Pillars – Pathways to Inclusive Labour Markets

Report

The Effect of Technological and Structural Transformations on the Transferability of Human Capital

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The Effect of Technological and Structural Transformations on the Transferability of Human Capital

Yuchen Guo[a,b], Simon Wiederhold[a,b,c]

[a] *KU Eichstätt-Ingolstadt* [b] *ifo Institute Munich* [c] *CESifo*

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1. Introduction

There is abundant literature on the aggregate decline of manual-routine occupations due to substitution by automation capital, as these occupations perform tasks that can be easily replaced by machines (e.g., Autor et al., 2003; Goos et al., 2009; Cortes, 2016; Acemoglu and Restrepo, 2018). Similarly, technological progress and reduced trade barriers put occupations at an increased risk of offshoring, as their tasks can be performed abroad (Jensen and Kletzer, 2005; Crino, 2009; Blinder, 2009; Blinder and Krueger, 2013; Goos et al., 2014). As employment opportunities for workers in manual-routine or offshorable occupations increasingly vanish due to technological change, structural transformation, and changing global value chains, these workers may face particularly difficult transitions on the labor market. Surprisingly, however, evidence on how these groups of workers fare after (technology- or trade-induced) displacement is lacking.

In this report, we empirically investigate the labor market transitions after job displacement of workers who are differently exposed to these labor market trends. At a more fundamental level, our work addresses the question of how capital deepening, embodied technological change, and changing global value chains affect the labor market prospects for different types of workers and generate differential adjustment frictions and reallocation costs.

We purport that specific human capital in combination with changes in the occupational structure is a major reason explaining why routine and offshorable workers might face particular difficulties to adjust to labor market shocks. A growing literature provides evidence for large task- and occupation-specific components of human capital (e.g., Gibbons and Waldman, 2004; Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann and Schoenberg, 2010). This literature introduces the mismatch of specific skills as a source of wage losses after (involuntary) occupational switches, since skills specific to the old job may become obsolete in the new job. Another stream of literature highlights that higher exposure to automation is associated with larger declines in employment in routine (e.g., Nedelkoska and Quintini, 2018; Arntz et al., 2019) and offshorable (e.g., Goos et al., 2014) occupations. Thus, the distance to other occupations in terms of task similarity might increase for these workers, as similar occupations in terms of the task content are disappearing (e.g., Autor et al., 2003; Goos et al., 2014; Arntz et al., 2016). This means that workers whose tasks are at risk of getting automated or outsourced abroad face higher costs of occupational reallocation: As they have to overcome a larger occupational distance when switching jobs, they incur larger losses of specific human capital and thus experience larger wage losses when being forced to switch (e.g., after involuntary job loss).

We use German administrative data to identify job displacements due to plant closures as a source of exogenous variation in job separations. We focus on plant closures for two reasons. First, selection into job separation might bias the estimated difference in labor market outcomes between routine and non-routine workers after job loss. For instance, it may be that only the most productive routine workers leave their jobs due to better outside options. At the same time, the reason for job separation is typically unobserved in labor market data. We thus cannot distinguish between voluntary and involuntary job separations, which have been shown to lead to fundamentally different subsequent labor market outcomes (e.g., Biewen and Steffes, 2010). By focusing on plant closures, we can cleanly identify involuntary job separations. Moreover, workers in different occupational groups might differ in the degree of (unobserved) occupational sorting and occupation-specific incentive contracts and separation rates. Job separations due to plant closures affect routine/non-routine and offshorable/non-offshorable workers along the entire productivity distribution in the closing establishment.

Second, displacements due to plant closures serve as a natural experiment where workers are exogenously separated from their current job. The ideal experiment to study the (differential) labor market experiences of routine (vs. non-routine) and offshorable (vs. non-offshorable) workers would be to randomly detach workers in different occupations from their jobs and follow them after the job separation. Any differences in the labor market trajectories after separation would reflect differences in adjustment frictions and reallocation costs between different groups of workers. Therefore, plant closures as unanticipated shocks provide a unique empirical setting to use involuntary job separations that are exogenous to worker characteristics and allow to analyze differential changes in the labor market experiences.

To estimate displacement costs, we employ a dynamic difference-in-differences model in the spirit of the seminal work by Jacobson et al. (1993), where treated units are workers laid off involuntarily due to plant closures. Moreover, to account for worker sorting into firms, we match on a large number of pre-displacement characteristics and outcomes. By combining plant closures with matching of displaced to non-displaced workers based on pre-displacement characteristics, job separations are as close to random as empirically possible.

Our event-study estimates show that manual-routine workers face substantial wage losses after displacement relative to their non-displaced counterparts, while the displacement-induced wage losses of non-manual-routine workers are much smaller. The higher wage losses of manual-routine workers comprise of both a higher probability of unemployment after job loss (extensive margin) and larger losses in real daily wages conditional on finding employment (intensive margin). We also observe that manual-routine workers have a higher propensity of occupational switching after displacement than non-manual-routine workers. This is in line with the documented secular decline of routine occupations (e.g., Goos et al., 2009; Cortes, 2016), which implies decreasing employment opportunities for routine workers in their pre-displacement occupation. Moreover, consistent with the increasing disappearance of manual-routine occupations — implying larger losses in occupation-specific human capital — we find that manual-routine workers switch to more distant occupations in terms of task content. This suggests that the loss of task-specific human capital is one major reason for the large displacement costs of manual-routine workers.

While we find considerable heterogeneities in labor market transitions following job displacement between manual-routine and non-manual-routine workers, we do not find such pronounced differences between offshorable and non-offshorable workers. One potential explanation for this result is that in Germany, offshorable occupations have not experienced a marked employment decrease in recent years (Dauth et al., 2014).

We further investigate whether the more difficult labor market transitions after displacement for manual-routine workers are gender-neutral or gender-specific.. As technological change and increased international trade have affected the jobs of men and women differently Black and Spitz-Oener (2010), we may expect gender differences in labor market prospects after job loss. Indeed, women displaced in manual-routine jobs are much more negatively affected than men displaced in similar jobs.[1] One potential explanation for this result is that declining employment opportunities in manual-routine occupations particularly affect female workers, e.g., because of a lower reliance on female earnings in traditional "male breadwinner" households. Consistent with the notion that wage losses at the intensive margin occur due to losses in occupation-specific human capital, female manual-routine workers switch more often and to less task-related occupations compared to their male counterparts. However, in contrast to what we observe for manual-routine occupations, male and female workers who are displaced from offshorable occupations experience very similar labor market transitions after displacement.

[1] Similar to recent evidence by Illing et al. (2021), we also observe that women generally suffer more difficult transitions after job loss than men.

This report proceeds as follows: Section 2 provides motivating aggregate evidence on the role of technological progress (affecting automation) and changing global value chains (affecting offshoring) on occupations' employment growth across Europe. We further explore which country features affect the extent to which employment growth is influenced by automation and offshoring. In the remainder of the report, we move to the individual level to provide arguably causal estimates on the impact of automation and offshoring on workers' labor market adjustments to employment shocks. Section 3 presents our empirical strategy. Section 4 describes our data and the matching strategy. Section 5 discusses the results. Section 6 concludes.

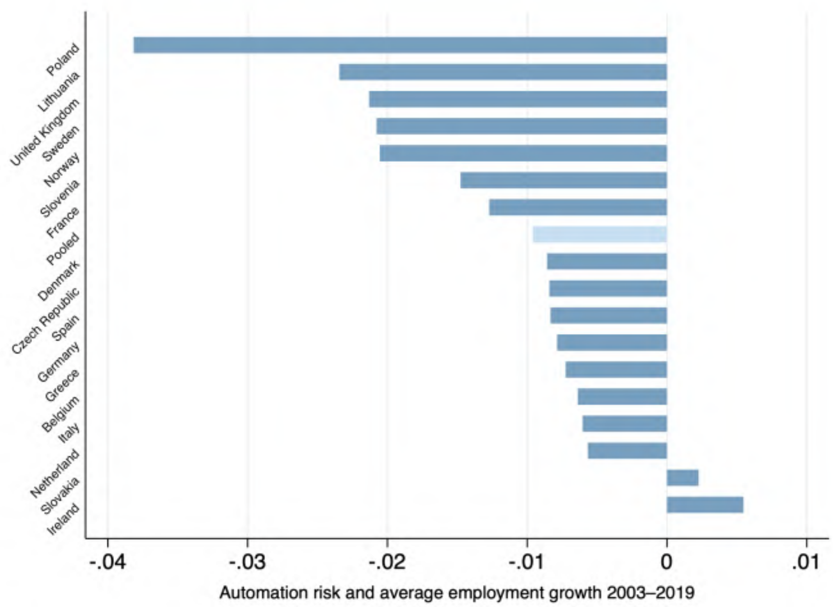
2. Motivating Evidence

We begin by presenting descriptive evidence on how the exposure to automation and offshoring affects the occupational structure across European countries. For this analysis, we draw on Eurostat's European Labor Force Survey (EU-LFS). The EU-LFS is a representative household survey conducted in all member states of the European Union and the United Kingdom. It provides data on labor force participation of individuals aged 15 and above, as well as information on the occupation at the two-digit level. We use EU-LFS to obtain the average annual growth rate in employment shares of occupations across European countries from 2003 to 2019.

Figure 1 shows the relationship between an occupation's exposure to automation and the average growth rate of its employment share. Our measure of automation risk stems from Nedelkoska and Quintini (2018), who construct a country-specific and occupation-specific measure of automation risk using data from the Programme for the International Assessment of Adult Competencies (PIAAC), administered by the OECD. This measure uses a task-based approach to identify the automation risk, ranging from 0 if none of the tasks in an occupation can be automated to 1 if all tasks in an occupation can be automated. The occupation with the highest risk of automation is agricultural work, with an average automation risk of 65% (i.e., 65% of tasks in this occupation can be automated). On the other end of the spectrum, production and service managers as well as teaching professionals face the lowest automation risk, with less than one-quarter of the tasks being automatable.

First, Figure 1 suggests a negative relationship between the risk of automation and employment growth for almost all European countries in our sample. On average across

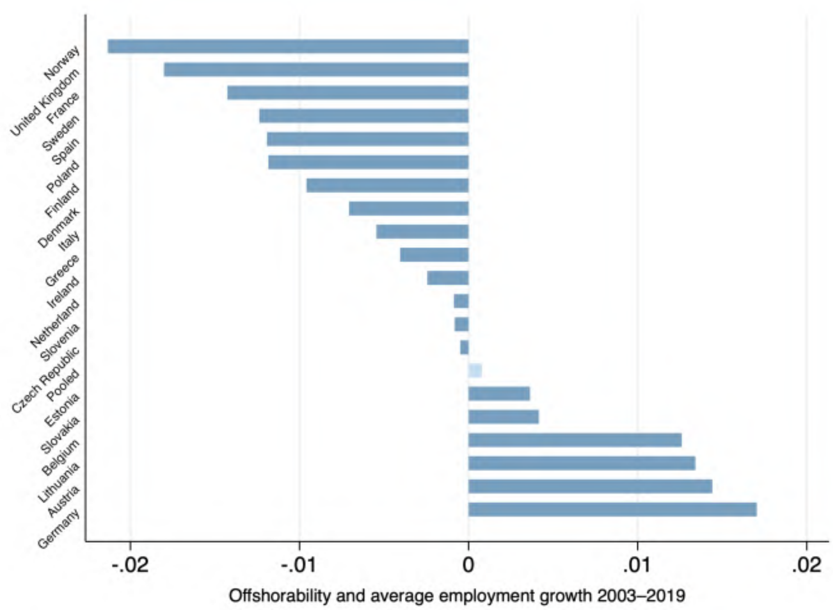
Figure 1: Automation Risk and Employment Growth across European Countries



Notes: This figure shows the coefficient of regressing an occupation's average annual growth in employment share between 2003 and 2019 on its automation risk, by country and pooled over all countries. Automation risk: country-occupation-specific measure ranging from 0 (no tasks in an occupation can be automated) to 1 (all tasks in an occupation can be automated), obtained from Nedelkoska and Quintini (2018). Growth in employment shares is obtained from EU-LFS.

countries, a 10% increase in an occupation's automation risk[2] is associated with a decrease of about 1%age point (pp) in that occupation's employment share. Thus, occupations that are at higher risk of automation clearly experienced a decline in employment shares across Europe. In Poland, Lithuania, the UK, Sweden, and Norway, the negative association between automation risk and employment growth is strongest. The only countries in which the association is positive (but very small) are Slovakia and Ireland.

Figure 2: Offshorability and Employment Growth across European Countries



Notes: This figure shows the coefficient of regressing an occupation's average annual growth in employment share between 2003 and 2019 on its degree of offshorability, by country and pooled across all countries. Offshorability: occupation-specific measure of the degree to which work can be performed from abroad, obtained from Blinder and Krueger (2013); offshorability index is standardized to standard deviation 1 across occupations. Growth in employment shares is obtained from EU-LFS.

Next, we draw on measures of the offshorability of occupations from Blinder and Krueger (2013). This measure is based on expert surveys and captures the degree to which the tasks in an occupation can be performed from abroad. As the original measures are based on data from the United States, we use the crosswalk between the Standard Occupational Classification (SOC) system to the ISCO (International Standard Classification of Occupations) occupational categories used in EU-LFS by Goos et al. (2014). For exposition, we standardize the resulting offshorability index to standard deviation 1

[2]This is approximately the difference in automation risk between food and garment workers and sales workers.

across occupations. For instance, stationary plant operators have the highest offshoring risk with 1.6 standard deviations above the mean, while sales workers show the lowest degree of offshorability with 0.6 standard deviations below the mean.

Figure 2 shows that an occupation's degree of offshorability is negatively associated with its employment growth in most countries. However, there is considerable heterogeneity in this relationship. For instance, while a one standard deviation higher offshorability is associated with a decline in employment by 2.1 pp in Norway, it is related to a 1.7 pp *growth* in employment in Germany. The result for Germany is consistent with e.g., Dauth et al. (2014), who find that globalization did not speed up the decline of the manufacturing sector in Germany, but even retained those jobs in the economy.

We now explore what drives these heterogeneities across countries. To do so, we rely on data on labor market institutions, educational attainment from the OECD and total factor productivity data from the Penn World Tables. We use the share of employees who are trade union members as a measure of union density. Further, we include a binary indicator for the existence of minimum wage regulations which takes a value of one if a country has a statutory minimum wage, and zero otherwise. To measure the strength of employee protection, we use an index that captures the strictness of employment protection against individual and collective dismissals of employees. Further, we include the average years of schooling of the labor force obtained from EU-LFS to measure educational attainment. Finally, we include a measure of total factor productivity (TFP) to measure productivity and distance to the technological frontier. We measure all variables at the beginning of our observation period, i.e., in 2003, and de-mean them for ease of interpretation. Interacting these country-specific characteristics with our measures of automation risk and offshorability shows how the relationship between these labor market trends and employment growth differs by country characteristics.

Table 1 provides the results. We first include the interactions with the various labor market trends individually, and the jointly. The joint specification in Column (6) indicates that higher levels of labor market protection in terms of employment protection and union density have a mitigating effect on the negative impact of automation risk on an occupation's employment growth. This suggests that higher levels of worker protection might render job separations from workers susceptible to automation more costly for employers.

Similarly, Table 2 shows a similar mitigating effect of employment protection on the impact of an occupation's offshorability on its employment growth (Column (6)). At the same time, in countries closer to the technological frontier (measured by TFP), the association between offshorability and employment growth is stronger.

However, it is important to note our descriptive analyses cannot rule out reverse causality: i.e., countries that are more efficient might also have less protected, more dynamic labor markets. Thus, from a policy perspective, this points to a potential trade-off between efficient growth and equitable growth. For instance, a recent series of papers suggests that the reshuffling of labor in response to advancing technology has positive effects on aggregate productivity (e.g., Aghion et al., 2020; Dauth et al., 2021).

Regardless of the aggregate ramifications of technological change and reconfigurations of global value chains on employment and productivity, there might be large costs at the individual level associated with the observed changes in the occupational structure of economies. In the following, we will investigate these costs associated with changing technology and global value chains for individual workers.

Table 1: Automation Risk and Employment Change, by Country Features

	(1)	(2)	(3)	(4)	(5)	(6)
Automation Risk × Minimum Wage Regulation	0.4159					0.7225
	(0.3429)					(0.4090)
Automation Risk × Employment Protection		0.8432				1.0186*
		(0.7137)				(0.5730)
Automation Risk × Union Density			0.9393			1.9278*
			(1.1114)			(0.9935)
Automation Risk × Average Years of Schooling				-0.0399		-0.0014
				(0.0647)		(0.1266)
Automation Risk × TFP					0.2158	-0.3078
					(0.3463)	(1.1882)
Observations	653	614	614	653	653	614
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	17	16	16	17	17	16

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Least squares estimation including occupation and country fixed effects. The dependent variable is the average country specific annual growth rate in the employment share of an occupation between 2003–2019. Growth in employment shares is obtained from EU-LFS. Automation risk: country-occupation-specific measure ranging from 0 (no tasks in an occupation can be automated) to 1 (all tasks in an occupation can be automated), obtained from Nedelkoska and Quintini (2018). Employment protection: composite indicator measuring strictness of employment protection for individual and collective dismissals. Minimum wage regulation: binary variable indicating whether country has a statutory minimum wage. Union density: share of employees in a country who are trade union members. Average years of schooling: average educational attainment of the labor force in terms of years of schooling. TFP: (residual) total factor productivity level, computed with GDP, capital stock and labor input data. All variables on country specific variables are de-meaned. Robust standard errors (adjusted for clustering at the country level) in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 2: Offshorability and Employment Change, by Country Features

	(1)	(2)	(3)	(4)	(5)	(6)
Offshorability × Minimum Wage Regulation	-0.0039					0.0062
	(0.0108)					(0.0057)
Offshorability × Employment Protection		0.0124**				0.0148**
		(0.0058)				(0.0053)
Offshorability × Union Density			-0.0118			0.0052
			(0.0101)			(0.0134)
Offshorability × Average Years of Schooling				0.0003		0.0012
				(0.0024)		(0.0025)
Offshorability × TFP					-0.0218	-0.0454*
					(0.0262)	(0.0218)
Observations	441	399	399	441	441	399
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	21	19	19	21	21	19

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Least squares estimation including occupation and country fixed effects. The dependent variable is the average country specific annual growth rate in the employment share of an occupation between 2003–2019 as dependent variable. Growth in employment shares is obtained from EU-LFS. Offshorability: occupation-specific measure of the degree to which work can be performed from abroad, obtained from Blinder and Krueger (2013); offshorability index is standardized to standard deviation 1 across occupations Employment protection: composite indicator measuring strictness of employment protection for individual and collective dismissals. Minimum wage regulation: binary variable indicating whether country has a statutory minimum wage. Union density: share of employees in a country who are trade union members. All variables on country specific variables are de-meaned. Employment protection: composite indicator measuring strictness of employment protection for individual and collective dismissals. Minimum wage regulation: binary variable indicating whether country has a statutory minimum wage. Union density: share of employees in a country who are trade union members. Average years of schooling: average educational attainment of the labor force in terms of years of schooling. TFP: (residual) total factor productivity level, computed with GDP, capital stock and labor input data. All variables on country specific variables are de-meaned. Robust standard errors (adjusted for clustering at the country level) in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

3. Empirical Strategy

To investigate how different workers with varying degrees of susceptibility to automation and offshoring cope with labor market shocks, we study how the labor market trajectories after job displacement differ between workers initially employed in manual-routine vis à vis non-manual-routine occupations and offshorable vis à vis non-offshorable occupations. To this end, we use plant closures as job separations that are arguably exogenous to individual worker characteristics (e.g., performance, continuation value, or outside options; see, e.g., Jacobson et al., 1993; Schmieder et al., 2022; Nedelkoska et al., 2022). [3] Following the existing job displacement literature, our identification strategy exploits the fact that plant closures are unexpected and outside a worker's individual control; thus, they affect workers along the entire productivity distribution in the closing establishment (e.g., Fackler et al., 2021). At the same time, we take into account recent developments in the difference-in-differences and event study literature (e.g., de Chaisemartin and D'Haultfoeuille, 2018; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021) to improve on existing estimates of displacement costs.

To investigate the labor market trajectories after displacement, we estimate the following event study specification:

$$
\begin{aligned}
y_{it} &= \alpha_i + \tau_t + X_{it}\Gamma + \sum_{k=\underline{j}}^{J} \beta_1^k T_{it}^k + \sum_{k=\underline{j}}^{J} \beta_2^k T_{it}^k \times Disp_i \\
&\quad + \sum_{k=\underline{j}}^{J} \beta_3^k T_{it}^k \times Occ_i + \sum_{k=\underline{j}}^{J} \beta_4^k T_{it}^k \times Disp_i \times Occ_i + \epsilon_{it},
\end{aligned} \tag{1}
$$

where y_{it} is the outcome of interest (e.g., log real daily wage) of individual i at time t, α_i is a worker fixed effect, τ_t are calendar year fixed effects, and X_{it} contains a quadratic polynomial in age as time-varying individual level control variables. In the event study specification above, $Disp_i$ is an indicator for being a worker affected by job displacement due to plant closure[4] at some point during our observation period, i.e., a "treated" worker.[5] Further, T_{it}^k are indicators for being observed at time k relative to the displacement event,

[3] Most closely related to the research focus of PILLARS, Nedelkoska et al. (2022) study how the costs of job displacement vary with the amount of skill mismatch that workers experience when returning to the labor market. This work is also part of the PILLARS project.

[4] See Section 4.1 for the empirical definition of plant closures.

[5] We distinguish between α_i and $Disp_i$ for ease of exposition, although $Disp_i$ is perfectly collinear to the individial fixed effects. Moreover, α_i is identified from the variation in periods $p < \underline{j}$.

which is defined to occur at time $k = 0$. Thus, $\beta_1^k T_{it}^k$ have the interpretation of event time fixed effects. Finally, Occ_i is a binary indicator taking a value of one if the worker is initially employed in a manual-routine occupation or an occupation at a high risk of offshoring, respectively, and 0 otherwise. Thus, the main coefficients of interest, β_4^k, measure the how the difference in the outcome of interest between displaced workers and non-displaced workers (i.e., the "control group") differs between manual-routine and non-manual-routine or offshorable and non-offshorable workers at time k relative to the displacement event. Note that parallel pre-trends imply that the coefficients β^k are not significantly different from zero for the periods $k < 0$ before displacement.

To estimate our event study model in Equation 1, we implement an alternative event study estimator proposed by Callaway and Sant'Anna (2021). In settings with staggered treatments, which in our context are displacement events in different calendar years, standard difference-in-differences estimates can be biased in unknown directions. This is because the standard ordinary least squares difference-in-difference estimator does not restrict which groups to compare with each other. Thus, under the standard ordinary least squares estimator, just treated units are also compared to already treated units, i.e., a false control group (see the discussions in de Chaisemartin and D'Haultfoeuille, 2018; Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak et al., 2022). This can lead to biased estimates, especially when there is an unequal number of treatment and control units and if there are heterogeneous treatment effects over time. While our matching procedure described below results in an equal number of treated and untreated units for every displacement event, there might still exist heterogeneities over time (across event time and calendar time) in the treatment effect of displacement. The alternative event study estimator by Callaway and Sant'Anna (2021) corrects for this source of bias.

4. Data

4.1. German Administrative Data

We use data from the Sample of Integrated Labor Market Biographies (SIAB), which are administrative German labor market data provided by the German Federal Employment Agency. These data are a 2% random sample drawn from the universe of employees in Germany from 1975–2019 subject to social security contributions. As around 80% of all individuals in the German workforce are subject to social security contributions (excluding civil servants and self-employed), the SIAB is representative of almost the entire German working population. Since employers are required by law to report the exact beginning and end of any employment relationship that is subject to social security contributions, the SIAB is the largest and most reliable source of employment information in Germany. Moreover, misreporting of earnings is punishable by law, which ensures high reliability of the earnings information. Moreover, the employee-level panel structure of the SIAB allows us to track the complete labor market biographies of workers exact to the day, including employment, wage, establishment, and occupational histories. Additionally, the data contain information about worker demographics (e.g., age, gender, and education) as well as on establishment characteristics (e.g., industry and location), which we use in our matching approach.

While the SIAB data depict comprehensive employment biographies, it does not contain information on the reason for employment changes, such as voluntary job separations or lay-offs due to low productivity or unanticipated reasons exogenous to the worker. To focus on exogenous job separations, we identify workers who are displaced due to plant closures by combining our worker-level data with establishment-level information from the German Establishment History Panel (BHP). These data are also provided by the German Federal Employment Agency and contain information on plant exits. Similar to the SIAB, the BHP includes the universe of all establishments in Germany observed between 1975–2019. We can thus identify potential plant closure events for each establishment that appears in our worker-level panel. Following the heuristics of Hethey-Maier and Schmieder (2013), we define plant closures as cases in which an establishment ceases to exist from one year to another, with no more than 30% of the plant original employees finding re-employment at the same plant in the subsequent year. We apply this definition by Hethey-Maier and Schmieder (2013) to discern true plant closures from mergers and restructurings. We restrict our sample of displaced workers to individuals who have been displaced only once in our observation period, since subsequent displacements can be regarded as endogenous to the first one (e.g., Fackler et al., 2021)

To classify the automation risk of the job workers held at the time of the plant closure, we combine the SIAB with information on the task composition of occupations by Dengler et al. (2014) These data are also provided by the German Federal Employment Agency, based on the dictionary of occupational titles (BERUFENET). Similar to other task categorizations, for instance, the classification by Autor et al. (2003) for the United States, the BERUFENET data are based on expert judgements on the tasks that have to be performed in an occupation. The data are highly detailed, distinguishing between roughly 8,000 different tasks (Dengler and Matthes, 2018). The data also provide a mapping of these tasks into five categories: (1) manual-routine tasks (2) manual non-routine tasks (3) cognitive routine tasks (4) analytical non-routine tasks, and (5) interactive non-routine tasks for around 144 occupations at the three-digit level. Following Dengler and Matthes (2015), we define routine workers as workers in occupations with an above-average share of routine *manual* tasks.[6] These workers are those that face the highest automation risk, as automation capital increasingly substitutes for workers that perform routine and codifiable tasks that can be accomplished by following explicit rules (Autor et al., 2003). Accordingly, we define non-manual-routine workers as workers in occupations with a below-median share of manual-routine tasks; i.e., these workers face a relatively low risk of getting replaced by technology.[7] After merging the BERUFENET data to the SIAB at the 3-digit occupational level, around 17% of displaced workers in our final sample are categorized as manual-routine workers and 83% of displaced workers are classified as non-manual-routine.

Finally, we measure the degree to which a worker's pre-displacement occupation is exposed to offshoring risks by drawing on measures of the offshorability of occupations from Blinder and Krueger (2013), as already described in Section 2. This measure is based on expert surveys and captures the degree to which the tasks in an occupation can be performed from abroad. In particular, it assesses the degree to which workers in this occupation need to be physically close to the work unit. Higher values on this index indicate a greater offshorability potential. Since the original measures are based on data from the United States, we first use the crosswalk between the Standard Occupational Classification (SOC) system to the ISCO (International Standard Classification of Occupations) occupational categories by Kaihovaara and Im (2020). Finally, we use the official conversion from ISCO to Klassifikation der Berufe (KldB), the occupational classification used in the SIAB, to merge the offshorability measures at the four-digit level to our worker sample in the SIAB. In our baseline estimates, offshorable occupations are defined as occupations with an offshorability index above the median across all occupations, while non-offshorable occupations are defined as occupations with an offshorability measure below the median. In our final sample, 37% of displaced workers are categorized as offshorable, and 63% as non-offshorable.

We follow the literature by restricting our sample to workers who are between 23–55 years of age at the time of displacement and have at least five years of labor market tenure before displacement (e.g., Fackler et al., 2021). The age restriction at the top ensures that

[6]The median share of manual-routine tasks in all tasks is 42%.

[7]Note that our definition of non-manual-routine workers also includes routine cognitive workers. We thus expect to estimate a lower bound of the differential displacement costs between routine and non-routine workers. Figure A1 shows the displacement effects on wages and task distance by the type of main task of the pre-displacement occupation.

individuals are observed at least ten years before retirement to track their employment and wage trajectories after displacement (e.g., Nedelkoska et al., 2022). Restricting our sample to high-tenured workers allows us to observe employment and wage paths prior to displacement, so we can test for parallel pre-trends. Moreover, pre-displacement wages are better proxies for unobserved worker productivity for workers with more extensive labor market experience (e.g., Altonji and Pierret, 2001; Hanushek et al., 2015).

Further, we restrict our sample to workers who have been employed full-time at the closing establishment for at least three years prior to displacement. We impose this condition since it is likely that strongly attached workers have a lower probability of leaving the establishment had the plant closure not occurred. This is motivated by the empirical finding that the probability of job change declines with tenure (e.g., Topel and Ward, 1992; Farber, 1994). Similarly, we restrict that workers have not switched their occupations at least three years before displacement. We impose this restriction to be confident that the occupation observed at displacement adequately captures the type of worker (manual-routine vs. non-manual-routine and offshorable vs. non-offshorable, respectively) and that the reemployment decision after displacement is not driven by being mismatched in the old occupation (Phelan, 2013).

In total, our sample comprises 21,776 individuals that were displaced once due to plant closures between the years 1980 and 2016 and fulfill our sample restrictions. We can track the wage and occupational histories of these workers five years before and up to ten years after involuntary job separation.

4.2. Matching

We study the differential labor market experiences after job loss between different groups of workers that are differentially exposed to automation and offshoring. We exploit plant closures to compare the wage and employment trajectories of these workers to their counterfactual developments in the absence of displacement. However, in the case of worker sorting into plants, workers affected by plant closures would differ systematically from non-displaced workers. To address remaining concerns of treatment selection at the establishment level, we match displaced workers to non-displaced workers (i.e., the control group) along pre-displacement outcomes and an array of pre-displacement worker and establishment characteristics. Thus, conditional on these covariates, we consider job separations due to plan closures to be as good as random within our matched sample of treated and control workers.

Specifically, we combine exact and propensity score matching to construct the control group consisting of observationally similar workers to those in the treatment group (i.e., displaced workers). Within the set of displaced and non-displaced workers who fulfill our baseline sample restrictions, we first match exactly on cells of calendar year, age, gender, educational categories, East/West Germany, occupation (4-digit), and industry (1-digit). Moreover, we match on the position (decile) in the distribution of establishment fixed effects, capturing unobserved productivity of establishments (Abowd et al., 1999).[8] Matching on the unobserved productivity of the establishment ensures that displaced and non-displaced workers work at similarly productive firms prior to (virtual) displacement. In a second step, we perform propensity score matching on pre-displacement real daily wages and days worked up to six years before displacement. We do so to account for unobserved productivity and labor supply preferences of workers, captured by the pre-displacement wage and employment patterns.

4.3. Sample Before and After Matching

Table 3 presents summary statistics for the displaced workers — as well as for their non-displaced peers — after imposing the sample restrictions (see Section 4.1). Before the matching, displaced workers are more likely to work in the manufacturing sector, are more often located in East Germany, and are less likely to have obtained a college degree compared to the overall sample. Moreover, displaced individuals earn a lower daily wage on average. We thus perform matching to align the characteristics of displaced and non-displaced workers.

While our matching procedure is demanding, around 75% of displaced workers in our sample can be matched to an observationally similar non-displaced worker in the donor pool. Our final matched sample includes 17,420 displaced workers and an equal number of non-displaced "statistical twins" (see Table 3). By construction, our treatment and control groups are perfectly balanced along the variables for which we employ exact matching. However, we neither observe statistically significant differences between our treatment and control groups for average pre-displacement real daily wages and days worked, for which we employ propensity score matching (see last column of Table 3). Thus, the matching exercise was successful in evening out all observable differences between displaced and non-displaced workers.[9]

[8] Establishment fixed effects are obtained from wage regressions for worker i in establishment j at time t as follows: $\log wage_{ijt} = \alpha_i + \phi_j + x'_{it}\beta + \varepsilon_{it}$, where α_i is a worker fixed effect, x'_{it} are time varying worker level controls, and ϕ_j is the establishment fixed effect, i.e., an establishment wage premium for all workers employed at establishment j. ε_{it} is an error term.

[9] Table A1 provides summary statistics for manual-routine vs. non-manual-routine workers, while Table A2 shows summary statistics for offshorable vs. non-offshorable workers in our matched sample of displaced workers.

Table 3: Summary Statistics of Unmatched and Matched Samples

	All Baseline	All Displaced	Difference	Matched Controls	Matched Displaced	Difference
% Manufacturing	59.02	65.62	6.6 (20.24)	63.91	63.91	0 (exact matching)
% Female	32.16	32.45	0.29 (0.95)	30.73	30.73	0 (exact matching)
% East Germany	11.43	19.09	7.66 (36.32)	6.07	6.07	0 (exact matching)
% College degree	7.42	5.53	1.89 (11.86)	3.69	3.69	0 (exact matching)
% Manual routine intensive	17.4	15.6	1.8 (2.38)	17.0	17.0	0 (exact matching)
% High Offshorability	36.6	35.9	0.7 (2.53)	37.1	37.1	0 (exact matching)
Age	41.50	41.43	0.07 (1.13)	41.28	41.28	0 (exact matching)
Real daily wage	111.96	110.89	11.29 (43.51)	110.89	109.54	1.35 (1.07)
Days working per year	362.03	361.80	0.14 (1.08)	362.12	362.35	0.23 (0.84)
Number of workers	731,643	21,776		17,420	17,420	

Notes: This table shows summary statistics of our data. The baseline sample consists of individuals that fulfill our baseline restrictions (see Section 4.1). The displaced sample is the subset of workers from the baseline sample that are displaced once due to a plant closure in the period 1980–2016. The matched displaced sample consists of displaced workers from the baseline sample that can be matched to an observationally similar never-displaced (control) workers. t-statistics for the differences in observables between between non-displaced (control) workers and displaced workers after the matching procedure are provided in parentheses. *Data:* Administrative German labor market records (SIAB).

5. Results

5.1. Labor Market Transitions after Displacement by Susceptibility to Automation and Offshoring

Figure 3 shows the labor market transitions for manual-routine workers in red and non-manual-routine workers in blue after displacement. Specifically, Panel (a) plots the event study estimates from Equation 1, where the outcome is (log) real daily wages. Note that for unemployed individuals, we assign social security payments as wages.[10] The horizontal axis indicates the relative time since displacement, while the vertical axis shows the relative losses for displaced workers relative to their matched non-displaced peers separately for routine and non-routine workers. Due to our matching procedure, the wages of displaced workers align very well to those of non-displaced workers in the pre-displacement periods. This visual inspection supports our assumption of parallel pre-

[10] In Germany, these typically amount to 60% of the previous net earnings.

trends between displaced and non-displaced workers and corroborates the idea that the matched controls serve as an appropriate counterfactual for the displaced workers in our sample. After displacement, both manual-routine and non-manual-routine workers face significant wage losses relative to non-displaced workers, and these losses persist up to ten years after displacement. This mimics the results from other studies that exploit mass-layoffs or plant closures as exogenous events of job displacement (e.g. Jacobson et al., 1993; Couch and Placzek, 2010; Bertheau et al., 2022; Nedelkoska et al., 2022; Schmieder et al., 2022). However, we add to previous findings by showing that manual-routine workers face significantly larger reductions in real daily wages than non-manual-routine workers immediately after displacement (39% vs. 28%). These differntial wage losses persist up to 3 years after displacement; afterwards, manual-routine workers catch up to the earnings trajectory of non-manual-routine workers.

Similarly, Panel (b) of Figure 3 shows higher post-displacement losses in terms of employment of manual-routine workers as compared to non-manual-routine workers. While there is no difference between displaced and non-displaced workers before (virtual) displacement for both types of workers, a significantly larger fraction of manual-routine workers remains unemployed compared to non-routine workers after displacement. Specifically, 26% of manual-routine workers are unemployed in the first year after displacement, compared to just 17% for non-manual-routine workers. These differences persist up to six years after displacement.

Panel (c) of Figure 3 shows that differential displacement costs between manual-routine and non-manual-routine workers also occur at the intensive margin. Conditional on being employed, manual-routine workers face reductions in daily wages of 24% compared to their non-displaced peers in the first post-displacement year, compared to only 17% for non-manual-routine workers. Thus, even when (immediately) finding employment again after the plant closure, the losses in real daily wages are more than 40% larger for manual-routine workers. These differences persist up to three years after job loss.

In sum, our event-study estimates suggest large and persistent wage and employment differentials between manual-routine and non-manual-routine workers after job loss. In particular, manual-routine workers are more likely to be unemployed after job displacement and remain unemployed for longer periods. Even conditional on finding employment again, manual-routine workers face larger wage losses than non-manual-routine workers.

Next, we explore possible reasons for the differential post-displacement trajectories of manual-routine vs. non-manual-routine workers. Our main hypothesis is that losses in occupation-specific human capital related to the secular decline of routine occupations are an important channel for the differential wage and employment losses between both worker types. A growing literature suggests losses in task- and occupation-specific human capital as a source of wage declines after (involuntary) occupational switches (e.g., Gibbons and Waldman, 2004; Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann and Schoenberg, 2010). With occupation-specific components of human capital, skills specific to the old job may be rendered obsolete after occupational changes.

Our descriptive evidence in Section 2, as well as the existing literature, finds that higher exposure to automation and structural change is associated with larger declines in employment in routine occupations (e.g., Autor et al., 2003; Goos et al., 2014; Cortes, 2016; Nedelkoska and Quintini, 2018; Arntz et al., 2016, 2019). Accordingly, manual-routine workers may exhibit a higher propensity of switching occupations after displacement. Panel (d) of Figure 3 plots the propensity to switch to a different (four-digit) occupation after displacement by the manual-routine intensity of the last pre-displacement job. Not surprisingly given our focus on tenured workers, displacement leads to more occupational switching for both manual-routine and non-manual-routine workers as compared to their non-displaced peers. However, manual-routine workers are significantly more likely to switch occupations after displacement than non-manual-routine workers; in the first post-displacement year, 44% of manual-routine workers change their occupation, compared to 33% for non-manual-routine workers. Thus, routine manual-workers are 33% more likely to switch occupations than non-manual-routine workers. There is hardly any fade-out in this difference in occupational switching over time; even 9 years after the plant closure, the this difference still amounts to 10%. This finding is consistent with a secular decline in routine occupations, limiting re-employment opportunities in the same occupation for routine workers.

Moreover, losses in occupation-specific human capital are larger if individuals switch to less skill-related occupations, i.e., to occupations with a larger skill distance to the pre-displacement (Nedelkoska et al., 2022). We expect that routine workers are disproportionately (negatively) affected by improvements in technology over time, implying both a higher propensity of switching and switching to more distant occupations due to vanishing skill-related occupations (e.g., Violante, 2002; Kogan et al., 2022). Indeed, we find evidence that is consistent with this idea in our data. Panel (e) of Figure 3 Panel (e) shows the task distance to the pre-displacement occupation. Specifically, the task distance is defined as the importance of the main pre-displacement task in the respective post-displacement occupation, with the main pre-displacement task being defined as the task that was performed most often in the last pre-displacement job. For instance, if the main task in the pre-displacement occupation were manual-routine tasks, with a share of 50%, and manual-routine tasks comprise 25% of the tasks in the new occupation, this would amount to a (relative) task change of 50%. Panel (e) suggests that manual-routine workers switch to more distant occupations in terms of task content: they experience a decline in their main task share of 23% compared to 12% for non-manual-routine workers. This evidence suggests that manual-routine workers not only switch occupations more often, but their skills are also less portable to the occupations they switch to.

Finally, we investigate differences in the spatial mobility of workers. Panel (f) of Figure 3 suggests that the share of workers who change the district of their workplace[11] is lower for manual-routine workers as compared to non-manual-routine workers. While the difference is only 4 pp (34% vs. 38 %.), it is highly statistically significant. This might suggest a trade-off between occupational and spatial mobility when finding a job after displacement; manual-routine workers seem to be less mobile in terms of job location, but switch occupations more often.

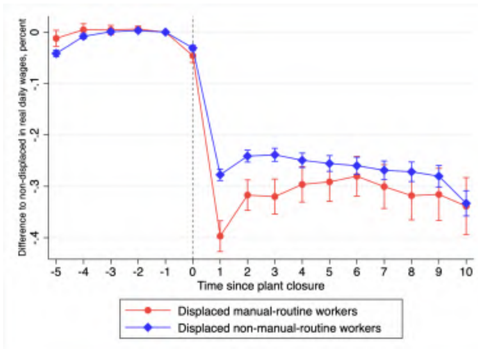
To summarize, individuals displaced from manual-routine occupations have a higher propensity to switch occupations compared to non-manual-routine workers, and switch to more distant occupations in terms of the task distance. These differences are highly persistent. Given that human capital is occupation- and task-specific, such differential switching is a likely source of the larger displacement-induced wage losses of manual-routine workers.

Figure 4 replicates the analysis from Figure 3, replacing an occupation's routine intensity by its degree of offshorability. Intriguingly, we do not find evidence for heterogeneous wage trajectories of offshorable vs. non-offshorable workers after displacement. Panel (a) shows that both groups of workers face losses in real earnings of 21% in the first year after displacement and have virtually identical wage trajectories afterwards. Moreover, while offshorable workers have a lower probability of re-employment immediately after displacement, they catch up to non-offshorable workers three years after the job loss (Panel (b)). Conditional on finding employment again, offshorable workers have somewhat higher wages than non-offshorable workers in the first three years after displacement; however, these differences are not statistically significant (Panel (c)).

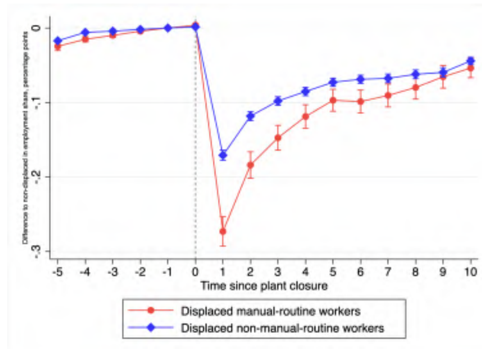
However, there are some differences in occupational mobility by degree of offshorablity of workers' pre-displacement occupation, but these differences are much more muted compared to those we observed by occupations' routine intensity. Workers initially employed

[11]In Germany, there are 402 districts.

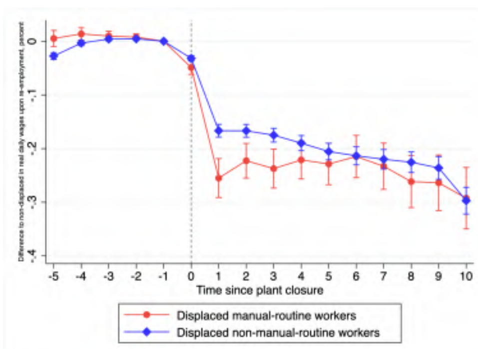
Figure 3: Labor Market Transitions of Displaced Workers by Routine Intensity



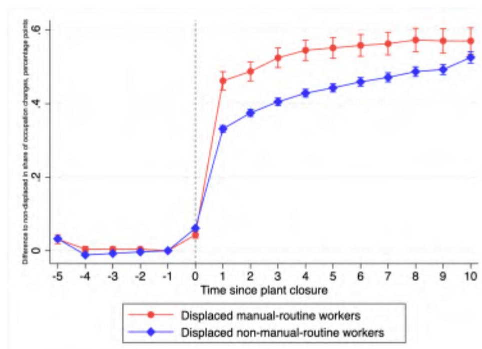
(a) Log Wages



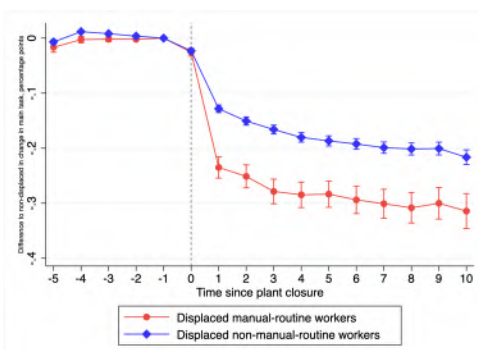
(b) Employment



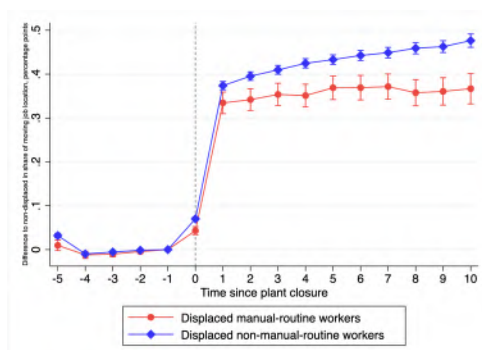
(c) Log Wages if Employed



(d) Occupational Switching



(e) Task Distance



(f) Change Job Location

Notes: This figure shows the effect of displacement due to plant closure by the manual-routine intensity of the last pre-displacement job. We implement the robust event study estimators by Callaway and Sant'Anna (2021). Panels (a) - (f) show event study coefficients for log wages, employment, log wages conditional on employment, occupational switching, task distance, and change of job location. During unemployment, individuals are assigned their social security benefits as wage income. Occupational switching is a binary variable indicating whether a worker has a different four-digit occupation after displacement than in the last pre-displacement job. Task distance is the change in the importance of the main pre-displacement task in the respective post-displacement occupation conditional on occupational switching; the main pre-displacement task is defined as the task that was performed most often in the last pre-displacement job (one of the following five tasks: manual routine, manual non-routine, cognitive routine, analytical non-routine, and interactive non-routine). Change job location is a binary variable indicating whether a worker works in a different district after displacement than in the last pre-displacement job. All outcomes of displaced workers are relative to those of matched non-displaced control workers. Manual-routine occupations are defined as occupations with shares of manual-routine tasks above the median across all occupations according to the BERUFENET data (Dengler et al., 2014); non-manual-routine occupations are defined as occupations with a share of manual-routine tasks below the median. Estimations control for a quadratic polynomial in age, individual fixed effects, calendar year fixed effects, and (virtual) event time fixed effects. The error bars report 95% confidence intervals based on standard errors clustered at the individual level. *Data:* Administrative German labor market records (SIAB).

in offshorable occupations have a likelihood to switch occupations of 38%, compared to 36% for non-offshorable workers (Panel (d) of Figure 4). The difference in occupational switching between manual-routine and non-manual-routine workers was more than five times as large (11 pp). Moreover, while offshorable workers are somewhat more likely to switch occupations than non-offshorable, these workers switch to more similar occupations in terms of the task distance to the last pre-displacement occupation (Panel (e) of Figure 4). Finally, we do not find significantly different spatial mobility patterns between offshorable and non-offshorable workers after displacement (Panel (f) of Figure 4).

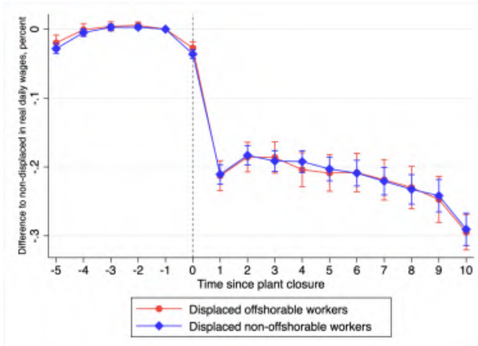
Overall, workers initially employed in offshorable occupations do not seem to suffer particularly difficult transitions after job displacement compared to non-offshorable workers. This is consistent with the evidence presented by Dauth et al. (2014), who find that employment opportunities in highly offshorable occupations did not decline in Germany. Our findings indicate that post-displacement employment opportunities for offshorable workers are much more favorable than those for manual-routine workers.

5.2. Labor Market Mobility by Gender

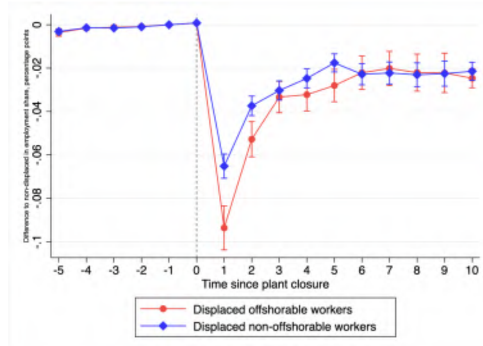
The recent literature suggests that technological change and increased international trade affect the jobs of men and women differently. For instance, using German data, Black and Spitz-Oener (2010) show that women have experienced a larger decrease in manual routine tasks over time than men, even within the same occupation. Thus, the impact of workers' exposure to automation risk and offshorability on the labor market transitions after job loss might differ by gender. At the same time, men and women might make different labor supply decisions after displacement due to differences in bargaining power within the household (e.g., Becker, 1991; Lundberg and Pollak, 1994).

We thus investigate how men and women differ in their wage trajectories and labor mobility after job loss. The results are shown in Figure 5. First, both male and female manual-routine workers experience large losses in real daily wages upon job loss, but men experience less severe wage declines: while the immediate wage decline is 36% for men (Panel (b)), it amounts to as much as 51% for women (Panel (a)). This is in line with Illing et al. (2021), who show that women generally experience larger displacement costs in terms of wages and employment than men. This is because of both a lower probability of finding employment again (extensive margin) and lower wages conditional on being employed (intensive margin). We find that the difference in wage losses between manual-routine and non-manual-routine workers are larger for women than for men on both margins. One potential explanation for this result is that the higher cost of job search related to declining employment opportunities in manual-routine occupations particularly

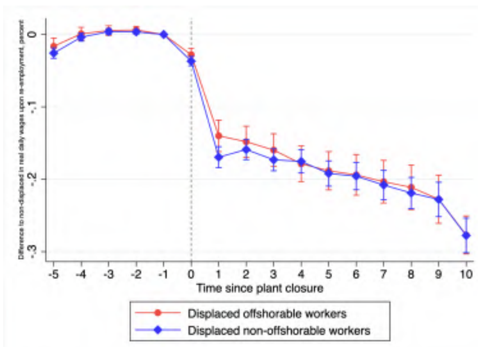
Figure 4: Labor Market Transitions of Displaced Workers by Offshorability



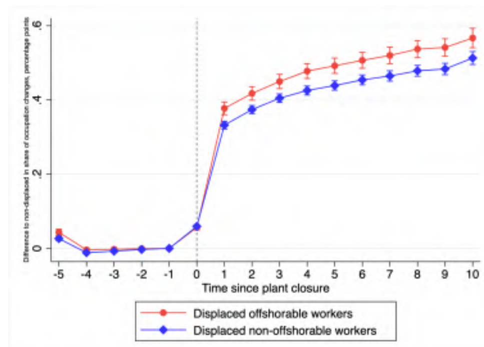
(a) Log Wages



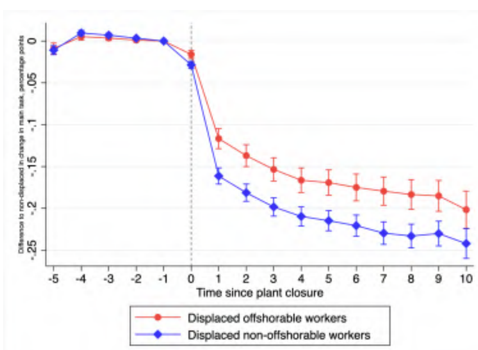
(b) Employment



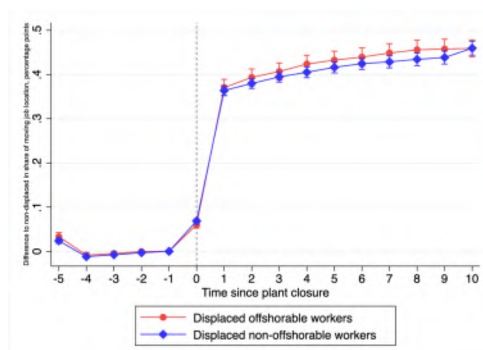
(c) Log Wages if Employed



(d) Occupational Switching



(e) Task Distance



(f) Change Job Location

Notes: This figure shows the effect of displacement due to plant closure by the offshorability of the last pre-displacement job. We implement the robust event study estimators by Callaway and Sant'Anna (2021). Panels (a) - (f) show event study coefficients for log wages, employment, log wages conditional on employment, occupational switching, task distance, and change of job location. During unemployment, individuals are assigned their social security benefits as wage income. Occupational switching is a binary variable indicating whether a worker has a different four-digit occupation after displacement than in the last pre-displacement job. Task distance is the change in the importance of the main pre-displacement task in the respective post-displacement occupation conditional on occupational switching; the main pre-displacement task is defined as the task that was performed most often in the last pre-displacement job (one of the following five tasks: manual routine, manual non-routine, cognitive routine, analytical non-routine, and interactive non-routine) Change job location is a binary variable indicating whether a worker works in a different district after displacement than in the last pre-displacement job. All outcomes of displaced workers are relative to those of matched non-displaced control workers. Offshorable occupations are defined as occupations with an offshorability index above the median across all occupations according to Blinder and Krueger (2013). Non-offshorable occupations are defined as occupations with an offshorability index below the median. Estimations control for a quadratic polynomial in age, individual fixed effects, calendar year fixed effects, and event time fixed effects. The error bars report 95% confidence intervals based on standard errors clustered at the individual level. *Data:* Administrative German labor market records (SIAB).

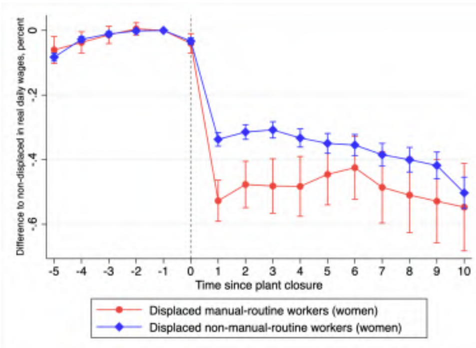
affect the reservation wage and labor supply decisions of female workers. This might be because of a lower reliance on female earnings in the traditional allocation of intra-household bargaining power under the “male breadwinner” model, which is still prevalent in Germany (e.g., Schneebaum and Mader, 2013).

Consistent with the notion that wage losses at the intensive margin occur due to losses in occupation-specific human capital, female manual-routine workers switch more often and to more distant occupations in terms of task content compared to their male counterparts (Panels (a)–(d) of Figure 6). Finally, female workers are less spatially mobile compared to male workers for all groups of displaced workers (Panels (e) and (f) of Figure 6). This is consistent with , e.g, Le Barbanchon et al. (2021), who show that female job seekers, especially those with children, are more willing to trade-off wages for a shorter commute. Moreover, while male manual-routine workers have a lower probability of changing job locations when re-employed after displacement than male non-manual-routine workers, this difference is not statistically significant for female workers during most of their post-displacement tenure. This might suggest that female workers face similar trade-off between wages and commuting distance regardless of the type of occupation they work in.

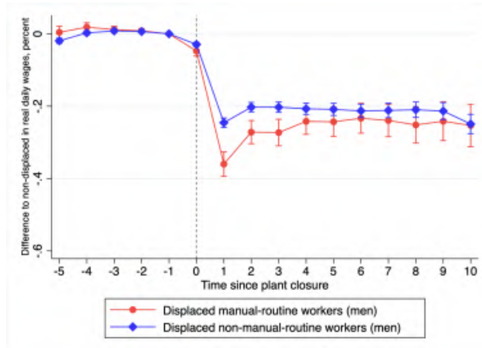
When considering gender differences in post-displacement labor market transitions by the degree of offshoring in Figure 7, we find that offshorable and non-offshorable workers of both genders fare very similarly after displacement (see Panels (a) and (b)). The same is true for employment (Panels (c) and (d)) and wages conditional on employment (Panels (e) and (f)).

However, Figure 8 shows that offshorable male workers are more likely to switch occupations compared to their less offshorable counterparts, while this difference is not statistically significant for women (Panels (a) and (b)). Upon switching occupations, female offshorable workers switch to more similar occupations in terms of the tasks performed at work than female non-offshorable workers, while we do not observe such difference for male workers (Panels (c) and (d)). Finally, Panels (e) and (f) show that both male and female offshorable workers are not substantially more spatially mobile than workers initially employed in less offshorable occupations.

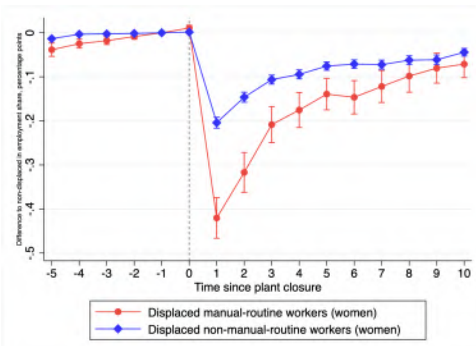
Figure 5: Wage Losses of Displaced Workers by Routine Intensity and Gender



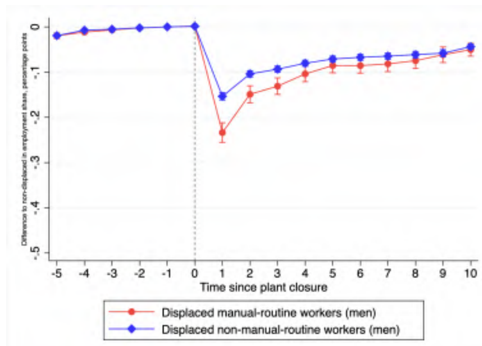
(a) Log Wages (Women)



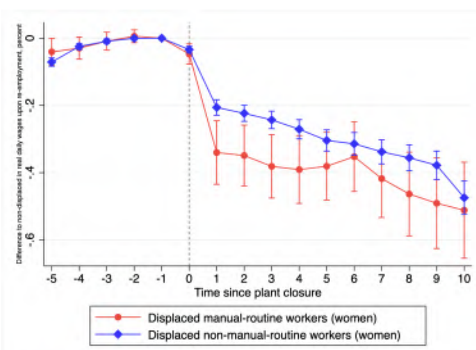
(b) Log Wages (Men)



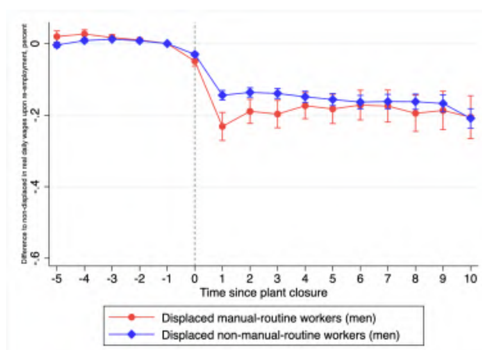
(c) Employment (Women)



(d) Employment (Men)



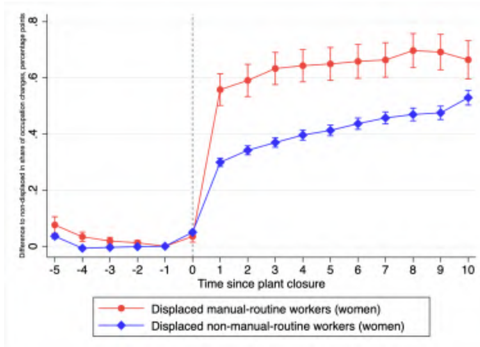
(e) Log Wages if Employed (Women)



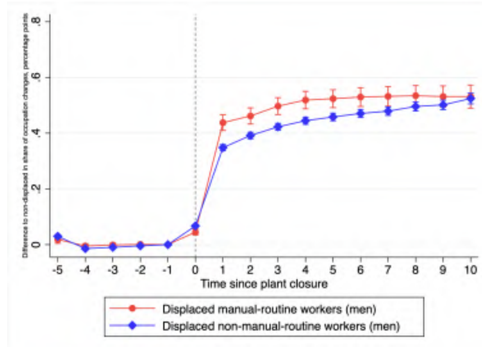
(f) Log Wages if Employed (Men)

Notes: This figure shows the effect of displacement due to plant closure on real wages by the manual-routine intensity of the last pre-displacement job separately for women and men. We implement the robust event study estimators by Callaway and Sant'Anna (2021). During unemployment, individuals are assigned their social security benefits as wage income. All outcomes of displaced workers are relative to those of matched non-displaced control workers. Manual-routine occupations are defined as occupations with shares of manual-routine tasks above the median across all occupations according to the BERUFENET data (Dengler et al., 2014); non-manual-routine occupations are defined as occupations with a share of manual-routine tasks below the median. Estimations control for a quadratic polynomial in age, individual fixed effects, calendar year fixed effects, and (virtual) event time fixed effects. The error bars report 95% confidence intervals based on standard errors clustered at the individual level. *Data:* Administrative German labor market records (SIAB).

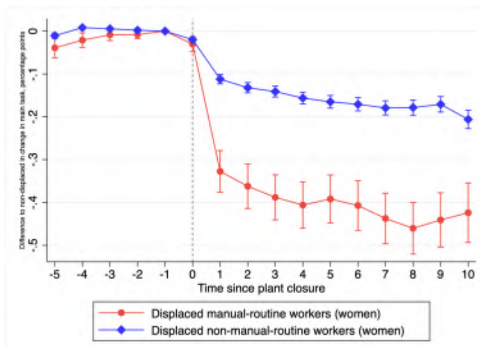
Figure 6: Labor Market Transitions of Displaced Workers by Routine Intensity and Gender



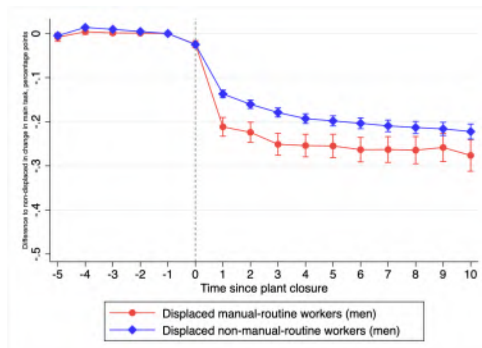
(a) Occupational Switching (Women)



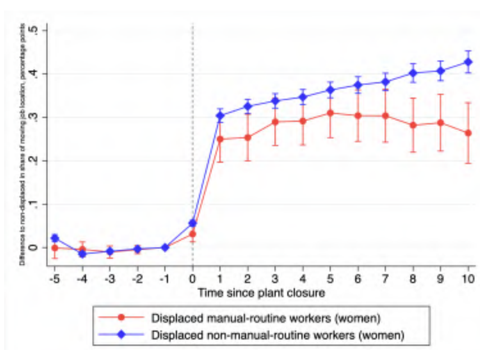
(b) Occupational Switching (Men)



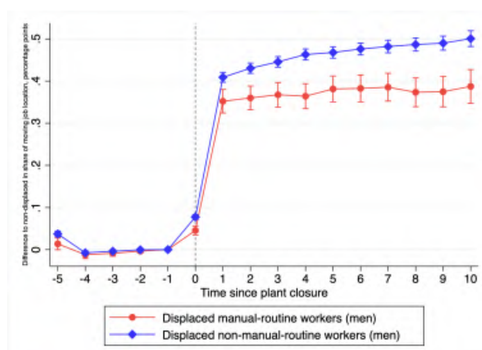
(c) Task Distance (Women)



(d) Task Distance (Men)



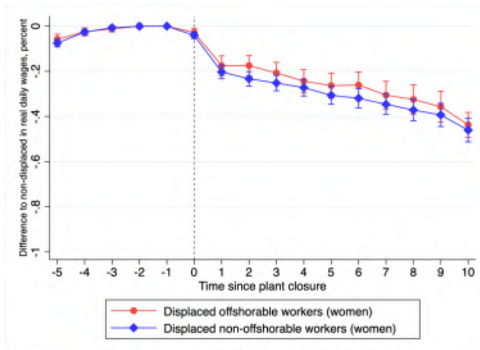
(e) Change Job Location (Women)



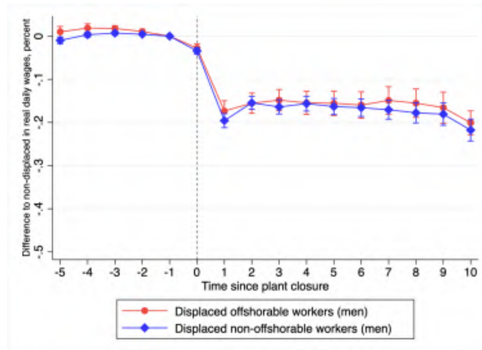
(f) Change Job Location (Men)

Notes: This figure shows the effect of displacement due to plant closure by the manual-routine intensity of the last pre-displacement job separately for women and men. We implement the robust event study estimators by Callaway and Sant'Anna (2021). Panels (a) - (f) show event study coefficients for occupational switching, task distance, and change of job location. Occupational switching is a binary variable indicating whether a worker has a different four-digit occupation after displacement than in the last pre-displacement job. Task distance is the change in the importance of the main pre-displacement task in the respective post-displacement occupation conditional on occupational switching; the main pre-displacement task is defined as the task that was performed most often in the last pre-displacement job (one of the following five tasks: manual routine, manual non-routine, cognitive routine, analytical non-routine, and interactive non-routine). Change job location is a binary variable indicating whether a worker works in a different district after displacement than in the last pre-displacement job. All outcomes of displaced workers are relative to those of matched non-displaced control workers. Manual-routine occupations are defined as occupations with shares of manual-routine tasks above the median across all occupations according to the BERUFENET data (Dengler et al., 2014). Non-manual-routine occupations are defined as occupations with a share of manual-routine tasks below the median. Estimations control for a quadratic polynomial in age, individual fixed effects, calendar year fixed effects, and (virtual) event time fixed effects. The error bars report 95% confidence intervals based on standard errors clustered at the individual level. *Data:* Administrative German labor market records (SIAB).

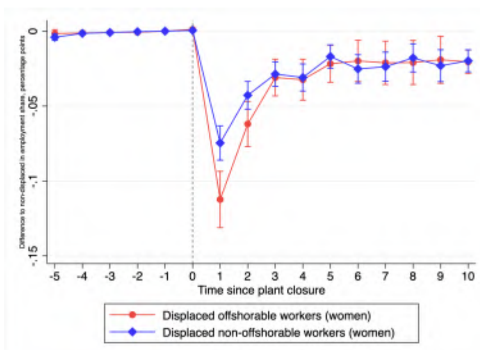
Figure 7: Wage Losses of Displaced Workers by Offshorability and Gender



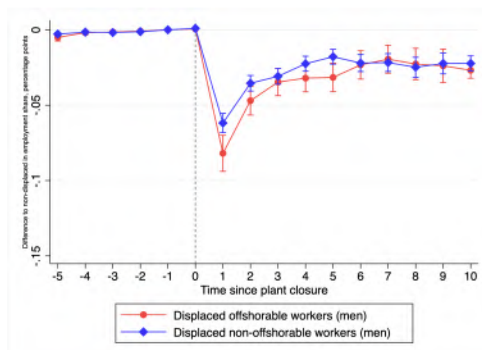
(a) Log Wages (Women)



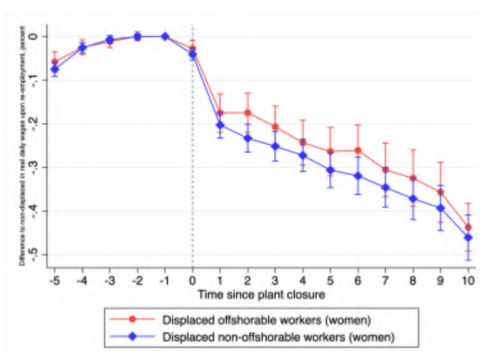
(b) Log Wages (Men)



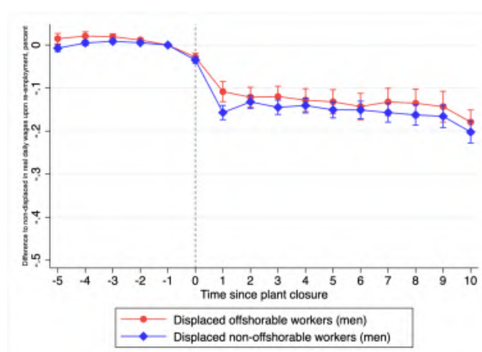
(c) Employment (Women)



(d) Employment (Men)



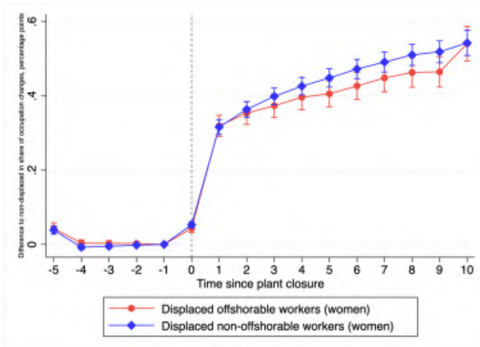
(e) Log Wages if Employed (Women)



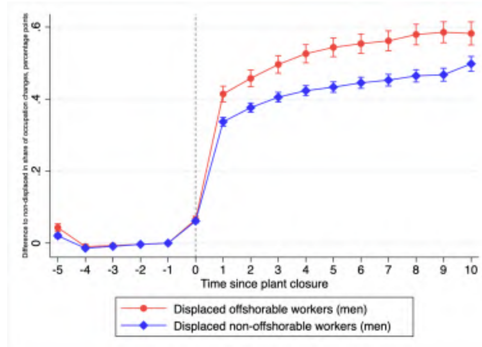
(f) Log Wages if Employed (Men)

Notes: This figure shows the effect of displacement due to plant closure on real wages by the offshorability of the last pre-displacement job separately for women and men. We implement the robust event study estimators by Callaway and Sant'Anna (2021). During unemployment, individuals are assigned their social security benefits as wage income. Offshorable occupations are defined as occupations with an offshorability index above the median across all occupations according to Blinder and Krueger (2013). Non-offshorable occupations are defined as occupations with an offshorability index below the median. Estimations control for a quadratic polynomial in age, individual fixed effects, calendar year fixed effects, and event time fixed effects. The error bars report 95% confidence intervals based on standard errors clustered at the individual level. *Data:* Administrative German labor market records (SIAB).

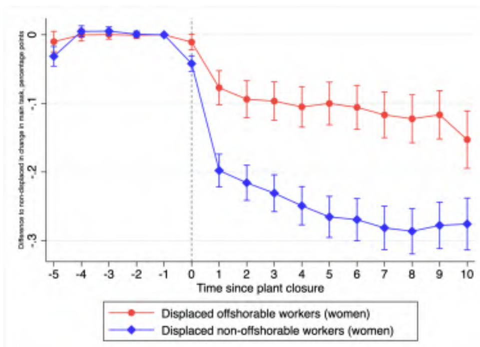
Figure 8: Labor Market Transitions of Displaced Workers by Offshorability and Gender



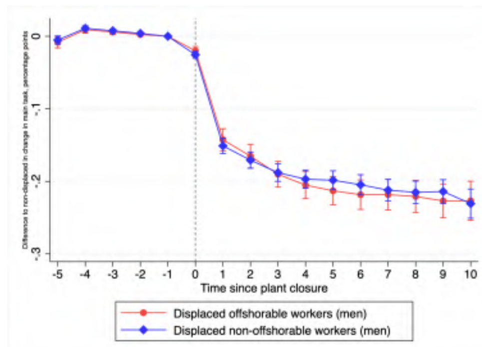
(a) Occupational Switching (Women)



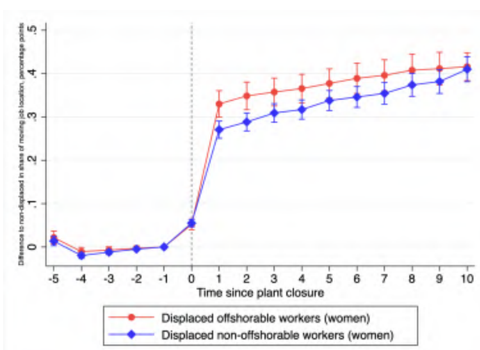
(b) Occupational Switching (Men)



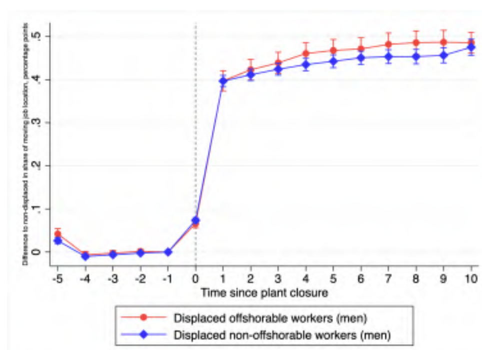
(c) Task Distance (Women)



(d) Task Distance (Men)



(e) Change Job Location (Women)



(f) Change Job Location (Men)

Notes: This figure shows the effect of displacement due to plant closure by the offshorability of the last pre-displacement job separately for women and men. We implement the robust event study estimators by Callaway and Sant'Anna (2021). Panels (a) - (f) show event study coefficients for occupational switching, task distance, and change of job location. Occupational switching is a binary variable indicating whether a worker has a different four-digit occupation after displacement than in the last pre-displacement job. Task distance is the change in the importance of the main pre-displacement task in the respective post-displacement occupation conditional on occupational switching; the main pre-displacement task is defined as the task that was performed most often in the last pre-displacement job (one of the following five tasks: manual routine, manual non-routine, cognitive routine, analytical non-routine, and interactive non-routine). Change job location is a binary variable indicating whether a worker works in a different district after displacement than in the last pre-displacement job. All outcomes of displaced workers are relative to those of matched non-displaced control workers. Offshorable occupations are defined as occupations with an offshorability index above the median across all occupations according to Blinder and Krueger (2013). Non-offshorable occupations are defined as occupations with an offshorability index below the median. Estimations control for a quadratic polynomial in age, individual fixed effects, calendar year fixed effects, and event time fixed effects. The error bars report 95% confidence intervals based on standard errors clustered at the individual level. *Data:* Administrative German labor market records (SIAB).

5.3. Entropy Balancing

The use of plant closures as exogenous job separation events, combined with our matching procedure, arguably allows for a causal interpretation of the event-study estimates of the effect of job loss on wage and employment transitions of workers differently exposed to automation and offshoring. In particular, our previous analyses suggest that particularly manual-routine workers face difficult transitions after displacement, and that these displacement costs are even larger for women than for men. However, while we are confident that the comparisons *within* occupational groups can be interpreted as causal because of the "clean" control group of non-displaced workers, the estimated differential displacement costs *across* occupational groups are not necessarily causal. The reason is that manual-routine and non-manual-routine workers or offshorable and non-offshorable workers differ in dimensions other than the tasks composition of their occupations. For instance, as shown in Appendix Table A1, displaced manual-routine workers are more likely to be male, tend to have lower education, are more often employed in manufacturing industries,and also have lower pre-displacement wages than non-manual-routine displaced workers. All these characteristics might also affect a worker's labor market prospects.

To account for these differences in the pre-displacement characteristics of manual-routine (offshorable) and non-manual-routine (non-offshorable) workers, we perform entropy balancing. Doing so, we get as close as possible to estimating a causal effect of the manual-routine intensity or offshorability of an occupation on the labor market experiences of workers previously employed in these occupations after displacement. When implementing the entropy balancing, we follow Hainmueller (2012) to obtain covariate balance between manual-routine and non-manual-routine workers and between offshorable and non-offshorable workers, respectively. In particular, we perform entropy balancing on observable worker characteristics, i.e., gender, education level, industry, age, pre-displacement wages to capture unobserved productivity, and pre-displacement days employed to capture labor supply preferences. By applying the weights received through the entropy balancing, we reweight manual-routine (offshorable) workers to non-manual-routine (non-offshorable) workers such that they become observationally identical.

Figure 9 shows our results after reweighting manual-routine workers to non-manual-routine workers. While the post-displacement differences in wage trajectories between the two occupational groups become smaller, reweighted manual-routine workers remain to experience significantly larger wage losses compared to non-manual-routine workers (Panel (a)). Moreover, even after reweighting, manual-routine workers also remain to have a lower probability of finding a job than non-manual-routine workers (Panel (b)). They also face larger wage losses upon finding employment (Panel (c)), have a higher probability of switching occupations (Panel (d)), and switch to more distant occupations in terms of task content (Panel (e)). However after reweighting, there remains no significant difference between manual-routine and non-manual-routine workers in the probability to switch to a plant in a different district than the pre-displacement plant (Panel (f)). In sum, even when accounting for pre-displacement differences in worker charatcteristcs, manual-routine workers have more difficult transitions after job displacement than non-displaced workers. This suggests that the pre-displacement occupation and, with it, occupation-specific human capital, is an important determinant of how workers adjust after labor market shocks.

In Figure 10, we compare the labor market transitions for reweighted offshorable and non-offshorable workers. The results in terms of real wages, employment probability, wages upon employment, and regional mobility are qualitatively unchanged compared to the estimates without entropy balancing (see Figure 4). However, reweighted offshorable workers have a higher probability to change occupations and switch to less distant occupations compared to workers with low offshorability potential.

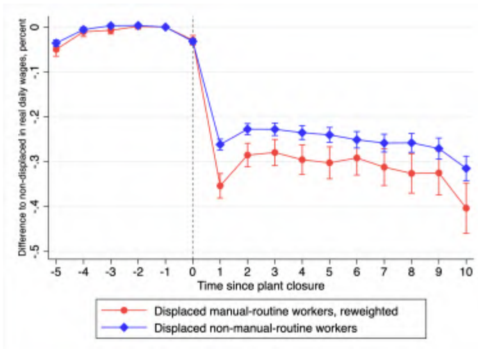
The above results show that even after applying entropy balancing, the differences between offshorable and non-offshorable workers are considerably less pronounced than those between manual-routine and non-manual-routine workers.

6. Conclusions

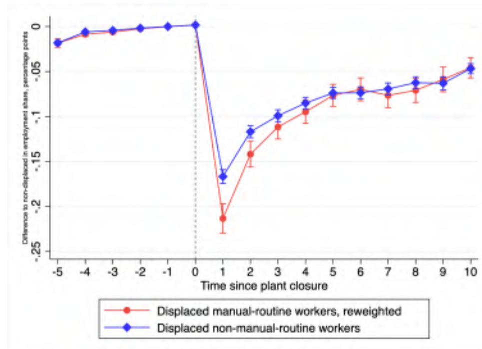
During the recent decades, major secular trends have significantly changed the occupational structure in European countries. In particular, labor-replacing technologies have reduced the employment shares of routine occupations which are characterized by workers performing tasks that can be easily replaced by machines. Similarly, technological progress and reduced trade barriers put workers in occupations in which tasks can be performed abroad at an increased risk of offshoring.

Even if the evidence on the impacts of these labor market developments on aggregate employment and productivity is mixed (e.g., Autor et al., 2003; Goos et al., 2014; Aghion et al., 2020; Dauth et al., 2021), we may expect that workers who are more exposed to automation and offshoring face particularly difficult labor market transitions at the individual level. We are the first to provide evidence on how workers who are differently affected by automation or offshoring fare after displacement, especially in terms of their occupational mobility. Doing so, we shed light on how capital deepening, embodied technological change, and changing global value chains affect the labor market prospects

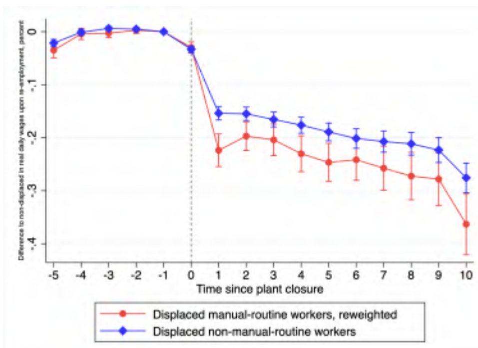
Figure 9: Labor Market Transitions of Displaced Workers by Routine Intensity, Entropy Balancing



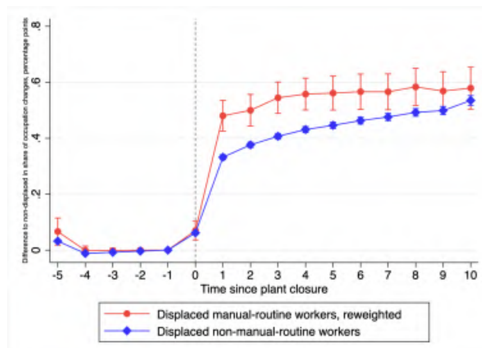
(a) Log Wages



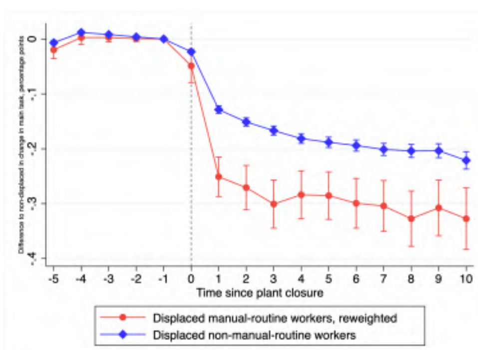
(b) Employment



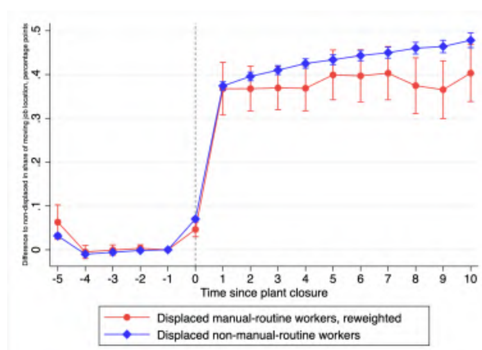
(c) Log Wages if Employed



(d) Occupational Switching



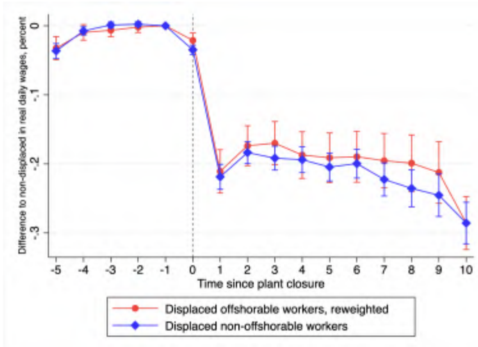
(e) Task Distance



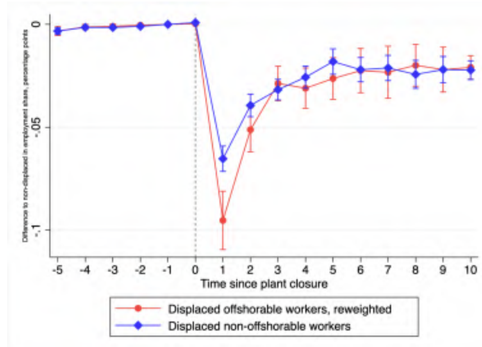
(f) Change Job Location

Notes: This figure shows the effect of displacement due to plant closure by the manual-routine intensity of the last pre-displacement job. We implement the robust event study estimators by Callaway and Sant'Anna (2021) and reweight manual-routine workers to non-manual-routine workers. Panels (a) - (f) show event study coefficients for log wages, employment, log wages conditional on employment, occupational switching, task distance, and change of job location. During unemployment, individuals are assigned their social security benefits as wage income. Occupational switching is a binary variable indicating whether a worker has a different four-digit occupation after displacement than in the last pre-displacement job. Task distance is the change in the importance of the main pre-displacement task in the respective post-displacement occupation conditional on occupational switching; the main pre-displacement task is defined as the task that was performed most often in the last pre-displacement job (one of the following five tasks: manual routine, manual non-routine, cognitive routine, analytical non-routine, and interactive non-routine). Change job location is a binary variable indicating whether a worker works in a different district after displacement than in the last pre-displacement job. All outcomes of displaced workers are relative to those of matched non-displaced control workers. Manual-routine occupations are defined as occupations with shares of manual-routine tasks above the median across all occupations according to the BERUFENET data Dengler et al. (2014); non-manual-routine occupations are defined as occupations with a share of manual-routine tasks below the median. Estimations control for a quadratic polynomial in age, individual fixed effects, calendar year fixed effects, and (virtual) event time fixed effects. The error bars report 95% confidence intervals based on standard errors clustered at the individual level. *Data:* Administrative German labor market records (SIAB).

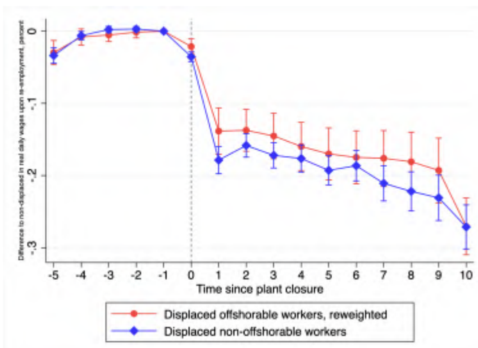
Figure 10: Labor Market Transitions of Displaced Workers by Offshorability, Entropy Balancing



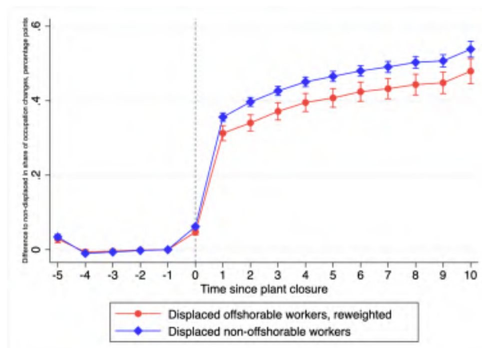
(a) Log Wages



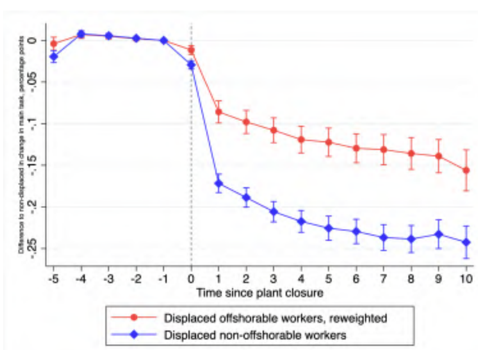
(b) Employment



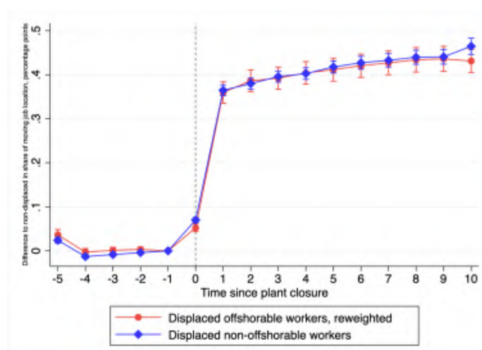
(c) Log Wages if Employed



(d) Occupational Switching



(e) Task Distance



(f) Change Job Location

Notes: This figure shows the effect of displacement due to plant closure by the offshorability of the last pre-displacement job. We implement the robust event study estimators by Callaway and Sant'Anna (2021) and reweight offshorable workers to non-offshorable workers. Panels (a) - (f) show event study coefficients for log wages, employment, log wages conditional on employment, occupational switching, task distance, and change of job location. During unemployment, individuals are assigned their social security benefits as wage income. Occupational switching is a binary variable indicating whether a worker has a different four-digit occupation after displacement than in the last pre-displacement job. Task distance is the change in the importance of the main pre-displacement task in the respective post-displacement occupation conditional on occupational switching; the main pre-displacement task is defined as the task that was performed most often in the last pre-displacement job (one of the following five tasks: manual routine, manual non-routine, cognitive routine, analytical non-routine, and interactive non-routine). Change job location is a binary variable indicating whether a worker works in a different district after displacement than in the last pre-displacement job. All outcomes of displaced workers are relative to those of matched non-displaced control workers. Offshorable occupations are defined as occupations with an offshorability index above the median across all occupations according to Blinder and Krueger (2013). Non-offshorable occupations are defined as occupations with an offshorability index below the median. Estimations control for a quadratic polynomial in age, individual fixed effects, calendar year fixed effects, and event time fixed effects. The error bars report 95% confidence intervals based on standard errors clustered at the individual level. *Data:* Administrative German labor market records (SIAB).

of different types of workers and lead to differential labor market adjustments at the individual level.

Our analysis draws on German administrative data and exploits job involuntary separations due to plant closures as natural experiments of unanticipated labor market shocks to individual workers. To study labor market transitions after displacement, we estimate a dynamic difference-in-differences model. To ensure that our estimates can arguably be causally interpreted, we match displaced workers to non-displaced workers on a large number of pre-displacement characteristics and outcomes, including pre-displacement wages as a measure of worker productivity.

Our empirical results show that manual-routine workers experience more difficult labor market transitions after displacement than non-manual-routine workers — both in the short term and in the longer term. In particular, manual-routine workers are more likely to remain unemployed after the job loss and also face larger losses in real daily wages conditional on finding employment. We also find that manual-routine workers are much more likely to switch occupations after displacement compared to non-manual-routine workers. This is in line with the documented secular decline of manual-routine occupations, which implies decreasing employment opportunities in the pre-displacement occupation for these workers. Moreover, we also provide evidence consistent with the notion that decreasing employment opportunities in manual-routine occupations force manual-routine workers to switch to more distant occupations in terms of task content, so these workers incur larger losses in occupation-specific human capital. This implies that the loss of task-specific human capital is a major reason for the large displacement costs of manual-routine workers. Importantly, these results are robust to reweighing manual-routine workers to non-manual routine workers such that they become statistically identical in characteristics such as gender, age, education, and pre-displacement wages, all of which may potentially be related to both manual-routine intensity and labor market prospects.

While our results suggest that manual-routine workers experience particularly difficult labor market transitions, we do not find pronounced differences between the labor market outcomes of offshorable and non-offshorable workers after displacement. As offshorable occupations have not experienced a marked employment decrease in Germany in recent years (e.g., Dauth et al., 2014), offshorable workers might face more favorable employment prospects compared to manual-routine-workers. Overall, our results suggest that the two major labor market trends, increasing automation and accelerated globalization, have very different implications for workers' labor market prospects.

Our results emphasize the role of firms' skill demand for workers' adjustment to labor market shocks. Our findings even suggest that labor market transitions are particularly difficult for workers who experience declines of employment opportunities in their own or skill-related occupations if they loose more of the human capital that was specific to their old occupation. When skill-related occupations decline, workers must seek employment in more distant occupations and lose more of their occupation-specific human capital, which constitutes an important component of their wages.

From a policy perspective, our results point to the importance of worker training to ease transitioning to other occupations that are less affected by technology- or trade-induced transformation. First, our results suggest that workers who have switched to more distant occupations might benefit from specific worker training that imparts the targeted skills required in the new occupation. In addition, our results highlight the benefits of equipping workers with skills that are portable and general in nature, as these skills render workers more employable over a wider spectrum of occupations, shielding them against declining employment prospects in their own or closely related occupation. For instance, digital skills have considerably gained significance across a broad range of occupations (see the report on PILLARS Tasks 2.4 and 2.5). Thus, equipping workers with more general and portable skills, such as better digital skills, may not only lead to immediate labor market benefits in terms of higher wages or better employment prospects, it may also improve workers' resilience against future shocks.

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Appendix A. Appendix

Table A1: Summary Statistics of Displaced Routine and Non-Routine Workers

	Displaced Manual-Routine Workers	Displaced Non-Manual-Routine Workers	Difference
% Female	20.74	33.26	12.52 (45.54)
% College degree	1.35	4.60	3.25 (27.66)
% Manufacturing	88.59	57.67	30.92 (110.97)
% East Germany	8.20	5.53	2.67 (18.66)
Age	40.67	41.41	0.74 (14.58)
Real daily wage	98.38	111.83	13.45 (64.02)
Days working per year	361.55	361.86	0.31 (2.70)
Number of workers	2,962	14,458	

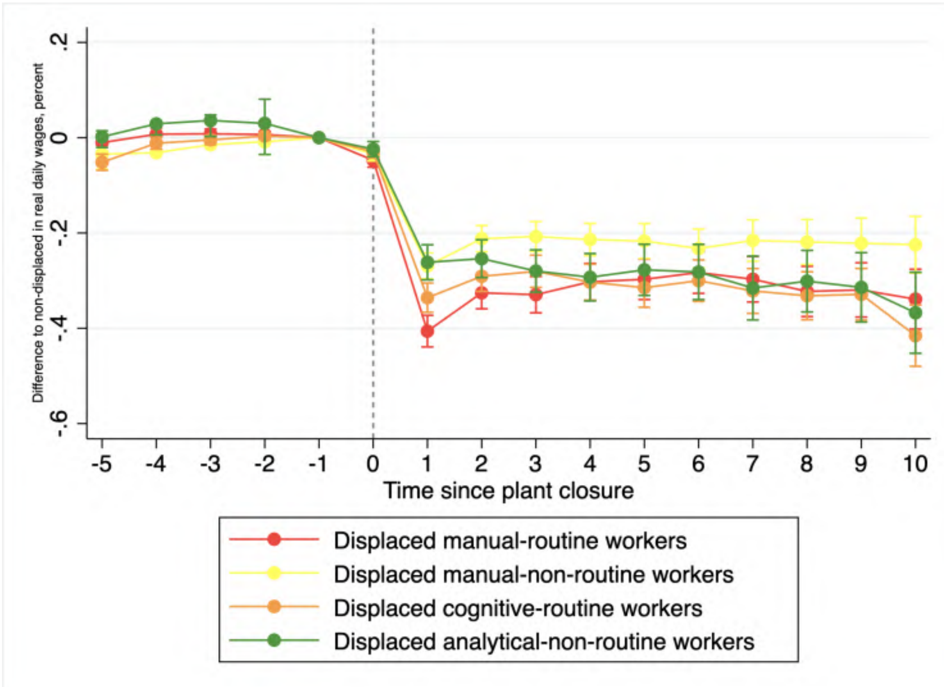
Notes: This table shows summary statistics of our sample of matched displaced workers by manual-routine intensity of the last pre-displacement occupation. t-statistics for the differences are provided in parentheses. *Data:* Administrative German labor market records (SIAB).

Table A2: Summary Statistics of Displaced Offshorable and Non-Offshorable Workers

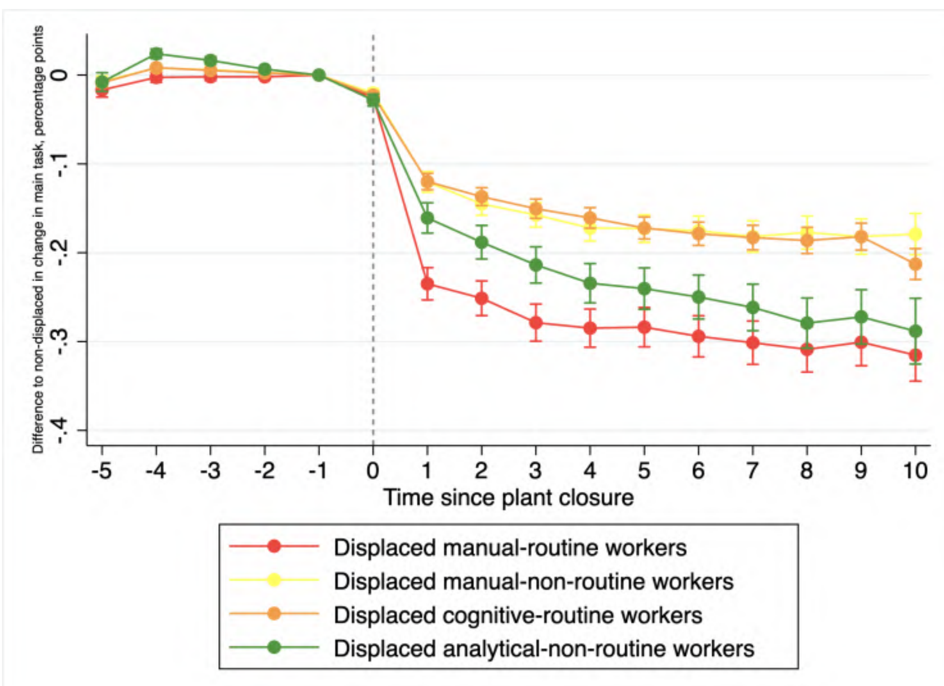
	Displaced Offshorable Workers	Displaced Non-Offshorable Workers	Difference
% Female	32.1	34.7	2.6
			(27.8)
% College degree	7.0	6.2	0.8
			(12.6)
% Manufacturing	48.7	20.8	27.9
			(115.2)
% East Germany	12.6	15.4	2.8
			(17.3)
Age	41.9	42.3	0.4
			(14.8)
Real daily wage	111.9	111.4	0.5
			(4.2)
Days working per year	361.1	361.4	0.3
			(2.6)
Number of workers	6,444	10,976	

Notes: This table shows summary statistics of our sample of matched displaced workers by degree of offshorability of the last pre-displacement occupation. t-statistics for the differences are provided in parentheses. *Data:* Administrative German labor market records (SIAB).

Figure A1: Labor Market Transitions of Displaced Workers by Different Occupational Groups



(a) Log Wages



(b) Task Distance

Notes: This figure shows the effect of displacement due to plant closure by the occupational group of the last pre-displacement job. Occupational groups are defined according to whether one of the following tasks constitutes the main task according to the BERUFENET data Dengler et al. (2014): (1) manual-routine tasks (2) manual non-routine tasks (3) cognitive-routine tasks (4) analytical-non-routine tasks. We implement the robust event study estimators by Callaway and Sant'Anna (2021) and reweight manual-routine workers to non-manual-routine workers. Panels (a) shows event study coefficients for log wages, Panel (b) shows event study coefficients for task distance. During unemployment, individuals are assigned their social security benefits as wage income. Task distance is the change in the importance of the main pre-displacement task in the respective post-displacement occupation conditional on occupational switching; the main pre-displacement task is defined as the task that was performed most often in the last pre-displacement job (one of the following five tasks: manual-routine, manual non-routine, cognitive-routine, analytical non-routine, and interactive non-routine). All outcomes of displaced workers are relative to those of matched non-displaced control workers. Estimations control for a quadratic polynomial in age, individual fixed effects, calendar year fixed effects, and (virtual) event time fixed effects. The error bars report 95% confidence intervals based on standard errors clustered at the individual level. *Data:* Administrative German labor market records (SIAB).