Structural Change Revisited: The Rise of Manufacturing Jobs in the Service Sector*

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Abstract

This paper reevaluates the labor market consequences of structural change over the past 43 years. Taking two different ways of defining manufacturing and service employment as point of departure – according to the industry classification of firms or establishments and according to the occupation and hence the tasks of the workers – we show that structural change is far less serious than generally perceived. Manufacturing and service employment numbers based on the occupations of workers deviate remarkably from the employment numbers based on the industry classification of employers. The decline in manufacturing jobs in Germany is far lower if the measurement of employment is based on the occupation of the worker. About 52% of manufacturing jobs that were lost in manufacturing industries between 1975 and 2017 are offset by new manufacturing jobs in service industries. Using detailed, comprehensive German social security data, we show at the worker level that the service sector increasingly acts as a valuable alternative employment option for workers with manufacturing occupations. We estimate the causal effects of a switch to the service sector on employment outcomes by following workers over time after mass layoffs. The results reinforce our claim that structural change is less significant than perceived, as workers who retain their initial occupation and switch to employment in the service sector experience no significant differences in future employment trajectories compared to workers who manage to stay in the manufacturing sector. This also has important implications for empirical applications. By way of example, we reestimate the effect of international trade on manufacturing employment based on the occupation of the worker. Contrary to previously identified negative effects, we cannot identify significant effects of import exposure on employment in manufacturing occupations.

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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 (e.g., through digitalization and robotization) are omnipresent.[1]

We show, using 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 (concept I) and according to the occupation and hence the tasks of the workers (concept O).

Traditionally, the economic literature uses the industry classification of firms or establishments, i.e., concept (I), when discussing structural change and identifying manufacturing and service employment.[2] The industry classification of a particular firm, which is generally based on the (primary) output produced by the firm, determines whether it belongs to the manufacturing or the service sector. In consequence, all workers of that firm are counted as either manufacturing or service employees – regardless of their actual occupation and tasks performed.

Accordingly, in the context of concept (I), 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 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 elsewhere in the economy. This possibility of changing jobs between industries and sectors without major frictions has been largely overlooked so far and instead, the manufacturing sector and the service sector are often treated and viewed as two separate and independent labor markets.

Concept (O) focuses on the occupation of the worker and accounts for the occupational distribution and shifts at the intensive margin, i.e., changes in the workforce composition within

[1] For instance, studies consider international trade as a driver see, e.g., Pierce and Schott (2016), Autor et al. (2013), or Dauth et al. (2014). Digitalization is studied by Autor et al. (2003), Frey and Osborne (2017) and robotization by Acemoglu and Restrepo (2019) and Dauth et al. (2021b).

[2] For instance, Pierce and Schott (2016) use the U.S. Census Bureau's Longitudinal Business Database that categorizes establishments according to 4-digit SIC or 6-digit NAICS industries. Autor et al. (2013) use employment by industry from the County Business Patterns data, while Acemoglu and Restrepo (2019) rely on the same data and enrich them with data on wages and employment of all workers in the manufacturing sector from the NBER-CES dataset.Dauth et al. (2014) and Dauth et al. (2021b) measure manufacturing employment across 222 distinct industries (including 101 manufacturing industries) using administrative data from the German Institute of Employment Research (IAB).

the manufacturing or service sector. Occupations are based on the actual tasks a worker performs. 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.[3] The official German classification of occupations in our data is based on the same foundations as that of the International Standard Classification of Occupations (ISCO) of the International Labour Organization (ILO).[4]

Usually, workers can perform the same tasks in either sector – one can drive a truck in any industry, one can be an office clerk in any industry, and one can even produce a hard-drive in any industry.[5] 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 2017, the number of workers with manufacturing occupations in the manufacturing sector was only about 1.3 times higher than the number of workers with manufacturing occupations in the service sector.[6] In 1975 the service sector employed 26% of all workers with manufacturing occupations. By 2017, this share had grown to 42%, and the trend indicates that this growth will continue in the future. The total number of manufacturing jobs in the service sector grew during this time period so that workers with manufacturing occupations are increasingly finding work in service industries.[7]

Concept (O) accounts for these facts by determining manufacturing and service employment at the worker level conditioning on their occupation. Accordingly, the work duties, tasks, and in some cases skills, education, and/or training required for the occupation define whether a worker is a manufacturing or service worker.[8] This concept gives a new perspective on the topic and might be better suited for analyzing structural change than the industry classification of firms or establishments.

In the first part of the paper, we revisit structural change and contrast the shift in occupational employment shares within the economy with the shift of total employment between sectors, i.e., concepts (I) and (O). Using unique, detailed matched employer-employee data in combination with establishment data for the years 1975 to 2017 for Germany, we provide new

[3] See also Duernecker and Herrendorf (2019).

[4] ILO states 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 or of his or her status in employment." Source: http://www.ilo.org/public/english/bureau/stat/isco/intro2.htm

[5] Table B.1 in the Appendix serves as further motivation of the importance of the distinction between concepts (I) and (O). For the anecdotal example on hard-drive production, consider IBM corporation: Starting as a traditional hardware manufacturer, IBM increasingly focused on the provision of customer services from the 1990s onwards (see Ahamed et al. (2013)). In 1990, IBM's service segment only accounted for approximately 16% in total revenues, whereas it reached a share of 63% in 2017 (Spohrer, 2017). Eventually, IBM was reclassified to a service firm after a particular threshold was met.

[6] Likewise, in 2017, more than 33% of the workers in the German manufacturing sector held service occupations. Boddin and Kroeger (2021) go into a more detailed discussion on servitization – manufacturing firms are increasingly offering service activities, for instance, after-sales services such as maintenance and repair, and are therefore exhibiting shifts in their employment composition towards a higher share of service jobs.

[7] Keeping in mind the previous example, and think, for instance, of large technology firms that mainly offer software solutions but also produce hardware, or of logistics firms that need technicians to set up a logistics infrastructure, etc.

[8] Note to clarify the terminology: In this paper, the term "jobs" is shorthand for the number of workers in different occupations. "Manufacturing jobs" are thus the total number of workers in a manufacturing occupation. We use this term throughout to refer to the different occupations independent of the employer.

stylized facts and show that standard definitions of service and manufacturing employment based on the firms' or establishments' industries considerably overestimate deindustrialization. Based on concept (O), we document that about 52% of manufacturing jobs that were lost in the German manufacturing sector between 1975 and 2017 are offset by new manufacturing jobs in the service sector. Overall, the discrepancy between the manufacturing employment share measured according to concept (I) – defined by the sector of the employing establishment – and concept (O) – measured by occupation or task of the worker – is increasing over time and reaches a maximum of 5.3 percentage points in 2017.

We explicitly show that workers switch from the manufacturing to the service sector in significant numbers. Roughly 60% of workers who hold a manufacturing occupation and leave the manufacturing sector find new employment in the service sector while keeping a manufacturing occupation. This pattern of movement is increasing over time and occurs for all manufacturing occupations. The share of all manufacturing occupations in the service sector is increasing and the numbers of jobs in the service sector is growing for the vast majority of manufacturing occupations.

Following these observations, we examine the consequences for affected workers on the basis of a number of factors such as wages in order to assess whether the service sector is an adequate employment option. In particular, we follow workers with manufacturing occupations that are affected by an exogenous mass layoff over time. A substantial share of these workers are reemployed in the service sector while retaining their occupation. To evaluate this alternative employment option, we match laid-off workers with non-laid-off counterparts with the same initial occupation within the same initial industry. We then compare employment paths to provide estimates of the causal effect of a sector switch on wages, accumulated income, etc. in a difference-in-difference setting (similar to Goldschmidt and Schmieder (2017) and Schmieder et al. (2020)). The initial treatment effect of a sector switch to the service sector on yearly income is a decline of about 4,000 euros in the first two years after dismissal, irrespective of the occupation at the new job. Subsequently, the effect diminishes over the following years and converges to 1,000 euros towards the end of the sample frame ten years after the layoff.

Once we differentiate between workers who retain a manufacturing occupation in the service sector and workers who (have to) take up a service occupation the picture, however, changes. For workers who keep a manufacturing occupation, the initial treatment effect on yearly income is 2,000 euros lower compared to workers with a new service occupation. For the latter the initial treatment effect is a decline of 5,000 euros in yearly income. The difference in treatment effects is persistent in subsequent years but declines over time. Keeping the original occupation is thus beneficial for workers as they experience lower wage cuts and a faster recovery compared to workers who change their occupation in addition to switching sectors. More so, the drop in income is in a similar range as the decline in income for workers who keep a manufacturing occupation and find new employment in the manufacturing sector after being laid off. Associated, only moderate, income losses reinforce that the service sector actually represents an employment alternative for workers with manufacturing occupations.

This paper provides indication that focusing on the actual occupation of workers regardless of the industry classification of the firm (offering the position) might be critical in order to assess the impact of shocks on the labor market, especially on types of employment such as manufacturing. Our findings have important implications pretty much whenever it comes to both discussions of labor market consequences, be it, for instance, through trade exposure, computerization, digitization or skill-biased technical change, and the assessment of (the need for) labor market policies (e.g., identification of workers at risk of layoffs, assessment of the need for retraining through labor market programs, etc.). Exemplarily, we estimate the impact of import and export exposure from China and Eastern Europe on the employment of workers in manufacturing occupations in Germany and compare the results with the impact of trade exposure on workers employed by manufacturing firms, as studied by Dauth et al. (2014) (cf. Autor et al. (2013) for the U.S. case). Trade exposure is often discussed as a potential driver of the decline in manufacturing employment (e.g., Autor et al. (2013), Caliendo et al. (2019a), Dauth et al. (2014), or Pierce and Schott (2016)), making it a well-suited topic for this purpose. Following precisely their identification strategy, we show that the results are different: While exposure to trade from China and Eastern Europe reduces employment in manufacturing establishments (cf. Dauth et al. (2014)), employment in manufacturing occupations is not affected. The documented fact that the employment decline in the manufacturing sector is moderated by employment opportunities for workers with manufacturing occupations in the service sector offers a suitable explanation for these findings.

Related Literature

This paper adds to a recent set of papers that deal with new aspects of structural change. For instance, Duernecker and Herrendorf (2019) document that economies during the course of structural transformation show a shift in employment numbers based on occupation categories (manufacturing or services) for a broad set of countries. Contrary to their paper, we evaluate the role of the service sector as an outside employment option for workers with manufacturing occupations and investigate the effect of cross-sectoral job switches at the worker level.

Fort et al. (2018) and Ding et al. (2019) analyze the decline in U.S. manufacturing and find that most of the decline in manufacturing employment (about 75%) occurs at continuing firms, i.e., the intensive margin, and that non-manufacturing employment at manufacturing firms is increasing until about 2000. The articles show that, in fact, about 38% of the increase in non-manufacturing employment is caused by growing non-manufacturing establishments of manufacturing firms.[9] Bernard et al. (2017) consider changes in aggregate employment numbers caused by firms for which the industry classification changes and also call for rethinking deindustrialization. Contrary to our paper, these papers, however, rely on concept (I) and thus regard manufacturing employment based on the manufacturing classification of firms. Hence, the finding of increasing non-manufacturing employment in manufacturing is due to new or growing establishments within the boundaries of firms that belong to the manufacturing sector. To the best of our knowledge, the current paper is the first to reevaluate structural change by focusing on the occupation of the worker.

[9] In this context, a firm can consist of multiple establishments or plants.

Naturally, this paper adds to the diverse economic literature on the employment structure of firms (e.g., Caliendo et al. (2015) and Caliendo et al. (2019b)) and its changes in response to a variety of shocks. This includes (but is not limited to) studies that discuss (a) reasons for structural change (using industry-based classifications) mentioned above[10], (b) task-based employment changes (see, for instance, Grossman and Rossi-Hansberg (2008) or Baldwin and Robert-Nicoud (2014)), (c) job polarization (e.g., Bárány and Siegel (2018), Goos and Manning (2007), Goos et al. (2014)), (d) skill-bias changes of the workforce (e.g., Spitz-Oener (2006)), and (e) the firm's (re-)organization in response to trade shocks (e.g., Davidson et al. (2017), Caliendo and Rossi-Hansberg (2012)).

Contrary to our paper, the vast majority of these studies are, however, not concerned with the change in the labor composition within firms and sectors per se, and the link to structural change is seldom established. Instead, measures such as tasks or skills are used to distinguish between different types of workers. Our paper is concerned with neither the performance of firms during adjustments in the employment composition nor their reasons, but instead puts emphasis on the fact that the standard approaches may fail to evaluate structural change properly.

In doing so, the current paper extends the literature on the occupational specificity of human capital by adding the perspective of changes across sectors that were previously thought to be widely different, i.e., manufacturing and services. Like the present paper, Kambourov and Manovskii (2009) argue for the use of occupations when studying employment dynamics and revisit the issue of strongly decreasing earnings after a job loss for the U.S. Related work has been carried out by Gathmann and Schönberg (2010), who study the mobility of accumulated skills in the labor market based on a task approach. Task-specific human capital accounts for more than half of overall wage growth. Their paper backs our understanding of occupational definitions in the sense that most workers move between related occupations that demand very similar tasks. Neal (1995), on the other hand, argues that industry specific human capital is important. However, the underlying data are limited and the author cannot control for occupational changes of workers.

Our exercise of following workers after displacements adds to the literature on occupational mobility and switching costs or earnings losses when displaced. For instance, Jacobson et al. (1993) and later Couch and Placzek (2010) study the earnings losses of displaced workers of distressed firms in Pennsylvania and Connecticut, respectively. The studies find earnings losses in the period immediately after the job loss of more than 30%. The losses are persistently in a range of 15-25% in later years following the displacement. Cortes and Gallipoli (2018) estimate mobility costs across occupations for the U.S. Dix-Carneiro (2014) estimates a structural dynamic equilibrium model of the Brazilian labor market under the assumption of job switching costs between sectors and imperfectly transferable human capital. Costs to transition between sectors are immense in the Brazilian case. Related work for Denmark has been done by Ashournia (2018) who also finds adjustment costs in the range of 10%-15% lower wages after transition. For Germany, we cannot confirm strong adjustment costs. This is presumably due to a strong and clear vocational training system through which workers acquire human capital

[10] See Herrendorf et al. (2014) for a summary of the macroeconomic literature.

that is widely transferable between industries. In their influential study on occupational mobility in the U.S., Moscarini and Thomsson (2007), similarly to the present paper, highlight the importance of the measurement of workers' activities, i.e., occupations. For the U.S., about one third of job-to-job switches involve no change in occupation. In addition, a large proportion of all occupation switches occurs without changing employers. We find similar results for the German labor market while arguing that, indeed, workers' occupations are crucial in determining their return to labor.

A recent study for Germany considers job losses over the business cycle (Schmieder et al., 2020).[11] The authors find persistent effects of job displacements during recessions. More recently, Gathmann et al. (2020) consider spatial spillovers of massive layoffs of more than 500 employees at very large, "systemic" firms. Another study on spillovers of employment responses to international trade shocks has been carried out by Helm (2019). Spatial clusters of industries lead to particular spillover effects. For instance, regions inhabited by high-tech industry clusters are the primary beneficiaries of increasing export opportunities.

The current paper is also related to the literature on assortative matching between employers and employees, and segregation of workers with different productivity levels across employers, e.g., Card et al. (2013) and Song et al. (2019). These papers consider the contribution of assortative matching between high-performing workers and extremely productive firms. We do not explicitly consider the effects of structural change on pay inequality in this paper[12], but our results suggest that mass layoffs triggered by structural change can contribute to pay inequality if only high-performing workers are able to keep their occupation and lower-performing workers have to switch their occupation. This paper is hence also related to recent studies on the declining demand for specific occupations, e.g., Edin et al. (2019).

Finally, this paper adds to the literature on the employment effects of increasing globalization and trade integration. We provide evidence that aggregate effects are less severe than has been previously reported (e.g., Autor et al. (2013) or Dauth et al. (2014)). We also add to the literature on occupational effects of trade; see Ebenstein et al. (2011), Ebenstein et al. (2015), Utar (2018), Traiberman (2019), Helm (2019) or Bloom et al. (2019). All these studies argue for the use of occupations when assessing effects of international trade on labor markets. However, while these studies identify strong negative consequences for workers in particularly heavily affected occupations, we find in the aggregate that total regional employment in manufacturing occupations is not hit by trade since the service sector functions as an alternative employment option for those workers. Ebenstein et al. (2015) argue, as does the present paper, that workers are forced out of the manufacturing into the service sector. They find strong wage penalties for workers forced out of the manufacturing sector and into the service sector by import competition and offshoring opportunities for the U.S. Dauth et al. (2021a) provide a similar analysis for Germany. For Germany, export opportunities outweigh the negative effects of import competition or offshoring of labor intensive tasks. The authors identify two equally important channels through which workers profit from increasing exports, be it (i) on the job or by (ii) switching employers to firms that benefit more from international trade than the pre-

[11] See also Davis and von Wachter (2011) for a study on the U.S. with similar results.

[12] However, we can highly recommend Boddin and Kroeger (2021) for a take on this matter.

vious firm within the same industry. The second channel mainly benefits high-skilled workers identified through two-way fixed effects (see Abowd et al. (1999)).

The remainder of the paper is organized as follows. In Section 2, we introduce the data. Thereafter, in Section 3, we compare the two measurements of structural change based on the sector of the establishment (concept (I)) and the occupation of the workers (concept (O)) and present new stylized facts on structural change and the decline of manufacturing employment in Germany. We present a short application highlighting differential results of the effect of trade integration on manufacturing employment. Section 4 shows that workers increasingly make use of the employment option in the service sector while carrying out manufacturing occupations. This holds for all occupations. We provide first evidence on the pay differences between the sectors. In Section 5, we assess the individual consequences for workers with manufacturing occupations when forced to switch to the service sector. In particular, we evaluate the impact of the service sector on workers' outcomes in its function as an alternative employment option. Section 6 concludes.

2 Data

For this paper, we rely on detailed datasets based on social security records provided by the Institute for Employment Research (IAB) of the German Federal Employment Office. The first is the Establishment History Panel (in German: Betriebs-Historik Panel (BHP)), a detailed establishment-level dataset. The second and third datasets are the detailed longitudinal linked employer-employee dataset (LIAB) and the sample of integrated employment biographies (SIAB), respectivley.[13]

These data are based on official administrative data and employers are required by law to submit reports for all employees subject to social security contributions to the responsible social security institutions at least once a year. This ensures that the data are highly reliable and not prone to misreporting.[14]

The BHP is a detailed representative 50% sample of all establishments in Germany ranging from 1975 to 2017 (for the 1975-1991 period, it includes only establishments in West Germany) with at least one employee subject to social insurance contributions.[15] It contains rich information on the labor structure of the establishment such as the labor composition in terms of the occupational mix (12 different occupation categories according to Blossfeld (1987)), the

[13]For further information on the data, see Heining et al. (2016) concerning the LIAB, Antoni et al. (2019) on the SIAB and Schmucker et al. (2018) concerning the BHP.

[14]The procedure is based on the integrated notification procedures for health, pension and unemployment insurance (DEÜV; formerly DEVO / DÜVO; see for further details: Bender et al. (1996), p. 4ff.; Wermter and Cramer (1988)). http://doku.iab.de/fdz/reporte/2019/DR_06-19.pdf

[15]In Germany, employers are required by law to provide information on the social insurance contributions of their employers. The legal basis for this is Section 28a Social Security Code IV (SGB IV). To enable establishments to participate in the automated social insurance registration process, they need an establishment number. The definition of establishments follows exact specifications. A holding is a regionally and economically separate unit in which at least one person subject to social security or marginal employment is employed. Regional assignment is based on the municipalities in Germany (more than 11,000 in 2017). That is, a firm with branches in different municipalities consists of different establishments with different establishment numbers.

For the analysis in this paper, we rely on the long-term data for West Germany. The figures and results all hold when we include East Germany for the respective time period.

education of the employees (employment by skill categories), the number of female and male workers, the share of foreign workers, the age structure, etc. Additionally, the dataset provides information on the wage structure and the industry of the establishment. The data cover between 640,000 and 1,500,000 establishments yearly and constitute an unbalanced panel, as establishments may drop out of or enter the sample.

The LIAB and the SIAB combine the establishment data extracted from the BHP and employee data on individuals' employment biographies. The matched employer-employee data are a 2% representative sample of all employees and their employers who have been subject to social security contributions at one point in time or were notified to the Federal Employment Agency over the 1975 to 2017 period. The dataset contains individual worker data on labor market variables such as occupations, hierarchy levels, time on the job, time at the employer, daily wages, and other variables influencing human capital such as schooling, university degrees, family status, etc.

The data cover the period between 1975 and 2017 and include between 1,006,028 and 1,533,327 persons and between 244,170 and 399,785 establishments per year.[16] The LIAB yields further information on a much broader set of firm-level information on production, exports, worker training, etc.

For our purpose, one feature of the BHP as well as the SIAB/LIAB is of central importance: The information about the occupation of the worker in addition to the industry classification of the establishment in order to assess structural change by defining it as a shift in occupations and in order to compare this measurement to the commonly used establishment-based classifications.

The BHP contains information on the aggregate numbers of workers' occupations by establishment code in the classification of Blossfeld (1987). The Blossfeld categories are constructed such that educational and task requirements are very homogeneous within and very heterogeneous across Blossfeld categories. In total, there are twelve occupational groups which can be divided into two main fields, i.e., manufacturing and services. Services occupations include the subcategory administrative services.[17] Each of the fields is subdivided further according to the skill requirement of the occupation (low, medium, and high skill). See Table A.1 for a more detailed description of the occupational groups as well as examples. The Blossfeld categories constitute aggregations over finer occupation definitions. This aggregation is carried out by the Federal Employment Agency once employers report information on their employees which includes the occupation of the worker at 5-digit level on a mandatory basis (see below).

The SIAB/LIAB data contain both the total number of workers by Blossfeld categories for the workers' establishment and the worker's occupation at 5-digit level according to the "Classification of Occupations" (in German: "Klassifikation der Berufe", KldB) (Federal Employment Agency, 2011).[18] This is reported by the employer to the Federal Employment Agency

[16] See Section A.1 in the Appendix for more information on the data cleaning. Naturally, the number of establishments is lower compared to the BHP as it is limited by the 2% IEB sample. The number of observations is larger in later years.

[17] Administration services, for instance, include occupations such as bookkeepers which are support staff for business operations or management occupations.

[18] This classification is also used in Spitz-Oener (2006) or Goldschmidt and Schmieder (2017)

on a mandatory basis.[19] The classification structure can be related and matched to ISCO-8 of the ILO[20], is hierarchical, and distinguishes 1,286 occupations at the 5-digit aggregation level.[21] Similar to the Blossfeld classification, the KldB is based on tasks but also on the hierarchy and delegating power within the establishment.[22]

We employ both the KldB and the Blossfeld categories for our analysis. The first classification is more detailed than the Blossfeld classification. However, the Blossfeld classification allows us to identify the total number of workers per category belonging to each establishment.[23] For comparison, we transfer the SIAB/LIAB's KldB occupational categories into Blossfeld categories using a crosswalk provided by the IAB.

Both the SIAB/LIAB and the BHP data contain information on the establishment's industry classification that would commonly serve to identify services and manufacturing employment. The industry classification of the establishments is determined by the Federal Statistical Office and available in the revision of 1993 ("Klassifikation der Wirtschaftszweige 1993", WZ93).[24] The WZ industry classification is a slightly adjusted version of the European NACE industry classification and of hierarchical structure.[25] The economic classification 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 also economically assigned to a single category only. This implies that all workers of this establishment are labeled as either service or manufacturing workers, regardless of their actual occupation, if the industry of the establishment is used as the basis for determining service or manufacturing employment.

This procedure is not purely a German phenomenon, but common international practice and the basis for determining the industry classification in the vast majority of datasets. For instance, in the data description for ILOSTAT's identifier of employment by economic activity, one of the main sources for labor statistics, the ILO describes the concept for categorizing the industry of a worker: *"Having detailed statistics on employment by economic activity allows for the calculation of the share of manufacturing in total employment* [...] *The classification by economic activity refers to the main activity of the establishment in which a person worked*

[19]The fact that reporting is mandatory (and at the annual level) has crucial advantages; e.g., Moscarini and Thomsson (2007) highlight the difficulties when working with the U.S. Current Population Survey in which occupations are self reported by workers.

[20]The ISCO and hence the 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 to which he or she is attached or of his or her status in employment." Source: http://www.ilo.org/public/english/bureau/stat/isco/intro2.htm

[21]For an example of this scheme, see Table A.2 in the Appendix.

[22]The occupational categorization is stored in the first three digits, the fourth digit of the classification captures the hierarchical aspect, and the fifth digit of the classification describes the skill intensity of the respective occupation. Accordingly, at the disaggregate level, the classification of workers might differ, if hierarchy and skill intensity differ, even if the occupations are identical.

[23]Since SIAB/LIAB data are based on a 2% sample, the data do not necessarily cover all workers for a specific establishment. Contrary, using BHP we know aggregate employer information at the establishment level, but not worker-level information.

[24]The industry classification is also available in a newer revision for later years. To ensure the uniformity of the data, however, we use WZ93.

[25]Overall, there are five levels of aggregation including sections (digit 1), divisions (digit 2), groups (digit 3), classes (digit 4), and subclasses (digit 5). The distinction between service and manufacturing categories is generally based on the sectional level.

during the reference period. The branch of economic activity of a person does not depend on the specific duties or functions of the person's job, but on the characteristics of the economic unit in which this person works.", International Labor Organisation ILO (2018).[26] Both the European NACE classification and the International Standard Industrial Classification (ISIC) follow the same procedure. SIAB/LIAB and BHP contain information on both the worker's industry classification based on the establishment's classification and the occupation of the worker, allowing the comparison between both measurements and a reevaluation of structural change.

One concern for this paper may be changing industry classification of establishments. For instance, Bernard et al. (2017) report for Denmark that such switchers account for about half of the overall decline in manufacturing employment for the period of 1994-2007. Contrary to Bernard et al. (2017), we find switchers to have much less of an impact on structural change in Germany, presumably as we focus on establishments (i.e., individual plants) rather than firms (i.e., whole firms including all plants of any industry). We find that switchers affect less than 0.1% of the workers and establishments. Additionally, the number of establishments (and the number of affected workers) that switch from manufacturing to services is approximately identical to the number of establishments that switch from services to manufacturing. Our focus is not on switchers, but on the occupational reorganisation at the establishment level.[27]

3 Structural Change revisited

In this section, we contrast the measurement of manufacturing and service employment based on the industry of the establishment (i.e., concept (I)) with the measurement based on the workers' occupations (i.e., concept (O)).[28] We show that the two measurements differ substantially, which entails serious risks of misclassification and misinterpretation, for example when discussing structural change and its consequences. The use of the occupation-based measurement offers new insights into structural change and the definition of services and manufacturing employment. In the following descriptive analysis, we will focus on West Germany to make use of the long-term data starting in 1975. Data for East Germany are available from 1991 onwards.[29]

3.1 Establishment vs. Occupation-based Measurements of Service & Manufacturing Employment

Figure 1 displays the shares of service and manufacturing employment from 1975 to 2017 in West Germany based on the industry classification of the establishment ((I) – dashed line)

[26]See https://www.ilo.org/ilostat-files/Documents/description_ECO_EN.pdf, page 1.

[27]As switchers are not the primary focus of the present paper, we refer the interested reader to Section E in the Appendix where we show that industry switching and re-classification are not affecting the patterns we present. In fact, merely .2% of observed establishments per year switch sector classes and the switches from service to manufacturing are in equal ranges as vice versa.

[28]For our analysis, we only consider establishments that are classified as service or manufacturing. This excludes the primary sector and construction as well as energy and water supply.

[29]The findings do not qualitatively differ when we focus on East Germany only or on West and East Germany combined. Analyzing both is only possible from 1991 onwards. Results are available upon request.

and based on the occupation of the worker ((O) – solid line). Both measurements indicate a significant decrease in the manufacturing employment share over the period of 43 years. The first measurement shows that employment in the manufacturing sector decreased from 45% in 1975 to only 25.8% in 2017 (from 7.1 million workers to 4.86 million), while the second measurement shows a decrease in the share of workers in manufacturing occupations from 44.2% to 31.1% in the same period (from 6.97 million workers to 5.38 million). Note that the latter measurement takes into account manufacturing occupations in both the manufacturing and service sector.

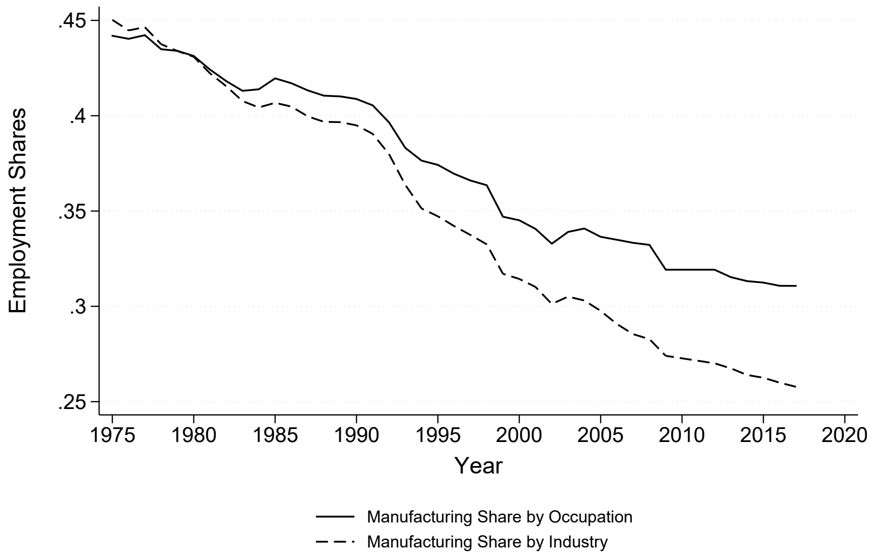
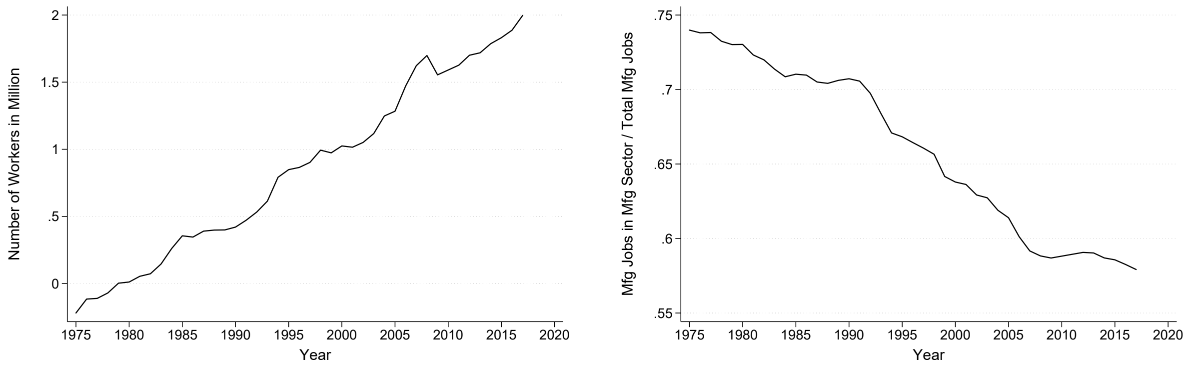


Figure 1: Manufacturing employment shares according to establishment- and occupation-based accounting methods
The graph depicts the shares in total employment for West Germany either by employment classified according to the industry classification of the establishment or according to the individual's occupation. Datasource: BHP.

Although the general trend is similar for both measurements, the magnitude differs considerably. First, we see that structural change is more pronounced when measured by concept (I), i.e., based on the establishment's industry. With this measurement, the share of manufacturing employment decreased by 19.2 percentage points from 1975 to 2017. Based on the occupations of the workers (concept (O)), the share of manufacturing employment decreased by 13.1 percentage points over the same period. The discrepancy between the two measurements generally increases over time and reaches a maximum of 5.3 percentage points in 2017, the last year of observation. The discrepancy between both measurements is increasing over time as manufacturing workers find more and more jobs in the service sector. On average, the share of employment in the manufacturing sector falls by 0.5 percentage points per year whereas the share of workers in manufacturing occupations falls only by 0.36 percentage points. Notice that the share of workers in the manufacturing sector in 1975 was .8 percentage points higher than the share of workers with manufacturing occupations. From 1980 onward, the latter share was higher and the diverging trend started to increase in speed.

Figure 2, Panel (a) translates this discrepancy into absolute numbers and shows the annual number by which establishment-based definitions would underestimate the number of manufacturing workers. From 1975 to 2017, the number of workers holding manufacturing occupations was on average 833,000 higher than the number of workers in manufacturing establishments. The highest discrepancy between both measurements corresponds to a difference of about 2 million workers in 2017. As before, the discrepancy between both measurements is explained by manufacturing workers who are increasingly employed in the service sector. The figure of -220,000, in the first year of observation, implies that in 1975, there were still more workers in the manufacturing sector than workers with manufacturing occupations. Figure 2, Panel (b) depicts the share of manufacturing jobs in the manufacturing sector in all manufacturing jobs in Germany. While almost 74% of workers with manufacturing occupations were employed in the manufacturing sector in 1975, this number had fallen to around 58% by 2017.



(a) Surplus of manufacturing workers when occupation rather than industry of the establishment is used to distinguish between services and manufacturing

(b) Number of manufacturing workers in manufacturing industries relative to total number of manufacturing workers

Figure 2: Trend of manufacturing occupations toward the service sector
West Germany. Datasource: BHP, Federal Statistical Office Germany.

Overall, we find that the measurements deliver very different results when determining manufacturing employment. The findings show that the use of the conventional industry-based measurement carries the risk of overestimating the structural change. The number of existing manufacturing workers is clearly underestimated, while the decline in manufacturing employment is overestimated. Of course, this has important implications for numerous applications, for example for the assessment of structural change and its causes or for the preparation or assessment of labor market policies and reforms (e.g., when determining whether retraining through labor market programs is necessary). Additionally, this also carries the risk of misjudging the potential extent of structural change that the economy could still be exposed to.

Keep in mind that we compare the occupation-based measurement with the measurement based on the *establishments'* industry classification. When using establishments, it is already ensured that establishments belonging to the same firm can have different locations or branches depending on their economic focus (e.g., production location, headquarters, office for customer services, etc.) and are thus treated independently. It is very likely that the misspecification when using firms as the basis for the division of manufacturing and service employment is much higher than when using establishments.

We rule out the possibility of our descriptive findings being attributable to technical factors. We are able to show in detail that (i) establishments entering or leaving the sample, (ii) establishments changing industries, and (iii) workers changing occupations cannot explain the difference in the measurements. Instead, our results are almost entirely explained by changes in the occupational structure of the establishments. The results are shown in Appendix Section E.

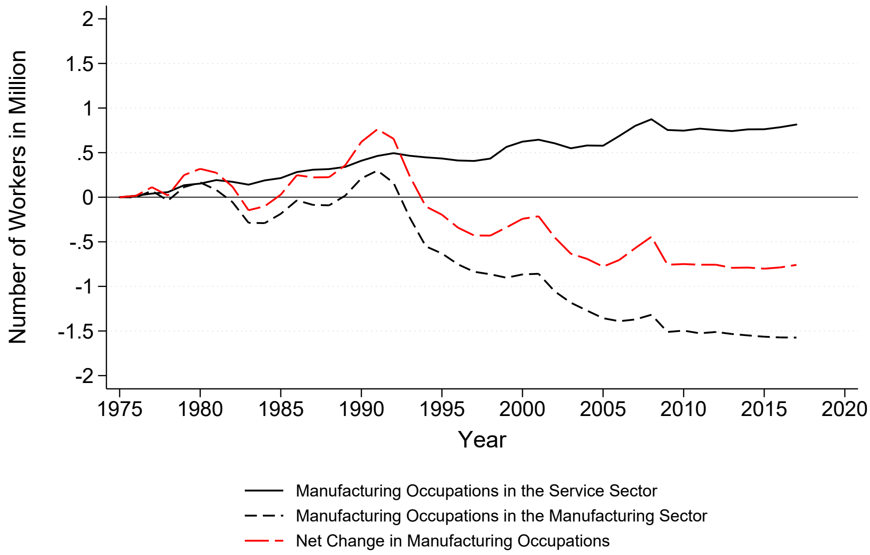


Figure 3: Total number of manufacturing jobs in the service and manufacturing sector (normalized to 1975=0), and the net change in manufacturing jobs across both sectors
West Germany. Datasource: BHP.

Figure 3 helps to gain a deeper understanding of why the proportion of manufacturing workers who are employed in the manufacturing sector decreases over time (cf. Figure 2, Panel (b)). The dashed, black line and the solid, black line show the total decrease and increase in manufacturing jobs compared to 1975 in the manufacturing sector and in the service sector, respectively. The long-dashed, red line shows the net change in manufacturing occupations.

Compared to 1975, the number of manufacturing jobs in the manufacturing sector decreased by approximately 1.6 million jobs from 5.2 million to 3.6 million. During the same time period, the number of manufacturing jobs in the service sector rose from 1.8 to 2.7 million. Accordingly, the net loss in manufacturing jobs totals about 760,000 jobs. This figure is much lower compared to the commonly mentioned numbers relating to the decline in manufacturing employment. The reason for this is that the reappearance of manufacturing jobs in the service sector offers an outside employment option for manufacturing workers in the manufacturing sector and greatly reduces the decline in total manufacturing employment. Overall, about 52% of the manufacturing jobs lost in the manufacturing sector between 1975 and 2017 are offset by new manufacturing jobs in the service sector.

4 The service sector as an alternative employment option

We have presented new stylized facts that stress the importance of focusing on workers' occupations when assessing certain labor market developments, reactions, and policies. While the manufacturing sector and, in particular, the number of manufacturing jobs in the manufacturing sector has been shrinking over the past 43 years, an increasing number of manufacturing jobs have emerged in the service sector. This development suggests that the service sector plays a mitigating role for workers with manufacturing occupations that are affected by the shrinking manufacturing sector. A sizeable share of lost manufacturing jobs in the manufacturing sector has been absorbed by growing employment in the service sector. In the period from 1975 to 2017, the number of manufacturing jobs in the manufacturing sector has decreased by about 1.6 million. During the same time period, the number of manufacturing jobs in the service sector has grown by more than 800,000. Thus, the net decline in manufacturing jobs in the German economy is just about half of the extent to which jobs in the manufacturing sector are lost.

In this section, we first document the distribution of workers with manufacturing occupations across the manufacturing and service sectors in more detail. We will show that the service sector is not just an alternative employment option for a mere handful of occupations, but rather a sizeable share of manufacturing jobs can be found in the service sector across almost all occupations.

Second, we provide evidence that workers switch between the manufacturing and service sector in significant numbers. Accordingly, the service sector does indeed present an outside employment option for manufacturing workers who are already employed in the manufacturing sector (and, e.g., not only for workers who enter the job market for the first time). A considerable proportion of the new manufacturing jobs in the service sector consists of sector switchers who were employed in the manufacturing sector before. We show that workers who are laid off when their employer in the manufacturing sector faces an exogenous negative shock are (in part) able to find a new job in the service sector. Overall, about a third of laid-off workers do not find a new job in a manufacturing occupation in the manufacturing sector. Roughly 80% of these unsuccessful workers switch to the service sector. Surprisingly, 50% even find a new job in their original occupation and this fraction is increasing over time. For the latter workers, the sector switch implies only minimal additional losses as such workers will lose less of their accumulated human capital than workers who have to switch both employer and occupation or workers who fall into (long-term) unemployment.

4.1 Distribution of Occupations Across Sectors

Table 1 shows the distribution of 2-digit occupations across the two sectors, manufacturing and services, for the years 1975 and 2017 in columns (1)-(4). A sizeable proportion of workers are present in establishments where the service or manufacturing affiliation of the establishment does not correspond to the service or manufacturing occupation of the worker. For the manufacturing occupations, which are of special interest for us (see rows 1 to 19 of Table 1), a share of between 3.7% (ceramic workers) and 46.6% (nutrition occupations) of all workers with these occupations can be found in the service sector in 1975 (cf. column 2). In 2017, this share has increased for all manufacturing occupations and ranges between 12.9% (ceramics workers) and 69.6% (nutrition occupations). The ranking of the shares according to which the occupations are present in the service sector almost remains constant over time.

In column (5), we show the shift of the distribution towards the service sector. For almost all occupations, the service sector employs a significantly higher share in 2017 than in 1975. This is due to two reasons: (i) the total number of workers in the manufacturing sector is shrinking, including the number of workers with manufacturing occupations and (ii) the number of jobs in the service sector is growing, including the number of manufacturing jobs for a large share of 2-digit occupations; see column (7).[30]

We also observe that almost all manufacturing occupations experience a decline in total numbers from 1975 to 2017, see column (6). This decline reflects the overall structural change, e.g., through technical change such as robotization and computerization but also changing organization of production through outsourcing and offshoring, and the split into global value chains across the globe. Notable exceptions to this decline are electricians and machinists and related occupations. The figures grow by a third for electricians and almost triple (an increase of 190%) for machinists. The increase in these occupations is very much in line with the increasing use and application of electrical machinery and the emergence of computerization and robotization in high-tech industries for which Germany is well known.

Table 1 thus once again stresses that structural change occurs for (almost) all manufacturing jobs and that it is a broad phenomenon covering a diverse set of industries and a comprehensive set of occupations. The change in distributions also illustrates that the service sector is increasingly offering jobs for manufacturing occupations. This is the case for all manufacturing occupations in significant shares. Accordingly, the figures support the statement that the service sector is an alternative employment option for almost all manufacturing occupations.

[30] A negative value in column (7) in combination with a positive value in column (5) would indicate that the number of workers in a given occupation decreases in the service sector, but the decrease in jobs in that occupation is even higher in the manufacturing sector.

Table 1: Occupations' distribution across sectors

Occupation	(1) 1975 Manufacturing	(2) 1975 Service	(3) 2017 Manufacturing	(4) 2017 Service	(5) 1975 - 2017 Δ to Service	(6) 1975 - 2017 Total %-Δ	(7) 1975 - 2017 Service sector %-Δ
Miners, oil quarriers	80.4%	19.6%	34.0%	66.0%	46.5 p.p.	-80.8%	-35.2%
Stone preparers, building material makers	94.5%	5.5%	80.9%	19.1%	13.6 p.p.	-42.0%	101.6%
Ceramics workers, glass makers	96.3%	3.7%	87.1%	12.9%	9.2 p.p.	-58.7%	42.6%
Chemical workers, plastics processors	92.4%	7.6%	79.2%	20.8%	13.2 p.p.	-20.8%	117.8%
Paper makers, printers	92.9%	7.1%	79.6%	20.4%	13.4 p.p.	-52.7%	36.7%
Wood preparers, wood products makers and related occupations	93.4%	6.6%	79.8%	20.3%	13.7 p.p.	-49.3%	55.8%
Metal producers	95.6%	4.4%	81.3%	18.7%	14.4 p.p.	-28.8%	204.7%
Toolmakers, smiths, mechanics	69.2%	30.8%	60.8%	39.2%	8.3 p.p.	-25.0%	-4.7%
Electricians	60.0%	40.0%	57.1%	42.9%	2.9 p.p.	33.3%	43.1%
Assemblers and metal workers (no further specification)	94.4%	5.6%	77.1%	22.9%	17.3 p.p.	-31.4%	182.5%
Textile processors	87.2%	12.8%	67.0%	33.0%	20.2 p.p.	-88.2%	-69.6%
Leather makers, leather and skin-processing occupations	86.5%	13.5%	72.1%	27.9%	14.4 p.p.	-87.3%	-73.8%
Nutrition occupations	53.4%	46.6%	30.4%	69.6%	23.0 p.p.	21.6%	81.6%
Construction workers	37.9%	62.1%	28.3%	71.7%	9.7 p.p.	-59.7%	-53.4%
Room equippers, upholsterers	58.0%	42.0%	45.6%	54.4%	12.4 p.p.	-36.7%	-18.1%
Carpenters, model makers	76.4%	23.6%	68.2%	31.8%	8.2 p.p.	-32.6%	-9.2%
Painters, lacquerers and related occupations	66.1%	33.9%	39.6%	60.4%	26.5 p.p.	-17.1%	47.6%
Goods examiners, despatchers	80.2%	19.8%	80.7%	19.3%	-0.5 p.p.	-76.2%	-76.8%
Machinists and related occupations	66.6%	33.4%	78.6%	21.4%	-12.0 p.p.	190.1%	85.8%
Technicians, technical specialists	67.4%	32.6%	56.0%	44.0%	11.4 p.p.	26.9%	71.2%
Engineers, chemists, physicists, mathematicians	59.1%	40.9%	51.1%	48.9%	8.0 p.p.	183.9%	239.7%
Wholesale and retail trade	19.7%	80.3%	17.8%	82.2%	1.9 p.p.	55.0%	58.7%
Services agents and related occupations	4.3%	95.7%	8.0%	92.0%	-3.7 p.p.	99.1%	91.4%
Transport occupations	31.6%	68.4%	18.9%	81.1%	12.7 p.p.	43.2%	69.8%
Administrative occupations, office occupations	33.2%	66.8%	20.4%	79.6%	12.9 p.p.	46.3%	74.5%
Security occupations	20.2%	79.8%	7.9%	92.1%	12.3 p.p.	118.2%	151.8%
Publicists, translators, artists	27.1%	72.9%	19.8%	80.2%	7.3 p.p.	104.5%	125.1%
Health service professions	1.1%	98.9%	0.5%	99.5%	0.6 p.p.	206.3%	208.2%
Social, education-related occupations, humanities specialists, scientists	4.7%	95.3%	3.0%	97.0%	1.7 p.p.	491.8%	502.5%
Housekeeping, cleaning, guest attendance occupations	12.4%	87.6%	3.1%	96.9%	9.3 p.p.	26.4%	39.8%

Notes: The table shows the distribution of 2-digit occupations across the two sectors, manufacturing and service, for 1975 and 2017 as well as the change toward the service sector from 1975 to 2017, and the change within the service sector. Δ stands for "change", %-Δ for "percentage change". Data: SIAB 7517, 1975-2017.

4.2 Flows of Manufacturing Workers Across Sectors

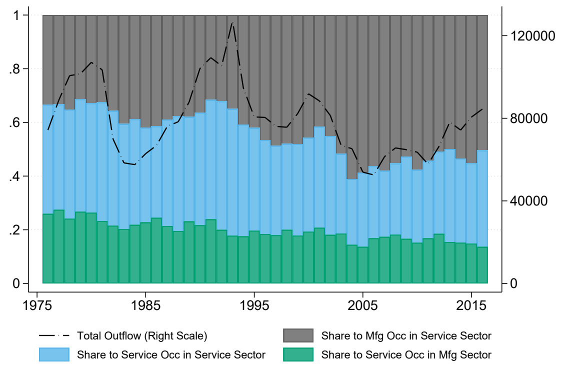
To reinforce our claim that the service sector presents an alternative employment option for manufacturing workers, it is important not only to show that a large number of manufacturing workers can be found in the service sector and that this number is increasing over time (cf. Section 3.1), but also that workers do indeed actively switch between the manufacturing and the service sector. The descriptive statistics in this section show that this is the case. Workers who originally hold manufacturing occupations increasingly switch from the manufacturing to the service sector and account for a large share of newly created manufacturing jobs in the service sector. This indicates that the barriers to a job switch across sectors are sufficiently low and rules out the notion that occupations in the service and manufacturing sector require different sets of skills.

Figure 4 shows the total outflow of workers with manufacturing occupations from the manufacturing sector (including shares by destination) in Panel (a) and the total inflow of workers with manufacturing occupations into the service sector (including shares by origin) in Panel (b). Neither figure includes workers who are out of employment. Starting with Panel (a), we observe fluctuating outflows out of manufacturing occupations in the manufacturing sector around a stable annual mean of approximately 79,700. The bars show the shares of alternative occupation-sector combinations into which the workers move. Over time, an increasing share of workers moves to manufacturing jobs in the service sector. In 1975, at the beginning of the sample period, only about 32% of workers leaving the manufacturing sector find a new job with a manufacturing occupation in the service sector. At the end of the period, in 2017, this share has increased to almost 50%. We observe a maximum of 60% in 2004. Simultaneously, the total share of workers switching to a service occupation is decreasing. In particular, the share moving to service jobs in the manufacturing sector declines from 25% in 1975 to 15% in 2017.

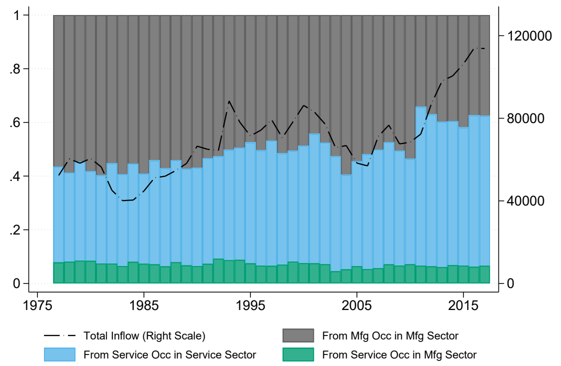
Panel (b) depicts the inflow into manufacturing jobs in the service sector. The total inflow into manufacturing jobs in the service sector is increasing over time. The yearly increase in the second half of the 1970s is between 60,000 and 65,000 jobs. In the late 2010s, this number has reached a value of 115,000 per year after several years with strong growth. The differentiation by origin shows that the share of workers switching from a service job in the service sector to a manufacturing job in the service sector is increasing over time and hence covers a large part of the newly created jobs. The share increases from about 42% in 1975 to about 60% in 2017. In addition, the share of workers moving from manufacturing occupations in the manufacturing sector into manufacturing occupations in the service sector is sizeable. The share is close to 60% throughout the 1970s and 1980s and about 50% in the following years. In the years after 2010 the share falls to 40%. Note that the absolute number of switchers into manufacturing occupations in the service sector is increasing over time. The decreasing share therein of workers moving from manufacturing occupations in the manufacturing sector is explained by an even larger increase in the numbers of workers moving from service occupations in the service sector.[31]

[31] Note that the shares reported in Figure 4 , Panels (a) and (b) are conditional on the fact that the underlying workers change jobs and are observed in the data in both years around the job switch. Also, the shares reported in Panel (a) consider as a denominator only workers who do not switch between two manufacturing jobs in the manufacturing sector. The numbers do not coincide with the figures presented in the previous section, since

In summary, the descriptives show that there are significant flows of workers between the sectors. Increasingly, workers with manufacturing occupations who were originally employed in the manufacturing sector switch to establishments in the service sector while retaining their manufacturing occupation. Likewise, we increasingly observe inflows into manufacturing occupations in the service sector. A sizeable fraction of these inflows comes from workers who previously held manufacturing jobs in the manufacturing sector. The trends once again confirm our claim that the service sector functions as an alternative employment option for workers with manufacturing occupations. Switches into the sector occur frequently and increasingly. Through its growth, the service sector is able to dampen the decline of jobs for workers with manufacturing occupations in the manufacturing sector.



(a) Outflow of manufacturing occupations in the manufacturing sector



(b) Inflow into manufacturing occupations in the service sector

Figure 4: Total flows of manufacturing occupations out of the manufacturing sector and into the service sector by other occupation-sector pairs.
Datasource: SIAB.

5 Wage effects through mass layoffs

The previous sections showed (i) that we overstate structural change when employment measurements are based on the industry classification of the firm instead of on the occupations of the workers, and (ii) that the service sector is able to absorb a large fraction of lost jobs for workers with manufacturing occupations. However, what remains to be shown in detail are the consequences for workers when they switch employment to the service sector. It is well known that involuntarily switching jobs is associated with a wage penalty and also that wage differences between the two sectors exist.[32] We show that across all workers with manufacturing occupations working in the service sector is on average associated with a 29% lower wage as

here we only consider persons who switched between the two sectors, manufacturing and service, whereas in the previous section, the figures included workers newly entering the labor force as well as workers moving out of the labor force, e.g., through retirement.

[32]See Appendix Section C.1 and Addison and Portugal (1989), Burda and Mertens (2001), Bender et al. (2002) or Schmieder et al. (2020).

compared to working in the manufacturing sector.[33] These figures give a first indication that workers with manufacturing occupations in the service sector will have to accept wage cuts compared to their previous remuneration in the manufacturing sector. However, they are based on workers who switch in either direction between the sectors.

To assess the actual causal effects of switching employment between the sectors on workers' outcomes, we thus resort to events where workers presumably are forced to leave their job for exogenous reasons (most likely triggered by structural change). In particular, we focus on mass-layoffs in manufacturing establishments that affect workers with manufacturing occupations. Since there are many potential drivers of structural change, we utilize events where an establishment shrinks by a significant fraction from one year to the next (i.e., mass layoffs, cf. Schmieder et al. (2020) and Gathmann et al. (2020)). We identify mass layoffs according to the regulations in the German Employment Protection Act.[34]

We use such mass layoffs because other methodology (e.g., as in Section F) is not able to differentiate between voluntary and involuntary job changes and the data do not allow us to determine the reasons why establishments shrink. Nonetheless, we argue it will mainly be exogenous reasons such as severe demand, competition or cost shocks that will force establishments to lose a sizeable portion of their overall employment over a short time. Any potentially endogenous (mis)management is still exogenous to the individual workers we consider and caused solely by actions of the firm's management. We only consider workers who were already working at the establishment at least two years prior to the layoff event. In addition, German labor regulations are very strict, which makes layoffs more difficult the longer a person has been employed in a firm – independent of the workers' productivity. Both factors make the layoff event itself even less endogenous for the worker. In that sense, our results represent a lower bound for the costs of switching sectors as voluntary switches (due to better job opportunities) are most likely not covered.[35]

First, we report numbers on such layoffs and flows of the affected workers into new, alternative employment by occupation and sector. Thereafter, we follow workers into their new jobs and evaluate the impact of the job switch on employment outcomes. To do so, we match laid-off workers with workers who are not laid off but employed in the same occupation-industry combination in the year before the layoff. Then, we estimate average treatment effects of being laid off on the laid-off workers (average treatment effect on the treated, ATT; cf. Goldschmidt and Schmieder (2017) and Schmieder et al. (2020)).

[33]Additionally, for 42 out of 47 2-digit occupation classes we find a (statistically significant) negative wage premium, i.e., a wage penalty, for working in the service sector. These range from -51% to -4%. See Appendix Section F for details on analysis and results.

[34]Under the Act, an employer is obliged to notify the employment agency of any event that terminates a significant proportion of its jobs between two reporting years. In particular, for establishments with more than 20 and less than 60 employees, an event is defined as firing at least 5 employees. For establishments with 60 to 500 employees, an event is defined as shrinkage by at least 10% or more than 25 employees. An event for establishments with more than 500 employees is defined as shrinkage by 30 or more employees from one year to the next. Most papers studying layoffs rely on larger shares for the reduction in employment to define mass-layoffs. However, we argue that our layoff definition covers more relevant layoffs since structural change is a slow process. In the following, whenever we mention 'layoffs' we refer to this concept of 'mass-layoffs'.

[35]See Jacobson et al. (1993) for an early study utilizing mass layoffs and arguing for exogeneity; likewise see Schmieder et al. (2020) for further reasoning behind the use of mass layoffs in the German context.

5.1 The incidence of mass layoffs

Figure 5 plots the observed total annual number of manufacturing establishments with mass-layoffs (dashed-dotted line, right scale), the total annual number of laid-off workers therein (blue bars, left scale), and the total annual number of laid-off workers with manufacturing occupations therein (grey bars, left scale).[36] The number of layoff events in the manufacturing sector is roughly stable across the years affecting around 2% of all establishments in a given year. The number peaks in the early 1990s due to restructuring after German reunification. The numbers of laid-off workers are similarly stable, with the exception of peaks after reunification and more recently after the global financial crisis. In recent years, the numbers have declined, but we still observe around 7,500 laid-off workers annually. The fraction of laid-off workers with manufacturing occupations therein is equally stable at a level of 50 to 60%.

A share of 70% of the laid-off manufacturing workers manages to find new employment in a manufacturing occupation in the manufacturing sector. However, 30% do not find new employment in their initial or a similar occupation in the manufacturing sector. For these, Figure 6 shows the shares of workers who find new employment in a manufacturing occupation in the service sector, a service occupation in the manufacturing sector, or a service occupation in the service sector. The share of workers finding new employment in a manufacturing occupation in the service sector grows continuously over the years, starting with a share of around 40% in the second half of the 1970s and clearly dominating with a share of more than 60% in 2017. Some 17-25% only change their occupation to a service occupation and remain in the manufacturing sector. Likewise, 25-35% change both occupation and sector so that they are re-employed in a service occupation in the service sector after being hit by a layoff. Both of the latter shares decrease over time.

In summary, mass layoffs occur frequently, while their incidence increases during crises and restructuring after large structural shocks, such as reunification. A significant proportion of workers with manufacturing occupations usually does not find new employment in a job where the occupation and industry of the employer are the same as before. Importantly, the service sector functions as a safety net for a sizeable share of these workers, and increasingly so during recent years. More than 60% of laid-off workers who have to switch either occupation or sector only switch to the service sector but keep their occupation. This proves to be important for future employment trajectories as we will show next.

5.2 Effects of a sector switch – exogeneity through layoffs

We identify workers affected by a mass layoff event. Similarly to Goldschmidt and Schmieder (2017) and Schmieder et al. (2020), we then compare the affected workers with a control group, which consists of workers with similar characteristics who held the same occupation in the same industry in the year prior to the layoff event but were not affected by mass layoffs (and also did

[36] Note that the underlying data are from the SIAB dataset, a matched employer-employee dataset that does not necessarily provide us with worker-level information for all laid-off workers. The data, however, always contains aggregated employment data for a given establishment such that layoff events are identified according to the total number of full-time workers. This explains why the number of laid-off workers is only approximately two times higher than the number of layoff events at manufacturing establishments.

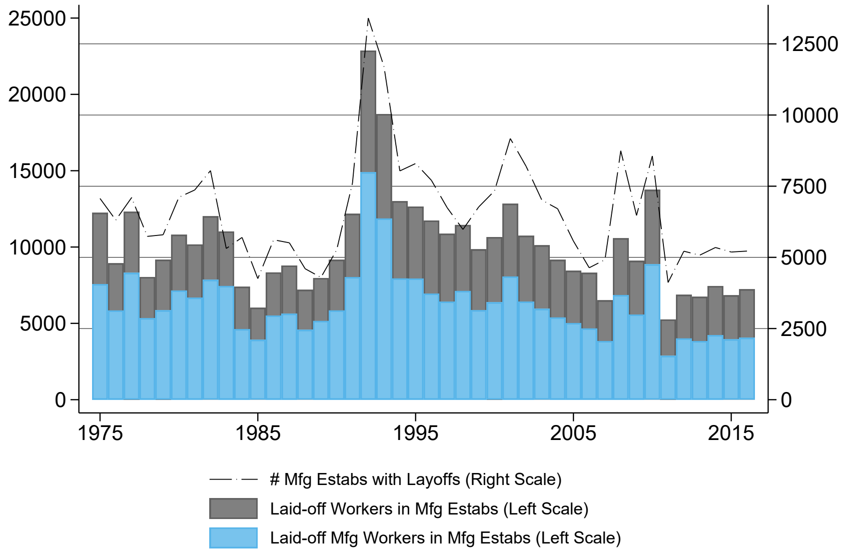


Figure 5: Layoffs and laid-off workers in the manufacturing sector

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 7517.

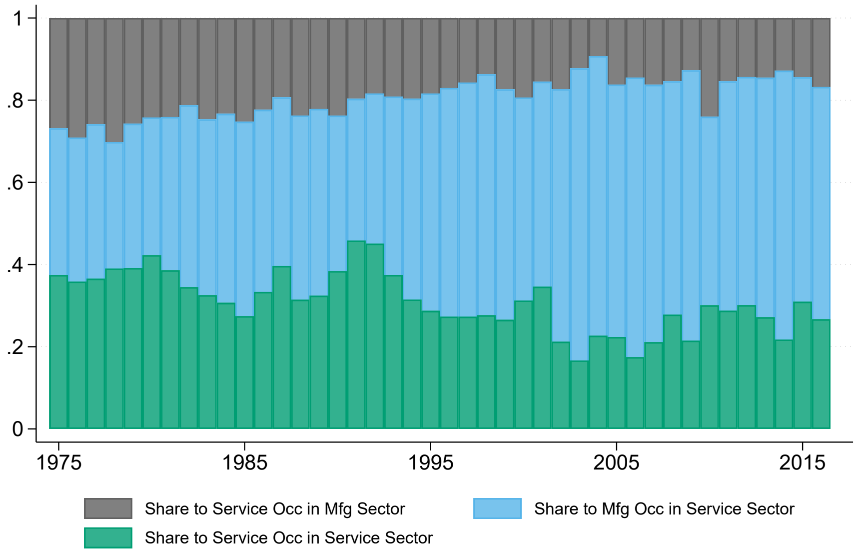


Figure 6: Laid-off manufacturing workers of manufacturing establishments and next year's occupation-sector combination

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 7517.

not change employers for other reasons). The set of treated persons is restricted to workers who are employed at an establishment that experiences a mass layoff and who hold a manufacturing occupation in the year of the layoff. We exclude workers who stay at an establishment where a layoff is observed.

We construct a control group from workers that do not become laid-off but show the same propensity to becoming laid-off within narrowly defined occupation-industry cells per year. More specifically, we build the control group from the set of workers who, in the year of the layoff, hold the same 3-digit occupation and are employed in the same 2-digit industry as the laid-off workers, but whose employer is not affected by a mass layoff in that year (and ever before). We compute the propensity score of being laid off in the following year with a probit regression using one and two-period lagged wages, tenure length, and the size of the establishment as covariates. Workers are matched according to the nearest neighbor principle and each potential control worker can function as control only once.[37]

Table C.1 in the Appendix reports basic characteristics of the treatment and control groups in the years immediately before and after the layoff event. The characteristics are remarkably similar for treated and matched control workers – even for characteristics on which we do not condition in the matching procedure – indicating a well functioning identification strategy.

Since layoff events occur every year, we therefore apply a difference-in-differences event study design combined with propensity score matching (c.f., Davis and von Wachter (2011) and Goodman-Bacon (2021)). We estimate Equations (1) and (2) on the full employment histories of the set of laid-off workers and their non-laid-off matched counterparts over a period from five years before the year of layoff to ten years after the layoff. Equation (1) estimates the time-average treatment effects ('static diff-in-diff') and Equation (2) estimates time-varying treatment effects ('dynamic diff-in-diff'). We assess effects on four different outcome variables y_{ijt} for persons i at establishment j in year t: the logarithmic (daily) wage in the workers main job, the accumulated yearly income, i.e., daily wages multiplied by days worked and summed across all jobs the worker has, the days in employment per year, and the number of different employers, as proxy for job volatility.

$$y_{ijt} = \gamma_\iota \mathbb{1}\{i = \mathcal{M}_\iota\} \times \mathbb{1}\{t \geq t^*\} + \beta_{t^*} \mathbb{1}\{t \geq t^*\} + \alpha_i + \chi_j + \theta_t + X'_{it}\xi + \epsilon_{it} \tag{1}$$

$$\begin{aligned} y_{ijt} = &\sum_{\kappa=-5}^{10} \gamma_{\kappa\iota} \mathbb{1}\{i = \mathcal{M}_\iota\} \times \mathbb{1}\{t = t^* + \kappa\} + \sum_{\kappa=-5}^{10} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} \\ &+ \alpha_i + \chi_j + \theta_t + X'_{it}\xi + \epsilon_{it} \end{aligned} \tag{2}$$

The estimation includes person (α_i), establishment (χ_j), and year (θ_t) fixed effects; t^* is the year in which a layoff occurs. We estimate the equations individually for each treatment of $\mathcal{M}$; in Appendix Section G.2 we additionally run a pooled estimation on the full set of treatments $\mathcal{M}$.

[37]See for instance Davis and von Wachter (2011), Schmieder et al. (2020) or Goldschmidt and Schmieder (2017) for similar matching approaches and their application to layoffs.

$$\mathcal{M} = \left\{ \begin{array}{l} \text{manufacturing occupation at manufacturing establishment,} \\ \text{manufacturing occupation at service establishment,} \\ \text{service occupation at manufacturing establishment,} \\ \text{service occupation at service establishment} \end{array} \right\}.$$

$\mathbb{1}\{i = \mathcal{M}_\iota\}$ indicates that worker i is treated according to the ι^{th} element out of the set of movements, i.e., potential new employment type, of laid-off manufacturing workers in a mass layoff. We bin the end points and do not report them. Note that for this difference-in-difference approach with matching $\mathbb{1}\{t \geq t^*\}$ and $\mathbb{1}\{t = t^* + \kappa\}$ vary also for the matched control-group workers.[38]

The approach allows us to identify the differences between workers' outcomes for workers who lost their job, presumably due to structural change, and for workers in the control group who were not affected by mass layoffs, hence the ATT. The coefficients γ_ι and $\gamma_{\kappa\iota}$ thus measure the difference in the dependent variable on average and for each year κ before and after the layoff occurred between the treatment and control group. The event study allows for the inclusion of other time-varying confounders, X_{it}, age, age^2, and age^3.

In Table 2 and accompanying figures, we contrast treatment effects across the four transition types of $\mathcal{M}$ after being laid off for the four outcomes introduced above. Table 2 contains the results for the static difference-in-difference estimation (1) and Figures 7 and 8 (as well as D.1, D.2 in the Appendix) for the dynamic difference-in-difference estimation (2).

Column (1) of Table 2 shows that effects on future wages depend heavily on the future occupation-sector combination the worker manages to obtain. Workers who find new employment in a manufacturing occupation in the manufacturing sector even experience an increase in future wages of on average 0.7%. All other transitions show negative treatment effects, but these vary greatly depending on the transition. As postulated in the previous sections, occupation specific human capital proves equally important for workers' wages as sector specific knowledge: Workers who find a new job in a manufacturing occupation in the service sector show an equally strong wage cut as compared to workers who find new employment in a service occupation in the manufacturing sector. Workers switching to a manufacturing occupation in the service sector lose about 5.3% in wage levels while workers with a new job with service occupation in manufacturing industries lose 5%. Nevertheless, the treatment effects of these two transition types are in a similar range and divert strongly from the large effect on wages for workers taking up a service occupation in the service sector following the layoff who experience a wage cut of about 14%. The event study results reported in Figure 7 broadly confirm these results while additionally revealing that changes in wages as result of a layoff are persistent. We do not observe strong convergence effects in the ten years following the layoff.

Similar figures emerge for accumulated income (column (2) of Table 2 and Figure D.1). It increases by about 205 euros for workers transitioning to a manufacturing occupation in manufacturing industries. It falls for the other transition types, again with similar ranges for

[38] For completeness, we report results of an event study without control group in Appendix Section G.

new manufacturing occupations in services and for new service occupation in manufacturing – we observe a decline of 1,452 euros and 1,005 euros, respectively. Again, workers transitioning to service occupations in the service sector are hit hardest by the layoff. They lose about 3,134 euros in accumulated income.

Figure 8 shows results on the days in employment, hence indicating search periods after becoming laid off. As before, workers who find new employment in manufacturing occupations in manufacturing show the shortest search periods, even with a slight increase in days employed per year (panel (a)). Workers transitioning to a new employer in the manufacturing sector but switching occupation type have also rather short search periods (panel (c)). Workers with new employment in a manufacturing occupation in the service sector search for longer but for the benefit of retaining a manufacturing occupation, presumably retaining much human capital (panel (b)). Longest search periods are shown by workers transitioning to a service occupation in services. Presumably, these workers searched for new jobs with similar features as their old jobs but were unable to find such an opening and after a search period they settled on an apparently less attractive job with new occupation at a very different employer, i.e., in the service sector.

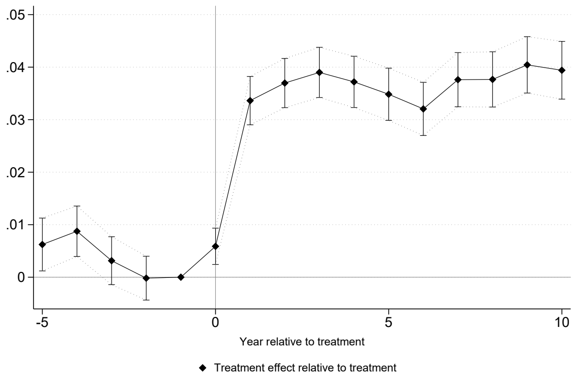
In comparison to the wage differences between sectors (cf. Appendix Section F), this exercise highlights that the unconditional wage differences and wage differences observed when including individually triggered job to job transitions are driven by other factors than wage differences across occupations between the sectors.

Thus, these results indicate that while workers on average manage to find new employment in reasonable time after a layoff, the accompanied changes in wages are persistent (cf. Figure 7). This observation once more highlights the importance to consider both a worker's occupation and the sector she is employed in.

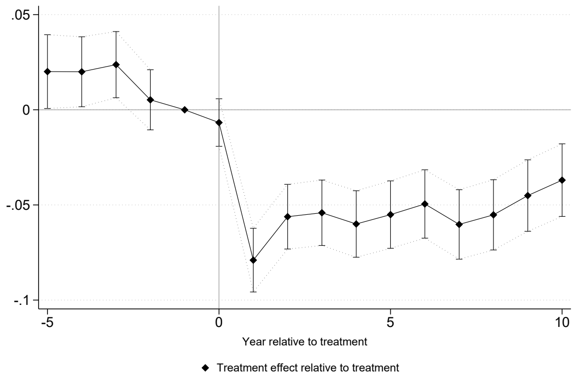
Table 2: Results: Difference-in-difference with matching – sample restricted to one treatment only

	(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	-0.00485***	205.18***	0.2312	0.0252***
	(0.00095)	(56.94)	(0.184)	(0.00068)
N	1,759,963	1,759,963	1,759,963	1,759,963
R^2	0.41	0.10	0.01	0.13
Panel B: Switch to service occupation in manufacturing sector				
γ	-0.0496***	-1005.76***	-0.980	0.031***
	(0.0053)	(364.68)	(0.933)	(0.003)
N	71,736	71,736	71,736	71,736
R^2	0.34	0.08	0.01	0.11
Panel C: Switch to manufacturing occupation in service sector				
γ	-0.0526***	-1452.38***	-2.875***	0.043***
	(0.0044)	(264.21)	(0.841)	(0.003)
N	136,510	136,510	136,510	136,510
R^2	0.38	0.09	0.01	0.07
Panel D: Switch to service occupation in service sector				
γ	-0.143***	-3134.52***	-0.141	0.037***
	(0.005)	(216.36)	(0.906)	(0.003)
N	131,931	131,931	131,931	131,931
R^2	0.31	0.08	0.01	0.07

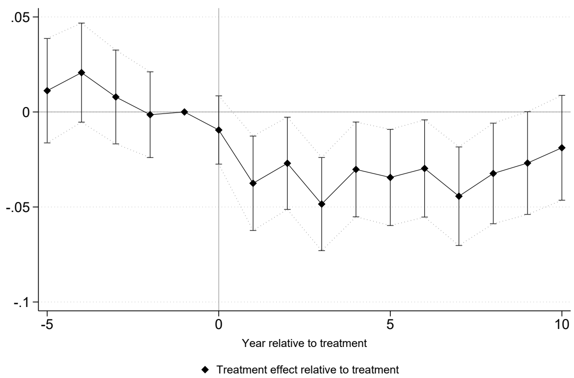
Notes: The table reports regression results of the the difference-in-difference terms γ of Equation (1). Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.



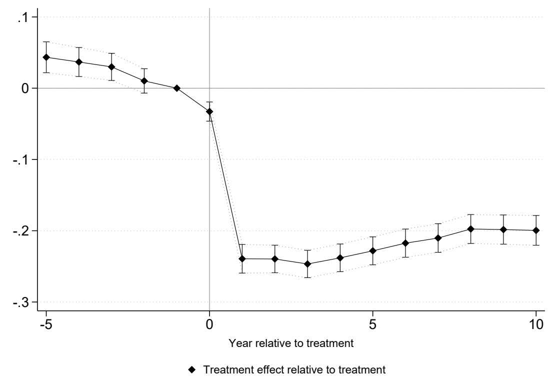
(a) Manufacturing occ. in manufacturing sector



(b) Manufacturing occ. in service sector



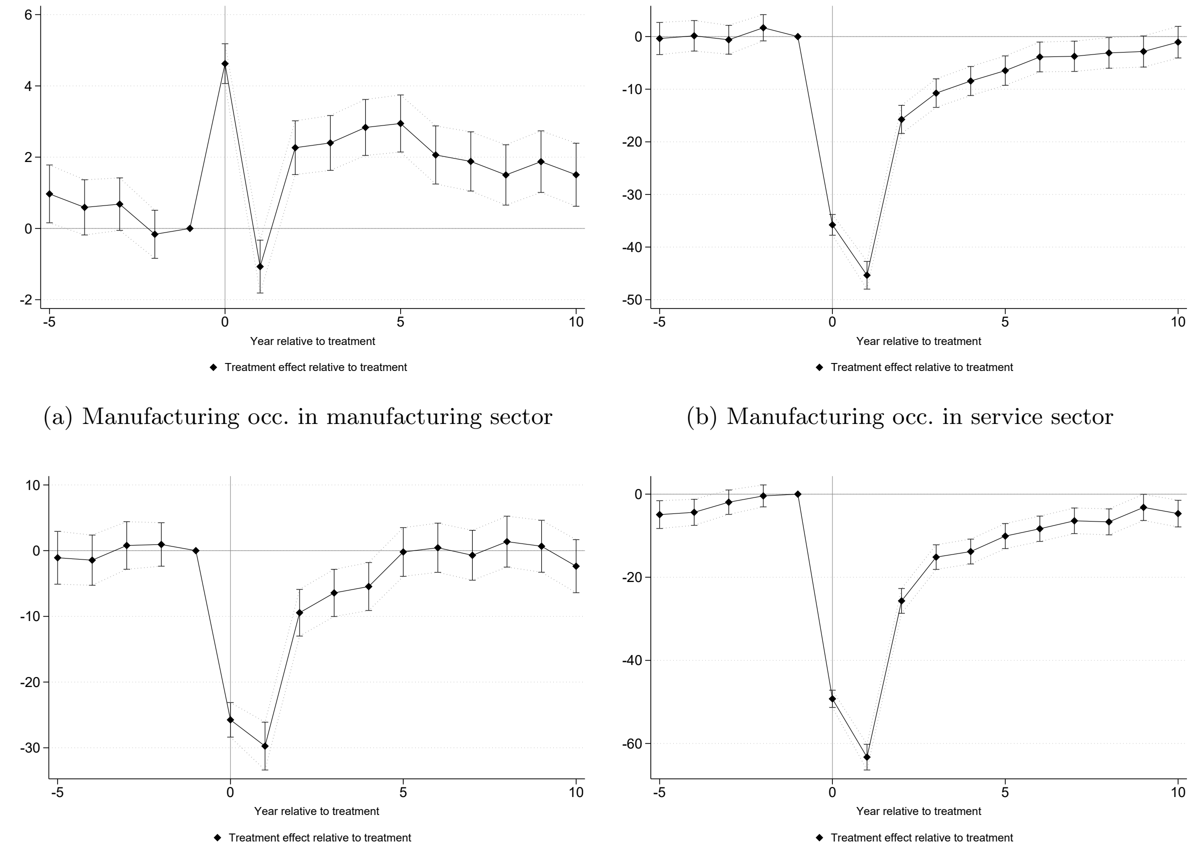
(c) Service occ. in manufacturing sector



(d) Service occ. in service sector

Figure 7: 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. Horizontal lines show the average treatment effect for the 10 years post layoff. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.



(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 8: 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. Horizontal lines show the average treatment effect for the 10 years post layoff. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

Our analysis complements related contemporary research on the impact of displacements on workers biographies. Relying on similar methodologies several papers study job transitions after mass layoffs. For instance, Davis and von Wachter (2011) show that transitions are more difficult and accompanied by larger earnings losses in recessions, Dauth et al. (2021a) discuss adjustments in light of increasing globalization and labor competition from low wage countries, Blien et al. (2020) differentiate by routine intensity. Here, however, we neither take a stance on the cause for the mass-layoff nor on the general economic environment (except controlling for year effects). The contribution rather shows that occupation specific human capital is important in determining job prospects. But also the sector of employment is important since the service sector in general pays lower wages irrespective of the occupation.

In fact, we can compare average treatment effects across the different new occupation-sector employment types after becoming laid-off. From Table 2 it becomes clear that both the occupation and the sector in which workers are employed matter for their outcomes equally. When we compare the treatment effects across new employment types where only one characteristic changes with respect to the job prior to the layoff, i.e., effects reported in Panels B and C, we observe that to change industries but to retain a manufacturing occupation hurts workers equally in terms of pecuniary outcomes as to change occupations but to remain in the manufacturing sector. Accordingly, we show that an occupation switch leads to lower losses than a sector switch, however, the difference in the treatment effects is small.[39]

In summary, the exercises in this section show that workers with manufacturing occupations do indeed find new employment in the service sector when displaced in an exogenous layoff event. A sizeable proportion of these manages to retain their initial occupation, which is beneficial for future employment trajectories. We can thus conclude that while there is structural change at the aggregate level, i.e., declining total employment in manufacturing industries, workers directly affected by this trend are not necessarily hit as hard as commonly perceived. They can rely on an increasing number of employment options in the service sector that require similar knowledge and skills as their previous jobs in the manufacturing sector. Switching to these outside employment options is associated with only moderate wage penalties.

5.3 Who moves where?

The analysis in the previous section suggests that the service sector indeed represents an alternative employment opportunity for workers in the manufacturing sector that are affected by structural shocks. Although there is a loss of human capital as a result of the sector change, the wage cuts of the laid-off workers are not as severe as might have been expected given the average wage differentials between sectors.

However, workers finding new employment in a manufacturing occupation in the service sector may differ from workers finding a job in another occupation-sector combination. Table 3 contains information on the characteristics of workers in the year immediately before layoff, broken down by the new occupation and sector combination after layoff. Indeed, workers

[39] The result that the occupation is similarly important for workers' outcomes as the industry, or in our context, sector, after a displacement confirms what previous studies for different contexts already indicated, e.g., Moscarini and Thomsson (2007).

are somewhat different. Workers finding new employment in a manufacturing job in the manufacturing sector are the youngest, least educated and have a higher proportion of women. Additionally, their tenure is the lowest, as is their average skill level. They were employed in the least productive establishments (proxied for by the AKM effect (Abowd et al., 1999)) and are themselves the worst-performing workers.

Table 3: Worker characteristics by movement type in year pre-layoff

	(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	4.15	4.53	4.50	4.37
	(0.62)	(0.53)	(0.66)	(0.66)
yearly income	26644.29	38013.79	40169.90	34810.16
	(19039.52)	(24077.24)	(32996.13)	(26630.16)
age	31.16	38.23	34.76	34.66
	(10.33)	(10.80)	(10.59)	(11.37)
college	0.04	0.06	0.12	0.09
	(0.20)	(0.24)	(0.33)	(0.29)
years in education	9.45	9.92	10.50	10.19
	(2.02)	(2.20)	(2.89)	(2.56)
tenure	3.22	6.34	4.98	4.08
	(3.28)	(6.12)	(5.18)	(4.38)
female	0.40	0.20	0.25	0.19
	(0.49)	(0.40)	(0.44)	(0.39)
Skill level $\{1 = \text{low}, 2 = \text{medium}, 3 = \text{high}\}$	1.56	1.71	1.82	1.88
	(0.68)	(0.74)	(0.78)	(0.75)
AKM person effect	4.21	4.39	4.43	4.37
	(0.36)	(0.36)	(0.44)	(0.37)
AKM firm effect	0.15	0.19	0.18	0.16
	(0.22)	(0.22)	(0.21)	(0.23)
N	12693	71887	4831	11083

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.

5.4 Matching within $\mathcal{M}$

Since the workers' characteristics in the four new occupation-sector combinations after layoff differ moderately on average, we extend the previous analysis accordingly. To uniquely identify the treatment effects of movement for each of the four combinations of $\mathcal{M}$, we repeat the mapping procedure such that we match groups of five workers consisting of four treated workers, one for each treatment (element) of $\mathcal{M}$, and a non-laid-off control worker.

The matching proceeds along the following steps: (i) We first select the treatment group with the fewest observations at any 3-digit occupational and 2-digit industry level combination. In our case this is the switch to a service occupation in the manufacturing sector. (This set is denoted by $\mathcal{M}_{\min\{|\iota|\}}$.) (ii) We restrict the matching sample to this group of workers in the year prior to layoff and potential non-laid-off control workers only. (iii) We estimate propensity scores and select and mark treatment-control pairs of workers based on the nearest-neighbor principle by year. (iv) We restrict the matching sample to $\mathcal{M}_{\min\{|\iota|\}}$ and workers of one of the remaining treatment groups in $\mathcal{M}$ for which the treatment year is the same. (v) We repeat step (iii) to (v) for all remaining treatment groups. This procedure results in matched groups of five workers as described above.[40] (vi) Finally, we extend the estimation sample to the full employment biographies for all workers that we identified as treatment-control group or treatment-treatment group match in the former procedure. We then and estimate the following difference-in-difference equations:

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

$$\begin{aligned} y_{ijt} = &\sum_{\kappa=-5}^{10} \sum_{\iota=1}^{4} \gamma_{\kappa\iota} \mathbb{1}\{t = t^* + \kappa\} \times \mathbb{1}\{i = \mathcal{M}_\iota\} + \sum_{\kappa=-5}^{10} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} \\ &+ \alpha_i + \chi_j + \theta_t + X'_{it}\xi + \epsilon_{it} \end{aligned} \tag{4}$$

As before, the estimation includes person (α_i), establishment (χ_j), and year (θ_t) fixed effects, as well as time-varying person characteristics (X'_{it}). $\mathcal{M}_\iota$ denotes the ι^{th} element from the set of movements, i.e., potential new employment types, of laid-off manufacturing workers after a mass layoff,

$$\mathcal{M} = \left\{ \begin{array}{l} \text{manufacturing occupation at manufacturing establishment,} \\ \text{manufacturing occupation at service establishment,} \\ \text{service occupation at manufacturing establishment,} \\ \text{service occupation at service establishment} \end{array} \right\}.$$

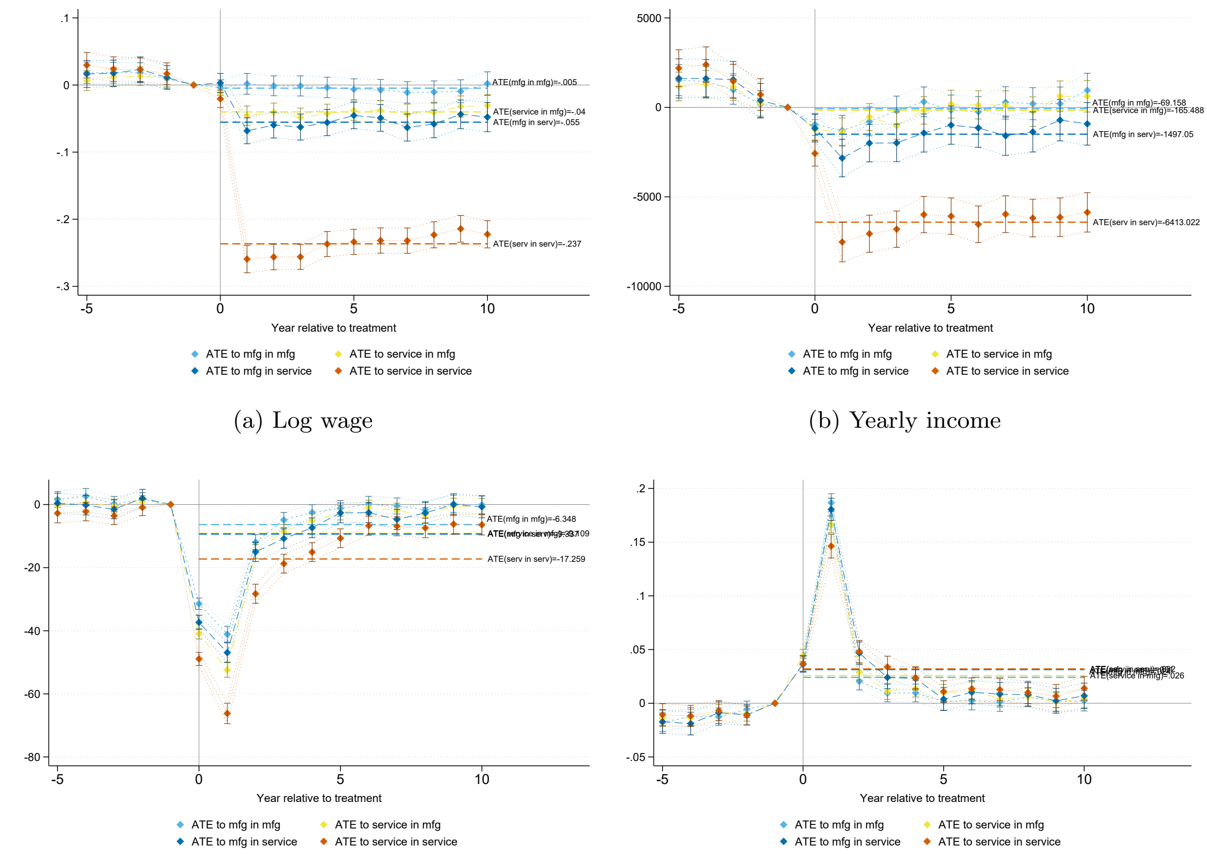
The results of this estimation (see figure 9) largely support the previous results qualitatively. We, however, no longer find statistically significant effects on the wages of workers who retain a manufacturing occupation and find new employment in the manufacturing sector, see panel (a). The wage effects for workers who, after being laid off, either move to a service occupation while remaining in the manufacturing sector or move to the manufacturing sector while retaining a manufacturing occupation remain statistically indistinguishable from one another. Workers who switch to a service occupation in the service sector after a mass layoff before a mass layoff are the hardest hit in this investigation with an average wage decline of 24% over the following ten years after layoff. Results of the remaining outcome variables remain largely as before.

[40]Matching statistics are shown in Table G.1 in the Appendix.

Table 4: Results: Difference-in-difference with multiple group matching

	(1) log(wage)	(2) Yearly income	(3) Number of days worked	(4) Number of employers
$\gamma_{\text{manufacturing occupation at manufacturing establishment}}$				
	-0.0145***	-661.75***	-2.42***	0.0272***
	(0.0026)	(153.77)	(0.52)	(0.0018)
$\gamma_{\text{service occupation at manufacturing establishment}}$				
	-0.0499***	-708.47***	-2.13***	0.0266***
	(0.0024)	(142.38)	(0.48)	(0.0017)
$\gamma_{\text{manufacturing occupation at service establishment}}$				
	-0.0722***	-2316.55***	-3.88***	0.0395***
	(0.0033)	(195.98)	(0.66)	(0.0023)
$\gamma_{\text{service occupation at service establishment}}$				
	-0.2329***	-6579.56***	-5.90	0.0327***
	(0.0032)	(189.39)	(0.64)	(0.0022)
N	344,078	345,181	345,181	345,181
R^2	0.34	0.08	0.01	0.04

Notes: The table reports regression results of the the difference-in-difference terms γ_ι of Equation (3). Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.



(a) Log wage

(b) Yearly income

(c) Days employed

(d) Number of employers

Figure 9: Regression results of coefficient γ_k from Equation (4)

The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. Horizontal lines show the average treatment effect for the 10 years post layoff. The sample is restricted to only laid-off workers. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

5.5 Occupational vs. Industry Employment – an empirical application

The discrepancies between the two measurement concepts raise concerns about our understanding of structural change and its severity, which is built upon previous studies that rely on concept (I), i.e., classification of manufacturing employment based on the industry of the firm. For a large number of research and policy questions, however, it is of importance to know what the consequences of certain shocks are for individual workers, including their transition in response to the shock.

Trade exposure is commonly discussed as one such shock and potential driver of shrinking manufacturing employment (e.g., Autor et al. (2013), Caliendo et al. (2019a), Dauth et al. (2014), or Pierce and Schott (2016)), making it a well suited topic to evaluate whether the distinction between occupation and industry-based (manufacturing) employment also implies different empirical findings. To do so, we estimate the impact of import and export exposure from China and Eastern Europe on the employment of workers in manufacturing occupations in Germany and compare the findings with the impact of exposure to international trade on workers employed in manufacturing industries as found by Dauth et al. (2014) (cf. Autor et al. (2013) for the U.S. case). We follow precisely their identification strategy, i.e., we use Bartik-type instruments of regional trade exposures that identify effects based on the cross-regional variation in the industry structure and use trade flows to other advanced economies as instruments for trade between Germany and Eastern Europe, respectively China. The estimating equation is

$$\Delta Manu_{rt} = \alpha + \beta_1 \Delta Exp_{rt}^{East} + \beta_2 \Delta Imp_{rt}^{East} + \Gamma' X_{rt} + \sigma_r + \kappa_t + u_{rt}, \quad (5)$$

$\Delta Manu_{rt}$ is computed as either the ten-year change in the share of all workers employed at establishments with a manufacturing industry class (concept (I); analyzed by Dauth et al. (2014)) in a region r's total working age population; or the share of all workers with a manufacturing occupation irrespective of the employer in the total working age population within region r (concept (O); proposed in this paper). ΔImp_{rt}^{East} and ΔExp_{rt}^{East} are the changes in regional import and export exposure to China and Eastern Europe, respectively, and X_{rt} is a vector of regional control variables. The regional trade exposures are constructed as shift-share instruments according to

$$\Delta(TradeExposure)_{rt}^{East} = \sum_j \Delta(TradeFlow)_{jt}^{East} \frac{E_{rjt}}{E_{jt}} \frac{1}{E_{rt}},$$

where j denotes industry and $E_{(\cdot)}$ is the employment in either region r, industry j, or industry j's employment in region r. Trade flows between Germany and "the East" are estimated in a first stage with corresponding trade flows of other advanced countries with "the East" as instruments to mitigate endogeneity issues such as German supply or demand shocks driving both employment changes and changes in international trade. We follow Dauth et al. (2014) and stack long differences from 1988 to 1998 and from 1998 to 2008. The first difference includes

West Germany only, the second difference includes reunified Germany.[41]

First, we replicate the baseline specification of Dauth et al. (2014) (see Panel (A) of Table 5). $\Delta Manu_{it}$ is the ten-year change in total employment in manufacturing industries as the share of the labor force in a region r, i.e., manufacturing employment is defined according to concept (I). The results – naturally identical to the findings of Dauth et al. (2014) – indicate job losses in manufacturing industries as a result of increased import exposure and job gains in manufacturing industries as a result of increased export exposure in a region. The preferred specification in column (5) contains a set of local labor-market controls and region-time fixed effects. The estimated coefficients of this specification "imply that a ten-year change of $1,000 per worker in import exposure reduces manufacturing employment relative to working age population by 0.19 percentage points, whereas export exposure increases this share by 0.4 percentage points", Dauth et al. (2014), p. 1656.

Second, we change the concept of measuring manufacturing employment to concept (O). We consider all workers with manufacturing occupations as manufacturing employment and $\Delta Manu_{it}$ accordingly is computed as the ten-year change of the share of workers with manufacturing occupations in a region r's total labor force. Results are displayed in panel (B) of Table 5. We can rely on the Bartik instruments to measure the effects of trade exposure in this definition since also total regional employment is differently affected by an increase in trade exposure depending on the industry structure (i.e., the underlying regional distribution of firms). By estimating whether total employment in manufacturing occupations within regions is differently affected by changes in trade exposure, we take job opportunities outside the previous employers into account. More precisely, we incorporate the possibility of workers finding a new job at a different employer in the same region – potentially belonging to the service sector – if the previous employer is negatively hit by import competition.

This approach is actually more closely related to the original reasoning behind the applicability of the shift-share design as proposed in Autor et al. (2013). Regions are treated as secluded labor markets without in- and outflow of workers and hence increasing exposure to imports or exports will have effects on labor demand and supply within that region dependent on the industry structure (and demand). If a regional labor market is shocked, there will be general equilibrium adjustments in wages which affect labor demand in all industries not only those directly competing with imports or exporting.

The specifications and control variables remain unchanged in comparison to Panel (A) of Table 5. The employment effects of the increase in export exposure are in a similar range as before (if not lower in the more reliable specifications of columns 3-5 when including fixed effects) and the estimates of controls are broadly comparable. The effect of import exposure on manufacturing employment measured as the total number of workers holding manufacturing occupations is, however, different from the effects on employment in manufacturing industries. We can no longer identify a significant effect of import exposure on manufacturing employment

[41] For a detailed description of the identification strategy, the data, the estimations and a more detailed description of the six different specifications, see Dauth et al. (2014). Panel (A) of Table 5 is identical to Table 1 of Dauth et al. (2014), page 1653, and is replicated using the files and data provided in their supplementary material.

(using the occupation-based measurement). This finding is in line with the previously presented observation that a large proportion of workers with manufacturing jobs who disappear from the manufacturing sector reappear in the service sector, where the number of workers with manufacturing occupations is increasing. Contrary to the importing side, where outside job opportunities seem to mitigate the negative effects of import exposure, the exporting side shows almost identical effects, as both the goods producing industries and also the goods producing occupations seems the be equally positively effected by foreign demand. Previous studies that evaluate the effect of trade on manufacturing generally do not consider these workers with manufacturing occupations employed in service industries.

Our result also matches recent findings of Bloom et al. (2019) and Caliendo et al. (2019a) who, based on a dynamic general equilibrium model of discrete job choice, show that a large fraction of workers in the U.S. relocate to construction and service industries when facing the "China shock". Their model, though, is not able to capture occupation choice. We provide evidence that previous occupations matter with respect to relocation and that the occupational composition of sectors is less different than widely perceived. By considering manufacturing employment according to workers' occupations, our approach also connects to recent findings that, in particular, workers in specific occupations are negatively affected by import shocks (Ebenstein et al. (2011), Ebenstein et al. (2015), Utar (2018), Traiberman (2019), or Helm (2019)). Our findings, however, take a slightly opposing stand in that occupational tenure is a main component of what determines human capital and thus wages are set irrespective of the employer's industry; see, e.g., Kambourov and Manovskii (2009). More importantly, on average, occupations that are negatively affected by import shocks in manufacturing industries are also in demand in service industries (cf. section 4.1) and the growth of this sector offsets the initial negative effects of international trade on import competing industries.

This empirical application has important implications, as it calls for a rethink of the way we measure structural change and classify employment in general. At present, the distinction between occupation and industry-based measurements of manufacturing oftentimes is not clear and, as we show, empirical effects and implications are different. Consequently, it is important to distinguish between the effects on employment in manufacturing industries and employment of workers holding manufacturing occupations, for instance when evaluating the effect of trade on manufacturing. The fact that import exposure leads to shrinking employment in the manufacturing sector does not imply declining employment in manufacturing occupations as well. Differentiating between the two is crucial, as the implications, for instance in terms of policy advice, e.g., concerning labor market reforms or policies, will differ.

Table 5: Industry vs. occupational measurement

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) OLS
Panel A: Manufacturing						
by Industry						
Δ import exposure	0.035	-0.028	-0.149**	-0.158**	-0.190***	-0.075
	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)	(0.05)
Δ export exposure	0.332***	0.444***	0.409**	0.425**	0.399*	0.442***
	(0.12)	(0.12)	(0.18)	(0.21)	(0.21)	(0.12)
manuf. of tradable goods	-0.108***	-0.083***	-0.073***			
	(0.01)	(0.02)	(0.02)			
high skilled		0.011	-0.046	-0.042	-0.039	-0.047
		(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
foreigners		-0.197***	-0.159***	-0.159***	-0.162***	-0.161***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
women		-0.057***	-0.062***	-0.061***	-0.060***	-0.060***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
routine occupations		-0.039	-0.025	-0.021	-0.014	-0.023
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
manuf. of other tradable goods				-0.073***	-0.068***	-0.083***
				(0.02)	(0.02)	(0.02)
manuf. of cars				-0.081**	-0.074**	-0.092***
				(0.03)	(0.03)	(0.03)
Panel B: Manufacturing						
by Occupation						
Δ import exposure	0.243***	0.179**	-0.004	0.010	-0.015	0.053
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)
Δ export exposure	0.467***	0.538***	0.281**	0.258**	0.239**	0.251***
	(0.07)	(0.07)	(0.11)	(0.11)	(0.10)	(0.06)
manuf. of tradable goods	-0.086***	-0.063***	-0.020			
	(0.01)	(0.01)	(0.02)			
high skilled		-0.127***	-0.067	-0.072*	-0.070*	-0.074*
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
foreigners		-0.063*	-0.092**	-0.093**	-0.096***	-0.095**
		(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
women		-0.040***	-0.035***	-0.036***	-0.034***	-0.035***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
routine occupations		-0.131***	-0.060**	-0.066***	-0.061**	-0.066**
		(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
manuf. of other tradable goods				-0.020	-0.015	-0.023
				(0.02)	(0.02)	(0.02)
manuf. of cars				-0.009	-0.004	-0.012
				(0.03)	(0.03)	(0.03)
Time dummies	-	-	yes	yes	-	-
Region dummies	-	-	yes	yes	-	-
Region x time dummies	-	-	-	-	yes	yes

Notes: Standard errors are clustered at the level of 50 labor market regions. $N = 739$ (326 regions in first and 413 regions in second period – Periods are ten year changes between 1988-1998 and 1998-2008). Panel A shows effects on total employment in manufacturing industries, Panel B shows the effects on employment in manufacturing occupations irrespective of the industry the workers are employed in.

6 Conclusion

In light of increasing concerns about rapidly shrinking manufacturing employment, this paper seeks to raise awareness of the limitations of commonly used employment measurements based on the industry classification of the firm or establishment. We use the occupation of the worker as a measurement for structural change instead and straighten out some relevant facts.

We show that structural change in Germany is significantly lower if the measurement is based on the occupation of the workers. While total employment in the manufacturing sector is shrinking, about 52% of manufacturing jobs that were lost in manufacturing industries between 1975 and 2017 are replaced by new manufacturing jobs in service industries. In 2017, the number of workers with manufacturing occupations in manufacturing industries is only about 1.3 times greater than the number of workers with manufacturing jobs in service industries, whereas this factor was 3 in 1975.

Numbers derived from measuring employment types according to the industry classification of the establishment can deviate enormously from the numbers based on the actual occupation of the workers. Both service and, in particular, manufacturing occupations are found in large numbers in establishments of the opposite category. The implications are critical for empirical research such as assessing the impact of shocks on the labor market, especially on types of employment such as manufacturing. This is evident when we assess the effect of international trade, especially import competition, on employment in manufacturing occupations. In this application, import exposure has no effect on employment in manufacturing occupations. Combined with the negative effect of import exposure on total employment in manufacturing industries, (Dauth et al., 2014), this implies that service industries are able to mitigate these effects by hiring substantial shares of the affected workers.

In line with this claim, we document that 40 to 60% of new manufacturing jobs in the service sector are filled by workers that were previously holding a manufacturing occupation in the manufacturing sector. We then assess the labor market consequences at the worker-level by exploiting mass layoff events in the manufacturing sector. A sizeable proportion of affected workers switches to the service sector while retaining their initial manufacturing occupation. For these workers, labor market consequences are fairly moderate overall. On average, they experience a decline in yearly income of approximately 490 euros.

The exercise highlights that the service sector offers an alternative employment option for dismissed manufacturing workers. Not only do we document that workers with manufacturing occupations switch from the manufacturing to the service sector in large numbers, we also show that the accompanying remuneration cuts are moderate and decreasing over time. Our exercise also shows that a clear separation between service and manufacturing based on the industry affiliation is becoming more and more difficult, in particular, when the focus lies on consequences for individual employees. Instead, the boundaries between the two categories are blurring, as the service sector is increasingly employing workers with manufacturing occupations, and vice versa, workers with service occupations are increasingly finding jobs in manufacturing industries.

Our findings call for a rethink of the way we measure structural change and classify employment in general. Of course, our findings also have important implications for numerous policy applications beyond the evaluation of structural change and its causes, e.g., when considering the preparation or evaluation of labor market policies and reforms.

This paper opens up an important area for future research. For instance, it would be crucial to check whether, apart from trade exposure covered in this paper, the influence of other drivers of structural change, such as digitalization or robotization, have similar differentiated effects on workers with manufacturing occupations and on total employment in the manufacturing sector.

The present paper stresses that structural change and particularly declining employment in the manufacturing sector needs to be assessed in a differentiated manner. Due to the overall growth of the service sector and the manufacturing occupations needed in the service sector, this sector provides a valuable alternative employment option for workers with manufacturing occupations. By focusing on mass layoffs, our exercise captures primarily involuntary switches. Workers that switch from the manufacturing to the service sector voluntarily due to better job opportunities are not covered. In that sense, it seems plausible to assume that our results represent an upper bound for the costs of switching sectors; the real average economic costs are likely to be lower.

Income losses and other labor market outcomes are similar for workers that, after being displaced, retain a manufacturing occupation irrespective of finding a new job in the manufacturing or the service sector. Accordingly, human capital seems to be firm-specific rather than industry-specific as the wage cut accompanying a switch in employment after a layoff is independent of the sector of the new employer. Industry-specific human capital thus appears to have little impact on workers' remuneration if they have to change employers.

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Online Appendix - Not for publication

A Additional Data Description

A.1 Processing of the employer-employee data

The reporting requirements of the Federal Employment Agency were altered during the observation period, which influences data precision. In 1999 marginal part-time workers were integrated into the notification procedure. This led to an increase in covered establishments, because the threshold for reporting was lowered to one part-time worker per establishment, and additionally overall worker numbers increased per establishment. We report in this section how we adjust the data to cope with this break in the reporting procedure.

In the data, the selection of the population of establishments in the BHP and the LIAB might be biased twofold: First, from 1992 onwards establishments in East Germany are included. We simply exclude them in our analysis for West Germany. Second, in 1999 marginal part-time workers were integrated into the notification procedure. On the one hand, this leads to a rise in the number of establishments covered in the dataset. Before, only establishments with at least one full-time employee subject to social security were reported, whereas from 1999 onwards one part time employee is a sufficient condition to be subject to reporting. We adjust for this bias by dropping these additional establishments. On the other hand, the inclusion of marginal part-time workers affects employment figures for establishments already subject to reporting (with at least one full-time employee). After the change in the reporting procedure, establishment-level employment figures now include both part-time and full-time workers. The BHP does not allow any adjustment for this bias. For every establishment, the total number of full and part-time workers is provided, but for other employment data such as the Blossfeld occupational categories, there is no distinction between the two categories. Nevertheless, to create a consistent and unbiased dataset despite changes in the reporting procedure, we make use of the individual worker-level data provided by the LIAB. For every worker, the data contain the full or part-time status as well as the classification of jobs under the German occupational classification scheme issued in 1988 (KldB88). Using a crosswalk between the KldB88 and the Blossfeld occupational categories provided by Stops (2016), we reclassify the data. Aggregating the data to the national level, we obtain information about the distribution of part-time workers across Blossfeld occupational categories. This information allows us to clean the BHP by subtracting part-time workers from the sample and also by adjusting for the reporting procedure bias within reporting establishments.

A.2 Occupational categories

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

Name of Occupational Group	Description of the Occupational Group	Examples
Manufacturing		
Agricultural occupations (agr)	Occupations with predominantly agricultural orientation	Farmers, agricultural workers, gardeners, fishermen
Unskilled manual occupations (emb)	All manual occupations with at least 60 percent unskilled workers in 1970	Miners, rock breakers, paper makers, wood industry occupations, printing occupations, road and rail-road construction workers
Medium-skilled manual occupations (qmb)	All manual occupations with at most 40 percent unskilled workers in 1970	Glassblowers, bookbinders, typesetters, locksmiths, precision instrument makers, electrical mechanics, coopers, brewers
Technicians (tec)	All technically trained specialists	Machinery technicians, electrical technicians, construction technicians, mining technicians
Engineers (ing)	Highly trained specialists who solve technical and natural science problems	Construction engineers, electrical engineers, production designers, chemical engineers, physicists, mathematicians
Service		
Unskilled services (edi)	All unskilled personal services	Cleaners, security guards
Medium-skilled services (qdi)	Essentially order and security occupations as well as skilled service occupations	Locomotive engineers, registrars
Semiprofessions (semi)	Service positions which are characterized by professional specialization	Interpreters, educators
Professions (prof)	All liberal professions and service positions which require a university degree	Statisticians, economists, social scientists
Service (administration)		
Unskilled commercial and administrational occupations (evb)	Relatively unskilled office and commercial occupations	Postal occupations, office hands, typists
Medium-skilled commercial and administrational occupations (qvb)	Occupations with medium and higher administrative and distributive functions	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	Managers, business administrators, deputies, CEOs

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

B Average distribution of occupation groups

Table B.1 displays the average distribution of manufacturing and service occupations within sectors and within the economy as a whole. The table highlights where the conventional wisdom comes from that somewhat bluntly equates industry classification of employers with workers' occupations. It shows the share of workers with manufacturing and service occupations within the manufacturing and the service sector (columns headed "within sector") and the share of the occupation-sector pair in the total economy (columns headed "in total") as simple average over all years – therefor not taking into account the time trends emphasized in the main part of the paper. Indeed, the average within-sector distribution shows that the majority of workers in manufacturing industries hold manufacturing occupations (71%) and the majority of workers in service industries hold service occupations (81%) but the table also shows that the distribution of in particular manufacturing occupations in the total economy is more equal. Only about two thirds ($\frac{25\%}{37\%}$) of workers that hold manufacturing occupations are employed in the manufacturing sector and in the main part of the paper we show that this share exhibits a clear, almost linear, decreasing trend over the last 43 years. The table thus makes clear once again that simply equating sector classifications with worker traits, i.e., occupations and tasks performed or more generally human capital, is not sensible for a variety of applications and research and policy questions.

Table B.1: Occupation shares within sectors and in total economy – average across 1975-2017

	Manufacturing sector		Service sector		Economy
	within sector	in total	within sector	in total	
manufacturing occupations	70.98%	25.02%	18.97%	12.28%	37.3%
service occupations	29.02%	10.23%	81.03%	52.48%	62.7%

Notes: The table shows the average distribution of occupation types within sectors and within the total economy over time. Data: BHP

C Matching quality

Table C.1 shows basic characteristics of the treatment and control groups in the years immediately before and after the layoff event. The characteristics are similar for treated and matched control workers – even for characteristics on which we do not condition in the matching procedure.

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

	(1)	(2)	(3)	(4)	(5)	(6)
		$t^* - 1$			t^*	
	Full Sample	Laid-off Workers	Non-laid-off Workers	Full 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, Full Sample includes both treatment and control group. We report the characteristics in the year before the layoff event occurs. 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.

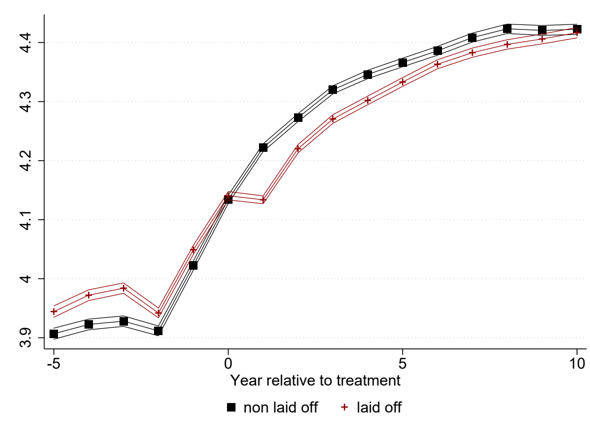
C.1 Wage trajectories: pre-trends and unconditional differences post layoff

It is illustrative to consider the trajectories of both, the treatment group (moving to the service sector after layoff) and the control group (matched workers in the same initial occupation and industry remaining at their employer in the manufacturing sector), after a layoff. Figure C.1, panels (a) and (b) show log daily wages and days in employment relative to the layoff event for laid-off and control workers. Before the layoff event, treatment and control group workers exhibit almost identical wage developments, indicating a well-functioning matching procedure. The same is true for the number of days worked before the mass layoff.

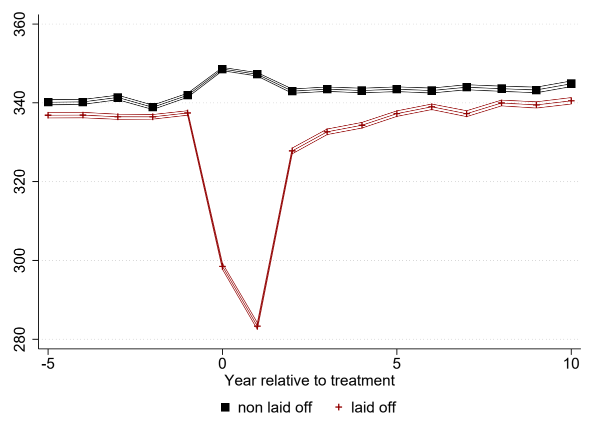
Once workers are laid off, they have to endure a cut in daily wages at their new employer. However, in subsequent years their wages appear to grow faster and by the end of our observation window ten years after the layoff, wages of laid-off and non-laid-off workers are identical again. A similar picture emerges for days in employment. Dismissed workers spent an average of 50 days less in employment, but the values for days in employment converge relative to the ones for the control group as well.

We repeat the exercise for a balanced panel in which we only include workers who we observe for the full 16-year window around the point in time the layoff occurred. In Figure C.1, panels (c) and (d), we plot unconditional means of log wages and days in active employment for the laid-off workers and their matched, non-laid-off counterparts relative to the treatment time for the balanced panel. Compared to the unbalanced panel, we observe a smaller dip in wages and days employed that both recover almost immediately in year two or three after the layoff.

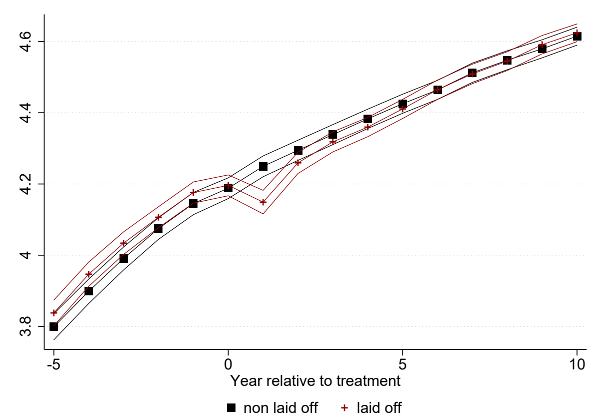
These unconditional average trajectories of employment outcomes strengthen the conjecture that structural change may not affect workers as strongly as previously perceived. Not only does the service sector offer an alternative employment option for dismissed manufacturing workers, but also the accompanying remuneration cuts are neither severe nor long-lasting. Note though, that these figures neither differentiate between the occupation nor the sector of the new job.



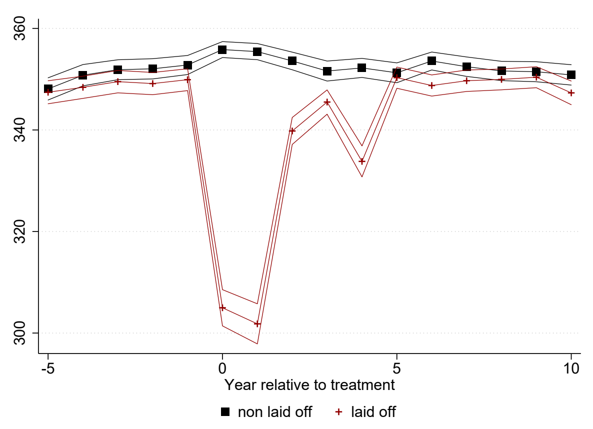
(a) Log wage



(b) Days employed



(c) Log wage – balanced panel

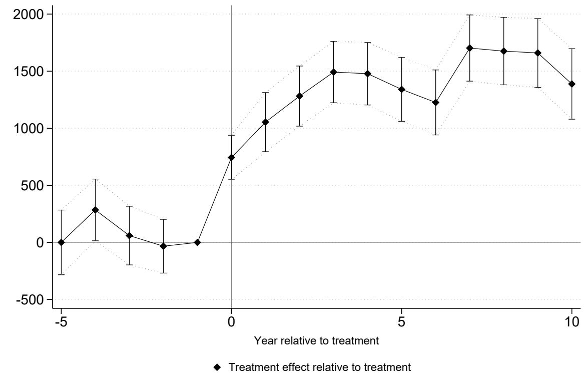


(d) Days employed – balanced panel

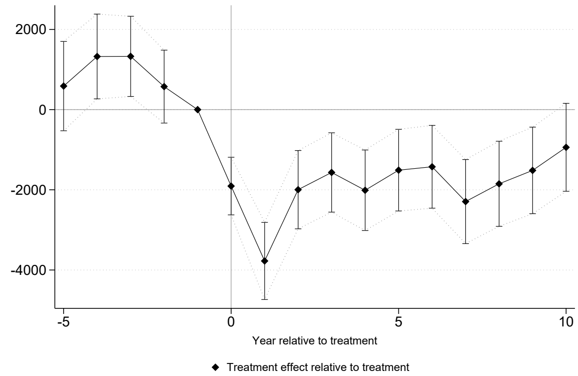
Figure C.1: Workers' outcomes of laid-off and non-laid-off persons relative to layoff time
The figure shows employment outcomes for laid-off and control group workers relative to the mass layoff event. For panels (c) and (d), the sample is restricted to worker pairs (treated and control) who we observe for the full 16-year window around the layoff event. The layoff occurs between June 30 year 0 and June 30 year 1. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. Datasource: LIAB, 1975-2017.

D Additional results: Diff-in-diff with matching

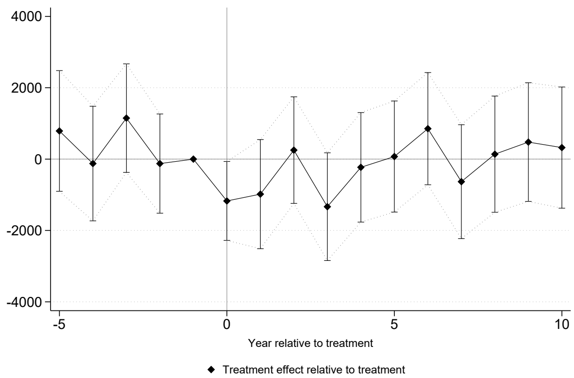
The following graphs show the dynamic effects of estimation of Equation (2) for which average effects are reported in in Table 2.



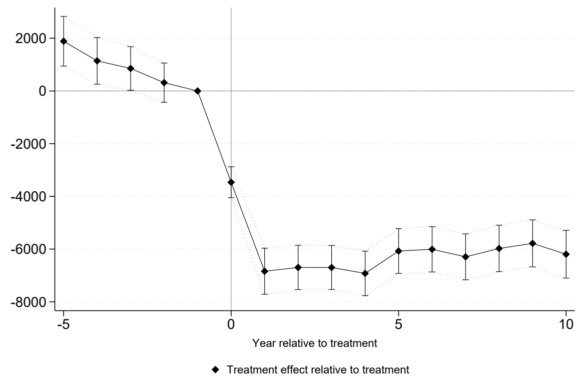
(a) Manufacturing occ. in manufacturing sector



(b) Manufacturing occ. in service sector



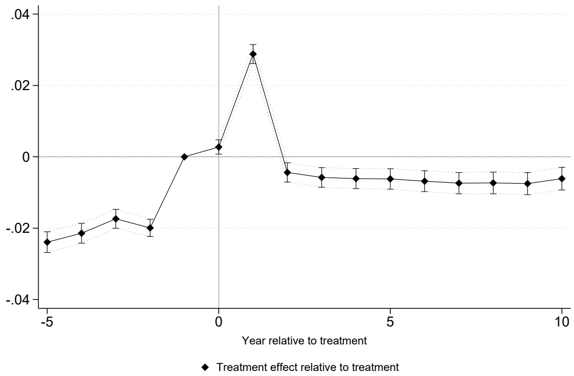
(c) Service occ. in manufacturing sector



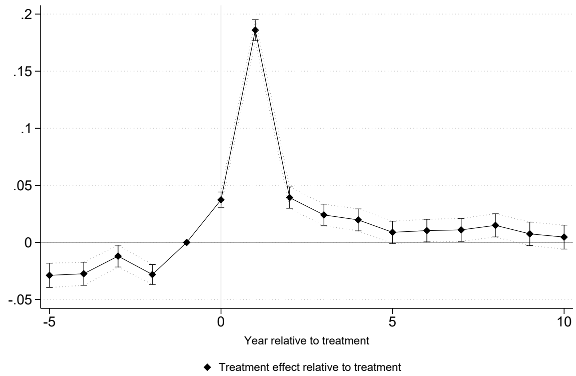
(d) Service occ. in service sector

Figure D.1: Difference in difference estimation with matching by treatment – yearly accumulated income

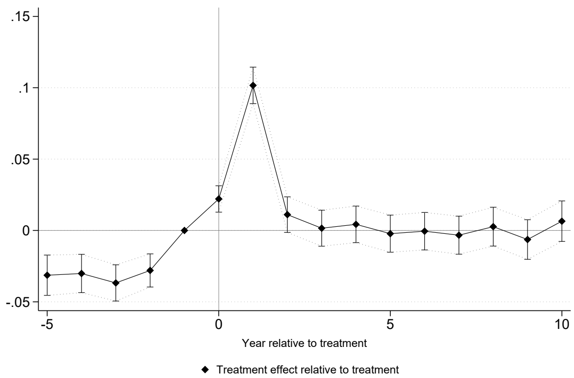
The figure plots coefficients $\gamma_{\kappa\iota}$ relative to the mass layoff event by treatment. Each regression is run only on the sample of treated workers within the respective transition group and their matches. Horizontal lines show the average treatment effect for the 10 years post layoff. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.



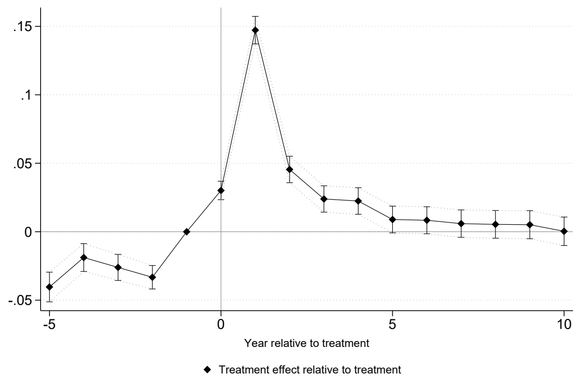
(a) Manufacturing occ. in manufacturing sector



(b) Manufacturing occ. in service sector



(c) Service occ. in manufacturing sector



(d) Service occ. in service sector

Figure D.2: 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. Horizontal lines show the average treatment effect for the 10 years post layoff. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

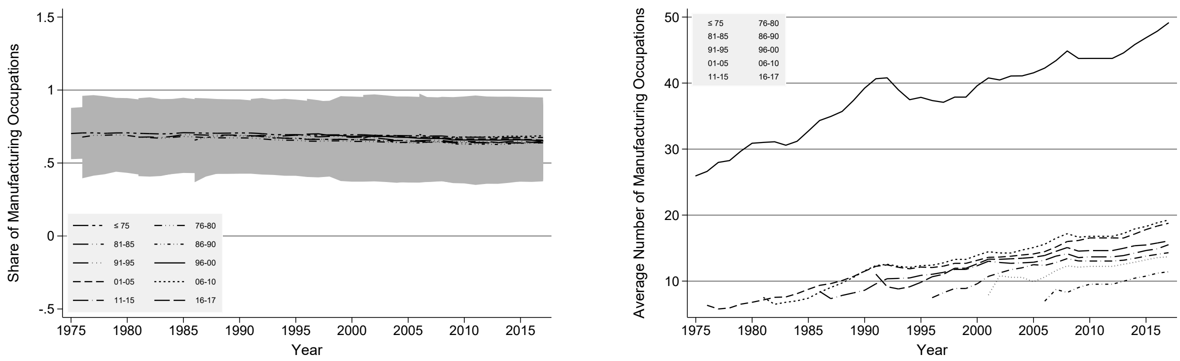
E Entering, Exiting, and Switching Establishments

In this section, we test if our findings are driven by purely technical reasons such as changes in the sample composition, i.e., by establishments entering or exiting the sample, or by establishments switching industries. We find that our results are almost completely explained by changes over time in the occupational structure of the establishments. The impact of occupation and workplace switchers and also the impact of technical reasons such as the reclassification of establishments are largely negligible. The same holds true for the impact of establishments entering or exiting the sample.

E.1 Entering and Exiting Establishments

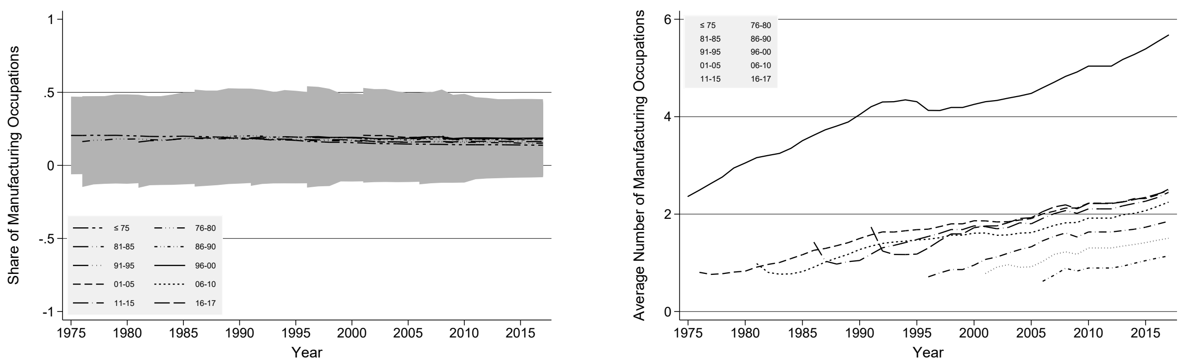
First, we check if our findings are driven by changes in the sample composition or by adjustments of the occupational structure within establishments, i.e., by the extensive or intensive margin of employment. Both, establishment entries and exits, could potentially drive the results if the service shares of entering or exiting establishments differed significantly from that of "old establishments" that were already in the sample in the previous years. It may be that new establishments cumulatively have a greater impact on our results over the years. It is possible that establishments that entered the market later will develop differently from those that have been in the market for a long time. We thus compare the average occupational employment structure of newly entered establishments with that of old establishments. Again, the outcome tells us whether our findings are driven by adjustments within establishments or through different occupational structures in newly entered establishments. We show the average share of manufacturing occupations in manufacturing industries (E.1) and service industries (E.2), respectively, for five periods in which the establishments first entered the market. The base period covers all establishments that first entered before 1991. The other periods cover five years each (1991-1995, 1996-2000, 2001-2005, 2006-2010). The data make apparent that the results are not driven by changes in the sample composition, i.e., by new establishments with a much lower manufacturing share entering the sample. Instead, our results are evidently driven by adjustments within existing establishments. Figure E.1 shows that the initial average manufacturing share of establishments that were first part of our sample before 1991 was considerably higher than the initial average share of all following periods. However, the average share of manufacturing occupations for these establishments is continuously decreasing such that the average manufacturing share of the original establishments is in similar ranges as the average initial manufacturing share of new establishments. Interestingly, the general trend is identical for all establishments independent from the period in which they first entered. The average share of manufacturing occupations is always highest after entering the market and then shrinks continuously over time. The data confirms that increasing servitization is triggered by changes in the occupational structure at the establishment level. Interestingly, for the service sector the average initial manufacturing share is very similar for all firms entering the sample in any of the five periods with exception of the first period. This if at all counters increasing servitization in the aggregate if entering establishments have lower service shares than incumbents. After entering the sample, the general trend of decreasing average shares of manufacturing occupations is identical for all establishments independent from the period in which they first entered. The picture is similar when we consider establishments that leave the sample.

This section confirms that our results are hardly driven by the extensive margin. Rather, technical or other developments affect all establishments and the labor composition is adjusted over time.



(a) Share mfg occupations (b) Avg. number of mfg occupations

Figure E.1: Establishment entrants' labor force composition: Manufacturing sector
Datasource: BHP



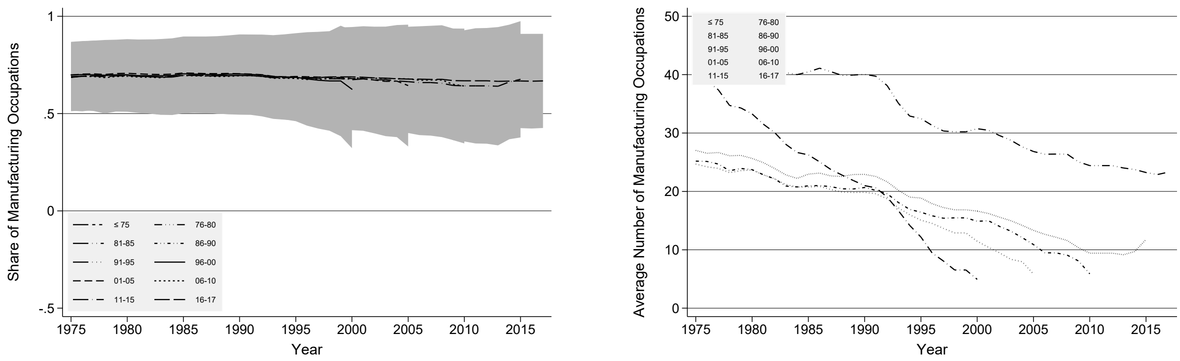
(a) Share mfg occupations (b) Avg. number of mfg occupations

Figure E.2: Establishment entrants' labor force composition: Service sector
Datasource: BHP

E.2 Reclassification - Switching Establishments and Workers

As previously mentioned, the industry 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, the classification may change over time, if the focus of the establishment shifts.[42] Bernard et al. (2017) report for Denmark on average

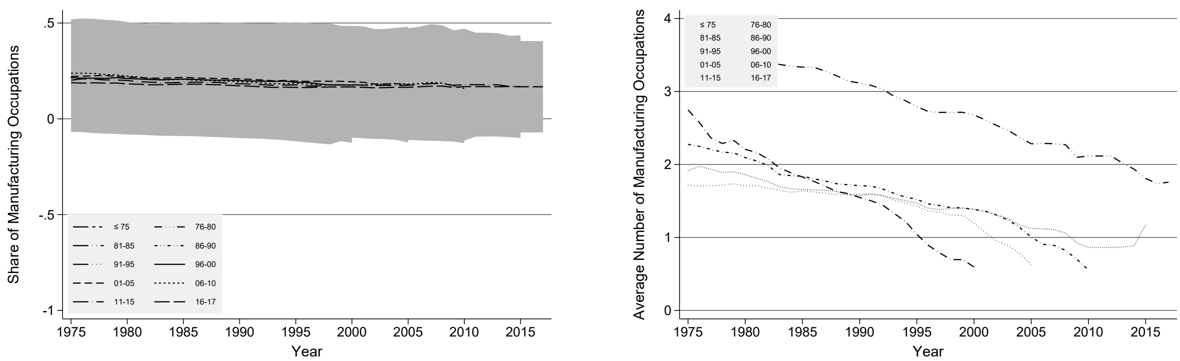
[42]One such example is IBM corporation. Starting as a traditional hardware manufacturer, IBM increasingly focused on the provision of customer services from the 1990s onwards (see Ahamed et al. (2013)). In 1990, IBM's



(a) Share mfg occupations

(b) Avg. number of mfg occupations

Figure E.3: Establishment exiters' labor force composition: Manufacturing sector
Datasource: BHP



(a) Share mfg occupations

(b) Avg. number of mfg occupations

Figure E.4: Establishment exiters' labor force composition: Service sector
Datasource: BHP

a share of 1.6% of manufacturing firms switching to service industries and a share of 1.1% of service firms switching to manufacturing. They find that switchers have a significant impact on industry employment: During the 2002 to 2007 period, 10% of the manufacturing firms switched industries from manufacturing to services which accounted for a substantial 42% of job losses in manufacturing.

In our analysis, we cannot confirm those findings for Germany. Both the number of establishments switching the sector as well as the number of affected workers is negligible.[43] Figure E.5a shows the number of establishments that switch from manufacturing to services (blue line) and from services to manufacturing (green line) for the 1975 to 2017 period based on BHP data. The number of switchers in both directions follows a very similar development over time. During the 40 years of observation, an average yearly number of 178 establishments switches

service segment only accounted for approximately 16% in total revenues, whereas it reached a share of 63% in 2017 (Spohrer, 2017). Eventually, IBM was reclassified to a service firm after a particular threshold was met.

[43] We also look at the impact from employees changing occupations while staying with the same employer, but cannot find newsworthy effects.

industries, which accounts for less than 0.0002% of the total number of establishments. The picture looks very similar for the number of workers of the switching establishments (Figure E.5b). Again, the number of workers whose establishment switches from services to manufacturing is very similar to that of the workers whose establishment switches from manufacturing to services. On average, a yearly share of 0.0003% of the population of workers is affected by switchers. Contrary to Bernard et al. (2017), the switchers do not account for manufacturing job losses. In fact, the switcher balance is even positive for manufacturing, with manufacturing employment increasing by a (negligible) net amount of 4,395 workers over the 40 years of observation. Switchers also play no role in increasing servitization.

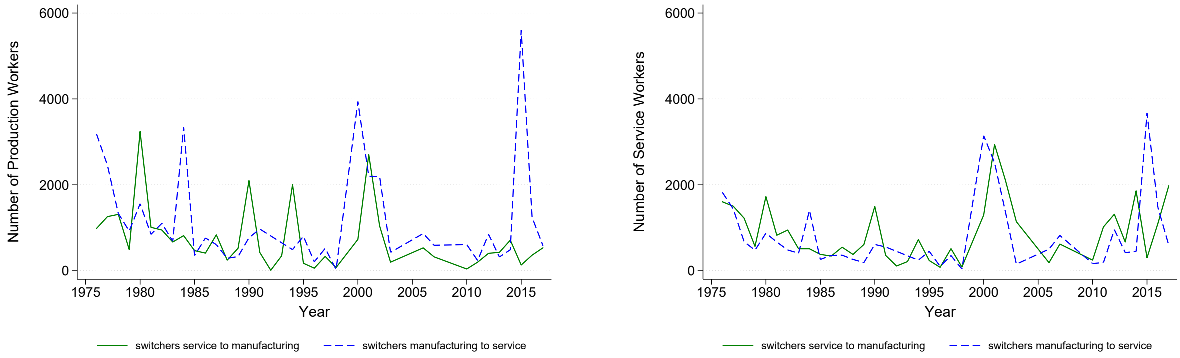
Figure E.6 breaks down the number of workers of switching establishments by service and manufacturing occupations. Again, the number of both workers holding service occupations and workers holding manufacturing occupations whose establishments switch from services to manufacturing and vice versa is about the same. Thus on average, a yearly net amount of around 262 workers with manufacturing occupations move from services to manufacturing industries, and a yearly net amount of 152 workers with service occupations move from manufacturing to service industries as a result of establishments switching their industries. In this respect, switchers generally have an influence that counteracts the servitization of establishments in manufacturing. However, the switcher effects are so small that they can be neglected.

(a) Number of establishments switching sector classification

(b) Number of workers in sector switching establishments

Figure E.5: Establishments switching sector classification and workers therein
Datasource: BHP 1975-2017

A likely reason for the differences in the importance of switchers between our paper and that of Bernard et al. (2017) is that we look at establishments while Bernard et al. (2017) focus on firms. On the one hand, of course, there is a greater likelihood that the industry will change at the firm level than at the establishment level. On the other hand, it is especially the large firms that would have to be subject to a change in the industry classification to gain a significant impact on our measurements. However, it is precisely the large firms, which often consist of different establishments that are subdivided according to economic focus. These firms would thus not show an industry switch at the establishment level, but only at the firm level. Again, this discussion highlights that the misspecification in the use of firms as a basis for the division



(a) Workers with manufacturing occupations

(b) Workers with service occupations

Figure E.6: Workers in classification switchers by type

Datasource: BHP 1975-2017

of manufacturing and service employment is most likely much higher as compared to the use of establishments.

F Wage differences across the manufacturing and service sectors

In this Appendix Section will provide preliminary evidence of the impact of such a switch between the sectors on workers' wages. Clearly, tasks performed in the manufacturing sector may differ slightly from tasks performed in the service sector. However, it seems reasonable to assume that tasks remain rather similar and that comparatively little human capital is lost if only the sector but not the occupation changes.[44] Hence, the presence and the increasing number of manufacturing jobs in the service sector offer a plausible channel through which negative consequences of structural shocks such as trade, automation or routine-biased technical change on manufacturing workers will be dampened.

Before going into more detail in evaluating the effects of the service sector on individual workers affected by structural shocks in Section 5, we first provide evidence of wage differences between the two sectors. We presume that a switch from the manufacturing sector to the service sector is associated with a wage penalty as the data show that the (unconditional) wage level is on average 30 euros lower in the service sector (corresponding to a difference of 28%). We follow Dube and Kaplan (2010) and estimate Equation F.1 as a first indicator.

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

[44] Anecdotally, think of a mechatronic technician working at a car manufacturer. Among other things, she has to lay wiring harnesses. When now displaced and re-employed at an auto repair workshop, she will no longer lay the wiring harnesses but repair them. In this example, the affected worker will perform very similar tasks and, more importantly, the previous knowledge is equally valuable in the new job. This is in line, for instance, with Kambourov and Manovskii (2009). By contrast, Neal (1995) stresses the importance of industry specific human capital. However, the underlying data are limited and the author cannot control for occupational changes of workers.

where $\text{wage}_{i(j)t}$ is the wage of person i employed at establishment j at year t. $\text{Service}_{i(j)t}$ is a dummy indicating that establishment j at which person i is employed 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 for workers who switch between the two sectors. The inclusion of person fixed effects (α_i) implies that the coefficient γ is identified through workers who at least once changed employers between the two sectors, manufacturing and services. X_{it} includes time-variant personal characteristics such as age, age squared, and education indicators.

Since the identification of the wage penalty relies on workers who switch in either direction, i.e., from the manufacturing to the service sector or vice versa, while holding a manufacturing occupation, this empirical strategy cannot differentiate between voluntary and forced switches. But the strategy makes it possible to draw general conclusions about the pay differences between the two sectors. We estimate Equation F.1 to retrieve the average effect of working in the service sector for all workers with manufacturing occupations.[45] For all estimations and all outcomes, we focus on the main employment spell only, i.e., the highest paying spell the person has on the cutoff date of June 30 of a given year (unless stated otherwise). Table F.1 reports results on the average wage penalty for working in the service sector across all workers with manufacturing occupations. Working in the service sector is on average associated with a 29% lower wage compared to working in the manufacturing sector.

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

	(1) coefficient	(2) std. error
Service (γ)	-.286***	(.0012)
Age	.198***	(.0002)
Age^2	-.002***	(.0000)
Years of schooling	.005***	(.0001)
College	.374***	(.0029)
Number of observations	11,062,219	
Number of groups	878,814	
R^2 (within)	0.6959	
R^2 (between)	0.2076	

Notes: The table reports the estimation results of Equation (F.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: LIAB, 1975-2017.

In addition, we further differentiated by 47 2-digit occupation classes. Table F.2 in the Appendix shows the results. For 42 out of these we find a (statistically significant) negative

[45] In the following analyses, we focus on 2-digit occupations and switches between these. We rely on a relatively high aggregation level, because occupation classes at the 2-digit level are sufficiently homogeneous to argue that workers can switch easily switch occupations within these classes without requiring retraining or losing human capital. Gathmann and Schönberg (2010) advocate this procedure. They argue that human capital, interpreted as the knowledge of task combinations and how to perform them, is easily transferable between occupations. Our focus on 2-digit occupations takes more specific tasks into account than Gathmann and Schönberg (2010), including knowledge on how to operate specific machines or tools, which is not considered in the task surveys underlying typical studies on the matter.

wage premium, i.e., a wage penalty, for working in the service sector. These range from -51% to -4%. By contrast, for only 2 out of 47 occupations, we find a (statistically significant) positive wage premium for working in the service sector, 3.25% for metalworkers and 7.6% for meat and fish processors. The remaining occupations do not show statistically significant effects.

In summary, the results indicate that workers with manufacturing occupations in the service sector will have to accept wage cuts compared to their remuneration in the manufacturing sector. Since this approach is not able to differentiate between voluntary and involuntary job changes, the effects may be biased downwards. If a person changes jobs voluntarily, we can assume that the new job is more desirable, which most often will also be reflected by a higher wage. 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.[46]

[46] We do find large, so far unexplained wage differences for the same occupations between the 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 (2021).

Table F.2: 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	-0.0495	(0.057)	17841	0.5
Building materials manufacturer	-0.111***	(0.000)	24633	0.463
Ceramist	-0.339***	(0.000)	27726	0.623
Glassmaker	-0.167***	(0.000)	51344	0.672
Chemical workers	-0.0548***	(0.000)	285378	0.642
Plastics processor	-0.216***	(0.000)	159024	0.54
Paper manufacturers and processors	-0.00807	(0.388)	66244	0.6
Printer	-0.0702***	(0.000)	78127	0.629
Wood processor and manufacturer	-0.259***	(0.000)	75559	0.497
Metal producers	-0.0260***	(0.001)	229277	0.782
Moulders, molding casters	-0.514***	(0.000)	86152	0.621
Metal deformers (non-cutting)	-0.393***	(0.000)	168890	0.509
Metal deformers (cutting)	-0.392***	(0.000)	320768	0.690
Metal surface processing, coating and coating	-0.222***	(0.000)	65591	0.654
Metal connectors	-0.320***	(0.000)	115895	0.568
Smiths	-0.127***	(0.000)	39464	0.609
Sheet metal workers, installers	-0.204***	(0.000)	372160	0.660
Locksmiths	-0.228***	(0.388)	1020913	0.706
Mechanics	-0.424***	(0.000)	710124	0.752
Toolmakers	-0.276***	(0.000)	216824	0.772
Metalworkers	0.0325**	(0.004)	40470	0.525
Electricians	-0.153***	(0.000)	836053	0.732
Assemblers and metal professions	-0.394***	(0.000)	534752	0.574
Spinning professions	-0.352***	(0.000)	24677	0.649
Textile manufacturers	-0.0895***	(0.000)	29440	0.592
Textile processors	-0.0482***	(0.000)	62509	0.461
Textile finishers	-0.00943	(0.643)	16848	0.541
Leather manufacturers, leather and fur processors	-0.0673***	(0.000)	25548	0.513
Bakery, confectionery manufacturers	-0.0385***	(0.000)	92356	0.615
Meat, fish processors	0.0761***	(0.000)	108267	0.585
Food processors	-0.204***	(0.000)	292126	0.472
Beverage and luxury goods manufacturers	-0.0845**	(0.003)	15646	0.610
Other nutritional professions	-0.0909***	(0.000)	131942	0.524
Bricklayer, concrete workers	-0.199***	(0.000)	230537	0.536
Carpenters, roofers, scaffolders	-0.189***	(0.000)	99707	0.475
Road and civil engineering occupations	-0.0936***	(0.000)	114007	0.537
Construction workers	-0.0912***	(0.000)	123112	0.321
Building outfitters	-0.210***	(0.000)	73389	0.445
Interior decorators, upholsterers	-0.0466***	(0.000)	50357	0.547
Carpenter, model makers	-0.0959***	(0.000)	195730	0.62
Painter, painter and allied professions	-0.306***	(0.000)	262979	0.614
Inspectors, dispatchers	-0.179***	(0.000)	393549	0.619
Auxiliary workers without detailed job description	-0.493***	(0.000)	554851	0.479
Machinists and related professions	-0.259***	(0.000)	428841	0.57
Engineers	-0.130***	(0.000)	887904	0.546
Technicians	-0.108***	(0.000)	945273	0.617
Technical specialists	-0.0357***	(0.000)	299636	0.716

Notes: The table reports the estimation results of coefficient γ of Equation (F.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: LIAB, 1975-2017.

G Robustness

G.1 Effects within the group of laid-off workers

In this section, we present results from a simple event study design without control group. We estimate the following regression on four different outcome variables for persons i at establishment j in year t. The logarithmic wage in the workers main job, the accumulated yearly income, i.e., daily wages multiplied by days worked and summed across all jobs the worker has, the days in employment per year, and the number of different employers, as proxy for job volatility:

$$y_{ijt} = \sum_{\iota=1}^{4} \sum_{\kappa=-5}^{10} \gamma_{\kappa\iota} \mathbb{1}\{t = t^* + \kappa\} \times \mathbb{1}\{i = \mathcal{M}_\iota\} + \alpha_i + \chi_j + \theta_t + X_{it}'\xi + \epsilon_{it}, \tag{G.1}$$

where t^* indicates the year the layoff occurs. α_i are person fixed effects, χ_j establishment fixed effects, and θ_t year fixed effects, X_{it} is a third-order age polynomial. $\mathcal{M}_\iota$ indicates the ι^{th} element in the set of movements, i.e., the potentially new employment type of laid-off manufacturing workers,

$$\mathcal{M} = \left\{ \begin{array}{l} \text{manufacturing occupation at manufacturing establishment,} \\ \text{manufacturing occupation at service establishment,} \\ \text{service occupation at manufacturing establishment,} \\ \text{service occupation at service establishment} \end{array} \right\}.$$

By nature of this exercise, the sample is restricted to laid-off workers that held manufacturing occupations previous to the layoff only and, hence, identification of the effect stems from different treatment years or so-called staggered adoption of treatment. The regression thus compares workers' outcomes relative to the point in time when the layoff occurred. By normalizing this point in time across workers, we are able to identify the effects of the layoff without relying on matching assumptions.[47]

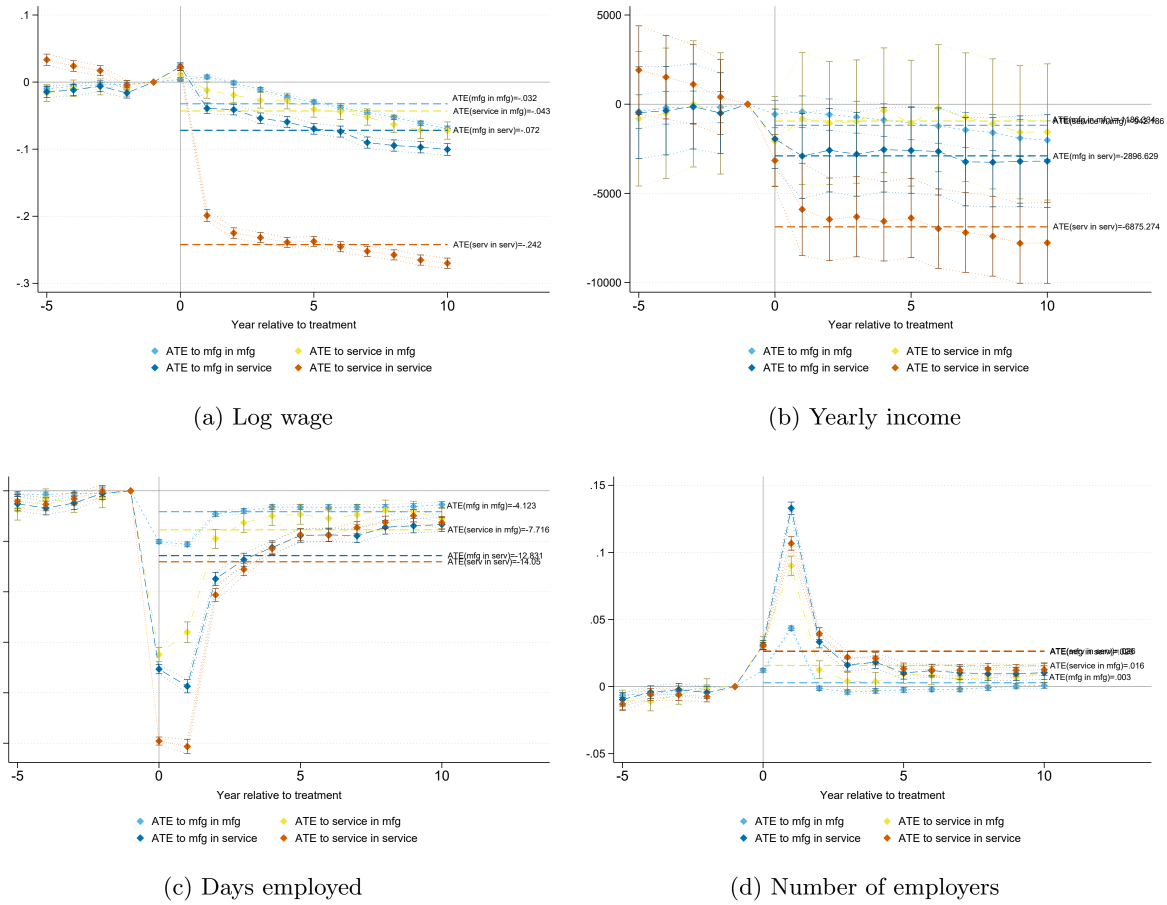
Figure G.1, panels (a)-(d) show the results for the four possible transitions $\mathcal{M}_\iota$ after a layoff (excluding unemployment) for the four outcomes. Outcome paths are negative and similar (parallel) for all four transitions but differ strongly in effect size. Workers that transition from a manufacturing occupation in the manufacturing sector to a service occupation in the service sector experience the strongest negative effect. The average treatment effect on wages is at a 24% decline in daily wages (panel (a)). Likewise, the accumulated annual income for these workers falls by almost 6,800 euro (panel (b)) – about 14% of the average yearly household income or about 1.62 times a household's gross monthly wage. These workers are also the ones who experience the longest unemployment periods (panel (c)).

Workers that switch to a manufacturing occupation in the service sector experience the second strongest effects. However, the effects on pecuniary outcomes are considerably smaller

[47] This design is able to identify causal estimates as discussed in a series of recent papers (Athey and Imbens (2021), Borusyak et al. (2021), and Sun and Abraham (2020)). We follow best-practice when estimating event-studies with unbalanced panels and bin the end points and do not report them (Goodman-Bacon, 2021).

than for the previously discussed group (service occupation in service industries). In fact, for wages and accumulated income the effects are statistically different but in very similar ranges as those of laid off workers who find a new job in the manufacturing sector, irrespective of their new occupation.

The outcomes of future job search and job stability (panels (c) and (d)) complement the previous results. Workers who switch their jobs retaining their manufacturing occupation within the manufacturing sector show the smallest effects on days in employment. On average, they are approximately employed 10 days less in each of the two years following the layoff (as compared to a situation in which the worker is not affected by a layoff). Workers who either switch sectors or switch their occupation experience significantly larger effects. Workers switching to a service occupation in the manufacturing sector and workers switching to a manufacturing occupation in the service sector experience similar effects; on average they are approximately employed 30 to 40 days less in each of the two years after the layoff. Workers who take up a service occupation in the service sector show about 50 days less in employment. From the third year after the layoff, the treatment effects on the days in employment decrease remarkably for all kinds of switchers. The picture for the number of employers shows the same pattern.



(a) Log wage

(b) Yearly income

(c) Days employed

(d) Number of employers

Figure G.1: Regression results of coefficient γ_k from Equation (G.1)

The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. Horizontal lines show the average treatment effect for the 10 years post layoff. The sample is restricted to only laid-off workers. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

G.2 Dynamic event study by individual treatment

This section presents results of the difference-in-differences design with matching when we pool all treatment types, i.e., next occupation-sector combination of the treated workers, in one estimation. It confirms results of the main analysis.

$$
\begin{aligned}
y_{ijt} = & \sum_{\kappa=-5}^{10} \sum_{\iota=1}^{4} \gamma_{\kappa\iota} \mathbb{1}\{t = t^* + \kappa\} \times \mathbb{1}\{i = \mathcal{M}_\iota\} + \sum_{\kappa=-5}^{10} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} \\
& + \alpha_i + \chi_j + \theta_t + X_{it}' \xi + \epsilon_{it}
\end{aligned}
\tag{G.2}
$$

The estimation includes person (α_i), establishment (χ_j), and year (θ_t) fixed effects, as well as time varying person characteristics (X_{it}'). $\mathcal{M}_\iota$ indicates the ι^{th} element out of the set of movements, i.e., potential new employment type, of laid-off manufacturing workers in a mass layoff,

$$
\mathcal{M} = \left\{ \begin{array}{l} \text{manufacturing occupation at manufacturing establishment,} \\ \text{manufacturing occupation at service establishment,} \\ \text{service occupation at manufacturing establishment,} \\ \text{service occupation at service establishment} \end{array} \right\}.
$$

We bin the end points and do not report them. t^* is the year in which a layoff occurs. Note that for the difference-in-difference approach with matching $\mathbb{1}\{t = t^* + \kappa\}$ varies also for the matched control-group workers.

Figure G.2 shows the difference-in-difference effects, $\gamma_{\kappa\iota}$, of a layoff on various worker level outcome variables for all four transition paths, i.e., elements of $\mathcal{M}$. Overall, pre-trends are zero or negligible, reinforcing our claim of well-functioning matching and a clear identification of the difference-in-difference effect. We only observe minor non-zero pre-trends for log wages and yearly accumulated income. This might be due to two reasons. First, firms may face structural change over longer time horizons which does not immediately lead to adjustments in employee numbers but which leads to adjustments in worker compensation. Since we match on characteristics one year before the layoff event, pre-trends have a positive sign and are declining even before the layoff event. This may lead to an underestimation of the treatment effect. The second reason why we observe non-zero pre-trends is purely technical. The estimates are for an unbalanced panel of workers and matches. Hence, we repeat the exercise for a balanced panel of treatment and control group pairs.

Panel (a) of Figure G.2 yields results on the logarithmized wage. As before in the pure event study, workers who switch to a service job in the service sector experience the cut in wages. Over the next 10 years, their wage declines on average by about 20% as compared to their matched control group. With respect to the narrative of this paper, the effect on workers switching to a manufacturing job in services is of interest. We do find a significant drop in wages which slowly converges over the next 10 years but never reaches the level of the control group workers. However, the cut in wages is far less strong as for the workers switching to a service occupation. Rather, manufacturing workers who switched to the service sector earn about 5%

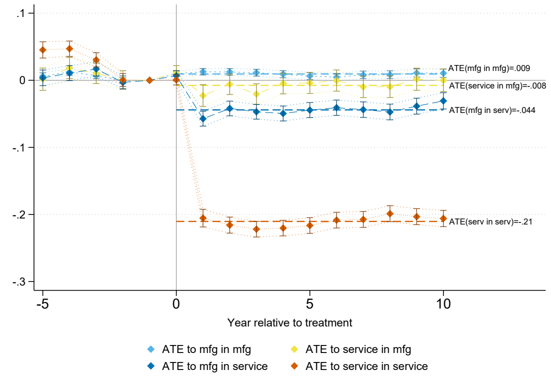
less than their non-laid-off counterparts immediately after the layoff. The average loss in wages is 4.7% over the ten-year period.

Workers remaining in the manufacturing sector do not experience economically significant changes in their wage. In fact, workers who manage to find a new job with manufacturing occupation in the manufacturing sector earn stably about 1% more than the matched counterpart. Quite possibly, these workers are more productive and manage to obtain a new job at an establishment that benefits from structural change (or manages to cope better with the negative shocks).

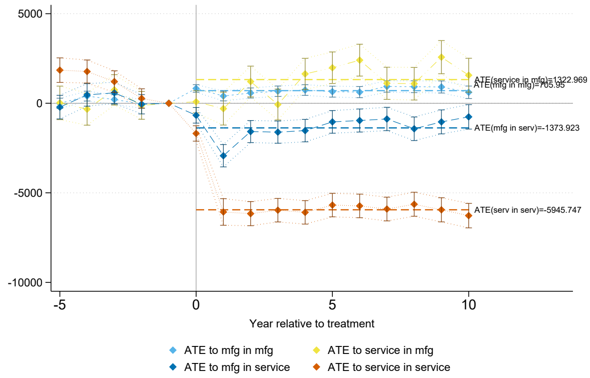
A similar pattern emerges for yearly income (Panel (b)) which, apart from the main employment spell, also takes secondary and tertiary jobs into account. For workers finding new employment in a manufacturing occupation in the service sector, the yearly income of a laid-off worker initially is by about 2,500 euros lower than that of the non-laid-off counterpart. Subsequently, yearly income recovers but remains around 1,000 euros lower. In total, affected workers lose about 14,800 euros during the ten-year period. Far harder hit are workers that have to switch to a service job in the service sector. They lose about 58,000 euros in income throughout the following ten years post layoff.

Panel (c) shows treatment effects for the days in employment per year. The number of days in employment per year drops after layoff for all treatment types (to different extend); however, it recovers quickly – with about even rate for all treatment types – and reaches the same level as that of the control group in the second to seventh year after treatment (dependent on treatment type). Whereas workers that switch to a service job in the manufacturing sector after the layoff do not experience strong effects on pecuniary outcomes we do observe that these workers seemingly take longer to find new and stable employment.

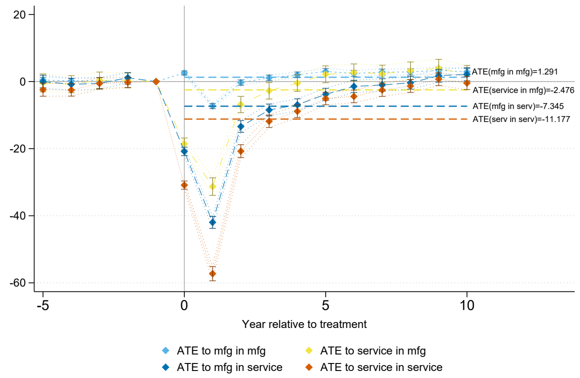
Similarly, the number of different employers experiences a peak in the two years following the layoff, hinting at more unstable employment spells after being laid off, but the effect phases out and four to five years after the layoff, no significant differences between laid-off and non-laid-off workers remain. (Panel (d) shows the effect on the number of different employers based on the main spell.)



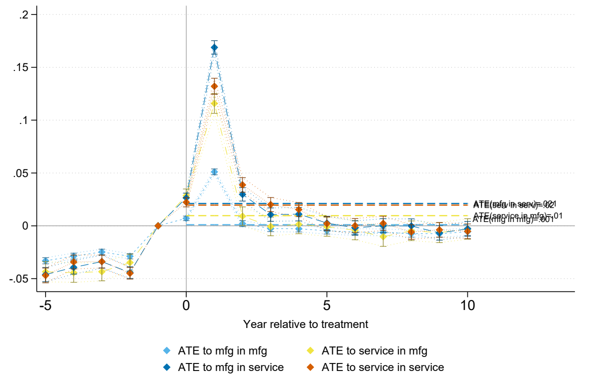
(a) Log wage



(b) Yearly income



(c) Days employed



(d) Number of employers

Figure G.2: Regression results of coefficient γ_k from Equation (G.2)

The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. Horizontal lines show the average treatment effect for the 10 years post layoff. The sample is restricted to only laid-off workers. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

G.3 Matching statistics of 4-time match

Table G.1: 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	0.54	4.29	0.54	0.01	(0.48)
wage	82.85	44.70	83.29	44.31	0.43	(0.44)
lagged wage	80.26	45.56	80.97	48.11	0.71	(0.69)
twice lagged wage	84.50	44.57	85.00	49.62	0.49	(0.42)
yearly income	29758.89	16595.91	29891.80	16337.20	132.91	(0.37)
age	33.25	10.69	33.55	10.53	0.30	(1.31)
college	0.04	0.19	0.04	0.19	-0.00	(-0.64)
years in education	9.43	1.93	9.43	1.86	0.00	(0.04)
tenure	3.99	4.03	3.84	3.83	-0.15	(-1.75)
gender	0.27	0.44	0.30	0.46	0.03***	(3.47)
skill level	1.54	0.65	1.53	0.65	-0.01	(-0.92)

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

	(1)		(2)		(3)	
	mean	sd	mean	sd	b	t
AKM person effect	4.28	0.34	4.26	0.34	-0.02*	(-1.97)
Employer size	1726.41	6204.88	1548.02	5663.81	-178.39	(-1.37)
AKM firm effect	0.14	0.22	0.14	0.22	0.00	(0.06)
Observations	4169		4168		8337	
	Serv occ in mfg sector		Mfg occ in serv sector		differences	
log wage	4.39	0.58	4.41	0.60	0.01	(0.89)
wage	94.61	57.06	96.17	56.76	1.55	(1.12)
lagged wage	90.71	54.19	92.92	56.05	2.22	(1.65)
twice lagged wage	97.69	63.91	98.82	60.20	1.13	(0.67)
yearly income	34009.87	20878.51	34777.07	20920.71	767.20	(1.51)
age	34.36	10.61	35.22	11.32	0.86**	(3.21)
college	0.08	0.26	0.07	0.25	-0.01	(-1.00)
years in education	9.87	2.39	9.97	2.20	0.10	(1.74)
tenure	4.33	4.39	4.39	4.62	0.06	(0.53)
gender	0.23	0.42	0.19	0.39	-0.04***	(-4.12)
skill level	1.68	0.73	1.81	0.72	0.13***	(7.28)
AKM person effect	4.36	0.37	4.39	0.36	0.03***	(3.61)
Employer size	1517.21	5304.17	1423.88	4922.98	-93.33	(-0.75)
AKM firm effect	0.14	0.22	0.14	0.22	-0.00	(-0.26)
Observations	3384		3389		6773	
	Serv occ in mfg sector		Mfg occ in mfg sector		differences	
log wage	4.42	0.56	4.41	0.59	-0.01	(-1.00)
wage	95.98	56.43	96.62	62.73	0.63	(0.62)
lagged wage	92.36	54.32	92.49	57.50	0.13	(0.14)
twice lagged wage	98.04	62.04	97.73	59.54	-0.30	(-0.26)
yearly income	34601.85	20912.79	34811.59	22971.26	209.73	(0.56)
age	34.76	10.75	35.45	11.55	0.70***	(3.66)
college	0.07	0.26	0.06	0.23	-0.02***	(-3.81)
years in education	9.83	2.36	9.74	2.11	-0.09*	(-2.28)
tenure	4.67	4.84	5.23	5.33	0.57***	(6.50)
gender	0.23	0.42	0.20	0.40	-0.03***	(-3.73)
skill level	1.65	0.74	1.70	0.72	0.05***	(4.20)
AKM person effect	4.36	0.38	4.39	0.36	0.03***	(4.27)
Employer size	2261.80	6863.36	2249.88	7028.23	-11.91	(-0.10)
AKM firm effect	0.15	0.22	0.15	0.23	-0.01	(-1.42)
Observations	6868		6837		13705	
	Serv occ in mfg sector		non laid-off		differences	
log wage	4.44	0.58	4.43	0.61	-0.01	(-1.53)
wage	99.80	65.58	100.09	73.82	0.29	(0.27)
lagged wage	96.34	63.39	96.18	70.10	-0.16	(-0.16)
twice lagged wage	101.40	69.38	99.04	67.62	-2.35*	(-1.99)
yearly income	35954.93	24296.93	36174.79	26815.35	219.86	(0.55)
age	35.17	10.79	37.80	11.61	2.63***	(15.01)
college	0.08	0.28	0.07	0.25	-0.02***	(-3.87)
years in education	9.97	2.48	9.91	2.25	-0.06	(-1.51)

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

	(1)		(2)		(3)	
	mean	sd	mean	sd	b	t
tenure	4.63	4.77	7.62	6.42	2.99***	(33.83)
gender	0.23	0.42	0.23	0.42	-0.00	(-0.40)
skill level	1.70	0.76	1.73	0.74	0.03**	(2.58)
AKM person effect	4.39	0.40	4.41	0.39	0.03***	(4.30)
Employer size	1637.88	5159.82	1501.87	4952.79	-136.02	(-1.72)
AKM firm effect	0.15	0.23	0.12	0.24	-0.03***	(-7.45)
Observations	8182		8188		16370	