits attention. Is this driven by a systematically smaller proportion of 'low-quality' establishments in service industries, information frictions, network effects, or systematic differences in hiring practices between manufacturing and service establishments? Addressing these barriers could substantially reduce transition costs.

6 Conclusion

The narrative of structural change as a dramatic shift from manufacturing to services fundamentally mischaracterizes recent labor market transformation when viewed through workers' actual occupations rather than establishment industry classifications. While manufacturing establishment employment declined sharply over the past four decades, this decline substantially overstates the displacement of manufacturing work—approximately two-thirds of lost manufacturing jobs in manufacturing establishments were replaced by manufacturing jobs in service establishments.

This paper demonstrates three core findings. First, measuring employment by occupation reveals that structural change has been more gradual and less disruptive than industry-based measures suggest. The employment share of manufacturing occupations declined modestly while manufacturing work reorganized across establishment types. Second, displaced manufacturing workers who retain their occupations face moderate sectoral transition costs—averaging 490 euros in annual income loss—driven to a large extend by sorting into lower-quality service establishments rather than occupation-specific skill depreciation. The service sector contains high-quality establishments where manufacturing skills command equivalent wages to manufacturing establishments. Third, occupation-specific human capital dominates sector-specific human capital: occupational switches involve substantially larger penalties than sectoral switches, and this ranking persists across four decades of economic transformation.

These findings revise our understanding of labor market adjustment costs and carry important policy implications. Workers displaced from manufacturing establishments face vastly different challenges depending on whether they retain occupations (modest adjustment costs, primarily establishment sorting) or switch occupations (substantial human capital depreciation requiring retraining). Current policies that treat all "manufacturing workers" identically fail to address these distinct needs. Moreover, concerns about "deindustrialization" should be tempered by recognizing that manufacturing work persists—its organizational form has evolved, not disappeared.

Our analysis underscores a broader methodological point: the choice between industry and occupation as the unit of analysis fundamentally shapes conclusions about structural change, worker displacement, and policy needs. For questions about worker outcomes and adjustment costs, occupation provides the more relevant lens. This occupational perspective should inform future research on trade exposure, automation, and technological change, e.g., through AI—phenomena typically analyzed through industry classifications but potentially better understood as occupational reallocations.

The blurring boundary between manufacturing and service sectors, when viewed through workers' occupations rather than establishment classifications, suggests that the traditional sectoral dichotomy may no longer adequately characterize modern labor markets. As manufacturing work increasingly occurs within service establishments, and service work within manufacturing establishments, labor market analysis must adapt its conceptual framework accordingly.

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Online Appendix

A.1 Data Details

A.1.1 The Establishment History Panel (BHP)

The BHP constitutes a detailed and representative 50% sample of all establishments in Germany from 1975 to 2019 with at least one employee subject to social insurance contributions. The dataset covers between 640,000 and 1,500,000 establishments annually. For the 1975-1991 period, it encompasses only establishments in West Germany. In Germany, employers are mandated by law to provide information on the social insurance contributions of their employees, as stipulated in Section 28a of the Social Security Code IV (SGB IV). A unit is considered an establishment if it is a regionally and economically distinct entity. Economic distinctness is determined by the industry of the establishment. Regional assignment is based on municipalities in Germany (exceeding 11,000 in 2019), meaning that a firm with branches in different municipalities constitutes different establishments with distinct establishment numbers. The dataset offers comprehensive information including occupational mix (12 Blossfeld categories), employee education levels, gender distribution, percentage of foreign workers, age distribution, establishment wage structure, and industry classification (WZ93). The data form an unbalanced panel, as establishments may enter or exit the sample. For this paper's analysis, we focus on West Germany. Results remain consistent when East Germany is included from 1991 onwards.

A.1.2 The Linked Employer-Employee Data (SIAB)

The SIAB provides detailed employment biographies by integrating individual employee data from the Integrated Employment Biographies (IEB) with establishment data from the BHP. This matched employer-employee dataset constitutes a 2% representative sample of all employees and their employers, encompassing between 1 million and 1.5 million individuals and 250,000 to 400,000 establishments annually. The data include individual worker information on occupations (both 5-digit KldB and aggregated Blossfeld categories), hierarchy levels, tenure, daily wages, schooling, university degrees, family status, gender, age, and employment status. Through the linkage with BHP, the SIAB also contains the total number of workers by Blossfeld categories for each establishment, establishment-level information on industry classification, establishment size, and geographic location.

A.1.3 Data Reporting and Quality

The reporting procedure is based on the integrated notification procedures for health, pension, and unemployment insurance (DEÜV; formerly DEVO / DÜVO). For details, see Bender et al. (1996), p. 4ff.; Wermter and Cramer (1988). Additional documentation: http://doku.iab.de/fdz/reporte/2019/DR_06-19.pdf. Moscarini and Thomsson (2007) highlight difficulties with self-reported occupation data in the U.S. Current Population Survey, emphasizing the advantages of administrative data. Our mandatory reporting minimizes measurement error and ensures reliability.

A.1.4 Occupational Classifications

Blossfeld Classification: The Blossfeld (1987) classification (updated by Stops (2016)) contains twelve occupational groups designed to have uniform educational and task requirements within each category while displaying heterogeneity across categories. In total, there are twelve occupational groups which can be divided into two main fields, i.e., manufacturing and services. Each field further subdivides based on occupation skill levels (low, medium, high). The groups are divided into manufacturing (agricultural occupations, unskilled manual, medium-skilled manual, technicians, engineers) and services (unskilled services, medium-skilled services, semiprofessions, professions, unskilled commercial/administrative, medium-skilled commercial/administrative, managers). For a detailed description, the classification into 'manufacturing' and 'service', and examples of occupational groups, refer to Table A.1.

KldB Classification: The SIAB contains workers' occupations at 5-digit level according to the "Classification of Occupations" (KldB) (Federal Employment Agency, 2011). Table A.2 provides an example. This classification is also used in Spitz-Oener (2006) and Goldschmidt and Schmieder (2017) and can be related to ISCO-8 of the ILO. It is hierarchical and distinguishes 1,286 occupations at the 5-digit aggregation level. Like the Blossfeld classification, the KldB is task- or activity-oriented. The 5-digit KldB aligns with ILO's ISCO-8. The ISCO and KldB are constructed such that "the basis of any classification of occupations should be the trade, profession or type of work performed by an individual, irrespective of the branch of economic activity." Source: ILO. The first three digits capture occupational categorization, the fourth digit the hierarchical aspect, and the fifth digit skill intensity.

Conversion: We utilize both the KldB and Blossfeld classifications. While the KldB offers a more detailed classification than the Blossfeld system, the latter allows us to determine the overall number of workers per category at each establishment. We convert the SIAB's KldB categories into Blossfeld categories using an IAB-provided crosswalk that maps each 5-digit code to the appropriate Blossfeld category based on task content and skill requirements to facilitate comparison.

Table A.1: Occupational classification of Blossfeld (1987)

Name of occupational group	Description of the occupational group	ISCO 08 equivalent	Examples
Manufacturing			
Agricultural occupations (agr)	Occupations with predominantly agricultural orientation	61-63, 92	Farmers, agricultural workers, gardeners, fishermen
Unskilled manual occupations (emb)	All manual occupations with at least 60 percent unskilled workers in 1970	93, 94	Miners, rock breakers, paper makers, wood industry occupations, printing occupations, road and railroad construction workers
Medium-skilled manual occupations (qmb)	All manual occupations with at most 40 percent unskilled workers in 1970	71-75, 81-83	Glassblowers, bookbinders, typesetters, locksmiths, precision instrument makers, electrical mechanics, coopers, brewers
Technicians (tec)	All technically trained specialists	31	Machinery technicians, electrical technicians, construction technicians, mining technicians
Engineers (ing)	Highly trained specialists who solve technical and natural science problems	21	Construction engineers, electrical engineers, production designers, chemical engineers, physicists, mathematicians
Service			
Unskilled services (edi)	All unskilled personal services	95-96	Cleaners, security guards
Medium-skilled services (qdi)	Essentially order and security occupations as well as skilled service occupations	51-54	Locomotive engineers, registrars
Semiprofessions (semi)	Service positions which are characterized by professional specialization	32-35	Interpreters, educators
Professions (prof)	All liberal professions and service positions which require a university degree	22-26	Statisticians, economists, social scientists
Service (administration)			
Unskilled commercial and administrational occupations (evb)	Relatively unskilled office and commercial occupations	41, 42	Postal occupations, office hands, typists
Medium-skilled commercial and administrational occupations (qvb)	Occupations with medium and higher administrative and distributive functions	43, 44	Credit and financial assistants, foreign trade assistants, data processing operators, bookkeepers, goods traffic assistants
Managers (man)	Occupations which control factors of production as well as functionaries of organizations	11-14	Managers, business administrators, deputies, CEOs

A.1.5 Industry Classifications

The industry classification of establishments is determined by the Federal Statistical Office and available in the revision of 1993 (“Klassifikation der Wirtschaftszweige 1993”,

Table A.2: Exemplary occupational hierarchy according to KldB2010 scheme

KldB2010 4-digit	
43	Informatics-, information- and communication technology occupations
431	Informatics
432	IT system analysis, IT consultancy and IT distribution
4321	Occupations in IT system analysis
4322	Occupations in IT consultancy
43223	Occupations in IT consultancy - complex specialists
43224	Occupations in IT consultancy - highly complex specialists
4323	Occupations in IT distribution
4329	Executive personnel – IT system analysis , IT consultancy and IT distribution

WZ93). The WZ industry classification is a slightly adjusted version of the European NACE industry classification and of hierarchical structure. The WZ93 has five aggregation levels: sections (digit 1), divisions (digit 2), groups (digit 3), classes (digit 4), and subclasses (digit 5). The manufacturing/service distinction is made at the sectional level. The economic classification of establishments follows the economic focus of the establishment, which depends on the purpose of the establishment or economic activity of the majority of the employees. Accordingly, establishments with activities in various areas are economically assigned to a single category only. This implies that all workers within such establishments are categorized as either service or manufacturing workers, irrespective of their specific occupation.

This approach is widely adopted international practice. For example, ILOSTAT states: *"The branch of economic activity of a person does not depend on the specific duties or functions of the person's job, but rather on the characteristics of the economic unit in which the person works"* (International Labor Organisation ILO, 2018). This methodology is consistent with international practice (NACE, ISIC). See ILO documentation.

A.1.6 Data cleaning

In 1999, marginal part-time workers were integrated into the notification procedure, increasing covered establishments and worker numbers. To create consistent time series, we: (i) drop establishments entering only due to marginal part-time reporting; (ii) use SIAB individual data to identify part-time/full-time status; (iii) subtract part-time workers to maintain comparability. We focus on West Germany for 1975-2019 consistency, as East Germany is included only from 1991. We convert all occupation codes to consistent Blossfeld categories using IAB crosswalks, handling transitions between KldB vintages (KldB-88, KldB-92, KldB-2010). Daily wages are censored at the social security contribution ceiling. We impute wages above the ceiling as is standard in the literature (cf., Schmieder et al., 2023). Wages are expressed in 2015-constant euros.

A.2 Main employment spell definition

For workers with multiple employment spells on a given date, we focus on the main employment spell, defined as the highest-paying spell on the reference date of June 30 of each year. This approach follows standard practice in the literature using German administrative data (Card et al., 2013; Goldschmidt and Schmieder, 2017) and ensures we capture workers' primary labor market attachment. In cases where workers hold multiple jobs simultaneously, secondary employment is excluded from the analysis. This is particularly relevant for the wage penalty analysis.

A.3 Additional evidence on structural change

A.3.1 Absolute surplus of mnufacturing workers

Figure A.1 shows the absolute difference between the number of workers in manufacturing occupations and the number employed in manufacturing establishments. In 1975, there were approximately 370,000 more workers in manufacturing establishments than in manufacturing occupations. This reversed from 1980 onward, with the gap growing monotonically. Over 1975-2019, workers in manufacturing occupations exceeded those in manufacturing establishments by 851,000 on average, reaching a maximum of approximately 1.8 million in 2018. This persistent and growing gap reflects manufacturing workers transitioning to service sector jobs, where they are counted as service sector employees under the industry-based approach while retaining their classification as manufacturing workers under the occupation-based approach.

A.3.2 Detailed occupational distribution across sectors

Table A.3 shows the distribution of 2-digit occupations between manufacturing and service sectors for 1975 and 2019. A significant number of workers are employed in establishments where the establishment's sector classification does not align with the worker's occupation classification.

For manufacturing occupations (rows 1-20), the share of workers in the service sector ranged from 3.0% (ceramics workers, glass makers) to 62.2% (construction workers) in 1975. By 2019, this share increased for almost all manufacturing occupations, ranging from 6.0% (metal producers) to 72.5% (construction workers). On average, the service sector share for manufacturing occupations rose from 24% in 1975 to 38% in 2019.

Column (5) shows the change in percentage points in occupational distribution toward the service sector. For most occupations, this increases over time. Column (6) shows that almost all manufacturing occupations experienced a decline in total numbers from 1975 to 2019. However, column (7) reveals that despite overall employment declines, the number

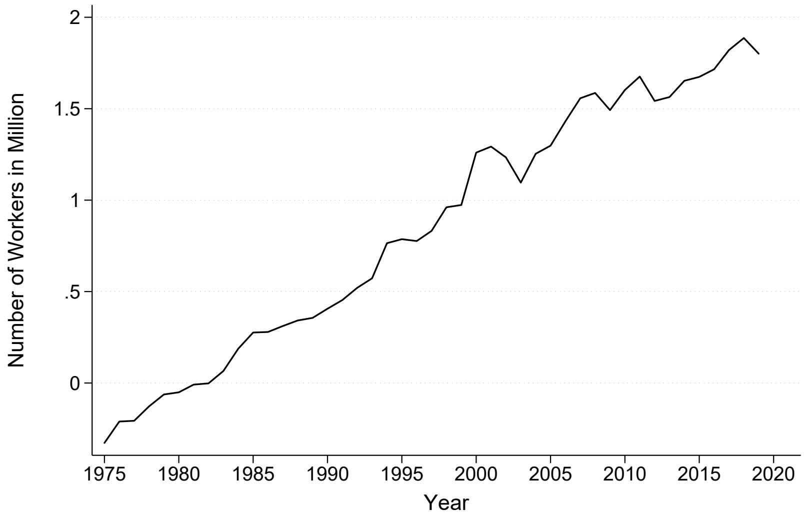


Figure A.1: Surplus of manufacturing workers when using occupation-based measurement
The figure shows the difference in the number of workers in manufacturing occupations and workers employed in manufacturing establishments in Germany. Datasource: BHP 1975-2019, Federal Statistical Office Germany.

of jobs within the service sector increased for the majority of manufacturing occupations: the service sector offers an increasing number of jobs for almost all manufacturing occupations.

Table A.3: Occupations' distribution across sectors

	Occupation	(1) 1975 Manufacturing	(2) 1975 Service	(3) 2019 Manufacturing	(4) 2019 Service	(5) 1975 - 2019 Δ to Service	(6) 1975 - 2019 Total %-Δ	(7) 1975 - 2019 Service sector %-Δ
1	Miners, Oil quarriers	85.8%	14.2%	30.0%	70.0%	55.8p.p.	-78.6%	5.0%
2	Stone preparers, building material maker	94.6%	5.4%	81.4%	18.6%	13.2p.p.	-23.5%	164.9%
3	Ceramics workers, Glass makers	97.0%	3.0%	90.4%	9.6%	6.6p.p.	-48.1%	66.0%
4	Chemical worker, plastics processor	92.7%	7.3%	86.6%	13.4%	6.1p.p.	-16.3%	54.2%
5	Paper maker, printer	92.8%	7.2%	82.8%	17.2%	10.1p.p.	-51.9%	15.9%
6	Wood preparers, wood products makers and related occupations	93.8%	6.2%	88.1%	11.9%	5.7p.p.	-39.6%	15.4%
7	Metal producers	95.4%	4.6%	94.0%	6.0%	1.4p.p.	-27.9%	-5.8%
8	Toolmakers, smiths, mechanics	68.4%	31.6%	62.6%	37.4%	5.8p.p.	-15.6%	-0.2%
9	Electricians	60.2%	39.8%	57.6%	42.4%	2.6p.p.	54.2%	64.2%
10	Assemblers and metal workers	94.0%	6.0%	84.1%	15.9%	9.9p.p.	-27.1%	94.4%
11	Textile processors	87.6%	12.4%	68.2%	31.8%	19.3p.p.	-87.0%	-66.6%
12	Leather makers, leather and skin processing operatives	84.4%	15.6%	77.4%	22.6%	7.0p.p.	-83.7%	-76.4%
13	Nutrition occupations	53.3%	46.7%	31.3%	68.7%	22.0p.p.	42.9%	110.1%
14	Construction workers	37.8%	62.2%	27.5%	72.5%	10.3p.p.	-49.9%	-41.6%
15	Room equippers, upholsterers	59.9%	40.1%	43.4%	56.6%	16.5p.p.	-28.5%	1.0%
16	Carpenters, model maker	74.9%	25.1%	68.6%	31.4%	6.3p.p.	-22.1%	-2.5%
17	Painters, lacquerers and related occupations	67.8%	32.2%	47.6%	52.4%	20.1p.p.	-15.2%	37.8%
18	Good examiners, despatchers	79.7%	20.3%	81.6%	18.4%	-1.9p.p.	-73.2%	-75.7%
19	Machinists and related occupations	67.2%	32.8%	81.1%	18.9%	-13.9p.p.	234.0%	92.6%
20	Technicians, technical specialists	68.5%	31.5%	54.1%	45.9%	14.4p.p.	49.5%	117.7%
21	Engineers, chemists, physicists, mathematicians	59.5%	40.5%	48.5%	51.5%	11.0p.p.	228.3%	318.0%
22	Wholesale and retail trade	20.2%	79.8%	17.0%	83.0%	3.2p.p.	84.1%	91.5%
23	Services agents and related occupations	4.1%	95.9%	7.8%	92.2%	-3.6p.p.	133.2%	124.4%
24	Transport occupations	31.4%	68.6%	19.1%	80.9%	12.3p.p.	63.0%	92.2%
25	Administrative occupations, office occupations	32.6%	67.4%	19.0%	81.0%	13.6p.p.	75.6%	111.0%
26	Security occupations	19.5%	80.5%	7.1%	92.9%	12.4p.p.	168.2%	209.6%
27	Publicists, translators, artists	25.9%	74.1%	15.9%	84.1%	10.0p.p.	151.0%	184.9%
28	Health service professions	1.2%	98.8%	0.5%	99.5%	0.7p.p.	276.8%	279.5%
29	Social, education-related occupations, humanities specialists, scientists	4.5%	95.5%	2.7%	97.3%	1.9p.p.	683.5%	698.7%
30	Housekeeping, cleaning, guest attendance occupations	12.3%	87.7%	2.9%	97.1%	9.3p.p.	53.1%	69.4%

Notes: The table presents the distribution of two-digit occupations across the manufacturing and service sectors for the years 1975 and 2019 (columns 1-4). Column (5) illustrates the shift in occupational distribution towards the service sector in percentage points. Column (6) indicates the percentage change in the total number of jobs for each occupation from 1975 to 2019. Column (7) shows the percentage change in the number of jobs for each occupation within the service sector over the same period. For example, in 1975 (2019) 85.8% (30.0%) of workers with occupation Miners, Oil quarriers worked in the manufacturing and 14.2% (70%) in the service sector. This represents a 55.8 percentage point increase in the share of these occupations within the service sector. Overall, the total number of jobs in this occupation decreased by 78.6%, yet within the service sector, the number of jobs increased by 5%. Data: SIAB 7519, 1975-2019.

A.3.3 Intensive vs. extensive margin: Entry, exit, and reclassification

This section addresses whether our findings reflect within-establishment changes (intensive margin) or sample composition changes through entry, exit, and reclassification (extensive margin). We show that the documented shift in manufacturing employment from manufacturing to service establishments occurs primarily through changes in the occupational composition within establishments rather than through establishments entering, exiting, or switching industry classifications.

Establishment entry and exit

To assess whether our findings reflect sample composition changes (extensive margin) or occupational adjustments within existing establishments (intensive margin), we examine establishments entering the sample at different points in time. We divide establishments into cohorts based on their year of entry: those already present before 1975, and five subsequent five-year cohorts (1975-1980, 1981-1985, 1986-1990, 1991-1995, 1996-2000).

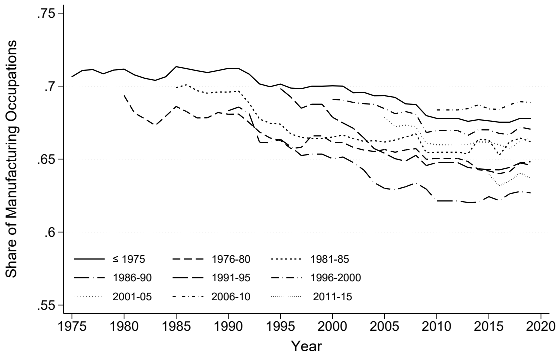
Figures A.2 and A.3 track these cohorts over time for manufacturing and service establishments, respectively. Panel (a) shows the average share of workers in manufacturing occupations, while panel (b) shows the average absolute number of manufacturing workers per establishment. Each line represents the same cohort followed over time, allowing us to observe within-cohort occupational adjustments.

For manufacturing establishments (Figure A.2), establishments entering before 1975 initially had manufacturing occupation shares near 80%, while later cohorts started with lower shares (65-70%). Critically, all cohorts exhibit parallel declining trends in their manufacturing occupation shares over time. The pre-1975 cohort experiences the strongest decline—from 80% to around 65% by 2019—converging to levels comparable to later entrants' initial shares. Despite these entry-year differences, in any given calendar year the manufacturing occupation shares across cohorts fall within a relatively narrow range (typically 5-10 percentage points), indicating that common economy-wide forces drive occupational restructuring within establishments regardless of entry cohort.

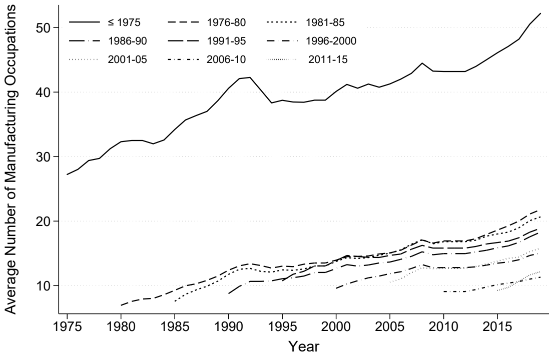
For service establishments (Figure A.3), cohorts entering in different periods show remarkably similar initial manufacturing occupation shares (consistently 15-20%) and follow nearly identical upward trajectories over time. This consistency across cohorts entering in different decades demonstrates that the aggregate increase in manufacturing occupations within service establishments reflects within-establishment changes rather than compositional effects from entry.

These patterns confirm that our main findings reflect genuine organizational changes within establishments—the intensive margin—rather than sample composition effects.

The parallel trends, convergence of older establishments to newer entrants' levels, and narrow ranges at given calendar years all indicate that establishments adjust their workforce composition in response to common forces regardless of their age or entry year. Analysis of exit patterns reveals symmetric findings: exiting establishments do not differ systematically in occupational composition from continuing establishments (see Figures A.4 and A.5).

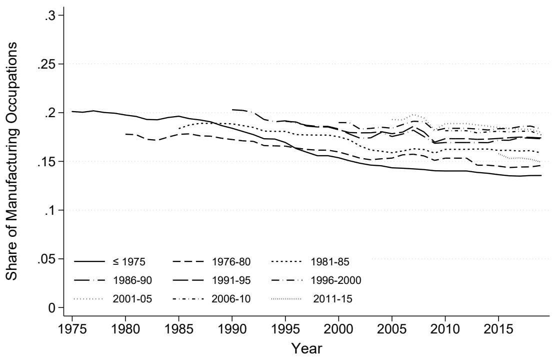


(a) Share mfg occupations

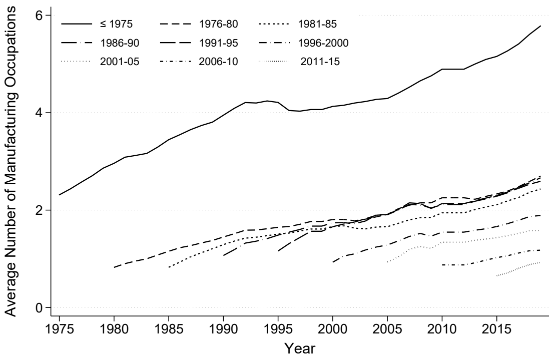


(b) Avg. number of mfg occupations

Figure A.2: Establishment entrants' labor force composition: Manufacturing sector
The figure shows the average share and number of workers in manufacturing occupations for establishment cohorts defined by entry year. All cohorts exhibit declining manufacturing occupation shares over time, with pre-1975 establishments experiencing larger absolute declines that bring them to levels comparable with later entrants. Datasource: BHP 1975-2019.

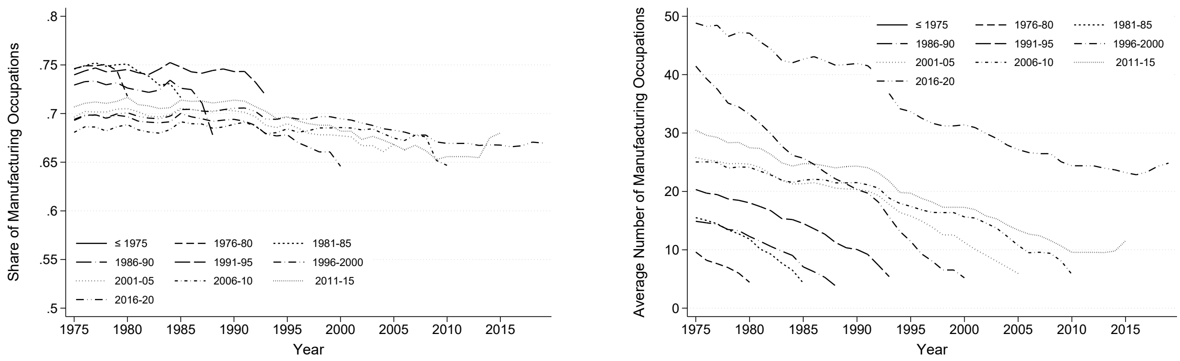


(a) Share mfg occupations



(b) Avg. number of mfg occupations

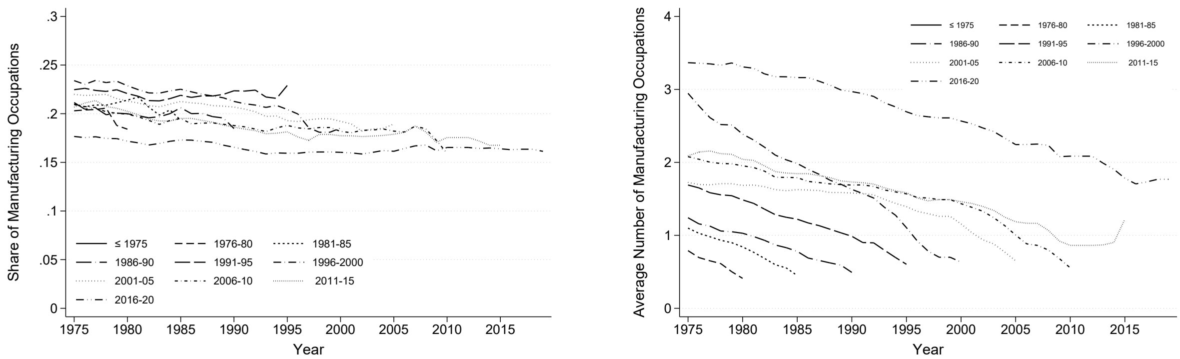
Figure A.3: Establishment entrants' labor force composition: Service sector
The figure shows the average share and number of workers in manufacturing occupations for establishment cohorts defined by entry year. Entrants across different periods show similar initial manufacturing occupation shares, all following parallel upward trends. Datasource: BHP 1975-2019.



(a) Share mfg occupations

(b) Avg. number of mfg occupations

Figure A.4: Establishment exiters' labor force composition: Manufacturing sector
Datasource: BHP 1975-2019



(a) Share mfg occupations

(b) Avg. number of mfg occupations

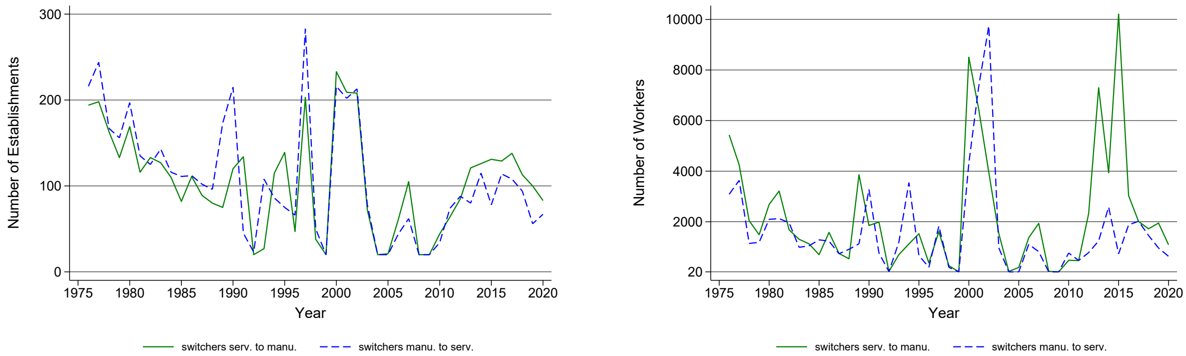
Figure A.5: Establishment exiters' labor force composition: Service sector
Datasource: BHP 1975-2019

Industry reclassification

Establishments may change their industry classification if their economic focus shifts, as occurred with IBM's transition from hardware manufacturing to services (Ahamed et al., 2013; Spohrer, 2017). Bernard et al. (2017) find that such reclassifications account for substantial employment shifts in Denmark: during 2002-2007, 10% of manufacturing firms switched to services, explaining 42% of manufacturing job losses.

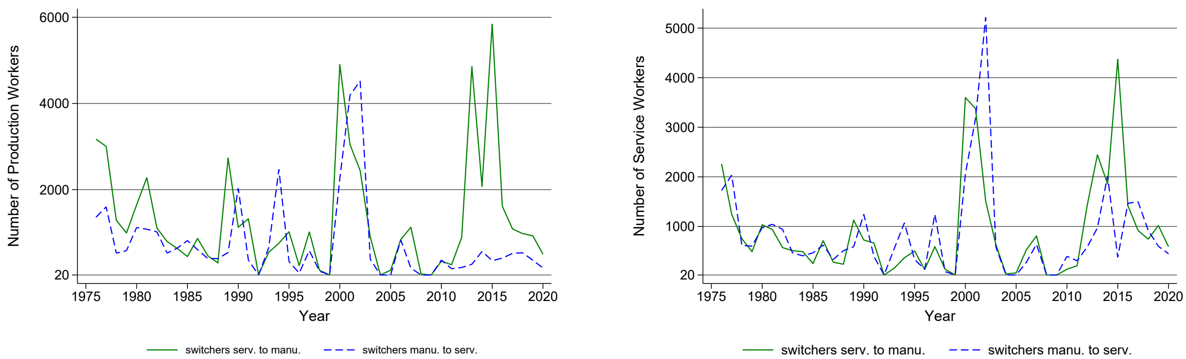
We find negligible reclassification effects in Germany. Figure A.6 shows annual flows of establishments switching between manufacturing and services (Panel a) and the associated workers (Panel b). Over 1975-2019, an average of 224 establishments switch classifications annually—less than 0.02% of all establishments. The number of workers affected averages 0.4% of total employment annually, with roughly symmetric flows in both directions. Cumulatively, industry switchers generated a net gain of 26,000 workers in manufacturing establishments over the 40-year period—a negligible amount compared to the 1.5 million decline in manufacturing employment.

Breaking down workers by occupation (Figure A.7) confirms that switchers contribute trivially to the documented employment patterns. Net annual flows average 582 manufacturing occupation workers moving from services to manufacturing, and 43 service occupation workers moving in the opposite direction—far too small to explain our aggregate findings.



(a) Establishments switching (b) Workers in switching establishments

Figure A.6: Industry reclassification: establishments and workers
Panel (a) shows the number of establishments switching from manufacturing to services (blue) and services to manufacturing (green) annually. Panel (b) shows the number of workers in these establishments. Flows are roughly symmetric and negligible in magnitude. Due to data confidentiality requirements, numbers of establishments or workers lower than 20 have not been released. For expositional purposes, these are set to 20 for these figures. Datasource: BHP 1975-2019.



(a) Manufacturing occupations (b) Service occupations

Figure A.7: Workers in switching establishments by occupation type
The figure decomposes workers in switching establishments by occupation. Net flows are negligible for both occupation types. Due to data confidentiality requirements, numbers of establishments or workers lower than 20 have not been released. For expositional purposes, these are set to 20 for these figures. Datasource: BHP 1975-2019.

The stark difference between Germany and Denmark likely reflects data structure: We analyze establishments while Bernard et al. (2017) study firms. Large firms often contain multiple establishments classified in different industries based on each establishment's primary activity. While the firm may reclassify (e.g., when IBM shifted focus to services), individual establishments maintain their classifications. Thus, firm-level reclassifications captured by Bernard et al. (2017) may not appear as establishment-level switches in our data. This distinction reinforces that establishment-level analysis provides more accurate measurement of worker-level employment patterns than firm-level aggregates.

The documented shift in manufacturing employment from manufacturing to service establishments reflects genuine within-establishment changes in occupational composition rather than sample composition effects. Entry and exit dynamics show parallel trends across establishment cohorts, while reclassifications affect a negligible fraction of establishments and workers. These results strengthen the interpretation that our findings capture fundamental changes in how production is organized rather than measurement artifacts.

A.3.4 Worker flows between sectors

Figure A.8 provides detailed evidence on the influx of workers into manufacturing occupations within the service sector, broken down by origin and, hence, complements Figure 4. The line represents the total annual influx (right axis), while the bars show the breakdown by previous occupation-sector combination (percentage shares, left axis).

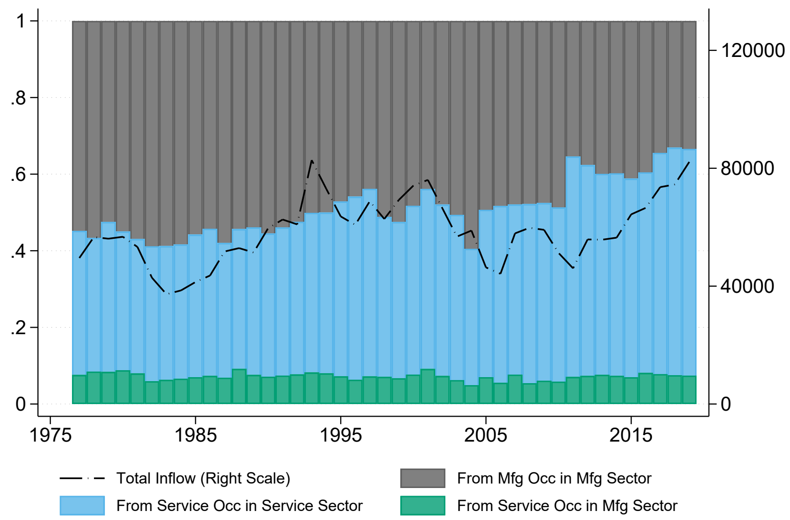


Figure A.8: Inflow into manufacturing jobs in the service sector by origin
The figure shows the total annual influx into manufacturing occupations in the service sector (right axis) and the breakdown by previous occupation-sector combination (percentage shares, left axis). Datasource: SIAB 7519, 1975-2019.

The overall influx into manufacturing jobs within the service sector exhibits a sustained upward trend over time. In the latter half of the 1970s and throughout the 1980s, annual numbers range from about 37,000 to 57,000 jobs. During the 2010s, this number has increased to up to 82,000 jobs per year, reinforcing the continuous demand for manufacturing workers in the service sector.

The proportion of workers transitioning from manufacturing occupations in the manufacturing sector to manufacturing occupations in the service sector is substantial. Throughout the 1970s and 1980s, this share remains consistently near 60%, gradually declining to around 50% in subsequent years. Post-2010, there is a further decrease to below 40%. It is crucial to emphasize that, despite the diminishing relative share, the absolute number of workers transitioning from manufacturing occupations in the manufacturing sector to manufacturing occupations in the service sector continues to rise over time.

This trend persists even as the overall number of manufacturing jobs in the manufacturing sector steadily declines. Concurrently, the number of workers transitioning from service occupations to manufacturing occupations within the service sector also rises. In recent years, the absolute count of these workers surpasses even those of manufacturing workers entering from the manufacturing sector, resulting in a diminishing influx share for the latter group.

A.4 Wage differences across the manufacturing and service sectors

To extend Section 4.1 and further examine wage differences across the manufacturing and service sectors, we differentiated by 47 2-digit occupation classes. Table A.4 shows the results. For 35 occupations, we find statistically significant negative wage premia for working in services, ranging up to -18.6%. By contrast, only 7 occupations show statistically significant positive wage premia. The remaining occupations show no statistically significant effects.

These results confirm that workers with manufacturing occupations in the service sector generally earn lower wages relative to the manufacturing sector. The 14% average gap (weighted across occupations) provides important context: The causal displacement effects documented in Section 4.3 (2-6% for workers retaining occupation or sector) are notably smaller, suggesting occupation-specific human capital provides substantial protection against wage losses. In this specification, it is also possible that switches from the service to the manufacturing sector are the dominant force, for instance if they are combined with promotions.[20]

[20] We find large, so far unexplained, wage differences for the same occupations between sectors. One reason not addressed in this paper could be outsourcing activities of manufacturing firms to service firms. Such activities have been shown to go in parallel with depressed wages at the new employers; see, e.g., Goldschmidt and Schmieder (2017) or Bilal and Lhuillier (2025).

Table A.4: Wage penalty of working in the service sector for occupation-hierarchy groups of manufacturing occupations

Occupation	(1) Coefficient	(2) Std. error	(3) Number of observations	(4) R^2 (within)
Stone workers	0.083***	(0.000)	20020	0.321
Building materials manufacturer	0.016	(0.113)	25756	0.174
Ceramist	0.122***	(0.000)	23802	0.201
Glassmaker	-0.025*	(0.020)	31531	0.221
Chemical workers	-0.040***	(0.000)	222050	0.341
Plastics processor	-0.016**	(0.008)	129663	0.216
Paper manufacturers and processors	-0.092***	(0.000)	91622	0.293
Printer	-0.055***	(0.000)	121637	0.338
Wood processor and manufacturer	-0.004	(0.562)	57653	0.193
Metal producers	-0.098***	(0.000)	51850	0.345
Moulders, molding casters	-0.127***	(0.000)	48203	0.271
Metal deformers (non-cutting)	-0.060***	(0.000)	92559	0.262
Metal deformers (cutting)	-0.124***	(0.000)	216598	0.392
Metal surface processing, coating, and coating	-0.078***	(0.000)	45004	0.211
Metal connectors	-0.032***	(0.000)	81004	0.262
Smiths	0.013	(0.521)	24854	0.331
Sheet metal workers, installers	-0.032***	(0.000)	265718	0.479
Locksmiths	-0.100***	(0.000)	593530	0.453
Mechanics	-0.186***	(0.000)	402750	0.520
Toolmakers	-0.047***	(0.000)	110847	0.510
Metalworkers	0.131***	(0.000)	79747	0.364
Electricians	-0.053***	(0.000)	580084	0.526
Assemblers and metal professions	-0.107***	(0.000)	392648	0.229
Spinning professions	0.047**	(0.001)	20338	0.206
Textile manufacturers	-0.001	(0.933)	28303	0.213
Textile processors	-0.049***	(0.000)	119285	0.137
Textile finishers	-0.019	(0.293)	14385	0.250
Leather manufacturers, leather and	-0.022**	(0.005)	46510	0.190
Bakery, confectionery manufacturers	-0.035***	(0.000)	83956	0.453
Meat, fish processors	0.110***	(0.000)	87456	0.385
Food processors	-0.126***	(0.000)	304580	0.260
Beverage and luxury goods manufact	0.001	(0.942)	20852	0.340
Other nutritional professions	-0.029***	(0.000)	61490	0.270
Bricklayer, concrete workers	-0.093***	(0.000)	289645	0.352
Carpenters, roofers, scaffolders	-0.068***	(0.000)	127388	0.367
Road and civil engineering occupations	-0.062***	(0.000)	128390	0.305
Construction workers	-0.100***	(0.000)	152162	0.156
Building outfitters	-0.023***	(0.000)	104753	0.285
Interior decorators, upholsterers	0.066***	(0.000)	40262	0.307
Carpenter, model makers	0.025***	(0.000)	203789	0.437
Painter, painter and allied professions	-0.169***	(0.000)	203423	0.424
Inspectors, dispatchers	-0.081***	(0.000)	286189	0.229
Auxiliary workers without detailed job description	-0.115***	(0.000)	152159	0.162
Machinists and related professions	-0.063***	(0.000)	232816	0.256
Engineers	-0.075***	(0.000)	499017	0.243
Technicians	-0.064***	(0.000)	730087	0.266
Technical specialists	-0.073***	(0.000)	217632	0.390

Notes: The table reports the estimation results of coefficient γ of Equation (1) for 2-digit occupations. Standard errors clustered at worker level and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Datasource: SIAB 7519, 1975-2019.

A.5 Supplementary Material: Wage effects through mass layoffs

A.5.1 Matching statistics matching with multiple treatments

Table A.5: Matching statistics $t = t^{*} - 1$

	(1)		(2)		(3)	
	mean	sd	mean	sd	b	t
	Serv occ in mfg sector		Serv occ in serv sector		differences	
log wage	4.29	0.53	4.30	0.52	0.01	(0.68)
wage	83.33	46.09	83.81	47.99	0.48	(0.47)
lagged wage	80.15	43.58	80.77	45.79	0.62	(0.64)
twice lagged wage	84.03	48.53	84.21	50.98	0.18	(0.15)
yearly income	29874.06	17089.90	30086.42	18007.99	212.36	(0.56)
age	33.28	10.61	33.59	10.59	0.30	(1.32)
college	0.04	0.19	0.04	0.19	-0.00	(-0.35)
years in education	9.47	1.93	9.50	1.90	0.02	(0.50)
tenure	3.99	4.01	3.77	3.63	-0.22**	(-2.62)
gender	0.26	0.44	0.31	0.46	0.05***	(5.56)
skill level	1.56	0.66	1.53	0.65	-0.03	(-1.88)
AKM person effect	4.27	0.34	4.25	0.35	-0.02*	(-2.54)
Employer size	1520.71	5570.33	1472.20	5410.94	-48.51	(-0.41)
AKM firm effect	0.14	0.22	0.14	0.22	0.00	(0.29)
Observations	4279		4285		8564	
	Serv occ in mfg sector		Mfg occ in serv sector		differences	
log wage	4.39	0.58	4.41	0.60	0.02	(1.13)
wage	94.87	59.47	96.79	59.74	1.91	(1.34)
lagged wage	91.42	58.29	93.27	59.96	1.85	(1.30)
twice lagged wage	96.89	66.10	99.96	68.19	3.07	(1.70)
yearly income	34110.73	21723.89	34929.66	21884.97	818.93	(1.56)
age	34.14	10.53	35.08	11.33	0.93***	(3.55)
college	0.08	0.26	0.07	0.25	-0.01	(-0.97)
years in education	9.98	2.39	10.01	2.26	0.03	(0.49)
tenure	4.25	4.32	4.21	4.36	-0.04	(-0.38)
gender	0.23	0.42	0.19	0.40	-0.03**	(-3.27)
skill level	1.73	0.74	1.83	0.71	0.10***	(5.71)
AKM person effect	4.35	0.38	4.39	0.36	0.04***	(3.90)
Employer size	1253.35	4765.97	1288.74	4737.81	35.39	(0.31)
AKM firm effect	0.14	0.22	0.14	0.22	0.00	(0.29)
Observations	3478		3464		6942	
	Serv occ in mfg sector		Mfg occ in mfg sector		differences	
log wage	4.42	0.56	4.41	0.58	-0.01	(-1.46)
wage	96.64	59.89	96.22	62.14	-0.42	(-0.41)
lagged wage	93.45	59.21	92.83	60.94	-0.62	(-0.62)

Table A.5: Matching statistics $t = t^* - 1$

	(1)		(2)		(3)	
	mean	sd	mean	sd	b	t
twice lagged wage	98.15	64.99	97.25	60.96	-0.90	(-0.77)
yearly income	34739.61	21890.71	34661.58	22720.90	-78.03	(-0.21)
age	34.76	10.72	35.69	11.50	0.93***	(5.03)
college	0.07	0.25	0.06	0.24	-0.01*	(-2.15)
years in education	9.87	2.37	9.80	2.20	-0.06	(-1.60)
tenure	4.64	4.83	5.12	5.22	0.49***	(5.78)
gender	0.22	0.42	0.20	0.40	-0.02**	(-2.93)
skill level	1.67	0.74	1.69	0.72	0.03*	(2.19)
AKM person effect	4.36	0.39	4.38	0.36	0.02**	(2.97)
Employer size	2232.64	6943.70	2014.96	6363.49	-217.68	(-1.96)
AKM firm effect	0.15	0.23	0.15	0.23	-0.00	(-0.88)
Observations	7200		7174		14374	
	Serv occ in mfg sector		non laid-off		differences	
log wage	4.45	0.58	4.44	0.59	-0.01	(-1.00)
wage	101.08	67.67	101.77	77.57	0.69	(0.62)
lagged wage	98.00	66.88	97.58	72.12	-0.43	(-0.40)
twice lagged wage	102.06	69.72	99.76	68.97	-2.30*	(-1.97)
yearly income	36310.51	24626.09	36784.85	28199.15	474.34	(1.17)
age	35.32	10.76	38.13	11.81	2.81***	(16.28)
college	0.08	0.27	0.06	0.24	-0.02***	(-4.45)
years in education	10.01	2.51	9.92	2.24	-0.09*	(-2.36)
tenure	4.62	4.74	7.55	6.55	2.93***	(33.60)
gender	0.22	0.42	0.22	0.42	0.00	(0.01)
skill level	1.72	0.77	1.74	0.75	0.02	(1.85)
AKM person effect	4.38	0.40	4.41	0.39	0.03***	(4.39)
Employer size	1634.30	5328.06	1447.62	4943.53	-186.67*	(-2.38)
AKM firm effect	0.15	0.23	0.13	0.24	-0.02***	(-6.60)
Observations	8559		8580		17139	

Notes: The table reports summary statistics by matched worker groups from the baseline 4-way matching exercise in Section 4.3. Datasource: SIAB 7519, 1975-2019.

A.6 Robustness

A.6.1 Pairwise matching

As a robustness check, we implement conventional pairwise matching where each displaced worker is matched to one control worker based on nearest-neighbor propensity scores, estimated separately for each of the four occupation-sector transitions. Unlike our main quintuplet approach, this method matches each treatment type independently and does not control for selection into specific post-displacement destinations across treatment types.

Table A.6 reports summary statistics for treated and control groups in years t^*-1 and t^*. Characteristics are remarkably similar across groups, even for variables not included in the matching procedure, confirming effective matching quality.

We estimate static and dynamic specifications (Equation (A.1) and (A.2), respectively) identical to the main text (Equations (2) and (3)), but run them separately for each treatment type rather than pooling all four types in a single regression.

$$y_{ijt} = \gamma_\iota \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t \geq t^*\} + \beta_{t^*}\mathbb{1}\{t \geq t^*\} + \alpha_i + \theta_t + X'_{it}\xi + \Lambda^+ + \Lambda^- + \epsilon_{it} \quad \text{(A.1)}$$

$$\begin{aligned} y_{ijt} = &\sum_{\kappa=-5\backslash=-1}^{10} \gamma_{\kappa\iota}\mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t = t^* + \kappa\} + \sum_{\kappa=-5\backslash=-1}^{10} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} \\ &+ \alpha_i + \theta_t + X'_{it}\xi + \Lambda^+ + \Lambda^- + \epsilon_{it} \end{aligned} \quad \text{(A.2)}$$

where we estimate each equation individually for each element of $\mathcal{M}$, and Λ^+ and Λ^- bin periods outside the estimation window.[21]

Table A.7 reports static estimates; Figures A.9 – A.12 show dynamic effects. Results confirm patterns from our main specification: workers retaining manufacturing occupations face the smallest penalties (1.2% wage loss remaining in manufacturing, 3.6% moving to services), while occupational switchers experience larger losses (2.9% for service occupations in manufacturing, 23.4% for both occupation and sector switches). However, estimated effects are approximately half the magnitude of our quintuplet estimates, likely reflecting selection bias—workers choosing different destinations may differ systematically, and pairwise matching cannot control for these differences across treatment types.

[21] Terms Λ^+ and Λ^- abbreviate the third and fourth lines of Equations 2 and 3, i.e., $\Lambda^- = \sum_{\iota=1}^{4} \lambda_\iota^- \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t < t^* - 5\} + \lambda_{\text{control}}^- \mathbb{1}\{t < t^* - 5\}$ and $\Lambda^+ = \sum_{\iota=1}^{4} \lambda_\iota^+ \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t > t^* + 10\} + \lambda_{\text{control}}^+ \mathbb{1}\{t > t^* + 10\}$. These terms collect any additional time varying changes that no longer are ATTs as discussed in Goodman-Bacon (2021).

Table A.6: Worker characteristics in years $t^* - 1$ and t^*

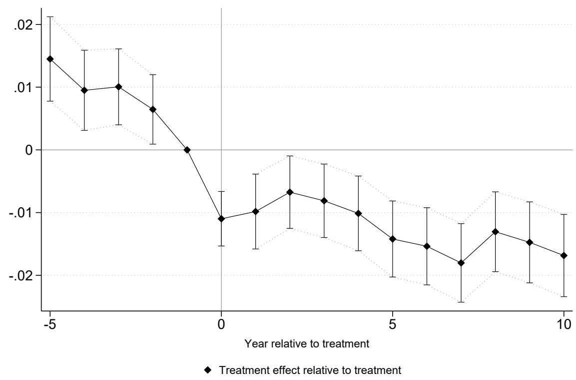
	(1)	(2) $t^* - 1$	(3)	(4)	(5) t^*	(6)
	Joint Sample	Laid-off Workers	Non-laid-off Workers	Joint Sample	Laid-off Workers	Non-laid-off Workers
Panel A: Demographics						
Year of birth	1954.90	1955.70	1951.19	1954.90	1955.70	1951.19
	(16.49)	(16.35)	(16.67)	(16.49)	(16.35)	(16.67)
Age	36.27	35.84	38.29	37.27	36.84	39.29
	(12.24)	(12.16)	(12.39)	(12.24)	(12.16)	(12.39)
Sex (0 male, 1 female)	0.22	0.22	0.25	0.22	0.22	0.25
	(0.42)	(0.41)	(0.43)	(0.42)	(0.41)	(0.43)
Years of formal education	9.72	9.74	9.65	9.79	9.81	9.70
	(2.14)	(2.17)	(1.99)	(2.13)	(2.16)	(1.99)
University degree obtained	0.06	0.06	0.05	0.06	0.06	0.05
	(0.23)	(0.23)	(0.21)	(0.23)	(0.23)	(0.21)
AKM person effect	4.33	4.33	4.32	4.34	4.34	4.33
	(0.34)	(0.33)	(0.36)	(0.34)	(0.34)	(0.36)
Panel B: Earnings Variables						
Daily wage	92.04	92.86	88.20	96.65	97.55	92.43
	(57.12)	(57.27)	(56.26)	(58.23)	(58.63)	(56.14)
Log wage	4.37	4.38	4.33	4.44	4.45	4.40
	(0.57)	(0.57)	(0.58)	(0.51)	(0.51)	(0.51)
Yearly income of worker	33269.17	33558.31	31915.37	34030.20	34156.48	33438.97
	(20952.66)	(20998.47)	(20683.48)	(21280.08)	(21396.71)	(20715.40)
Lifetime income	278787.20	282838.67	259817.45	312558.46	316660.90	293350.02
	(334400.65)	(339480.39)	(308808.30)	(346710.79)	(351790.39)	(321171.69)
Tenure	6.30	6.05	7.47	4.93	4.97	4.77
	(5.99)	(5.85)	(6.47)	(4.98)	(5.03)	(4.75)
Skill	1.69	1.69	1.68	1.69	1.69	1.69
	(0.72)	(0.72)	(0.71)	(0.72)	(0.73)	(0.71)
Panel C: Firm Characteristics						
Employment in year	1830.43	1959.33	1226.90	1824.51	1946.53	1253.20
	(5329.88)	(5514.18)	(4313.80)	(5293.36)	(5464.75)	(4357.87)
AKM firm effect	0.18	0.19	0.14	0.19	0.20	0.15
	(0.21)	(0.20)	(0.22)	(0.20)	(0.20)	(0.22)
Number of Observations	170500	140494	30006	170500	140494	30006

Notes: Average characteristics of individuals, Non-laid-off Workers refers to the matched control group, Joint Sample includes both treatment and control group. Characteristics are reported for the year before layoff ($t^* - 1$) and the layoff year (t^*). Standard deviations in parentheses. Yearly income of worker refers to days worked × daily wage (for all employment spells of a person). Lifetime income is computed as accumulated, deflated income for all years the person is observed.
Datasource: SIAB 7519, 1975-2019.

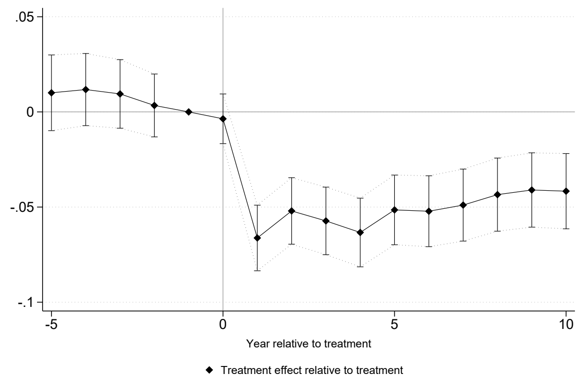
Table A.7: Pairwise matching results: Treatment effects by destination

	(1) log(wage)	(2) Yearly income	(3) Number of days worked	(4) Number of employers
Panel A: Switch to manufacturing occupation in manufacturing sector				
γ	-0.012***	-289.24***	-1.538***	0.028***
	(0.001)	(60.07)	(0.162)	(0.001)
N	1,829,949	1,836,661	1,836,661	1,836,661
R^2	0.49	0.18	0.01	0.14
Panel B: Switch to service occupation in manufacturing sector				
γ	-0.029***	132.02	1.38**	0.025***
	(0.003)	(203.18)	(0.533)	(0.018)
N	194,297	194,983	194,983	194,983
R^2	0.45	0.15	0.02	0.09
Panel C: Switch to manufacturing occupation in service sector				
γ	-0.036***	-1132.79***	-1.790***	0.040***
	(0.003)	(190.37)	(0.467)	(0.002)
N	242,487	243,248	243,248	243,248
R^2	0.47	0.15	0.01	0.07
Panel D: Switch to service occupation in service sector				
γ	-0.234***	-6904.57***	-0.853*	0.033***
	(0.003)	(120.00)	(0.449)	(0.001)
N	313,560	314,859	314,859	314,859
R^2	0.37	0.16	0.01	0.07

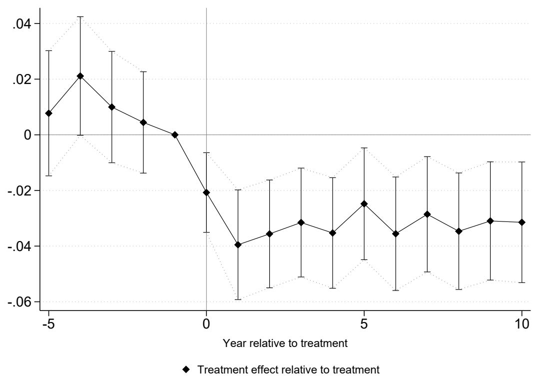
Notes: The table reports regression results of the difference-in-difference terms γ of Equation (A.1). Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Data: SIAB 7519, 1975-2019.



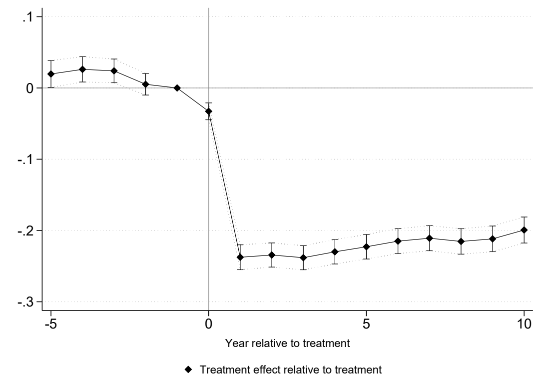
(a) Manufacturing occ. in manufacturing sector



(b) Manufacturing occ. in service sector



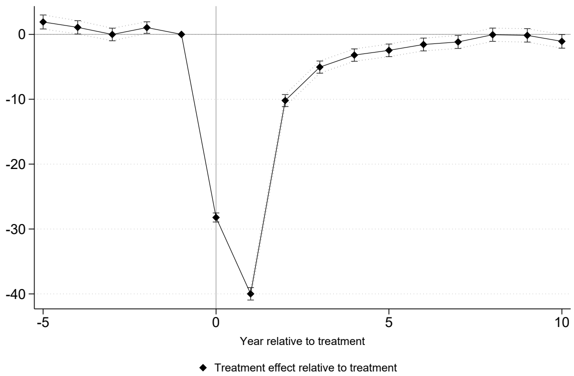
(c) Service occ. in manufacturing sector



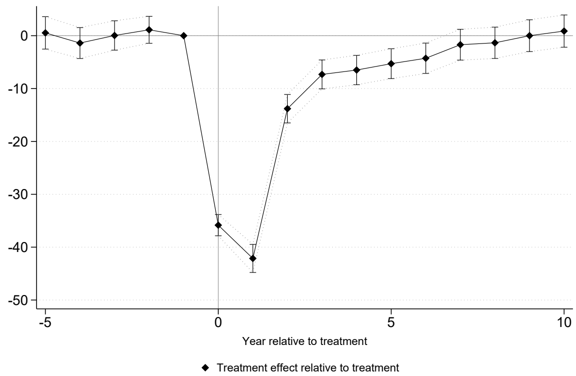
(d) Service occ. in service sector

Figure A.9: Difference in difference estimation with matching by treatment – log(wage)

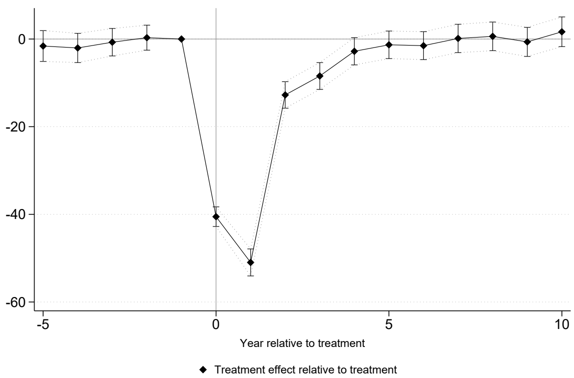
The figure plots coefficients $\gamma_{\kappa\iota}$ relative to the mass layoff event by treatment. Each regression is run only on the sample of treated workers within the respective transition group and their matches. Each panel shows results for one treatment group matched to controls based on pre-layoff characteristics. Datasource: SIAB 7519, 1975-2019.



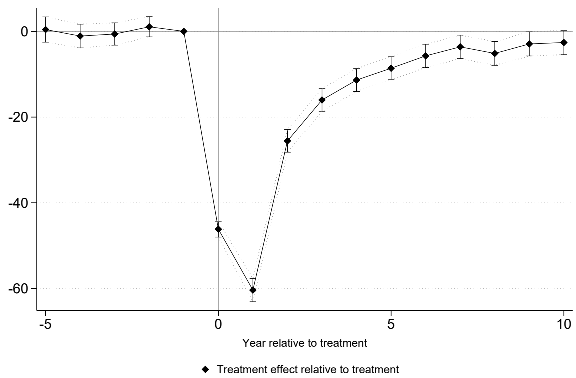
(a) Manufacturing occ. in manufacturing sector



(b) Manufacturing occ. in service sector



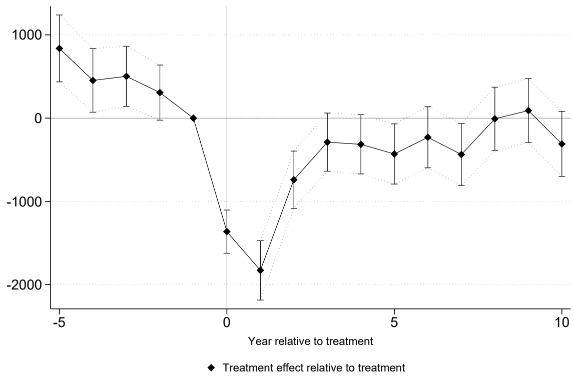
(c) Service occ. in manufacturing sector



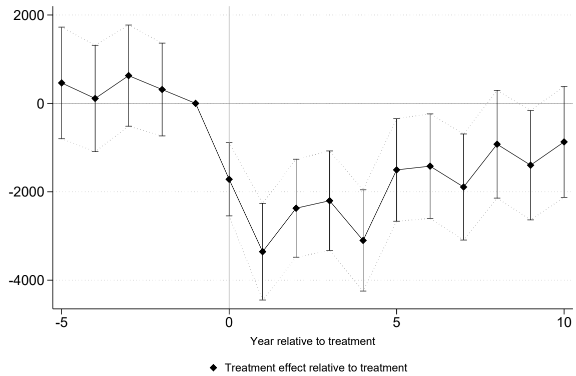
(d) Service occ. in service sector

Figure A.10: Difference in difference estimation with matching by treatment – days in employment

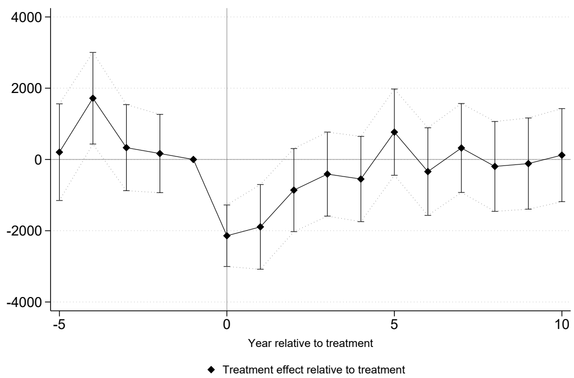
The figure plots coefficients $\gamma_{\kappa\iota}$ relative to the mass layoff event by treatment. Each regression is run only on the sample of treated workers within the respective transition group and their matches. Each panel shows results for one treatment group matched to controls based on pre-layoff characteristics. Datasource: SIAB 7519, 1975-2019.



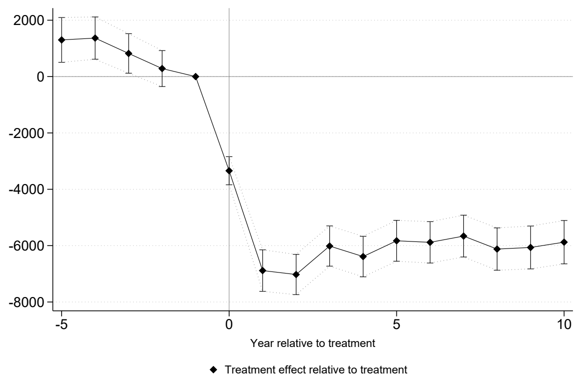
(a) Manufacturing occ. in manufacturing sector



(b) Manufacturing occ. in service sector



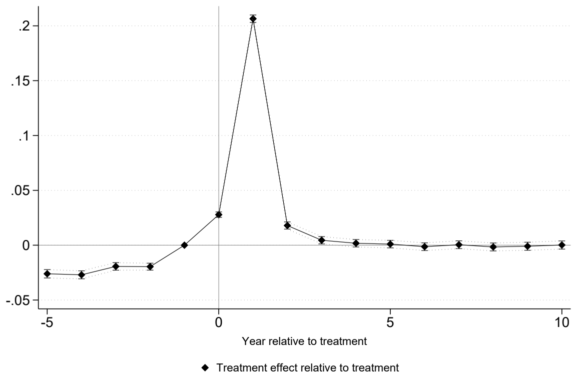
(c) Service occ. in manufacturing sector



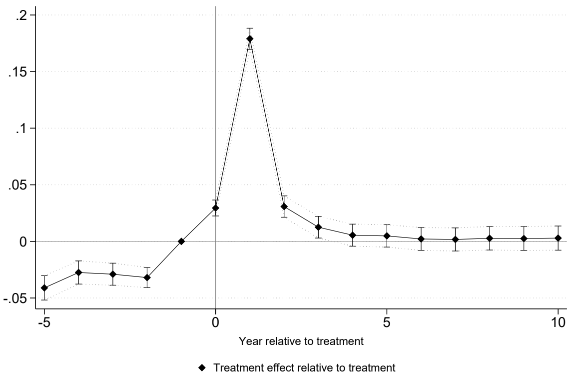
(d) Service occ. in service sector

Figure A.11: Difference in difference estimation with matching by treatment – yearly accumulated income

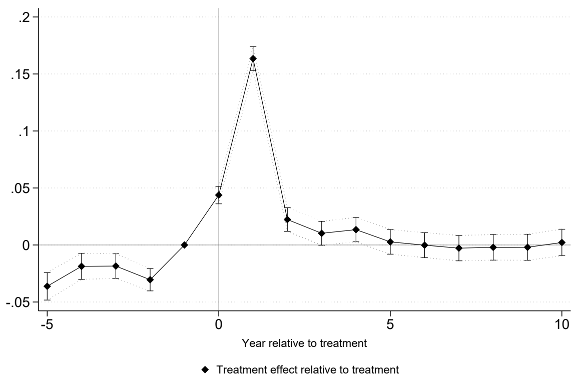
The figure plots coefficients $\gamma_{\kappa\iota}$ relative to the mass layoff event by treatment. Each regression is run only on the sample of treated workers within the respective transition group and their matches. Each panel shows results for one treatment group matched to controls based on pre-layoff characteristics. Datasource: SIAB 7519, 1975-2019.



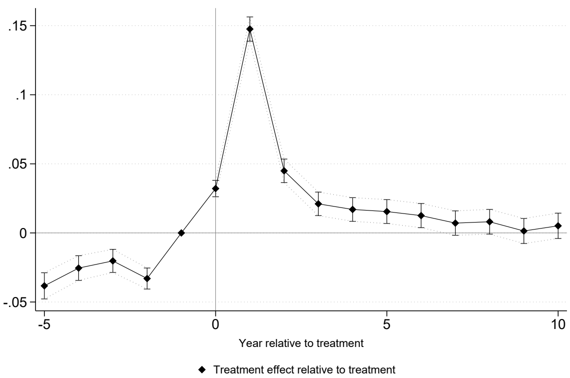
(a) Manufacturing occ. in manufacturing sector



(b) Manufacturing occ. in service sector



(c) Service occ. in manufacturing sector



(d) Service occ. in service sector

Figure A.12: Difference in difference estimation with matching by treatment – number of employers

The figure plots coefficients $\gamma_{\kappa\iota}$ relative to the mass layoff event by treatment. Each regression is run only on the sample of treated workers within the respective transition group and their matches. Each panel shows results for one treatment group matched to controls based on pre-layoff characteristics. Datasource: SIAB 7519, 1975-2019.

A.6.2 Event study without matched controls

As an alternative identification strategy, we estimate an event study using only displaced workers, exploiting variation in layoff timing across years. This approach does not rely on matching assumptions and identifies treatment effects from staggered adoption, following Athey and Imbens (2021), Borusyak et al. (2024), and Sun and Abraham (2021).

The sample includes only workers displaced from manufacturing occupations. Identification stems from comparing outcomes at different points relative to each worker's pre-displacement year $t^* - 1$. We again estimate static and dynamic specifications:

$$y_{ijt} = \sum_{\iota=1}^{4} \gamma_\iota \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t \geq t^*\} + \alpha_i + \theta_t + X'_{it}\xi + \Lambda^- + \Lambda^+ + \epsilon_{it} \tag{A.3}$$

$$y_{ijt} = \sum_{\kappa=-5\backslash=-1}^{10} \sum_{\iota=1}^{4} \gamma_{\kappa\iota} \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t = t^* + \kappa\} + \alpha_i + \theta_t + X'_{it}\xi + \Lambda^- + \Lambda^+ + \epsilon_{it} \tag{A.4}$$

where α_i are worker fixed effects, θ_t are year fixed effects, and $X'it$ is a cubic age polynomial. As in the main specification, Λ^- and Λ^+ bin periods outside the estimation window.[22] The term $\mathcal{M}_\iota$ indicates the post-displacement occupation-sector combination, with $\mathcal{M}$ defined as in the main text.

Table A.8 reports static estimates; Figure A.13 shows dynamic effects. Treatment effects are substantially smaller than in our main matched specification. Workers retaining manufacturing occupations in manufacturing experience negligible wage effects (-0.07%, not statistically significant), compared to -2.2% in the main specification. Those moving to manufacturing occupations in services face 0.8% wage losses (vs. -5.9% main), while occupational switchers show 2.4% losses for service occupations in manufacturing (vs. -4.6% main) and 25.1% for service occupations in services (vs. -29.9% main).

The smaller effects reflect the staggered nature of the design: in the post-treatment period, recently displaced workers are compared to workers displaced in earlier years who have already experienced wage declines. This implicit comparison group of previously treated workers—with their already depressed wages—attenuates the estimated treatment effects. In contrast, our main specification compares displaced workers to never-

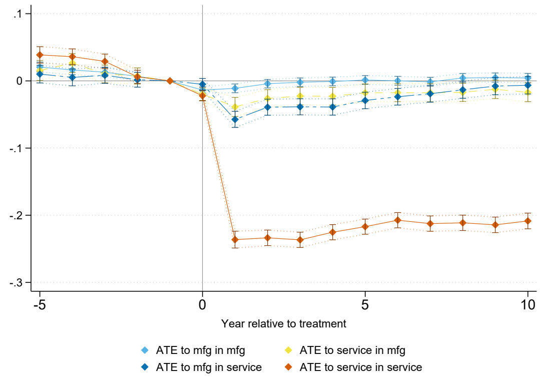
[22] Λ^+ and Λ^- abbreviate the corresponding terms to the third and fourth lines of Equation 3, i.e., $\Lambda^- = \sum_{\iota=1}^{4} \lambda_\iota^- \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t < t^* - 5\}$ and $\Lambda^+ = \sum_{\iota=1}^{4} \lambda_\iota^+ \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t > t^* + 10\}$. These terms collect any additional time varying changes that no longer are ATTs as discussed in Goodman-Bacon (2021).

displaced matched controls with stable earnings trajectories, yielding larger and more conservative estimates of displacement costs. Critically, however, the ranking across destinations remains identical: workers retaining manufacturing occupations face substantially smaller penalties than those switching occupations, regardless of sector. This confirms our core findings are robust to alternative identification strategies.

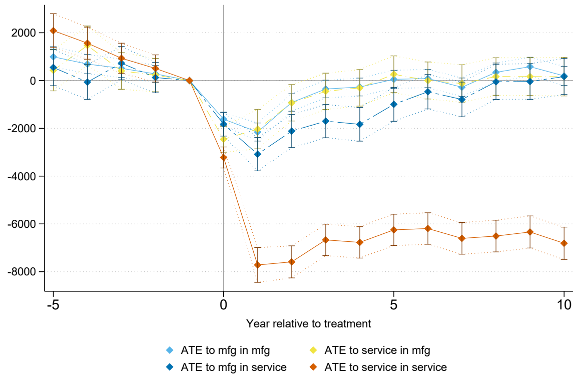
Table A.8: Results: Event study

	(1) log(wage)	(2) Yearly income	(3) Number of days worked	(4) Number of employers
$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$				
	-0.001	-117.92*	-1.15***	0.009***
	(0.001)	(60.97)	(0.17)	(0.001)
$\gamma_{\text{service occupation at manufacturing establishment}}$				
	-0.024***	-81.48	3.386***	0.004***
	(0.002)	(126.82)	(0.35)	(0.001)
$\gamma_{\text{manufacturing occupation at service establishment}}$				
	-0.008***	-30.76	-1.060***	0.023***
	(0.002)	(114.70)	(0.32)	(0.001)
$\gamma_{\text{service occupation at service establishment}}$				
	-0.251***	8377.67***	1.09***	0.015***
	(0.002)	(105.87)	(0.29)	(0.001)
N	2,300,805	2,308,981	2,308,981	2,308,981
R^2	0.46	0.17	0.01	0.06

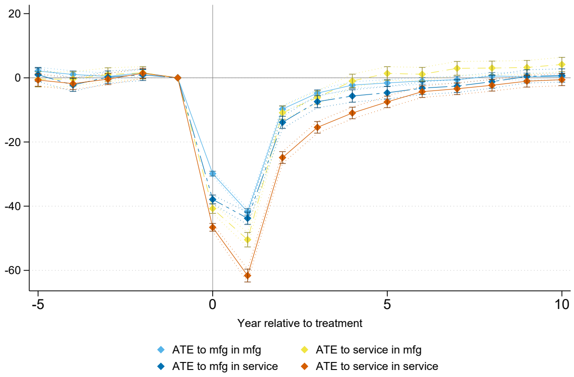
Notes: The table reports regression results of the event study terms γ_ι of Equation (A.3). Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Data: SIAB 7519, 1975-2019.



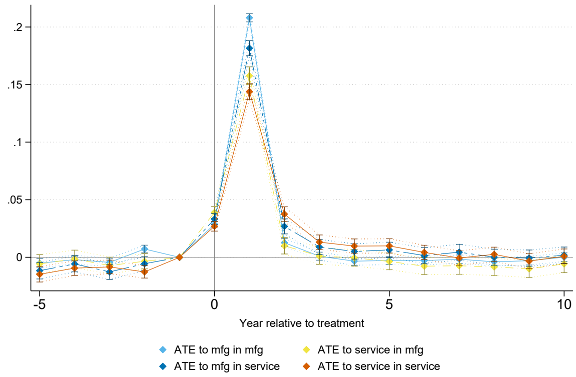
(a) Log wage



(b) Yearly income



(c) Days employed



(d) Number of employers

Figure A.13: Regression results of coefficient γ_k from Equation (A.4)
The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. The sample is restricted to only laid-off workers. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB 7519, 1975-2019.

A.6.3 Sample restricted to men

Following standard practice in the displacement literature, we verify our results restricting the sample to men.[23] While our main sample already comprises predominantly male workers (approximately 78%), restricting to men only ensures comparability with prior studies that focus exclusively on male displacement. Since our matching procedure conditions on gender, we simply restrict the estimation sample to matched quintuplets of male workers and re-estimate Equations (2), (3), and (4).

Table A.9 and Figure A.14 present results for the quintuplet matching specification (Equations (2) and (3)). Effects are quantitatively very similar to the full sample: workers retaining manufacturing occupations in manufacturing face 1.7% wage losses (vs. 2.2% in main specification), while those moving to manufacturing occupations in services experience 5.3% losses (vs. 5.9% main). Occupational switchers show 3.0% and 26.6% wage

[23]See Illing et al. (2024) for a study on gender differences in earnings losses after job loss.

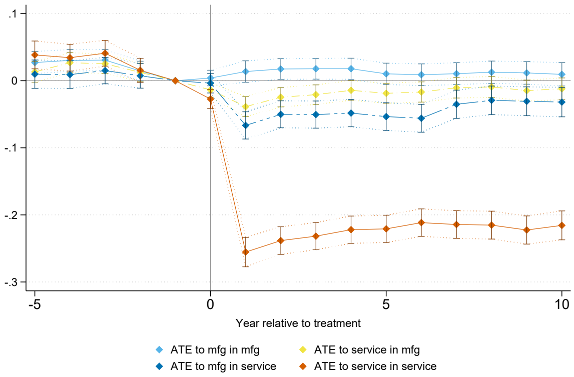
penalties for service occupations in manufacturing and services, respectively (vs. 4.6% and 29.9% main). The ranking across destinations and the relative magnitudes remain virtually identical.

Table A.10 decomposes effects by sector and occupation switches (from Equation (4)). Results confirm our main findings: occupation switches generate larger penalties (5.6% wage loss) than sector switches (3.9%), with the combined effect producing a 28.2% wage decline. This closely matches the full sample pattern where occupation-specific human capital is approximately twice as important as sector-specific human capital.

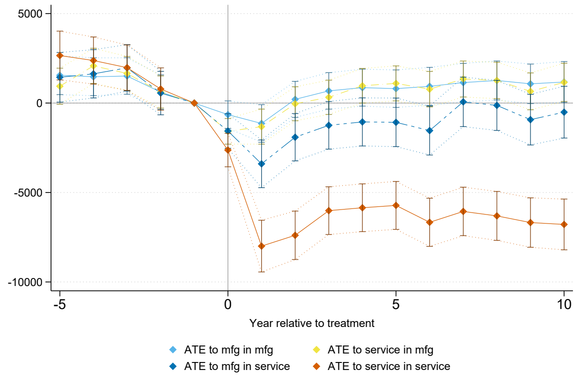
Table A.9: Results: Difference-in-difference with multiple group matching – Sample restricted to men

	(1) log(wage)	(2) Yearly income	(3) Number of days worked	(4) Number of employers
$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$				
	-0.017***	-906.05***	-1.82***	0.018***
	(0.003)	(164.67)	(0.42)	(0.001)
$\gamma_{\text{service occupation at manufacturing establishment}}$				
	-0.030***	-148.91	-0.86***	0.019***
	(0.002)	(153.62)	(0.39)	(0.001)
$\gamma_{\text{manufacturing occupation at service establishment}}$				
	-0.053***	-2417.18***	-3.31***	0.032***
	(0.003)	(211.25)	(0.54)	(0.002)
$\gamma_{\text{service occupation at service establishment}}$				
	-0.266***	-9454.19***	-4.40***	0.029***
	(0.003)	(211.11)	(0.54)	(0.002)
N	571,063	572,371	572,371	572,371
R^2	0.54	0.19	0.01	0.06

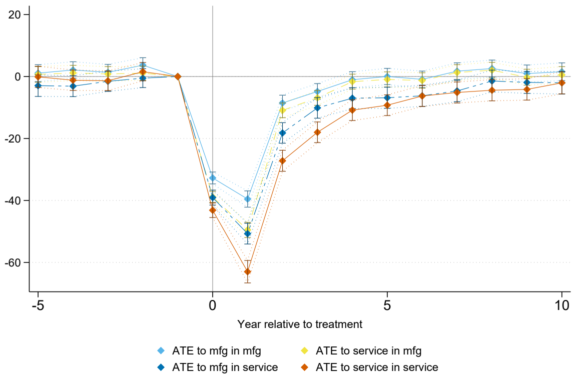
Notes: The table reports regression results of the difference-in-difference terms γ_ι of Equation (2). Sample is restricted to men. Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Data: SIAB 7519, 1975-2019.



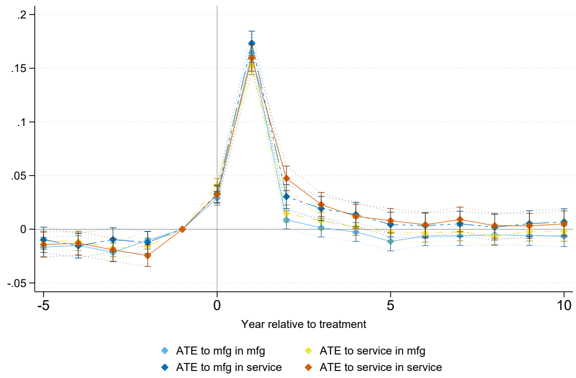
(a) Log wage



(b) Yearly income



(c) Days employed



(d) Number of employers

Figure A.14: Regression results of coefficient γ_k from Equation (3) – Sample restricted to men

The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. The sample is restricted to men. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB 7519, 1975-2019.

Table A.10: Sector and occupation switch disentangled – Sample restricted to men

	(1) log(wage)	(2) Yearly income	(3) Number of days worked	(4) Number of employers
$\mathbb{1}\{\text{sector switch}\} \times \mathbb{1}\{t \geq t^*\}$				
	-0.039***	-1491.96***	-2.18***	0.017***
	(0.002)	(137.59)	(0.336)	(0.001)
$\mathbb{1}\{\text{occupation switch}\} \times \mathbb{1}\{t \geq t^*\}$				
	-0.056***	-1895.97***	2.44***	-0.002
	(0.003)	(175.04)	(0.427)	(0.001)
$\mathbb{1}\{\text{sector switch}\} \times \mathbb{1}\{\text{occupation switch}\} \times \mathbb{1}\{t \geq t^*\}$				
	-0.188***	-7054.23***	-3.57***	-0.003
	(0.004)	(241.76)	(0.590)	(0.002)
N	697,913	699,332	699,332	699,332
R^2	0.52	0.17	0.01	0.03

Notes: Standard errors are clustered at the individual level. Sample restricted to men. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Data: SIAB 7519, 1975-2019.

A.6.4 Large layoffs only

As a robustness check, we restrict the sample to large displacement events: layoffs affecting more than 30% of employees at establishments with more than 50 full-time workers. This specification captures more severe displacement shocks than our main definition, which follows German labor law thresholds for mass layoffs.[24] We re-estimate Equations (2) and (3) on this restricted sample.

Table A.11 and Figure A.15 present results. Large layoffs disproportionately affect workers who remain in manufacturing occupations within the manufacturing sector, while effects for other transitions remain largely unchanged. Workers retaining manufacturing occupations in manufacturing experience 3.5% wage losses compared to 2.2% in the main specification—an increase of approximately 60%. In contrast, effects for the other three destinations are nearly identical to the baseline: manufacturing occupations in services show 6.2% losses (vs. 5.9% main), service occupations in manufacturing show 5.0% (vs. 4.6% main), and service occupations in services show 29.9% losses (identical to main).

This differential impact is consistent with labor market crowding effects following large-scale layoffs at major manufacturing establishments. When numerous workers with similar manufacturing-specific skills simultaneously seek reemployment in the same occupation-sector combination, increased competition depresses wages even for those who successfully find new manufacturing jobs (Gathmann et al., 2020). Workers who switch either occupation or sector appear to access less saturated labor market segments. The income effects support this interpretation: workers remaining in manufacturing occupations within manufacturing experience substantially longer unemployment spells (an additional 2.1 days unemployed compared to the main specification), consistent with increased search frictions in crowded markets.

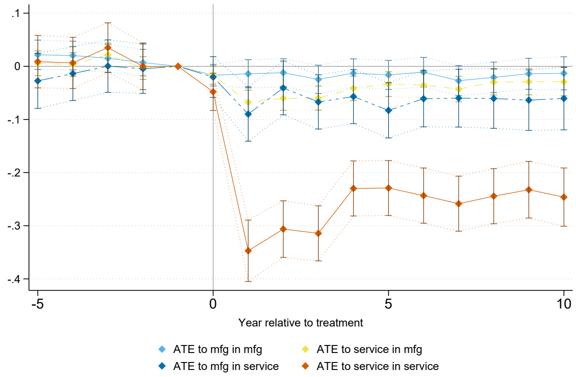
The ranking across destinations and the relative importance of occupational versus sectoral human capital remain unchanged across both specifications.

[24] Our main specification defines mass layoffs as: (i) dismissal of at least 5 employees for establishments with 20-59 employees; (ii) reduction by at least 10% or more than 25 employees for establishments with 60-500 employees; (iii) reduction by 30 or more employees for establishments with 500+ employees.

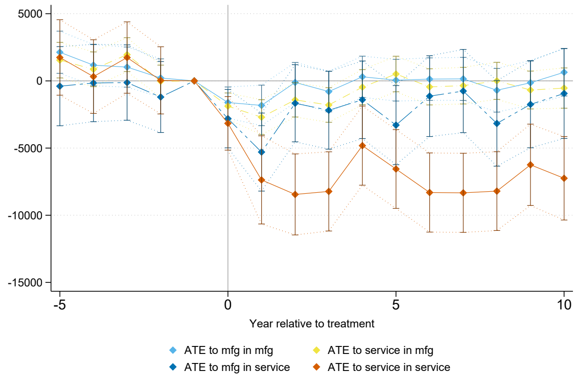
Table A.11: Results: Difference-in-difference with multiple group matching – Alternative layoff specification

	(1) log(wage)	(2) Yearly income	(3) Number of days worked	(4) Number of employers
$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$				
	-0.035***	-1581.29***	-4.25***	0.029***
	(0.004)	(241.13)	(0.71)	(0.002)
$\gamma_{\text{service occupation at manufacturing establishment}}$				
	-0.050***	-1555.39***	-2.35***	0.022***
	(0.004)	(205.04)	(0.60)	(0.002)
$\gamma_{\text{manufacturing occupation at service establishment}}$				
	-0.062***	-2503.40***	-6.96***	0.043***
	(0.008)	(471.23)	(1.39)	(0.005)
$\gamma_{\text{service occupation at service establishment}}$				
	-0.299***	-9640.66***	-5.13***	0.042***
	(0.008)	(445.72)	(1.31)	(0.005)
N	178,972	179,482	179,482	179,482
R^2	0.46	0.17	0.01	0.06

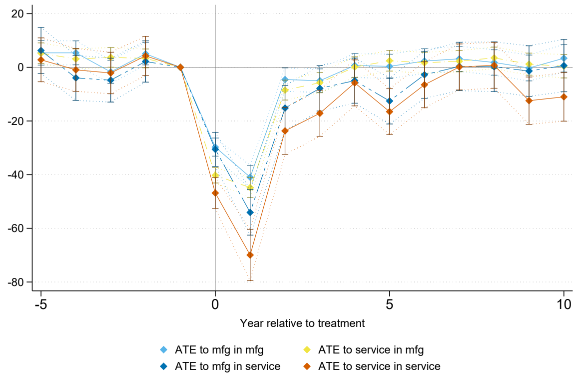
Notes: The table reports regression results of the difference-in-difference terms γ_ι of Equation (2). The sample is restricted to only layoffs of establishments larger than 50 employees and more than 30% laid-off in one year. Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Data: SIAB 7519, 1975-2019.



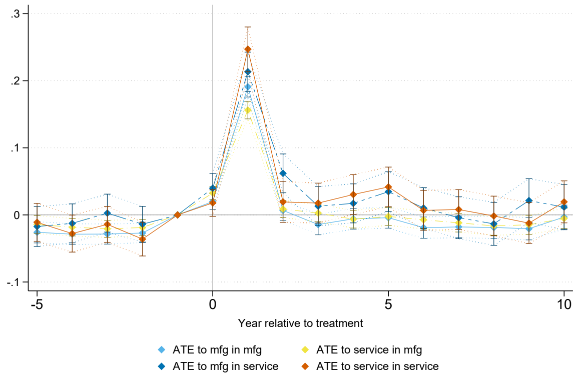
(a) Log wage



(b) Yearly income



(c) Days employed



(d) Number of employers

Figure A.15: Regression results of coefficient γ_k from Equation (3) – Alternative layoff specification

The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. The sample is restricted to only layoffs of establishments larger than 50 employees and more than 30% laid-off in one year. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB 7519, 1975-2019.

A.6.5 Controlling for establishment wage premia

Following Helm et al. (2023), we assess whether wage losses reflect transitions to lower-quality establishments or genuine skill depreciation by including AKM establishment fixed effects (Abowd et al., 1999). The AKM framework decomposes wages into person and establishment components, with establishment effects capturing wage premia independent of worker composition. We use establishment effects estimated by Card et al. (2013) for Germany based on full social security records, made available by the IAB.

We augment our main specifications with establishment fixed effects $\hat{\phi}_{j(i)t}$, where $j(i)$ denotes the establishment employing worker i at time t:

$$
\begin{aligned}
y_{ijt} =& \sum_{\iota=1}^{4} \gamma_\iota \mathbb{1}\{i \in \mathcal{M}_\iota\} \times \mathbb{1}\{t \geq t^* \wedge t \leq t^* + 10\} + \beta \mathbb{1}\{t \geq t^* \wedge t \leq t^* + 10\} \\
& + \alpha_i + \hat{\phi}_{j(i)t} + \theta_t + X'_{it}\xi + \Lambda^- + \Lambda^+ + \epsilon_{it}
\end{aligned} \tag{A.5}
$$

$$
\begin{aligned}
y_{ijt} =& \sum_{\kappa=-5\setminus=-1}^{10} \sum_{\iota=1}^{4} \gamma_{\kappa\iota} \mathbb{1}\{t = t^* + \kappa\} \times \mathbb{1}\{i \in \mathcal{M}_\iota\} + \sum_{\kappa=-5\setminus=-1}^{10} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} \\
& + \alpha_i + \hat{\phi}_{j(i)t} + \theta_t + X'_{it}\xi + \Lambda^- + \Lambda^+ + \epsilon_{it}
\end{aligned} \tag{A.6}
$$

$$
\begin{aligned}
y_{ijt} =& \beta \mathbb{1}\{t \geq t^*\} + \gamma \mathbb{1}\{\text{sector switch}\} \times \mathbb{1}\{t \geq t^*\} \\
& + \delta \mathbb{1}\{\text{occupation switch}\} \times \mathbb{1}\{t \geq t^*\} \\
& + \mu \mathbb{1}\{\text{sector switch}\} \times \mathbb{1}\{\text{occupation switch}\} \times \mathbb{1}\{t \geq t^*\} \\
& + \alpha_i + \hat{\phi}_{j(i)t} + \theta_t + X'_{it}\xi + \Lambda^- + \Lambda^+ + \epsilon_{it}
\end{aligned} \tag{A.7}
$$

where Λ^- and Λ^+ bin periods outside the estimation window as in the main specification.

Results: Establishment quality versus skill depreciation. Table A.12 and Figure A.16 show that controlling for establishment premia substantially reduces treatment effects across all groups. Workers who retain manufacturing occupations while moving to service sectors experience no statistically significant wage penalty: the coefficient falls from -5.9% in the main specification to -0.5% (p>0.10) when controlling for establishment quality. This 92% reduction indicates that the observed penalty in our main specification stems largely from displaced workers sorting into service establishments with lower wage premia rather than from skill depreciation. Substantively, this confirms our core finding that the service sector provides viable employment alternatives for workers with manufacturing occupations: when establishment quality is comparable, these workers face no wage penalty from sectoral transitions. The modest penalty in our main specification reflects that displaced workers, on average, access lower-quality service establishments rather than losing occupation-specific skills in service sector contexts.

This pattern differs notably from occupational switches, where substantial penalties persist even after controlling for establishment quality. Workers moving to service occupations in manufacturing face 2.3% wage losses (vs. 4.6% main), while those switching both occupation and sector experience 17.0% losses (vs. 29.9% main). These 50-60% reductions indicate that approximately half the penalty for occupational switchers reflects establishment sorting, while the remainder represents occupational human capital depreciation.

Workers remaining in manufacturing occupations within manufacturing show 0.9% losses (vs. 2.2% main), driven primarily by unemployment duration rather than lower wages at new establishments. Overall, establishment premia account for 30-60% of observed wage penalties across groups, with the proportion highest for workers retaining occupations (92% for Mfg-Srv, 60% for Mfg-Mfg) and lowest for dual switchers (43% for Srv-Srv).

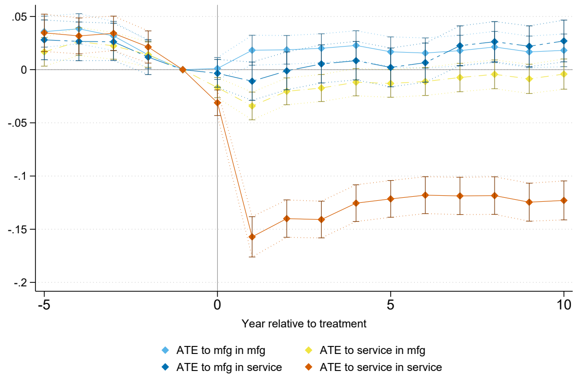
Table A.12: Results: Difference-in-difference with multiple group matching – Including AKM firm-fixed effects

	(1) log(wage)	(2) Yearly income	(3) Number of days worked	(4) Number of employers
$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$				
	-0.009***	-585.08***	-1.65***	0.018***
	(0.002)	(140.27)	(0.39)	(0.001)
$\gamma_{\text{service occupation at manufacturing establishment}}$				
	-0.023***	-17.63	-0.53	0.019***
	(0.002)	(129.48)	(0.36)	(0.001)
$\gamma_{\text{manufacturing occupation at service establishment}}$				
	-0.005	-803.41***	-2.26***	0.030***
	(0.003)	(181.99)	(0.51)	(0.002)
$\gamma_{\text{service occupation at service establishment}}$				
	-0.170***	-6250.75***	-0.12	0.023***
	(0.003)	(173.98)	(0.48)	(0.002)
N	694,776	697,040	697,040	697,040
R^2	0.53	0.19	0.02	0.06

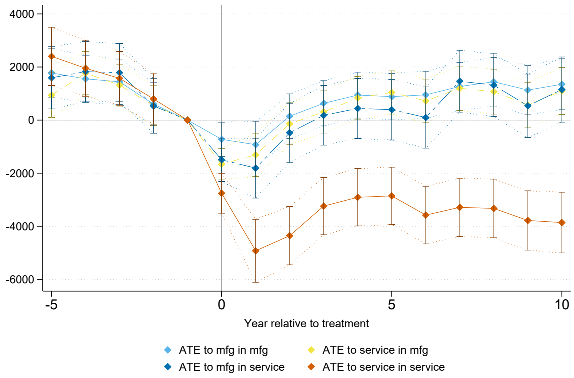
Notes: The table reports regression results of the difference-in-difference terms γ_ι of Equation (A.5). Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Data: SIAB 7519, 1975-2019.

Decomposition results. Table A.13 decomposes effects while controlling for establishment quality based on Equation (4) augmented by $\hat{\phi}_{j(i)t}$. The sector switch coefficient becomes significantly positive (+0.7%, SE=0.002), indicating that conditional on establishment quality, moving from manufacturing to service sectors does not reduce wages. This confirms that sectoral wage differences in our main specification operate through establishment sorting rather than sector-specific human capital.

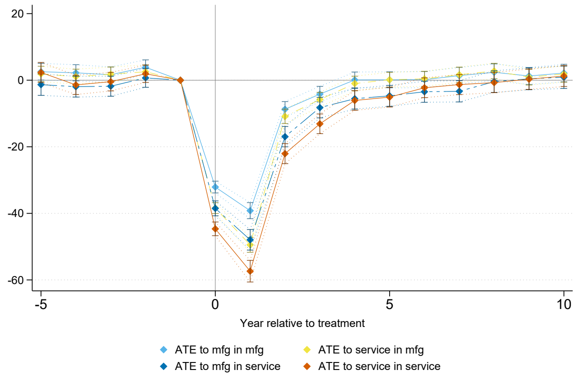
In contrast, the occupation switch coefficient remains large and negative (-5.3%, vs. -6.8% main), declining by only 22%. Occupational human capital losses persist regardless of establishment quality, confirming that occupational skills are less portable across



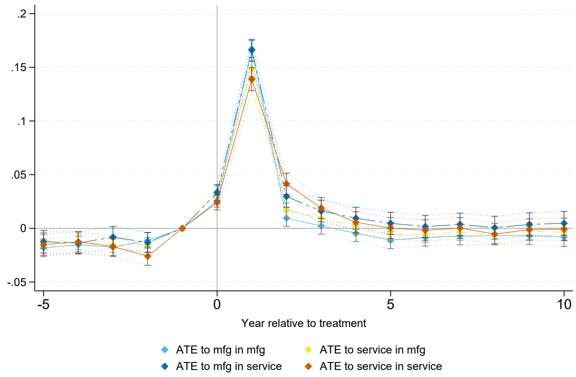
(a) Log wage



(b) Yearly income



(c) Days employed



(d) Number of employers

Figure A.16: Regression results of coefficient γ_k from Equation (3) – Including AKM firm-fixed effects

The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event from specification (A.6). The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB 7519, 1975-2019.

occupations than across sectors. The interaction effect (-14.1% vs. -20.8% main) shows that workers switching both dimensions face penalties from both establishment sorting and skill depreciation, with establishment quality accounting for approximately one-third of the combined effect.

These findings align with Helm et al. (2023), who emphasize establishment premia as important drivers of displacement costs, and Card et al. (2024), who show that industry accounts for approximately one-third of establishment wage premia variation. Our results demonstrate that occupation-specific human capital provides protection against displacement costs: workers who retain occupations can access comparable-quality establishments across sectors— even though there are fewer such establishments in services—, while occupational switches involve human capital losses even conditional on establishment quality.

Table A.13: Sector and occupation switch disentangled – Including AKM firm-fixed effects

	(1) log(wage)	(2) Yearly income	(3) Number of days worked	(4) Number of employers
$\mathbb{1}\{\text{sector switch}\} \times \mathbb{1}\{t \geq t^*\}$				
	0.007***	26.14	-1.31***	0.015***
	(0.002)	(118.65)	(0.319)	(0.001)
$\mathbb{1}\{\text{occupation switch}\} \times \mathbb{1}\{t \geq t^*\}$				
	-0.053***	-1826.27***	2.69***	-0.002*
	(0.002)	(147.49)	(0.397)	(0.001)
$\mathbb{1}\{\text{sector switch}\} \times \mathbb{1}\{\text{occupation switch}\} \times \mathbb{1}\{t \geq t^*\}$				
	-0.141***	-5448.16***	-0.448	-0.005***
	(0.003)	(201.06)	(0.540)	(0.002)
N	853,777	856,392	856,392	856,392
R^2	0.52	0.18	0.02	0.03

Notes: Table shows results from specification (A.7). Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Data: SIAB 7519, 1975-2019.

A.6.6 Time period heterogeneity

Following Schmieder et al. (2023), we assess whether treatment effects vary with macroeconomic conditions by estimating effects separately for four decade-long periods: 1975-1985, 1985-1995, 1995-2005, and 2005-2015. We re-estimate Equations (2) and (3) for each period.

Table A.14 presents static estimates across periods; Figure A.17 shows dynamic effects. Treatment effect magnitudes vary across decades—for instance, workers switching both occupation and sector experience wage penalties ranging from 21.8% (1975-1985) to 31.2% (1995-2005). The ranking of treatment effects shows some variation but two patterns remain consistent across all periods: workers retaining manufacturing occupations in manufacturing face the smallest penalties, and dual switchers experience the largest losses. The relative ordering among the intermediate groups (Mfg-Srv, Srv-Mfg) varies somewhat across decades, though all remain substantially smaller than the dual-switcher penalty.

Figure A.18 plots differences in treatment effects relative to the Mfg-Mfg baseline across periods. The large differential between retaining versus switching occupations persists across all decades, confirming that the importance of occupation-specific human capital is not specific to particular economic conditions.

Income effects show somewhat greater temporal variation. Table A.15 decomposes sector and occupation effects by period using Equation (4). Sector switch penalties increase modestly over time (from 769 euros in 1975-1985 to 1,247 euros in 2005-2015; in constant 2015 euros), consistent with Helm et al. (2023)'s finding that sectoral transitions became more costly for low-wage workers. However, occupation switch penalties remain approximately twice as large as sector switch penalties across all periods, reinforcing our core finding about the relative importance of occupational versus sectoral human capital.

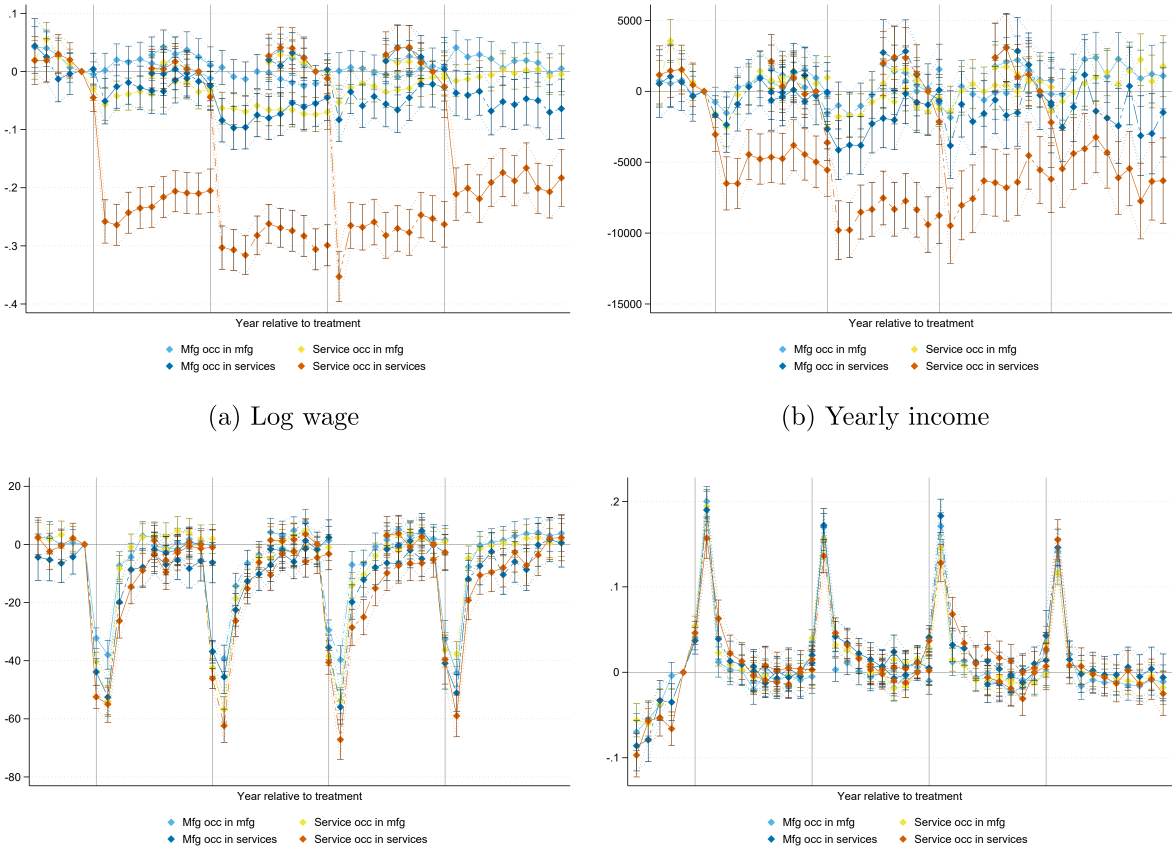
Days employed show increasing displacement costs over time, with unemployment spells lengthening in later periods across all transition types. This likely reflects both compositional changes in the types of establishments experiencing mass layoffs and evolving labor market conditions. Critically, the relative ranking—workers retaining occupations experience shorter unemployment regardless of sector—holds consistently across all decades.

Table A.14: Treatment effects by time period

	(1) 1975-1985	(2) 1985-1995	(3) 1995-2005	(4) 2005-2015
Panel A: Log wage				
$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$	-0.000	-0.022***	-0.024***	-0.002
	(0.005)	(0.005)	(0.004)	(0.005)
$\gamma_{\text{service occupation at manufacturing establishment}}$	-0.036***	-0.066***	-0.036***	-0.010**
	(0.005)	(0.004)	(0.004)	(0.004)
$\gamma_{\text{manufacturing occupation at service establishment}}$	-0.036***	-0.041***	-0.050***	-0.070***
	(0.007)	(0.006)	(0.006)	(0.007)
$\gamma_{\text{service occupation at service establishment}}$	-0.218***	-0.309***	-0.312***	-0.249***
	(0.006)	(0.005)	(0.006)	(0.007)
N	146,475	217,418	182,863	171,360
R^2	0.346	0.439	0.482	0.555
Panel B: Yearly income				
$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$	176.285	-312.917	-1,393.844***	-650.951**
	(268.691)	(252.987)	(273.888)	(294.435)
$\gamma_{\text{service occupation at manufacturing establishment}}$	285.033	-740.263***	-535.134**	-69.734
	(250.583)	(235.617)	(252.776)	(268.669)
$\gamma_{\text{manufacturing occupation at service establishment}}$	-359.594	-669.544**	-2,974.398***	-3,535.946***
	(353.045)	(310.236)	(346.036)	(414.783)
$\gamma_{\text{service occupation at service establishment}}$	-5,482.331***	-10,062.551***	-10,038.278***	-8,203.335***
	(312.327)	(284.245)	(342.489)	(417.663)
N	147,132	218,252	183,332	171,731
R^2	0.138	0.154	0.165	0.209
Panel C: Days in employment				

$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$	2.266**	-1.706**	-3.441***	-5.273***
	(0.911)	(0.707)	(0.708)	(0.788)
$\gamma_{\text{service occupation at manufacturing establishment}}$	4.151***	-0.554	-2.861***	-4.314***
	(0.850)	(0.658)	(0.653)	(0.719)
$\gamma_{\text{manufacturing occupation at service establishment}}$	2.050*	-2.732***	-5.166***	-9.931***
	(1.198)	(0.867)	(0.894)	(1.110)
$\gamma_{\text{service occupation at service establishment}}$	3.365***	-2.451***	-6.507***	-9.477***
	(1.059)	(0.794)	(0.885)	(1.117)
N	147,132	218,252	183,332	171,731
R^2	0.016	0.013	0.017	0.016
Panel D: Number of employers				
$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$	0.033***	0.020***	0.015***	0.023***
	(0.003)	(0.002)	(0.002)	(0.003)
$\gamma_{\text{service occupation at manufacturing establishment}}$	0.037***	0.022***	0.015***	0.021***
	(0.003)	(0.002)	(0.002)	(0.002)
$\gamma_{\text{manufacturing occupation at service establishment}}$	0.052***	0.033***	0.030***	0.031***
	(0.004)	(0.003)	(0.003)	(0.004)
$\gamma_{\text{service occupation at service establishment}}$	0.055***	0.028***	0.025***	0.029***
	(0.004)	(0.003)	(0.003)	(0.004)
N	147,132	218,252	183,332	171,731
R^2	0.137	0.051	0.025	0.013

Notes: The table reports static difference-in-differences estimates from Equation (2) estimated separately for four decade-long periods. Standard errors clustered at worker level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Datasource: SIAB 7519, 1975-2019.



(a) Log wage

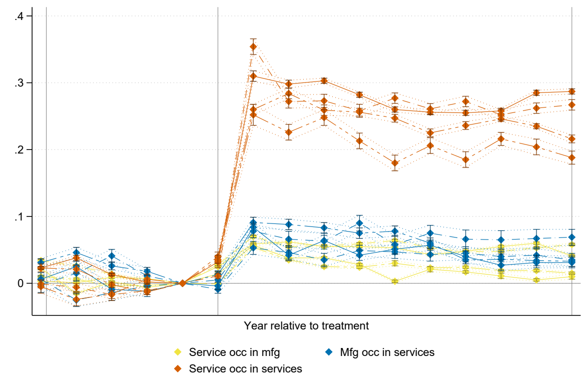
(b) Yearly income

(c) Days employed

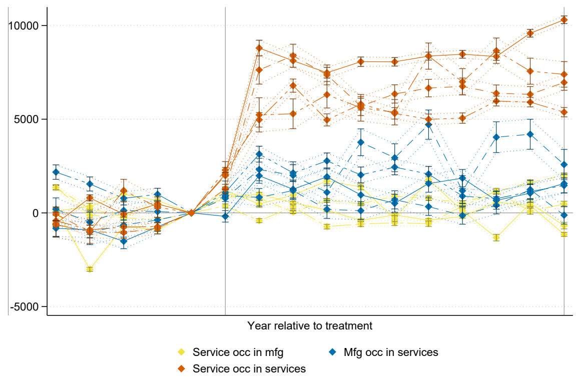
(d) Number of employers

Figure A.17: Regression results of coefficient γ_k from Equation (3) for four ten-year windows

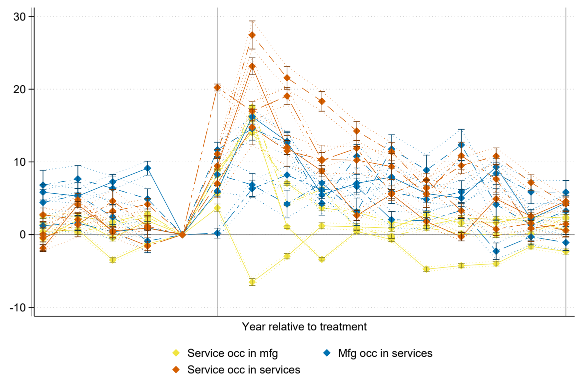
The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB 7519, 1975-2019.



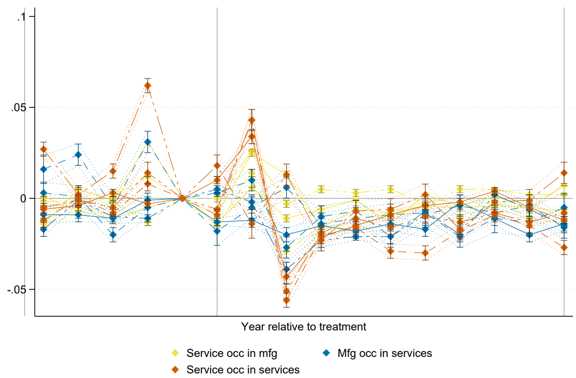
(a) Log wage



(b) Yearly income



(c) Days employed



(d) Number of employers

Figure A.18: Difference in regression results of coefficient $\gamma_{\kappa\iota}$ from Equation (3) to "manufacturing in manufacturing" treatment

The figure plots the difference in coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the "manufacturing in manufacturing" treatment over time relative to layoff occurrence. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB 7519, 1975-2019.

Table A.15: Decomposing sector and occupation effects by period

	(1) 1975-1985	(2) 1985-1995	(3) 1995-2005	(4) 2005-2015
Panel A: Log wage				
Sector switch (γ)				
	-0.039***	-0.027***	-0.041***	-0.034***
	(0.005)	(0.004)	(0.003)	(0.005)
Occupation switch (δ)				
	-0.071***	-0.082***	-0.054***	-0.024***
	(0.006)	(0.004)	(0.004)	(0.006)
Both switches (μ)				
	-0.134***	-0.206***	-0.229***	-0.218***
	(0.008)	(0.006)	(0.006)	(0.009)
N	171,606	297,196	259,553	155,566
R^2	0.335	0.418	0.470	0.543
Panel B: Yearly income				
Sector switch (γ)				
	-768.725***	-662.763***	-1,523.765***	-1,247.165***
	(256.547)	(220.188)	(198.585)	(269.492)
Occupation switch (δ)				
	-1,236.49***	-3,037.52***	-1,940.34***	-788.64**
	(292.442)	(252.044)	(266.516)	(360.786)
Both switches (μ)				
	-4,919.300***	-7,839.836***	-7,092.739***	-7,003.962***
	(402.964)	(344.724)	(360.449)	(494.177)
N	172,322	298,291	260,130	155,890
R^2	0.124	0.136	0.167	0.207
Panel C: Days in employment				
Sector switch (γ)				
	-0.020	-1.039*	-3.118***	-4.206***
	(0.802)	(0.565)	(0.512)	(0.758)
Occupation switch (δ)				
	4.573***	2.182***	1.508**	0.657
	(0.914)	(0.646)	(0.687)	(1.015)
Both switches (μ)				
	-1.736	-3.291***	-2.449***	-3.356**
	(1.260)	(0.884)	(0.929)	(1.391)
N	172,322	298,291	260,130	155,890
R^2	0.018	0.015	0.021	0.015
Panel D: Number of employers				
Sector switch (γ)				
	0.020***	0.016***	0.012***	0.020***
	(0.003)	(0.002)	(0.002)	(0.002)
Occupation switch (δ)				
	-0.001	0.001	0.001	-0.000
	(0.003)	(0.002)	(0.002)	(0.003)
Both switches (μ)				
	0.001	-0.004	-0.002	0.000
	(0.004)	(0.003)	(0.003)	(0.004)
N	172,322	298,291	260,130	155,890
R^2	0.070	0.030	0.028	0.013

Notes: The table reports estimates from Equation (4) estimated separately for four decade-long periods. Coefficients show effects of switching sectors (γ), occupations (δ), or both (μ). Standard errors clustered at worker level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Datasource: SIAB 7519, 1975-2019.