Training or Retiring? How Labor Markets Adjust to Trade and Technology Shocks

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Training or Retiring? How Labor Markets Adjust to Trade and Technology Shocks[*]

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Abstract

How do firms and workers adjust to trade and technology shocks? We analyze two mechanisms that have received little attention: training that upgrades skills and early retirement that shifts adjustment costs to public pension systems. We combine novel data on training participation and early retirement in German local labor markets with established measures of exposure to trade competition and robot adoption. Results indicate that negative trade shocks reduce training—particularly in manufacturing—while robot exposure increases training—particularly in indirectly affected services. Both shocks raise early retirement among manufacturing workers. Structural change thus induces both productivity-enhancing and productivity-reducing responses, challenging simple narratives of labor market adaptation and highlighting the scope for policy to promote adjustment mechanisms conducive to aggregate productivity.

Keywords: training, retirement, trade, technological change, automation, robots, firms, workers, labor market

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1. Introduction

When faced with major disruptions in their markets, firms and workers can either respond by adjusting workers' skills to meet the new requirements or by facilitating their exit from the labor market. These adjustment mechanisms have very different implications for aggregate productivity: training tends to enhance aggregate productivity, whereas early retirement tends to reduce it by leaving production factors idle. While the literature on firm training has documented positive effects on worker productivity and wages (Black, Skipper, and Smith 2023), we know relatively little about how training decisions respond to major exogeneous shifts in labor demand such as those induced by international trade and technological change. Firms and workers may either increase training to reskill for new tasks, or they may reduce training because they lack the resources due to liquidity constraints induced by the disruptions. Similarly, while the literature on retirement has extensively studied how workers' retirement decisions respond to incentives created by the design of pension and unemployment benefit schemes (e.g., Dorn and Sousa-Poza 2010, Inderbitzin, Staubli, and Zweimüller 2016), far less attention has been paid to early retirement as an adjustment mechanism for firms and workers during periods of structural change. The stated policy objective of early retirement schemes—a common feature in many welfare states across the world (Börsch-Supan and Coile 2025)—is often to improve labor market prospects for younger workers, but they effectively externalize private adjustment costs to public pension systems.

This paper studies training and early retirement as key adjustment mechanisms through which local labor markets can respond to major economic disruptions. We analyze these mechanisms in the context of trade integration and robot adoption in Germany between 1994 and 2014. Despite their potential importance, these adjustment mechanisms have received limited attention in the literature, primarily due to data constraints on training and early retirement in this context.

Our empirical analysis builds on novel data construction that combines training and retirement information from two main sources. We measure training participation in the German Microcensus, aggregating harmonized annual individual data to local labor markets, allowing us to study how skill investments respond to regional shock exposure. We develop a comprehensive measure of early retirement using the administrative employment records from the Institute for Employment Research (IAB) at the German Federal Employment Agency, identifying the employment biographies of workers who permanently exit the labor force before reaching the statutory retirement age. We distinguish between direct retirement and retirement following an initial unemployment spell, which we term “golden handshake” retirement.

Following established methodologies in the literature on trade and technology shocks, we use a shift-share approach to construct regional exposure measures. Our trade shock captures the rise of China and Eastern European countries as import competitors and export destinations (Autor, Dorn, and Hanson 2013; Dauth, Findeisen, and Suedekum 2014). Our technology shock measures regional exposure to industrial robot adoption (Acemoglu and Restrepo 2020; Dauth et al. 2021). To address endogeneity concerns, we instrument regional shock exposure using industry-specific changes in other high-income countries, following standard practice in this literature to prevent bias from shocks to labor supply or demand that are specific to German industries or regions.

Our results reveal distinct patterns across adjustment mechanisms and shock types. Robot exposure increases training participation, but the effect is concentrated in service industries rather than in the directly affected manufacturing sector. This finding suggests that automation generates positive spillovers to complementary sectors that require additional skills to serve expanded manufacturing productivity. The pattern is consistent with robots augmenting rather than replacing human labor in the German institutional context, as documented by Dauth et al. (2021), but highlights that the complementarity operates through intersectoral linkages rather than within-firm adjustment. Our detailed data on training intensity suggest that the effect is not restricted to short training courses but also applies to intensive month-long training.

Trade shocks generate opposing effects on training depending on the direction of the shock. Export expansion increases training investment, likely reflecting firms’ need to develop market-specific capabilities to serve foreign customers. Import competition reduces training, consistent with resource constraints limiting human capital investment during periods of economic stress. Firms and workers facing increased import competition do not seem to use skill upgrading as a potential buffer. This asymmetry in the training response to positive versus negative trade shocks suggests that training functions as a complement to positive economic opportunities rather than a substitute for declining economic performance.

Both robot and import exposure increase early retirement rates among manufacturing workers, though through different institutional paths. Robot-exposed workers primarily retire directly without unemployment spells, while import-exposed workers more frequently use unemployment benefits as a bridge to pension eligibility. Export exposure generates the opposite pattern, with workers delaying retirement, presumably because firms retain experienced employees during periods of expansion.

In sum, training and retiring are relevant adjustment mechanisms used by firms and workers in intricate ways to react to structural change requirements. Robot adoption has two effects with opposing implications for aggregate productivity: Firms and workers in indirectly affected service industries increase their training in response to robot exposure in manufacturing. But manufacturing firms and workers also use early retirement to respond to robot exposure, taking the opportunity to externalize some of the adjustment costs. Firms' and workers' responses to trade shocks of opposite sign reinforce their respective impacts on the aggregate economy: They increase training and reduce early retirement in response to positive export shocks but do the opposite in response to negative import shocks.

Our findings contribute to three distinct literatures. First, we extend research on labor market consequences of globalization and technological change beyond employment and wage effects to examine adjustment mechanisms. The seminal studies by Autor, Dorn, and Hanson (2013, 2016) on the China shock and Acemoglu and Restrepo (2020, 2022) on robot adoption established the importance of these economic forces on US local labor markets. Parallel research on Germany documented less disruptive effects, suggesting that institutional differences may shape adjustment patterns (Dauth, Findeisen, and Suedekum 2014, 2017, 2021; Dauth et al. 2021).[1] We contribute to this literature by showing that training and early retirement are important adjustment strategies of firms and workers in response to trade and technology shocks. In particular, the positive training responses to robot exposure and export opportunities provide deeper insight into mechanisms underlying the positive effects of robots on new jobs in services (Dauth et al. 2021) and of export exposure on job stability and earnings (Dauth, Findeisen, and Suedekum 2014). By contrast, the finding that robot exposure led to labor market exit of elderly workers adds important nuance to the literature on the labor market effects of robots in Germany, which found little direct substitution effects (Dauth et al. 2021).

Second, we advance understanding of training decisions during periods of structural change. While existing research demonstrates that training increases productivity and wages (e.g., De Grip

[1] Recent contributions advance the analysis of robots to other outcomes such as family and college outcomes (Anelli, Giuntella, and Stella 2024; Di Giacomo and Lerch 2025) and to the firm level (Koch, Manuylov, and Smolka 2021; Bessen et al. 2025).

and Sauermann 2012; Schwerdt et al. 2012; Konings and Vanormelingen 2015; Dong, Hyslop, and Kawaguchi 2024), few studies examine training responses to aggregate economic shocks. Training has been studied following specific disruptions such as offshoring (Hummels et al. 2012), automation (Schmidpeter and Winter-Ebmer 2021; Heß, Janssen, and Leber 2023), and organizational change (Battisti, Dustmann, and Schönberg 2023). We add to this literature by studying how training responds to major shifts in labor demand induced by aggregate trade and technology shocks.

Third, we provide new evidence on early retirement as an adjustment mechanism of labor markets to structural change. The retirement literature typically focuses on individual optimization problems and fiscal consequences for pension systems (e.g., Coile and Levine 2007; Dorn and Sousa-Poza 2010; Inderbitzin, Staubli, and Zweimüller 2016; Riphahn and Schrader 2023; Gudgeon et al. 2023). Frimmel et al. (2018) show that early retirement is not just a phenomenon of workers' optimization, as firms with steep seniority wage profiles have an incentive to dismiss older workers before retirement. We demonstrate that early retirement serves as an adjustment mechanism that allows firms and workers to externalize private transition costs to public systems, with usage patterns that vary systematically across shock characteristics.

The paper proceeds as follows. Section 2 describes our data construction and provides institutional background on German training and retirement systems. Section 3 presents the empirical strategy and Section 4 the results. Section 5 discusses policy implications and concludes.

2. Background and Data

2.1 Employment, Robots, and Trade Shocks

The basic setup of data on employment, automation, and trade closely follows earlier work by Dauth et al. (2021). In particular, we use extensive employer-employee data from administrative social security records provided by the IAB. These data can be matched to trade and technology shocks at the level of 402 local labor markets, disaggregated by 20 industries for which data on sectoral trade flows and the stock of robots are available. Sectoral trade flows refer to gross annual export and import flows between Germany on the one hand and China and 21 Eastern European countries on the other hand. Data on the stock of robots are provided by the International Federation of Robotics (IFR) for 1994-2014, which defines our period of analysis.

Following standard practice (e.g., Autor, Dorn, and Hanson 2013; Acemoglu and Restrepo 2020; Dauth et al. 2021), we use a shift-share approach to convert the industry data to the local labor market level based on initial local industry compositions. This allows us to compute local import and export exposure, robot exposure, and standard measures for local labor market performance such as employment and earnings growth in exactly the same way as in the previous literature, in particular Dauth et al. (2021), in order to facilitate a direct comparison.

2.2 Training

The first new focus of this paper is labor market training as a productivity-enhancing response to shocks. We exploit a novel data source which measures training activities at the individual level. To introduce it into our empirical model, we aggregate the data to the industry level and transform them to the level of local labor markets.

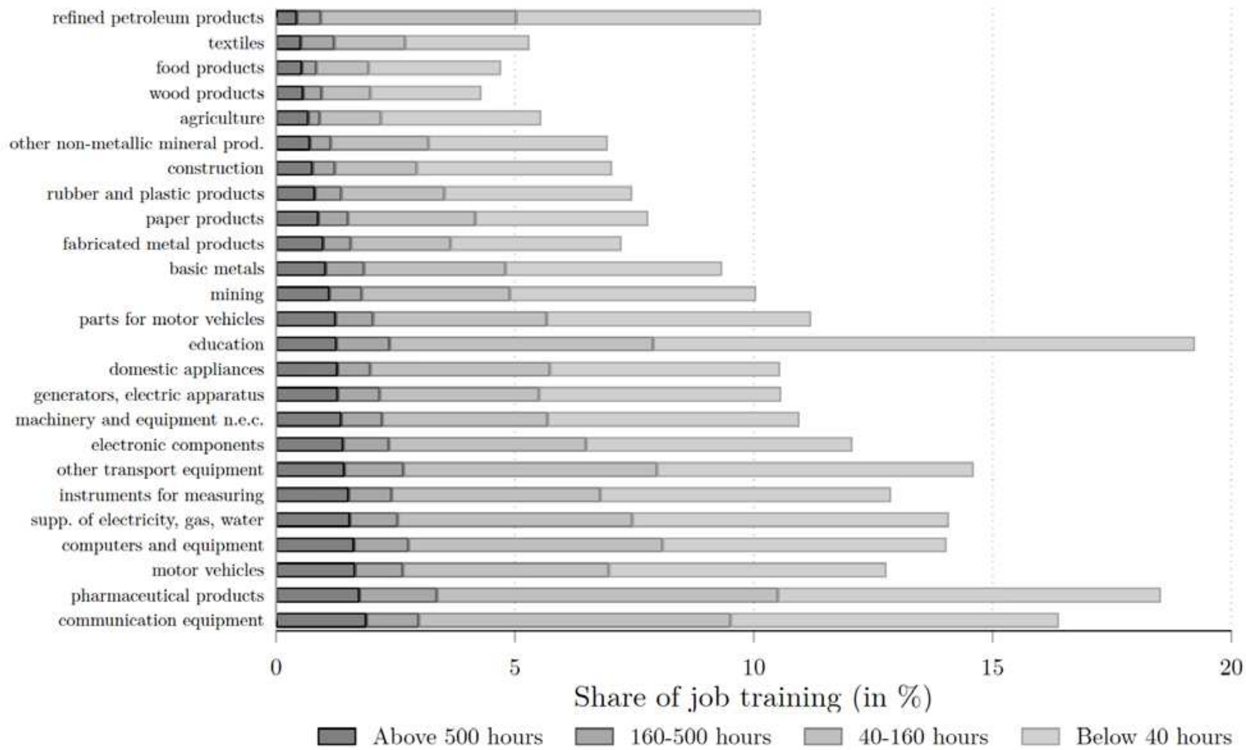
To provide context, labor market training takes place within the worker-firm relationships of the German model of industrial relations (e.g., Jäger, Noy, and Schoefer 2022). Training can be both formal and informal. The informal part is usually a spontaneous side effect of normal work procedures and as such not generally recorded. In this paper, we focus on formal training activities where workers interrupt their regular job tasks in order to complete coursework of varying lengths. There is no formal entitlement for workers to such training. But the possibility to integrate coursework ("*Weiterbildung*") into the work schedule, and the cost sharing between firms and workers, is typically featured in labor contracts and is a matter of bargaining between unions and employer associations both at the industry and firm level.

We derive our novel measure of job training from the German Microcensus, which allows us to consistently identify work-related training of different intensities over a long period of time (see Appendix A for details). The Microcensus is a repeated cross-sectional annual household survey that covers one percent of the German population. Participation is mandatory, leading to unit non-response consistently below three percent in our observation period (Statistisches Bundesamt 2015). Training data are available for the 19 annual waves from 1996 to 2014. The number of individuals per wave lies between 450,000 and 500,000, providing us with around 9 million observations in total.

For each individual, we classify whether the person has participated in job training in the previous year. The data allow us to distinguish four duration lengths from less than one week (40 hours) to over three months (500 hours) that reflect the intensity of the training. To ensure that we capture only job training, we restrict our sample to employed individuals (Black, Skipper, and Smith 2023), disregard non-work-related training incidents, and do not consider training of individuals who are still in vocational school. The available measure refers to formal coursework, which can be provided either by the employer or by an external provider, and does not include informal or spontaneous on-the-job training.

In a first step, we aggregate the individual data to the industry level, measuring the share of workers who participated in job training in each year. Figure 1 illustrates the average training share across industries over the observation period (1996-2014). There are substantial differences at both the extensive and the intensive margin. Across industries, the most intensive type of training of more than a quarter of a year is most common in communication equipment, pharmaceutical products, and motor vehicles and least common in refined petroleum products, textiles, and food and wood products. Considering also short training incidents, over 15 percent of workers in education, pharmaceuticals, and communication equipment participated in training each year, but less than 5 percent did so in food and wood products.

Figure 1: Job training intensities across industries



Notes: Average share of workers participating in job training, 1996-2014, separated by training intensities in hours per year. Data source: Microcensus.

In a second step, we combine this industry-level variation with initial regional industry employment shares to obtain a shift-share-style predictor for regional training intensity. More specifically, training intensity TI of region r is calculated as

$$TI_r = \sum_j \overline{\left(\frac{T_j}{E_j}\right)} \times \frac{E_{rj}}{E_r} \tag{1}$$

where $\left(\overline{T_j/E_j}\right)$ is the average training per worker from 1996 to 2014 in industry j, which is weighted by the initial local employment shares in the respective region.[2] This standard procedure is adopted to obtain a consistent measure that can be easily combined with the existing measures of local trade and technology shocks. We use this measure of regional training intensity as one of our main outcome variables in the empirical analysis.

Appendix Table A1 shows descriptive statistics at the level of local labor markets. On average, 11.7 percent of workers have engaged in any formal training. About half of them participated in short courses with an overall length below 40 hours per year. But 1.4 percent of workers also engaged in massive training activities exceeding 500 hours per year. There is also substantial variation in training across space, reflecting the variance in local industry specialization patterns.

2.3 Early Retirement

The second main focus of this paper is early retirement as a response to local labor market shocks. The regular retirement age for workers in Germany over much of the observation period is 65 years. It is possible to retire earlier, but under normal circumstances this leads to actuarially fair reductions in later pension payments. There are some exceptions to this principle, however, for instance in cases of job-related incapacity or if workers have already paid social security contributions for over 45 years. Of particular interest in our setting is the case of early retirement after unemployment (§ 237 SGB VI). Under certain conditions, it was possible for elderly workers in acute labor market stress to retire already at age 60 (or even earlier in some cases) without having to face the full deductions in pension payments (e.g., Gudgeon et al. 2023). This age limit was later raised to 63, and eventually the rule was abandoned for workers born after 1952. But for

[2] In the baseline analysis, we divide local industry employment E_{rj} by total regional employment E_r. In some specifications, we focus on the manufacturing sector, in which case E_r refers to total regional manufacturing employment.

much of the observation period, these favorable conditions for early retirement—which aimed to improve the labor market prospects of younger workers by reducing labor supply of older workers—raised the effective expected replacement income and thereby created an incentive to terminate employment contracts since parts of the adjustment costs were borne by the social security system (e.g., Dorn and Sousa-Poza 2010).

Our administrative employment data allow us to develop a proxy measure for early retirement. While the data report spells of employment and unemployment for individual workers, they do not explicitly indicate entry into (early) retirement as a reason for labor market exit. We therefore assume a case of early retirement if a worker permanently leaves the administrative records from an existing employment spell at age 50 or later but before the official retirement age, and neither death nor emigration are recorded. We focus on incumbent workers in 1996 who were born between 1949 and 1964 to ensure that workers are aged at least 50 by the end of the observation period but young enough to be potentially observed until reaching the statutory retirement age of 65. We are confident that our proxy accurately measures early retirement, since other explanations for the sudden but permanent exit from the labor market can either be explicitly excluded (death, emigration) or should be very rare exceptions.[3]

We distinguish two subcategories of early retirement. i) After leaving the employment spell, the person is first recorded as unemployed and then disappears from the labor market statistics and never reappears (as employed or unemployed) until the official retirement age. ii) After leaving the employment spell, the person immediately disappears from the labor market statistics without any initial unemployment spell and never reappears in the data. We refer to the first case as a "golden handshake", because the person first receives unemployment benefits for a maximum duration of two years, which initially offered a higher replacement rate than the regular pension. For workers born before 1952, the pension system even offered a formal pathway to retire at age 60 after an unemployment spell (Gudgeon et al. 2023), but later cohorts also had incentives to use unemployment benefits as a bridge towards retirement. Often, these benefits were also topped up by one-off separation payments by the employer. Around 28 percent of all early retirement cases

[3] In principle, the older workers (aged 50+) could leave the social security system altogether because they start self-employment. Another possibility is to become an official civil servant (*Beamte*), which is particularly rare since entering this status is usually restricted to people younger than 45.

follow this pattern. In the second case (accounting for the other 72 percent), workers use a direct pathway into early retirement without the initial unemployment detour.

In a final step, we aggregate the individual-level data for early retirement to the local labor market level. Descriptive statistics in Appendix Table A1 reveal a sizeable average early retirement rate of 16.3 percent in the local workforces. The average retirement age is 58.4 years, substantially below the official retirement age of 65, suggesting that early retirement is a salient feature of the German welfare state.

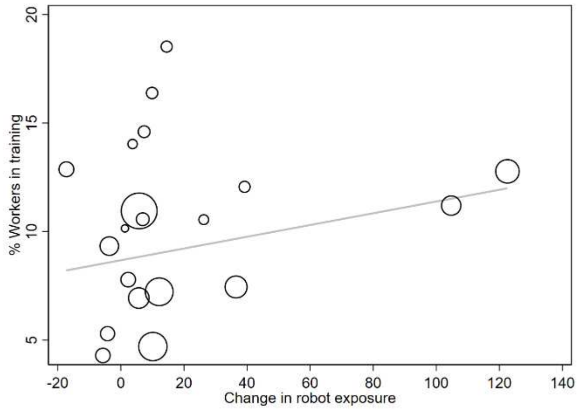
2.4 Descriptive Associations at the Industry Level

Before coming to our core empirical analysis, we present suggestive associations at the industry level. The four panels of Figure 2 plot the average share of workers in training and the share of early retirees at the industry level against the industry-level increases in robot and trade exposure, respectively.[4] Both stronger technology shocks (more robots) and positive trade shocks (increased net exports) are associated with more training. By contrast, technology shocks are mildly positively, and positive trade shocks negatively, associated with early retirement. While these industry-level associations are suggestive, they draw on only 20 industry observations and do not always reach statistical significance. In the following, we turn to the main empirical analysis at the level of local labor markets.

[4] Appendix Table A2 shows the corresponding industry-level regressions, distinguishing export and import exposure.

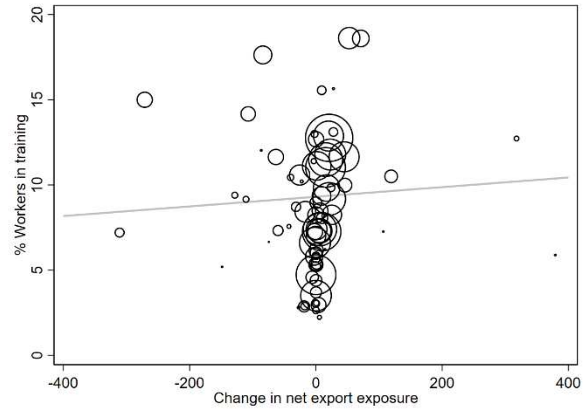
Figure 2: Training and early retirement by technology and trade shocks at the industry level

Panel A: Training



Slope: 0.027 (s.e.=0.011)

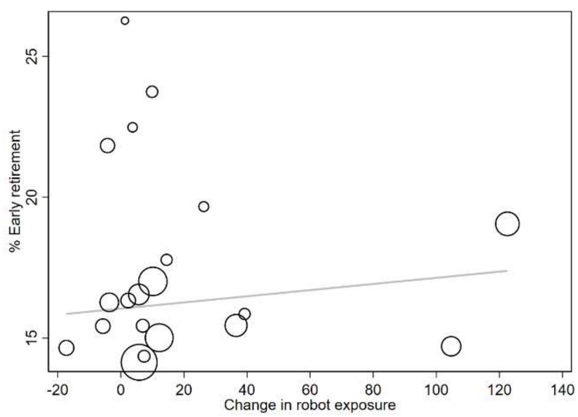
a) Robot exposure and training



Slope: 0.003 (s.e.=0.004)

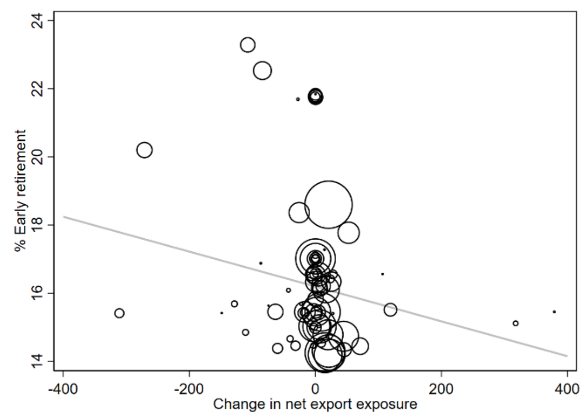
b) Net export exposure and training

Panel B: Early retirement



Slope: 0.011 (s.e.=0.014)

c) Robot exposure and early retirement



Slope: -0.005 (s.e.=0.003)

d) Net export exposure and early retirement

Notes: Industry-level associations average annual training intensity and share of early retirees with robot and trade exposure, respectively. Training (share of workers participating in job training) and early retirement (of workers who were employed in the respective industry in 1996) refer to 1996-2014, robot and trade exposure (from Dauth et al. 2021) refer to 1994-2014. Trade exposure is displayed as net export exposure: Δ(exports-imports)/worker. Numbers of observations: 20 NACE Rev. 2 equivalent aggregate manufacturing industries for robot exposure and 92 NACE Rev 1 equivalent 3-digit manufacturing industries for trade exposure. Trade scatterplots are trimmed at -400,000 and +400,000 Euros/worker, omitting 10 industries that comprise 0.17 percent of total employment. Regression lines and coefficients refer to the full data.

3. Empirical Model

We study how training intensity and early retirement respond to trade and technology shocks. Our empirical model closely follows the literature on labor market effects of globalization and technological change, with specifics taken from Dauth et al. (2021). We estimate the following model at the level of 402 German counties:

$$Y_r = \alpha \cdot x_r + \beta_1 \cdot \Delta \widehat{robots}_r + \beta_2 \cdot \Delta \widehat{exports}_r + \beta_3 \cdot \Delta \widehat{imports}_r + \varphi_{REG(r)} + \varepsilon_r \qquad (2)$$

Here, Y_r denotes average regional training intensity or early retirement over the period 1996-2014, as described above, which we regress on the predicted changes in regional robot, export, and import exposures. For consistency, these standard measures for regional trade and technology shocks are taken directly from Dauth et al. (2021); their data appendix provides a detailed description. The choice of control variables also follows their model: We control for standard demographic characteristics of the local workforce such as age, gender, and qualification, as well as predicted exposure to ICT equipment. We also include the employment shares of nine broadly defined industry groups, as well as four dummies $\varphi_{REG(r)}$ to capture broad regional trends. Standard errors are clustered at the level of 50 clusters that represent a higher geographical aggregation of local labor markets.[5]

For identification, we also follow the standard approach and use industry-specific trade exposure and robot adoption, respectively, in other high-income countries as instrumental variables, thereby preventing bias from supply and demand shocks specific to German industries or regions. The validity and interpretation of this type of shift-share analysis has been discussed extensively in recent years (see Borusyak, Hull, and Jaravel (2025) for a comprehensive survey). Our analysis conforms to the design with many exogenous shifts, first expounded by Borusyak, Hull, and Jaravel (2022). In this case, the regional industry shares are not required to be exogenous, and identification comes from the exogeneity of the industry-level shift variables, i.e., the industry-level changes in robot adoption and trade volumes measured in foreign countries. Dauth et al. (2021) discuss the validity of this approach; they show that the shift-share variables employed in

[5] When we alternatively use standard errors adjusted for correlation of industry structures across regions as proposed by Adão, Kolesár, and Morales (2019), results on trade exposure remain significant, whereas some of the coefficients on robot exposure become insignificant at conventional levels because of the limited number of industry-level robot observations.

our analysis are neither correlated with pre-trends of employment growth nor with regional characteristics measured at the beginning of the analysis period.

4. Results

Our empirical analysis uses the two novel outcomes—training intensity and early retirement—to study new adjustment mechanisms of local labor markets to trade and technology shocks.

4.1 Effects on Training

Firm training can equip workers with different skills when their existing skills are rendered obsolete by major disruptions in labor demand. Firms and workers exposed to a technology shock might therefore engage in re- or upskilling in order to perform different and potentially higher-quality tasks, thus increasing aggregate productivity. Yet, when labor is mainly substituted by technology, such adverse labor demand effects might also effectively reduce training efforts, since liquidity-constrained firms and workers might lack the resources to invest in human capital. Which impact prevails is, ultimately, an empirical question. The same is true for trade shocks: New export opportunities might induce firms and workers to acquire specific skills pertaining to new markets, while labor market stress and lack of resources after an import shock might distract firms and workers from training.

Main Results. Table 1 presents our main results on training responses to trade and technology shocks. Panel A reports effects on local training intensity across all industries, while Panel B focuses specifically on the manufacturing sector. Column 1 examines any training activity, while columns 2-4 differentiate training by course length measured in annual hours.

Table 1: The effect of trade and technology shocks on training

Panel A: All industries

	Any training	Training intensity (hours per year)		
		≥ 40	≥ 160	≥ 500
	(1)	(2)	(3)	(4)
Δ predicted robot exposure	0.012**	0.009***	0.003***	0.002***
	(0.005)	*(0.003)*	*(0.001)*	*(0.001)*
Δ predicted export exposure	0.052***	0.027***	0.008***	0.004***
	(0.012)	*(0.008)*	*(0.003)*	*(0.002)*
Δ predicted import exposure	-0.036***	-0.022***	-0.008***	-0.004***
	(0.008)	*(0.005)*	*(0.002)*	*(0.001)*
Kleibergen-Paap weak ID test	21.227	21.227	21.227	21.227
Hansen *J* *p*-value	0.080	0.079	0.049	0.168
R^2	0.861	0.876	0.894	0.900
Mean (dependent variable)	11.73	5.92	2.36	1.43

Panel B: Manufacturing

	Any training	Training intensity (hours per year)		
		≥ 40	≥ 160	≥ 500
	(1)	(2)	(3)	(4)
Δ predicted robot exposure	0.003	0.004	0.0005	0.0004
	(0.010)	*(0.006)*	*(0.002)*	*(0.001)*
Δ predicted export exposure	0.164***	0.091***	0.031***	0.016***
	(0.041)	*(0.025)*	*(0.008)*	*(0.005)*
Δ predicted import exposure	-0.073***	-0.042***	-0.015***	-0.007**
	(0.024)	*(0.015)*	*(0.005)*	*(0.003)*
Kleibergen-Paap weak ID test	21.227	21.227	21.227	21.227
Hansen *J* *p*-value	0.248	0.208	0.196	0.261
R^2	0.667	0.668	0.699	0.717
Mean (dependent variable)	9.06	4.57	1.75	1.06

Notes: County-level regressions of average annual training intensity (share of workers participating in job training) on shift-share variables for robot and trade exposure. Training refers to 1996-2014, robot and trade exposure (from Dauth et al. 2021) to 1994-2014. Number of observations: 402 local labor markets. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent.

The results in Panel A reveal distinct patterns across shock types. Robot exposure leads to higher training participation, as does export exposure, whereas import exposure reduces training. All coefficients are statistically significant, and the diagnostic tests confirm instrument validity. These effects are consistent across different training intensities, from short courses to programs exceeding 500 hours annually.

Robot Exposure and Sectoral Spillovers. The results on effects of robot exposure contribute new insights to the automation literature for Germany. Prior work by Dauth et al. (2021) documented that incumbent manufacturing workers benefited from robot adoption through reassignment to higher-paying occupations with upgraded task content. However, it remained unclear whether this occupational upgrading reflected intentional training policies or informal mechanisms.

Results in Panel B reveal a crucial nuance: Robot exposure shows no significant impact on training within the manufacturing sector where robots are actually deployed. This suggests that formal training responses to automation occur primarily in indirectly exposed service industries rather than in directly affected manufacturing. Manufacturing workers apparently achieve their upgrading without formal coursework.

This pattern aligns with spillover effects to local service sectors. As manufacturing productivity increases through automation, demand expands for complementary services such as management consulting, technical services, and research and development.[6] Results in Appendix Table A3, which decomposes the effect of robot exposure by 15 industry groups, confirm this interpretation: The aggregate training effect stems primarily from professional services industries which include industries such as auditing, management, (technical) consulting, and research and development, whereas some manufacturing subsectors such as production and capital goods contribute negatively to the overall effect.[7]

[6] Dauth et al. (2021) showed that robot exposure led to new labor demand in the local service sector that offset the negative employment effects in manufacturing.

[7] For this analysis, we group all NACE Rev. 2 industries—only available for 2008-2014—that we can distinguish in the training data into 15 industry groups. We recalculate the shift-share-style predictor for regional training intensity of equation (1) 15 times, setting T_j equal to zero for the respective 14 other industries. This approach yields 15 variables that add up to the total training intensity, allowing to additively decompose the main coefficient into the contributions of the individual industry groups. Note that for training in the period 2008-2014, the total effect of robots is around half the size as for the full period and not statistically significant.

Export Expansion and Training in Manufacturing. Overall, the training responses generated by trade shocks are larger than those generated by robot exposure. Comparing regions at the upper and lower quartiles of export exposure yields a $0.052 \times 5.581 = 0.290$ percentage point difference in training intensity. The analogous comparison for robot exposure produces only a $0.012 \times 3.103 = 0.037$ percentage point difference.

Unlike robot exposure, export expansion tends to generate direct rather than indirect training effects, concentrated within manufacturing itself. Appendix Table A3 indicates that capital goods industries—including automobiles, machinery, and electrical equipment—drive this pattern. Export-oriented firms likely require market-specific capabilities such as language skills for serving foreign customers, leading to increased formal training participation, though primarily in shorter courses under 40 hours annually.

Import Competition. Import exposure reduces training participation both within manufacturing and in other sectors. This finding contrasts with a potential alternative where skill upgrading serves as a buffer against adverse trade shocks. Instead, the results support the hypothesis that negative economic shocks depress human capital investments through resource constraints.

Prior research has documented earnings and employment losses from import competition in Germany (Dauth, Findeisen, and Suedekum 2017). Our findings suggest that affected firms and workers lack the financial resources, time, or institutional capacity to pursue formal retraining as an adjustment strategy. This asymmetry between positive and negative shocks has important implications for the timing and targeting of active labor market policies.

Interpretation and Implications. The contrasting patterns across shock types suggest different underlying mechanisms. Robot adoption generates productivity gains that create complementary skill demands in the service sector, leading to training investments in industries positioned to capture spillover benefits. Export expansion creates direct skill demands within affected manufacturing industries, particularly for market-specific capabilities. Import competition, however, creates resource constraints that limit training investments across affected regions.

These findings challenge simple narratives about technological adaptation and highlight the importance of distinguishing between direct and indirect effects of economic shocks. The concentration of robot-induced training in the service sector rather than manufacturing suggests that policies targeting directly affected industries may miss important adjustment dynamics occurring elsewhere in the local economy.

4.2 Effects on Early Retirement

Early retirement schemes reduce the deductions in pension payments that elderly workers are confronted with when they consider exiting the labor market before the statutory retirement age. The German labor market traditionally offered quite generous exit conditions for the elderly. When faced with major labor market disruptions, firms and workers may make use of these early retirement incentives to adjust to the reduced demand for labor with incumbent skill sets. Such responses would shift some of the adjustment burden to the contributors of the social security system and leave potential labor input idle, decreasing aggregate productivity.

Main Results. Table 2 presents the results of our analysis of early retirement responses to trade and technology shocks. We examine three outcome measures: the overall probability of early retirement (column 1), the share using unemployment as a bridge to retirement ("golden handshake," column 2), and average retirement age (column 3). Panel A reports results across all industries, while Panel B focuses on manufacturing.

Table 2: The effect of trade and technology shocks on early retirement

Panel A: All industries

	Share early retirement (1)	Share “golden handshake” retirement (2)	Average retirement age (3)
Δ predicted robot exposure	0.054***	0.004	-0.004
	(0.015)	*(0.005)*	*(0.003)*
Δ predicted export exposure	-0.012	-0.031*	0.015*
	(0.035)	*(0.016)*	*(0.009)*
Δ predicted import exposure	0.039	0.033**	-0.010*
	(0.037)	*(0.014)*	*(0.006)*
Kleibergen-Paap weak ID test	21.227	21.227	21.227
Hansen *J* *p*-value	0.076	0.170	0.277
R^2	0.392	0.500	0.643
Mean (dependent variable)	16.3	3.2	58.3

Panel B: Manufacturing

	Share early retirement (1)	Share “golden handshake” retirement (2)	Average retirement age (3)
Δ predicted robot exposure	0.131***	0.011	-0.020***
	(0.031)	*(0.008)*	*(0.005)*
Δ predicted export exposure	-0.006	-0.062***	0.042**
	(0.058)	*(0.022)*	*(0.019)*
Δ predicted import exposure	0.046	0.047**	-0.017*
	(0.058)	*(0.020)*	*(0.009)*
Kleibergen-Paap weak ID test	21.227	21.227	21.227
Hansen *J* *p*-value	0.072	0.164	0.146
R^2	0.220	0.294	0.467
Mean (dependent variable)	16.4	3.2	58.8

Notes: County-level regressions of share of early retirees and average early retirement age on shift-share variables for robot and trade exposure. Early retirement variables refer to 1996-2014 for workers who were employed in the respective industry in 1996, robot and trade exposure (from Dauth et al. 2021) to 1994-2014. Number of observations: 402 local labor markets. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent.

Results again show distinct effects for different shocks. Robot exposure leads to increased usage of early retirement in the local labor market, with the effect being most pronounced in manufacturing. Opposing trade shocks again have opposing effects: Import exposure increases early retirement in the form of golden handshakes, whereas export exposure decreases it.

Robot Exposure and Direct Retirement Pathways. Robot exposure significantly increases early retirement probability, with effects concentrated in manufacturing (Panel B). The manufacturing sector also experiences reduced average retirement ages under robot exposure. Quantifying the impact through interquartile comparisons, regions with high robot exposure have $0.131 \times 3.103 = 0.41$ percentage points (approximately 2.5 percent) more early retirees in manufacturing than low-exposure regions. Appendix Table A4 indicates that capital goods and consumer goods manufacturing drive this aggregate effect.

These findings reveal previously unrecognized adjustment costs of automation in Germany. Prior research by Dauth et al. (2021) found no evidence that robots caused job or earnings losses for incumbent German manufacturing workers, contrasting sharply with US evidence from Acemoglu and Restrepo (2020). Our training results similarly suggested that German labor markets adapted effectively to technological change through skill upgrading mechanisms. However, the early retirement patterns indicate that displacement effects were not entirely absent but were channeled through alternative pathways. Rather than experiencing immediate job loss, older manufacturing workers facing robot exposure appear to have negotiated transitions into early retirement.

Robot-induced early retirement occurs primarily through direct pathways rather than unemployment-bridged transitions (column 2). This pattern may reflect the institutional context surrounding robot adoption. Since automation in Germany generated overall employment stability and wage gains for younger workers, formal unemployment spells for older workers—which officially require demonstrable involuntary contract termination—may have been difficult to justify or arrange.

Import Exposure and Golden Handshakes. Import exposure generates different retirement patterns. Manufacturing workers facing import competition more frequently utilize unemployment benefits as a bridge to pension eligibility, the “golden handshake” pathway (column 2). This institutional difference reflects the broader economic context: Import shocks demonstrably caused earnings and job losses for younger workers (Dauth, Findeisen, and Suedekum 2017), creating legitimate grounds for unemployment claims by older workers.

Quantifying this effect, regions at the upper quartile of import exposure show $0.047 \times 5.167 = 0.243$ percentage points more manufacturing workers using the golden handshake pathway than regions at the lower quartile. This institutional arbitrage allows workers to access higher replacement rates through unemployment benefits before transitioning to pension eligibility.

Export Expansion and Delayed Retirement. Export opportunities generate opposite effects, with workers in export-exposed regions retiring later than their counterparts elsewhere. This pattern likely reflects firms' retention strategies during demand expansion. When export opportunities create positive labor demand shocks, firms may delay hiring new workers while retaining experienced employees to meet increased production requirements. This does not necessarily imply that workers are retained beyond the statutory retirement age since the average retirement age is well below this threshold throughout the entire German labor force. Instead, workers in export-exposed regions are more likely to retire closer to this threshold.

This finding complements the training results showing increased skill investments in export-oriented regions. Firms facing positive demand shocks appear to pursue adjustment strategies that retain and upgrade their existing workforce rather than replacing older workers with new hires.

Interpretation and Implications. The contrasting retirement responses across shock types highlight how institutional frameworks shape adjustment pathways. Robot adoption creates early retirement through negotiated direct transitions, import competition facilitates retirement through unemployment insurance mechanisms, and export expansion delays retirement through workforce retention strategies.

These patterns suggest that early retirement serves as an adjustment tool that operates differently depending on economic context and institutional constraints. However, all forms of shock-induced early retirement transfer private adjustment costs to public pension and unemployment insurance systems, creating fiscal externalities that may not be immediately apparent in studies focusing solely on employment and wage outcomes.

The findings also indicate that German labor market resilience to technological change may partly benefit from the availability of early retirement as a pressure valve for older workers, even while younger workers benefit from automation through job upgrading and wage growth. This age-differentiated adjustment pattern has important implications for evaluating the distributional consequences of technological change and the sustainability of public pension systems during periods of rapid automation.

5. Conclusion

When firms and workers are confronted with adjustment pressures from trade and technological disruptions, their responses fundamentally shape aggregate economic outcomes. These responses can either enhance productivity through human capital development or diminish it by withdrawing productive resources from the economy. This paper investigates two critical adjustment mechanisms with likely opposing aggregate effects: worker training that builds productive capacity and early retirement schemes that remove experienced workers from the labor force.

Our results from Germany indicate that both adjustment mechanisms operate simultaneously. In response to robot adoption, local labor markets increased training in indirectly affected services while raising early retirement rates in directly affected manufacturing. In response to trade integration with China and Eastern Europe, local labor markets exposed to import competition reduced training in manufacturing and increased early retirement through unemployment-bridged pathways ("golden handshakes"). Local labor markets exposed to export expansion exhibited the opposite pattern. Thus, while firms and workers employed both productivity-enhancing and productivity-reducing adjustments in response to robot adoption, their responses to trade shocks were uniformly positive or negative depending on shock direction.

These findings reveal the complexity of labor market adjustment to structural change. The coexistence of multiple adjustment mechanisms within the same institutional setting demonstrates that simple narratives about technological adaptation or trade integration miss important heterogeneity in how different sectors and worker groups respond to economic disruptions.

To promote aggregate productivity during economic transformation, policymakers should consider designing policies that support productivity-enhancing, rather than productivity-reducing, adjustment mechanisms. Training policies that target regions affected by structural shocks might consider adopting a comprehensive scope that extends well beyond directly impacted industries. Our analysis reveals particularly significant spillover effects in the service sector within automation-exposed regions.

The asymmetric responses to positive versus negative trade shocks suggest that training-focused policy measures may be particularly needed in regions exposed to import competition.

Without policy support, import-exposed firms and workers reduce training investment, possibly due to resource constraints during periods of economic stress. This pattern implies that trade adjustment assistance may be particularly important in import-competing regions where training that could restore firms' and workers' competitiveness or enable workers to switch to other industries does not occur.

While early retirement rules have become less generous in Germany since our period of study, important exemptions remain and generous early retirement continues to be widespread (Deutsche Bundesbank 2025). The demographic transition toward an aging workforce and increasing dependency ratios make this issue more rather than less pressing for aggregate economic performance. A policy framework that incentivizes adjustment through skill upgrading while limiting adjustment through early retirement may better serve long-term productivity objectives.

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Appendix A: Data on Training

This appendix describes the derivation of our data on training. We use comprehensive data from the German Microcensus to create a training dataset that consistently measures work-related training over a long period of time.[8] Few data sources allow harmonization of training data over an extended time period, which is necessary to address the common challenge in measuring job training to account for its heterogeneity and multiple facets (e.g., Black, Skipper, and Smith 2023). The Microcensus first records training in a consistent way in 1996, and we use all annual waves until 2014, consistent with the available data on robot penetration. Thus, the data allow us to create a consistent training measure that harmonizes training information over 19 years.

Our main indicator of training participation is coded as one if an individual participated in at least one work-related training session during the past year. This approach allows for the calculation of the proportion of individuals within each industry who engaged in job training. Over large parts of the observation period (2005-2014), the main questionnaire item on training records whether individuals participated in 'educational events in the form of courses, seminars, conferences, or private lessons for general or vocational further education' over the past year (see Table A5 for the wording of employed questionnaire items).

The Microcensus survey also allows us to identify *work-related* training and separate it from other types of training. Based on supplementary questionnaire items, we take three steps to restrict our training measure to work-related training. First, we restrict the sample to employed individuals. Second, we use an additional survey item on the purpose of the training to exclude instances from our training measure whose reported purposes were non-work-related activities such as dance lessons or private cooking classes. Third, we disregard training instances by respondents who are currently enrolled in a vocational school and by respondents who cite 'first vocational training' as their training purpose, thereby excluding initial apprenticeship education and restricting the training measure to instances of further training.

The Microcensus data also allow us to measure the intensity of training incidents. In the 2005-2014 survey waves, participants are asked how many hours they spent in training courses over the past year. This information allows us to capture training of different lengths, constructing

[8] In our analysis, we use the scientific use files which provide 70-percent random subsamples of the Microcensus. See Research Data Center of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/12211.1996.00.00.3.1.0 to 10.21242/12211.2014.00.00.3.1.0.

indicators for job training that exceeds thresholds of 40 hours (one week), 160 hours (four weeks), and 500 hours (roughly a quarter of a year) during the year, respectively.

Prior to 2005, the wording of the different questionnaire items varies slightly (see Table A5). From the available data, we derive training measures as consistent as possible with the ones available for the subsequent period. Before 2005, the training question lists the month in the previous year from which the respondent was asked to recall participation in training instead of asking about participation in training in the previous 12 months. Before 2003, the training question does not include examples of training events and does not allow respondents to list participation in more than one training event. In 1996-1998 and 2002, the main training question refers to participation in 'any vocational training, further training or retraining.' In 1999-2001, the response options to participation in 'any educational program' distinguish between general and work-related training, allowing us to consider only work-related training and exclude other types of training. Questionnaire items on the intensity of training also vary prior to 2005. In 2003 and 2004, the reported hours of training cover the previous four weeks. To approximate annual training hours, we multiply these four-week values by 11.5, reflecting an annual schedule of 46 working weeks after accounting for standard vacation and holiday periods. From 1996 to 2002, we combine information on the number of training hours per week with information on the duration of training in months.

To aggregate the training measures to the industry level, we use the three-digit industry classification developed by the German Federal Statistical Office. The German Microcensus uses classification WZ03 until 2007 (199 industries) and WZ08 since 2008 (247 industries). These classifications are closely aligned with European and international standards, with WZ03 based on NACE Rev. 1.1 and WZ08 based on NACE Rev. 2. We merge the training measures to a plant-level dataset based on the Establishment History Panel (BHP) which provides imputed time-consistent industry classifications. We then calculate weighted averages of the measures at the level of the 20 manufacturing industries for which the robot data are available.

Appendix B: Additional Tables

Table A1: Descriptive statistics

	Mean	SD	p25	p50	p75	IQR
Training: all industries						
Any	11.73	0.98	11.08	11.60	12.22	1.14
≥ 40 hours per year	5.92	0.60	5.50	5.81	6.20	0.70
≥ 160 hours per year	2.36	0.23	2.20	2.32	2.47	0.27
≥ 500 hours per year	1.43	0.13	1.34	1.41	1.49	0.15
Training: manufacturing						
Any	9.06	1.28	8.19	8.91	9.66	1.47
≥ 40 hours per year	4.58	0.77	4.04	4.49	4.94	0.90
≥ 160 hours per year	1.76	0.26	1.58	1.72	1.89	0.31
≥ 500 hours per year	1.06	0.15	0.96	1.05	1.15	0.19
Early retirement: all industries						
Share early retirement	16.27	1.58	15.28	16.25	17.24	1.95
Share "golden handshake" retirement	3.19	0.59	2.75	3.15	3.56	0.81
Average retirement age	58.37	0.37	58.19	58.36	58.56	0.37
Early retirement: manufacturing						
Share early retirement	16.39	2.13	15.01	16.27	17.73	2.72
Share "golden handshake" retirement	3.24	0.89	2.68	3.17	3.69	1.01
Average retirement age	58.77	0.51	58.45	58.72	59.05	0.60
Transformation shocks						
Δ predicted robot exposure	4.62	8.03	1.44	2.61	4.54	3.10
Δ predicted export exposure	7.85	5.16	4.39	7.05	9.97	5.58
Δ predicted import exposure	6.89	4.39	3.81	6.01	8.98	5.17
Employment growth rates						
Total	-1.05	17.94	-12.15	-1.67	9.45	21.61
Manufacturing	-9.72	25.43	-27.06	-12.31	5.39	32.45
Non-manufacturing	4.74	22.41	-6.64	6.41	16.93	23.58

Notes: Means, standard deviations (SD), percentiles, and interquartile ranges (IQR) at the level of 402 local labor markets. Training and early retirement refer to 1996-2014, transformation shocks and employment growth rates to 1994-2014.

Table A2: Industry-level associations of training and early retirement with robot and trade exposure

Panel A: Training

	Any training		
	(1)	(2)	(3)
Δ predicted robot exposure	0.027**		-0.006
	(0.011)		*(0.025)*
Δ predicted export exposure		0.076**	0.081***
		(0.028)	*(0.027)*
Δ predicted import exposure		0.017	0.017
		(0.023)	*(0.023)*
R^2	0.103	0.567	0.571

Panel B: Early retirement

	Share early retirement		
	(1)	(2)	(3)
Δ predicted robot exposure	0.011		0.022
	(0.014)		*(0.015)*
Δ predicted export exposure		-0.045*	-0.060*
		(0.025)	*(0.033)*
Δ predicted import exposure		0.039**	0.039*
		(0.018)	*(0.020)*
R^2	0.032	0.195	0.290

Notes: Industry-level regressions of average annual training intensity and of share of early retirees, respectively, on shift-share variables for robot and trade exposure. Training (share of workers participating in job training) and early retirement (of workers who were employed in the respective industry in 1996) refer to 1996-2014, robot and trade exposure (from Dauth et al. 2021) refer to 1994-2014. Numbers of observations: 20 NACE Rev. 2 equivalent aggregate manufacturing industries for which robot exposure is available. Robust standard errors in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent.

Table A3: Decomposing the effect of trade and technology shocks on training by industry group

Any training	All	Agriculture and mining	Consumer goods	Production goods	Capital goods	Supply and disposal	Construction	Retail
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ predicted robot exposure	0.006	0.0008	0.009	-0.015***	-0.023***	-0.003	0.0008	-0.004
	(0.008)	*(0.001)*	*(0.007)*	*(0.005)*	*(0.007)*	*(0.002)*	*(0.001)*	*(0.004)*
Δ predicted export exposure	0.075***	0.0008	0.029	0.029	0.046**	-0.005	0.003	-0.007
	(0.018)	*(0.002)*	*(0.023)*	*(0.020)*	*(0.019)*	*(0.003)*	*(0.005)*	*(0.010)*
Δ predicted import exposure	-0.041***	-0.001	-0.005	-0.009	-0.025**	-0.007***	0.005*	0.008
	(0.009)	*(0.001)*	*(0.015)*	*(0.008)*	*(0.013)*	*(0.003)*	*(0.003)*	*(0.007)*
Kleibergen-Paap weak ID test	21.227	21.227	21.227	21.227	21.227	21.227	21.227	21.227
Hansen *J* *p*-value	0.139	0.520	0.339	0.282	0.155	0.091	0.431	0.243
R^2	0.842	0.638	0.520	0.686	0.896	0.325	0.788	0.602

	Transport and logistics	Hospitality	Communi-cation	Finance, insurance	Professional services	Other comm. services	Other pers. services	Public sector
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Δ predicted robot exposure	0.007**	0.002*	0.007	-0.0006	0.020***	0.002	0.002	0.003
	(0.003)	*(0.001)*	*(0.004)*	*(0.003)*	*(0.006)*	*(0.004)*	*(0.002)*	*(0.007)*
Δ predicted export exposure	-0.019	0.003	-0.003	0.011	0.004	-0.009	-0.002	-0.007
	(0.013)	*(0.003)*	*(0.010)*	*(0.010)*	*(0.019)*	*(0.006)*	*(0.005)*	*(0.017)*
Δ predicted import exposure	0.010	-0.002	0.007	-0.007	-0.006	-0.010**	0.003	-0.002
	(0.012)	*(0.002)*	*(0.007)*	*(0.007)*	*(0.012)*	*(0.004)*	*(0.005)*	*(0.015)*
Kleibergen-Paap weak ID test	21.227	21.227	21.227	21.227	21.227	21.227	21.227	21.227
Hansen *J* *p*-value	0.110	0.241	0.303	0.504	0.814	0.179	0.230	0.366
R^2	0.391	0.334	0.633	0.573	0.633	0.536	0.523	0.806

Notes: County-level regressions of average annual training intensity (share of workers participating in job training) on shift-share variables for robot and trade exposure, decomposed by industry groups. Coefficients of columns (2)-(16) sum up to the respective coefficient in column (1). Training refers to 2008-2014, robot and trade exposure (from Dauth et al. 2021) to 1994-2014. Number of observations: 402 local labor markets. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent.

Table A4: Decomposing the effect of trade and technology shocks on early retirement by industry group

Share early retirement	All	Agriculture and mining	Consumer goods	Production goods	Capital goods	Supply and disposal	Construction	Retail
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ predicted robot exposure	0.054***	0.0008	0.020***	-0.014***	0.051***	-0.0006	0.003	-0.005
	(0.015)	*(0.002)*	*(0.007)*	*(0.005)*	*(0.007)*	*(0.002)*	*(0.002)*	*(0.004)*
Δ predicted export exposure	-0.012	-0.004	-0.020	0.023	0.015	-0.003	0.001	-0.004
	(0.035)	*(0.003)*	*(0.018)*	*(0.015)*	*(0.013)*	*(0.004)*	*(0.004)*	*(0.012)*
Δ predicted import exposure	0.039	0.0003	0.017	-0.012	-0.009	-0.005**	0.005*	0.010
	(0.037)	*(0.002)*	*(0.012)*	*(0.008)*	*(0.008)*	*(0.002)*	*(0.002)*	*(0.008)*
Kleibergen-Paap weak ID test	21.227	21.227	21.227	21.227	21.227	21.227	21.227	21.227
Hansen *J* *p*-value	0.076	0.239	0.208	0.387	0.151	0.154	0.350	0.084
R^2	0.392	0.701	0.741	0.705	0.945	0.381	0.849	0.571

	Transport and logistics	Hospitality	Communi-cation	Finance, insurance	Professional services	Other comm. services	Other pers. services	Public sector
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Δ predicted robot exposure	0.0004	0.002*	0.004	-0.0000	-0.005	-0.0002	0.0007	-0.003
	(0.002)	*(0.001)*	*(0.003)*	*(0.002)*	*(0.004)*	*(0.002)*	*(0.002)*	*(0.005)*
Δ predicted export exposure	-0.013*	0.005	-0.005	-0.003	-0.001	-0.012**	0.001	0.009
	(0.008)	*(0.005)*	*(0.008)*	*(0.006)*	*(0.007)*	*(0.006)*	*(0.004)*	*(0.013)*
Δ predicted import exposure	0.006	-0.0002	0.010	-0.002	0.003	0.002	0.006	0.009
	(0.007)	*(0.002)*	*(0.007)*	*(0.003)*	*(0.006)*	*(0.006)*	*(0.005)*	*(0.010)*
Kleibergen-Paap weak ID test	21.227	21.227	21.227	21.227	21.227	21.227	21.227	21.227
Hansen *J* *p*-value	0.206	0.419	0.444	0.970	0.841	0.430	0.043	0.342
R^2	0.580	0.331	0.570	0.654	0.466	0.742	0.481	0.807

Notes: County-level regressions of share of early retirees and average early retirement age on shift-share variables for robot and trade exposure, decomposed by industry groups. Coefficients of columns (2)-(16) sum up to the respective coefficient in column (1). Early retirement refers to 1996-2014 for workers who were employed in the respective industry in 1996, robot and trade exposure (from Dauth et al. 2021) to 1994-2014. Number of observations: 402 local labor markets. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Significance level: *** 1 percent, ** 5 percent, * 10 percent.

Table A5: Questionnaire items on training available in the German Microcensus

Year	Question
Panel A: Participation in training in the last year (yes/no)	
2005–2014	In the last 12 months, have you participated in one or more educational events in the form of courses, seminars, conferences, or private lessons for general or vocational further education, or are you currently participating in any?
2004	Since the end of March 2003, have you participated in one or more educational events in the form of courses, seminars, conferences, or private lessons for general or vocational further education, or are you currently participating in any?
2003	Since the end of April 2002, have you participated in one or more educational events in the form of courses, seminars, conferences, or private lessons for general or vocational further education, or are you currently participating in any?
2002	Are you currently participating in any vocational training, further education, or retraining, or have you participated in any such training since the end of April 2001?
1999–2001	Are you currently participating in an educational program, or have you participated in one since the end of April 1998 [or 1999, 2000 respectively]?
1996–1998	Have you participated in any vocational training, further education, or retraining since the end of April 1995 [or 1996, 1997 respectively]?
Panel B: Training intensity (hours of training)	
2005–2014	How many hours have you spent in the last 12 months participating in one or more educational events?
2003–2004	How many hours have you spent in total in the reporting week and the three weeks prior participating in one or more educational events for professional purposes?
1996–2002	How many hours does (or did) the training measure comprise in total per week?
1996–2002	How long does (or did) this measure last in total?
Panel C: Supplementary questions	
1996–2014	Are you currently attending a school (including a vocational school) or a university (including a university of applied sciences)?
1996–2014	What kind of school is it?
2005–2014	What was the purpose of your further training in the last 12 months?