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Robots and Unions: The Moderating Effect of Organised Labour on Technological Unemployment

Henri Haapanala[1], Ive Marx[1], Zachary Parolin[2]
[1] Herman Deleeck Centre for Social Policy (University of Antwerp). Belgium
[2] Department of Social and Political Sciences (Bocconi University). Italy

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Abstract

We analyse the moderating effect of trade unions on industrial employment and unemployment in countries facing exposure to industrial robots. Applying random effects within-between regression to a pseudo-panel of observations from 28 advanced democracies over 1998-2019, we find that stronger trade unions in a country are associated with a greater decline in the industry sector employment of young and low-educated workers. We also show that the unemployment rates for low-educated workers remain constant in strongly unionised countries with increasing exposure to robots, whereas in weakly unionised countries, low-educated unemployment declines with robot exposure but from a higher starting point. Our results point to unions exacerbating the insider-outsider effects of technological change within the industrial sector, which however is not fully passed on to unemployment.

Keywords: trade unions, technological change, outsiders/insiders, dual labour market, unemployment, labour economics

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INTRODUCTION

The labour market impacts of industrial robots and automation are attracting widespread attention in social and economic sciences, with the scope of the research recently extending from employment and wages to social outcomes such as worker well-being and support for welfare policies (Im, 2021). Concerns raised by automation mostly centre on what John Maynard Keynes titled ‘technological unemployment’: the loss of jobs ‘due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour’ (Keynes, 1930). However, several empirical analyses are pointing out that the main contribution of industrial robots to labour markets is not necessarily mass unemployment, but rather the reallocation and displacement of work from blue-collar, manual and routine industries to complex non-routine roles in public and private services, often requiring tertiary education (Frey and Osborne, 2017; Acemoglu and Restrepo, 2020; Dauth *et al.*, 2021).

This leaves the blue-collar routine worker without higher education in a difficult position: is it possible to keep their current role in the industrial workplace alongside robots, or gain further job-specific education or training to operate the advanced machinery – or will the future hold unemployment and precarious work in low-paid service sector occupations? In this paper, we ask whether the outcomes for industrial workers are moderated by the strength of trade unions in their countries. The landmark research papers from Germany and the United States (US) find that increasing exposure to robots leads to worse outcomes for labour in the latter context. However, while it is known that organised labour in the US is considerably weaker than in Germany and several other Western European countries, there has not yet been a systematic comparative analysis of the joint effects of trade unions and robot exposure on employment and unemployment.

We contribute to the literature with an analysis of robots and unions in 27 European countries and the US. Our main findings suggest that union strength contributes to insider-outsider dynamics in the industrial labour force: when workers are exposed to robots, employment in the industrial sector declines more strongly for young and low-educated workers in strongly unionised countries. Conversely, industrial workers over the age of 35 and with tertiary education are the main beneficiaries of robot exposure where unions are strong. This suggests that although industrial unions are largely successful in preserving jobs for their currently employed members until retirement, this comes at the cost of excluding labour market entrants from industry sector jobs. Additionally, we find that stronger unions in a country contribute to a low and constant rate of unemployment among low-educated adults, which does not decline with increasing rates of technological change. These findings emphasise the difficult position of organised labour, where even solidaristic efforts to stand up for low-educated workers are obstructed by the increasing returns to non-routine skills and high formal education in the labour market.

Background

The puzzle of automation and labour market dualisation

In recent years there has been great scholarly interest on the employment effects of automation, motivated by innovations in robotics, machine learning and artificial intelligence often referred to as the ‘fourth industrial revolution’ (Frey, 2019). Inspired by the landmark paper of Frey and Osborne (2017) which suggested almost half of all currently existing jobs in the US are threatened by computerisation and computer-controlled machinery, some theorists have raised concerns that with each successive generation of industrial robotics we are moving closer to the point where human labour becomes fully redundant, or the proverbial ‘end of work’ (Upchurch, 2018). As technological progress allows more tasks to be automated, firms will discover more opportunities to cut back on labour. However, the large empirical literature on industrial robots presents a more nuanced picture, as job losses in manual and routine occupations are compensated by rising productivity which facilitates the creation of new jobs in both the industrial and service sectors (Acemoglu and Restrepo, 2019, 2020; Bessen, 2019; Dauth *et al.*, 2021; Chiacchio *et al.*, 2018; Graetz and Michaels, 2018; Südekum *et al.*, 2020). The common denominator for the emerging jobs, as predicted by the dominant argument of routine-biased technological change (RBTC), is non-routineness: a high share of social, problem-solving, or creative tasks where humans retain a comparative advantage (Frey and Osborne, 2017).

Therefore, the question appears to be not whether industrial robots destroy jobs *en masse*, but what their distributional consequences will be. The jobs most readily displaced by industrial robots, such as the manufacturing and assembly of goods, are usually located in rural towns and overwhelmingly held by male blue-collar workers without college education (Rodgers and Freeman, 2019). These workers face two structural issues in access to alternative employment opportunities: firstly, the lack of formal qualifications required for the high-paying expert roles in the service economy, and secondly, the lack of geographical access to the jobs emerging in urban centres (Autor, 2019). In brief, industrial robots have contributed to the trend of labour market dualisation, where tertiary education is an essential precondition for stable and well-paid careers (Autor and Dorn, 2013).

However, there is a cross-country puzzle in the employment effects of automation. Taking into account both the labour-displacing and labour-creating effects of robots, evidence from the US suggests that robotisation contributes to a net reduction in labour demand, whereas in Germany the net effect is positive (Acemoglu and Restrepo, 2020; Dauth *et al.*, 2021). Other studies from technologically advanced Western European countries back up this puzzle, finding the negative employment and wage effects of robots to be less pronounced in Europe than the US (Chiacchio *et al.*, 2018; Graetz and Michaels, 2017). How to explain this transatlantic difference? We argue that labour market institutions are key to solving the puzzle. In particular, we posit that the strength of trade unions in a country moderates the effects of robot exposure on technological unemployment and industry sector employment. Our argument and empirical test provide a key role for institutional context, something that has been largely absent from the previous literature on RBTC. Our large-n comparative analysis of 27 European countries and the US also extends the scope of the research to more countries than have been previously covered. We now proceed with outlining the theoretical relationship between robots and trade unions.

Making sense of the puzzle: theories of unionism

The mission of trade unions is to represent the interests of their members within their respective economic sector in negotiations with employers and the state, and to support the working class more broadly by allocating a greater share of economic profits to labour. This double role, combining the advocacy for highly specific interests with a broader 'social mission' (Gumbrell-McGormick and Hyman, 2013: 152), has made trade unionism a subject of political and scholarly controversy. As outlined in the seminal work of Freeman and Medoff (1984), unions can simultaneously act as both monopolistic and social organisations, improving working conditions and wages as well as giving workers 'voice' and a platform to liaise with management. At its heart, all forms of unionism share the goal of improving the well-being of workers, whether through pursuing better working conditions, higher pay, shorter working hours, or training and technologies that improve worker productivity.

When it comes to the relationship between unions and technological change, it is important to understand which of the 'two faces' of unionism is dominant. The two main theoretical perspectives, power resources theory (PRT) and insider-outsider theory (I-O), suggest different responses to the question.

The main claim of the *power resources theory* is that redistributive and egalitarian labour market outcomes are the product of a strong and united working class (Korpi, 1983). Indeed, a wide range of empirical evidence demonstrates that countries with higher union density, greater coverage of collective agreements, or centralised bargaining institutions have greater wage equality, lower unemployment and higher employment rates (OECD, 2017; Garnero, 2020). However, the foundations of a 'united working class' – if such concept has ever truly existed – have been constantly undermined since the 1980s by the collective onslaught of forces such as market liberalisation, globalisation, deindustrialisation and the expansion of precarious work. Furthermore, Oude Nijhuis (2021) distinguishes between working-class and middle-class unionism, arguing that the success of egalitarian policies requires not only a strong working-class union movement but also the absence or relative weakness of middle-class organised interests.

Many authors find the PRT assumption of 'united labour' or cross-class solidarity lacking or at least outdated, especially following the decline of mass manufacturing and the increasing returns to skill and education in non-routine occupations. In the 1990s and 2000s, the locus of unionism has shifted from blue-collar industries towards the public sector and (some) skilled professionals, increasingly representing workers with relatively high earnings and secure, permanent jobs (Visser, 2012; Becher and Pontusson, 2011). Of course, while one should not ignore the fact that the comfortable socio-economic position for many of these occupations is an achievement of unions in their own right, it is worth highlighting that the preferences of unions representing high-wage workers tend to sway less towards egalitarianism and more towards preserving status differences, especially when there is little interaction with low-wage workers (Mosimann and Pontusson, 2017).

Building upon the argument that the united working class is a predominantly theoretical concept, the *insider-outsider theory* embraces the ‘narrow interests’ and ‘monopoly face’ interpretations of unionism (Rueda, 2007). This perspective suggests that unions accept or even exacerbate the phenomenon of labour market dualisation, characterised by major differences in the employment security and incomes of ‘insider’ or ‘core’ workers employed on full-time, permanent contracts on the one hand, and ‘outsider’ or ‘peripheral’ workers with non-standard employment contracts, irregular working hours and fluctuating incomes on the other (Carver and Doellgast, 2020). Moreover, Simoni and Vlandas (2020) argue that union contribution to dualisation was less a conscious choice than the outcome of individually optimal decisions made in the effort to stand up for their members and maintain organisational influence in the post-industrial economic paradigm: namely, when unions are unable to block the introduction of liberalising or dualising reforms, their second-best strategy is to accept dualisation with the condition that unionised workers or sectors are not affected. This risks creating or expanding labour market peripheries for groups such as low-educated, young and migrant workers (Gorodzeisky and Richards, 2013).

We argue that whether unions, when faced with the introduction of industrial robots, respond in the solidaristic manner associated with PRT or the stratifying manner associated with I-O depends in part on the type of *worker* and the type of *union* that are affected. To illustrate variation in potential union responses, we present three stylised response types to the threat of automation: ‘downright acceptance’, ‘lukewarm acceptance’, or ‘downright opposition’. We emphasise that these stylised response types are a useful conceptual tool to theorise the different possible impacts that unions may have on the employment and unemployment outcomes of workers affected by automation, though we do not measure the response types directly on our empirical approach.

The downright acceptance and opposition stances are relatively straightforward; the former implies no resistance to automation or explicit requests from the union itself to introduce more automation, whereas the latter implies active opposition through industrial action or other means. In between these extremes sits the category of ‘lukewarm acceptance’: this, we argue, is a calculated stance for unions to support automation, even if labour-displacing in the short term, for the sake of preserving jobs in the long term. History knows several examples of unionised workers aggressively resisting technological change, the Luddites being the most famous of them, only to see their opposition accelerate the demise of their industries (Dowrick and Spencer, 1994; Frey, 2019).

PRT suggests a homogeneous approach of lukewarm acceptance of automation by all unions. Thus, if PRT dominates, we may expect that the employment effects of technological change across worker groups do not significantly depend on the strength of unions. I-O theory, in contrast, would expect downright acceptance from white-collar unions and either lukewarm acceptance or downright opposition from blue-collar unions. Thus, if I-O dominates, we may expect more favourable employment outcomes for the currently-employed but with reduced entry to industrial employment among younger and lower-educated workers. We now elaborate on these hypotheses.

Hypotheses

Industrial employment. The industrial sector, defined here as manufacturing, mining, and the supply of utilities, is the natural starting point for assessing the role of robot exposure and organised labour on employment outcomes. Indeed, the International Federation of Robotics dataset applied by empirical researchers highlights the hyper-concentration of industrial robots not only in the industrial sector, but also in sub-sectors including the manufacturing of cars, electronics, and rubbers and plastics. This line of research has identified clear trends of labour market dualisation and increasing returns to education, with highly educated non-routine workers benefitting and manual or routine workers with few formal qualifications losing out from exposure to robots (Acemoglu and Restrepo, 2020; Autor and Salomons, 2018; Goos *et al.*, 2014; Graetz and Michaels, 2018; Dauth *et al.*, 2021). At the same time, one of the main purposes of labour-saving as well as labour-augmenting technologies is to increase worker productivity, allowing the same amount of output to be produced with fewer workers. All other things equal, this has the effect of reducing overall employment in sectors exposed to robots (Autor and Salomons, 2018: 27).

Blue-collar and encompassing industrial unions in particular have two ways of adapting to this dilemma: in the lukewarm acceptance scenario, which is more consistent with PRT, they focus on salvaging what is salvageable. This implies sheltering routine occupations, pushing for further training and upskilling of existing workers, or arranging early retirement pathways. For instance, Dauth *et al*. (2021: 24-5) find that robot-exposed manufacturing workers are twice as likely to remain with their original employer in German regions with stronger unionisation. In Finland, automation-exposed workers have a higher likelihood of early retirement, which might be interpreted as another channel of protecting workers from technological unemployment (Yashiro *et al.*, 2020; Ebbinghaus, 2001).

In the downright opposition scenario associated with I-O theory, unions that strongly resist the displacement of low-skilled routine jobs or unilaterally extract wage premiums will only further encourage employers to invest in labour-displacing technologies (Acemoglu, 2003). Since this appears to be a self-defeating strategy, the choice for blue-collar unions boils down to lukewarm acceptance of robotisation as the lesser of two evils. In contrast to the Keynesian hegemony of the 1960s and 70s, the political-economic logic of the day seems to be running against industrial unionism, making it difficult for the working class to achieve anything greater than ‘modest but deferred gains’ (Simoni, 2013: 331).

Highly educated industrial workers and skilled professionals, on the other hand, are poised to gain from robot exposure since the introduction of advanced technologies shifts labour demand towards complex non-routine skills such as management and coordination, or advanced technical skills such as robot maintenance and reprogramming (Eurofound, 2018; Dauth *et al.*, 2021). Consistent with the I-O perspective, these workers are thus likely to downright accept the introduction of robots and communicate this preference through unions. The contrast with blue-collar workers is particularly strong in the case of craft unions which pursue the interests of skilled workers exclusively, without regard to the dualising consequences (Oude Nijhuis, 2009). Overall, the I-O perspective suggests divergent industrial employment outcomes by skill and education level with stronger unionisation, whereas the PRT perspective expects unions to contribute equally to changes in industrial employment with robot exposure.

- H1a (power resources hypothesis): stronger unions do not meaningfully influence the effect of robot exposure on industrial sector employment.
- H1b (insider-outsider hypothesis): stronger unions reduce the overall share of employment in the industrial sector at higher levels of robot exposure, while increasing the relative share of high-educated professionals.

Unemployment hypotheses. As a supplement to the analysis of industrial employment, we also focus on unemployment outcomes. The net employment effect from the displacement of industrial workers will crucially depend on the spillover effects of job creation in sectors not exposed to robots (Acemoglu and Restrepo, 2019). Therefore, we expect the rate of unemployment to move inversely to the net employment effect of robotisation – if fewer jobs are created than displaced by robots, unemployment increases and vice versa. Of course not all changes in employment directly correspond to changes in unemployment, for example if displaced workers exit the labour force to education or (early) retirement, but we analyse this outcome since it corresponds with the routine-to-unemployment trajectory applied in recent empirical work (Kurer, 2020).

While the effect of robot exposure on unemployment depends on the sum of job displacement and creation across economic sectors, the relationship between union strength and unemployment also encloses several conflicting dynamics. First of all, inferences between union strength and unemployment must take into account that the unemployed do not have the same incentives to be union members in every country (Checchi and Nunziata, 2011). In countries with the Ghent system of unemployment insurance – Belgium, Finland, Sweden and Denmark – where trade unions are directly involved in the administration of earnings-related unemployment benefits, workers have a major incentive to remain unionised during unemployment, increasing union density across all sectors and occupations (Van Rie *et al.*, 2011; Høgedahl and Kongshøj, 2017). After taking into account the institutional context, the power resources and insider-outsider theories suggest yet further divergence.

First, following PRT, one would expect unions to prefer a lower rate of unemployment because the bargaining power of workers is greater when labour demand exceeds supply. Stronger unions may also contribute to a ‘virtuous circle’ of long employment spells, reduced transitions to and from unemployment, and low unemployment rates in general (Doellgast *et al.*, 2018; Parolin, 2020; Garnero, 2020). Furthermore, we expect the unemployment-reducing effect of union strength to be independent of robot exposure and occupational status, following the ‘solidaristic’ principles of wage moderation, generous but time-limited unemployment benefits and active employment transitions established in the Rehn-Meidner model of 1960s Sweden (Moene and Wallerstein, 1995). In other words, we expect the interaction effect between automation exposure and union strength to be zero.

In contrast, the I-O perspective would expect stronger unions to increase the equilibrium rate of unemployment. According to this model, unions behaving in a monopolistic way, either raising the wage floor for entry-level occupations or extracting wage premiums for experienced workers, will result in higher unemployment for marginal workers not covered by the union (Krusell and Rudanko, 2016). In this case we expect divergent outcomes for the high-educated 'insiders' and low-educated 'outsiders' as exposure to robots increases: for the high-educated, union strength will have a negative or neutral effect on technological unemployment, whereas for the low-educated union strength will increase technological unemployment. This sums up our second set of hypotheses which we will proceed to test empirically.

- *H2a (power resources hypothesis): stronger unions reduce unemployment for all groups of workers regardless of robot exposure.*
- *H2b (insider-outsider hypothesis): stronger unions reduce high-skilled unemployment at all levels of robot exposure, while further increasing low-skilled unemployment with robot exposure.*

DATA AND METHODS

In analysing the joint effect of trade unions and robot exposure on employment outcomes within and between countries, we merge individual-level data on socioeconomic status and employment with country-level data on unionisation and industrial robots. The benefit of a multi-country comparative approach is that it exploits the variation in union strength and robotisation between countries, which tend to be greater than the relatively similar trends within countries over the study period 1998-2019. Furthermore, we analyse the within-country and between-country components separately as different dynamics are at play for these levels of variation (Georgieff and Milanez, 2021).

We apply a pseudo-panel, random effects within-between regression design which is still relatively novel in sociological research, but suitable for the analysis of multilevel phenomena using repeated cross-sectional datasets (Biegert, 2017). This method involves assembling cohorts based on time-constant and strictly identifying characteristics, such as sex, education level and age group, and calculating cohort-specific means of the variables of interest for each wave of a repeated cross-sectional survey (Deaton, 1986).[1] Provided that each survey wave is sampled consistently and the sample sizes for each cohort are sufficiently large, this method produces a 'pseudo panel' of averages by cohort C, where the definition of C remains constant but the values of C are drawn from a different random sample of the population at each time of observation (Verbeek, 2008). Panel data methods are then applied to the cohort-averages. This enables us to extend the two most prominent cross-nationally comparable labour force surveys, EU-LFS and US-CPS, over time as well as between countries.

[1] Using education as a cohort identifying variable assumes that the individual will have achieved their highest education level at time of sampling. This assumption is more likely to be satisfied for individuals full-time active in the labour force than those still in education.

Our main dependent variables are the cohort-wise employment shares in industrial employment[2] and unemployment for active labour market participants aged 20-64. Employment shares are calculated by cohort-year as percentages across the sample of employed and actively unemployed workers, applying the survey-specific design weights. Cohort-averages are weighted by the square root of the number of observations to give greater weight to estimates from larger cohorts (Biegert, 2017). Mean cohort size is just over 6,900 observations, which together with the weighting procedure should be large enough to produce unbiased estimates.

We are particularly interested in the moderating effect of country-level unionisation on country-specific changes in industrial employment and unemployment at different rates of technological change. Therefore, our main interest is in the interaction of within-country changes in robot exposure and between-country levels of union density. Using the country mean levels of unionisation captures the most relevant empirical dynamics as union density is strongly path-dependent, exhibiting gradual within-country changes and persistent between-country differences (Bryson *et al.*, 2011). Moreover, the exponential increase in robot exposure across Europe and the US has occurred at roughly the same time during the early 21st century. We will also specify three-way interaction models to further explore the demographic characteristics of technological unemployment, adding categorical variables for education and age respectively to the main robots-unions interactions.

We specify the core model as follows:

$$Y_{ct}^{W} = \alpha_c + \beta_1 R_{ct}^{W} + \beta_2 U_{ct}^{W} + \beta_3 \bar{R}_c + \beta_4 \bar{U}_c + \beta_5 R_{ct}^{W} \bar{U}_c + \beta_6 X_{ct} + \delta_t + \varepsilon_{ct}$$

where Y_{ct}^{W} represent change in the employment share of cohort *c* at time *t*. The key explanatory variables, union density U and robot exposure R, are decomposed to their within- and between-components. All within-components are of the form $Y_{ct}^{W} = Y_{ct} - \bar{Y}_t$, in other words the de-meaned variants of the cohort-year observations. Including both within- and between-effects of explanatory variables enables precise identification of variation along the respective dimensions, improving upon the conventional fixed effects specification since the within-coefficients are identical to coefficients obtained with a FE model, but between-coefficients are lost in the strict FE specification (Bell *et al.*, 2018). Using the within-component as the dependent variable enables a straightforward interpretation of the results as deviations from the cohort-specific mean, regardless of absolute values which vary substantively between cohorts and countries. X_{ct} represents a vector of country-year controls including whether the country has the Ghent system of unemployment insurance, annual GDP growth, and mean routine task intensity. We also add year dummies δ_t to capture time trends mutual to all countries. ε_{ct} is the cohort-country-year error term.

Our main interest is on coefficient β_5 for the robots-unions interaction. We also specify three-way interactions of the type $R_{ct}^{W} \bar{U}_c C_c$, where C_c stands for a categorical variable for worker

[2] Industry sector = mining and quarrying + manufacturing + electricity, gas and water supply

ages 18-34; 35-54; and 55-64 in the age model, and education categories below upper secondary; upper secondary; and tertiary degree as the highest achieved degree in the education model.

Data

We construct the country-age-sex-education cohorts using individual-level data from the EU Labour Force Survey and US Current Population Survey, covering a total of 18 cohorts for each of the 28 countries[3] followed over 22 years. Some country-year-cohort cells are omitted due to missing data or small sample sizes, leaving 10,200 cohort-years in the final dataset. Sex is a binary category for males and females, age has three bands (18-34; 35-54; 55-64), and so does education (lower secondary; upper secondary; tertiary).

The employment sector categorisation is based on the top-level SNA/ISIC A*10/11 aggregation of occupational codes, broken down into agriculture, industry, construction, and five subsets of service sector occupations. This grouping remains sufficiently general to be comparable across multiple countries and over time, bridging the 2008 revision of NACE occupational codes applied by LFS which are identical to the ISIC classifications at the top levels (Eurostat, 2008). Our main interest is in industry sector employment and unemployment, but we also run the model for three sub-categories of service sector employment, namely trade and hospitality, business services, and the public sector. These results are available in the Online Appendix.

The main explanatory variables, robot exposure and union density, are measured at country level using the most prominent cross-nationally comparable datasets for their respective phenomena. Robot exposure is derived from the International Federation of Robotics indicator of the stock of industrial robots per thousand workers in the active labour force (IFR, 2020), following the approach in Acemoglu and Restrepo (2019) and Dauth *et al.* (2021). The number of workers is fixed to baseline year 1995, so the robot exposure indicator only captures year-on-year changes in robot stocks rather than changes in labour force participation. Union density is derived from the OECD/AIAS ICTWSS database on trade unions, measuring the share of union members out of wage and salary earners in employment (OECD and AIAS, 2021). However, since union strength is not only a function of membership but includes elements such as the institutionalisation and centralisation of bargaining (Gordon, 2015; Garnero, 2020), we run alternative specifications of unionisation as robustness checks. The choice to keep the main indicators at the country level is again determined by data availability, as the number of countries with reliable statistics on robots and union strength at sector level is considerably lower.

[3] Austria, Belgium, Bulgaria, Switzerland, Czechia, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Latvia, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovenia, Slovakia, United Kingdom, United States

RESULTS

Descriptive statistics

Figure 1 displays bivariate scatterplots for country mean levels of robot exposure and industry employment shares over the study period 1998-2019. While the overall association between the two variables appears very weak (Panel A), distinguishing between the postindustrial Western European economies and the industry-oriented Central and Eastern European countries highlights the strong positive association between exposure to industrial robots and employment in the industrial sector (Panel B). This presents the first suggestive evidence that the automation of industrial workplaces in export-oriented advanced economies has not only labour-displacing but also labour-augmenting tendencies (Cséfalvay, 2019). The preservation of industry sector jobs in Europe and the US is to a large extent dependent on the productivity gains from industrial robots. The change-over-time scatterplots, available in the Online Appendix, lend further support to this interpretation, since country-years with greater increases in robot exposure are not associated with stronger declines in industry employment. In brief, robot exposure alone does not seem to account for the decline in industry sector employment.

Figure 1. Scatterplots of mean industry employment share and robot exposure by country, 1998-2019.

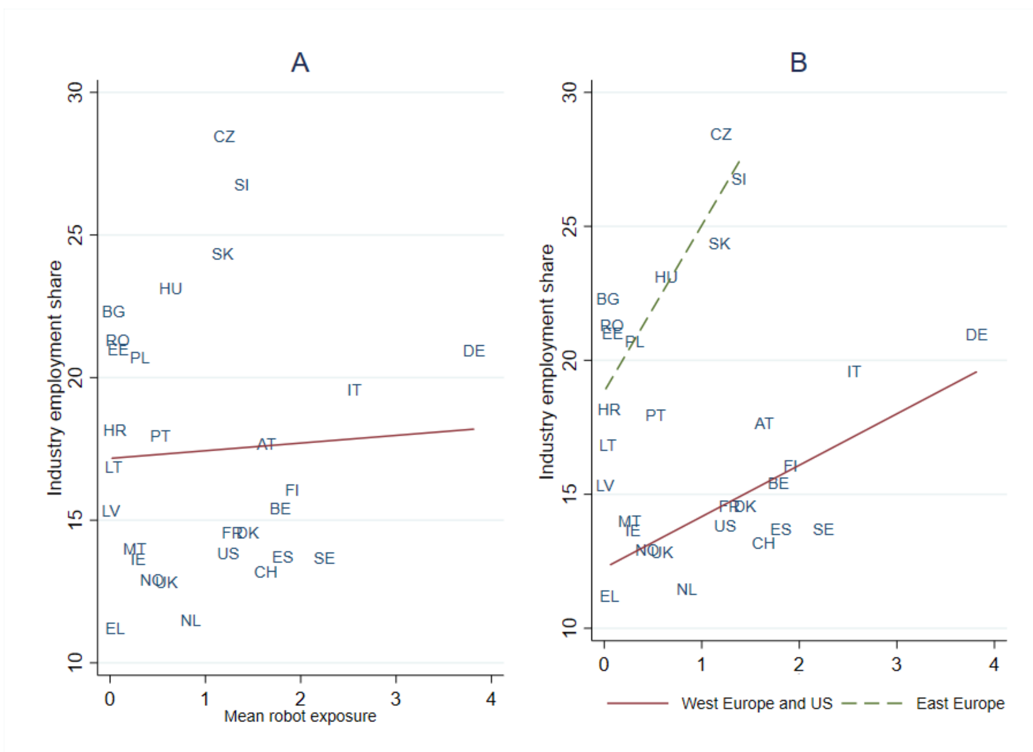
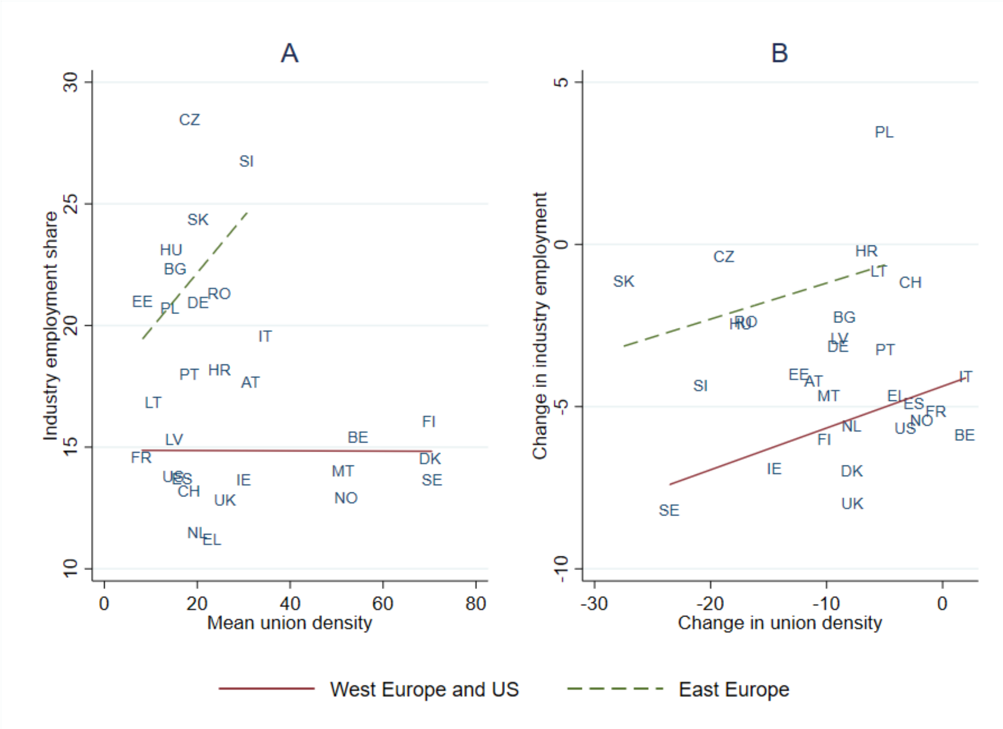


Figure 2. Scatterplot of industry employment share and union density, country mean levels and changes 1998-2019.



Lastly, some complementarities emerge between industry employment shares and union density, as countries with the smallest declines in industry sector employment also tend to have the smallest union density decline (Figure 2). This is consistent with the model of 'industrial unionism', according to which national union density is largely driven by the size of the industrial sector as blue-collar manufacturing workers are a traditional stronghold of the union movement (Visser, 2012; Ibsen and Tapia, 2017).

These descriptive statistics provide an initial overview of the interdependencies between industrial employment, robot exposure and union density. The decision to show trendlines for Western and Eastern European countries separately reflects the different political economies in these country groups, since the generally larger and more labour-intensive industrial sectors of Eastern Europe are often interpreted as a source of competition for manufacturing in Western Europe and the US (Caséfalvay, 2019; Dauth *et al.*, 2021). Nonetheless, some parallel trends emerge: while the increase of robot exposure over time coincides with declining industrial employment shares and union density, countries with the largest industrial sectors also have the highest intensity of robot use. The next step is to analyse in detail the interaction between organised labour and robot exposure for different groups of workers.

Multivariate results

Industry sector employment

Table 1 presents the results of four REWB models, regressing the within-cohort change in industrial employment on robot exposure, union density, and control variables at the country and cohort levels. Model 1 is our baseline model incorporating the within- and between-country effects of robots and unions, Model 2 adds the interaction of within-country changes in robot exposure and country-mean levels of union density, and Models 3 and 4 incorporate three-way interactions of robots and unions with education and age respectively.

Table 1. REWB regressions predicting industry sector employment: robots, unions, demographics and interactions.

	DV: Change in industry sector employment			
	(1)	(2)	(3)	(4)
Robot exposure (within-country)	0.682**	1.521***	1.553***	0.918**
	(0.317)	(0.430)	(0.431)	(0.393)
Robot exposure (between-country)	-0.009	-0.009	-0.012	-0.012
	(0.039)	(0.040)	(0.040)	(0.039)
Union density (within-country)	-0.046	-0.068	-0.066	-0.068
	(0.061)	(0.055)	(0.057)	(0.056)
Union density (between-country)	-0.000	0.002	0.004	0.005
	(0.005)	(0.005)	(0.005)	(0.004)
Robot exposure (within) * union density (between)		-0.036***	-0.035***	-0.020
		(0.011)	(0.011)	(0.012)
Education (ref: upper secondary)				
Lower secondary	0.020	0.026	0.146*	0.039
	(0.053)	(0.050)	(0.075)	(0.050)
Tertiary	0.578***	0.543***	0.568***	0.550***
	(0.162)	(0.155)	(0.175)	(0.158)
Age group (ref: 35-54)				
18-34	-0.156**	-0.145**	-0.146**	-0.016
	(0.061)	(0.057)	(0.057)	(0.083)
55-64	0.289**	0.286**	0.291**	0.414**
	(0.123)	(0.123)	(0.122)	(0.170)
Robot exposure (W) * educ (lower secondary)			0.029	
			(0.430)	
Robot exposure (W) * educ (tertiary)			-0.092	
			(0.448)	
Union density (B) * educ (lower secondary)			-0.004**	
			(0.002)	
Union density (B) * educ (tertiary)			-0.002	
			(0.002)	
Robots (W) * unions (B) * educ (lower secondary)			-0.018	
			(0.013)	
Robots (W) * unions (B) * educ (tertiary)			0.017*	
			(0.009)	
Robot exposure (W) * age (18-34)				1.158***
				(0.351)
Robot exposure (W) * age (55-64)				0.781**

				(0.337)
Union density (B) * age (18-34)				-0.003
				(0.002)
Union density (B) * age (55-64)				-0.007**
				(0.003)
Robots (W) * unions (B) * age (18-34)				-0.058***
				(0.010)
Robots (W) * unions (B) * age (55-64)				-0.002
				(0.010)
Number of cohorts	10,200	10,200	10,200	10,200
Number of countries	28	28	28	28
R-squared	0.210	0.224	0.232	0.242

Notes: Robust standard errors clustered by country are given in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Across all models, within-country changes in robot exposure have a large and statistically significant positive effect on changes in industry sector employment. In the baseline model (Model 1), the introduction of one additional robot per thousand workers is associated with an approximate 0.68 percentage point increase in the industrial employment share. On the other hand, the main effects of union density, either within or between countries, are much smaller and fail to reach statistical significance.

For the interaction models 2-4, it is not as straightforward to read off effect sizes from the coefficients, so we present key results in graphical form alongside the discussion. The interaction term for within-country robot exposure and between-country union density (Model 2) is negative and statistically significant, suggesting reduced increases in industry employment shares with robotisation in countries with higher union density. This combines two somewhat surprising results: firstly, the effect of robot exposure itself does not contribute to a decline but an increase in industry sector employment. Secondly, union strength appears to act against industry employment growth rather than support it. This is consistent with the insider-outsider hypothesis: not only does automation complement overall industry employment, but the complementary effect is greater when labour market institutions are weak, suggesting less frictions in the labour market transitions of workers (Krusell and Rudanko, 2016).

However, Model 2 takes no account of either the quality of industry jobs or the demographics of industry workers affected by robot exposure. Following the insider-outsider hypotheses, we expect union strength to have divergent effects on the high-educated and low-educated, as well as tenured and early-career workers. This is indeed what we find in Models 3 and 4: at the intersection of high union density and robot exposure, the expected change in industry employment is negative for young and low-educated workers, largely neutral for middle-age and older workers, and positive for tertiary educated workers (Figures 3 and 4). Stronger trade unions at the country level are then associated with a stronger dualisation of industry sector employment as robot exposure increases, rewarding skill and tenure for workers employed alongside robots. These findings are consistent with Dauth *et al.* (2021: 24-5), who argue that unions tend to prioritise the needs of their existing members when jobs are threatened or reorganised by robots. Furthermore, union members in technologically advanced countries may be explicitly in favour of robotisation to the extent that it makes their work safer, more interesting and more productive, as demonstrated by the Industrial Union of Finland (Anttila, 2021).

Figure 3. Predicted change in industry employment by robot exposure, union density and education.

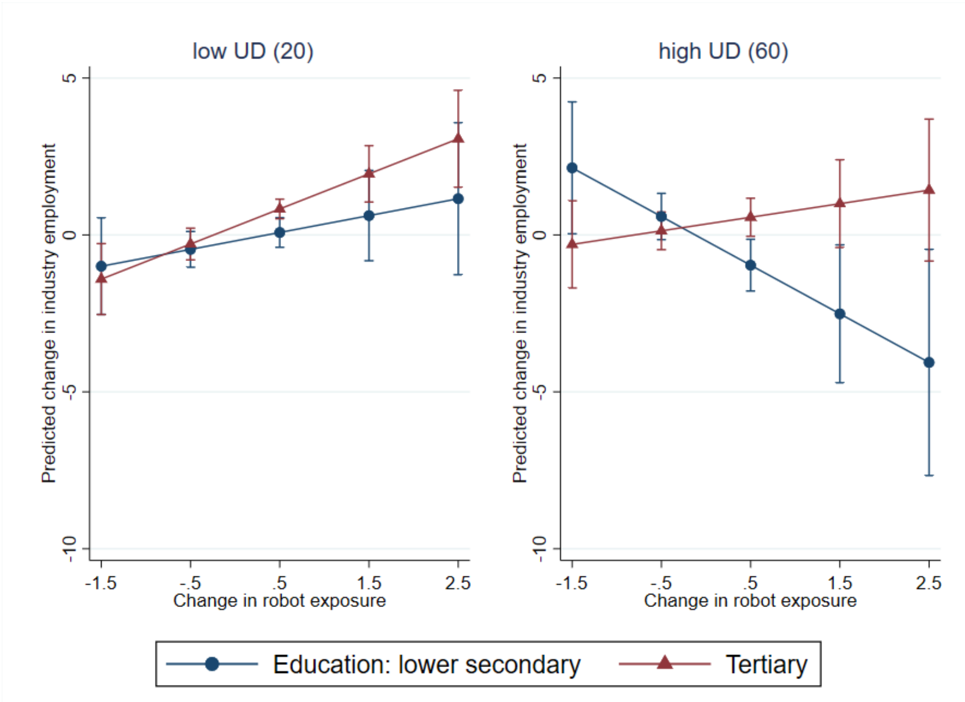
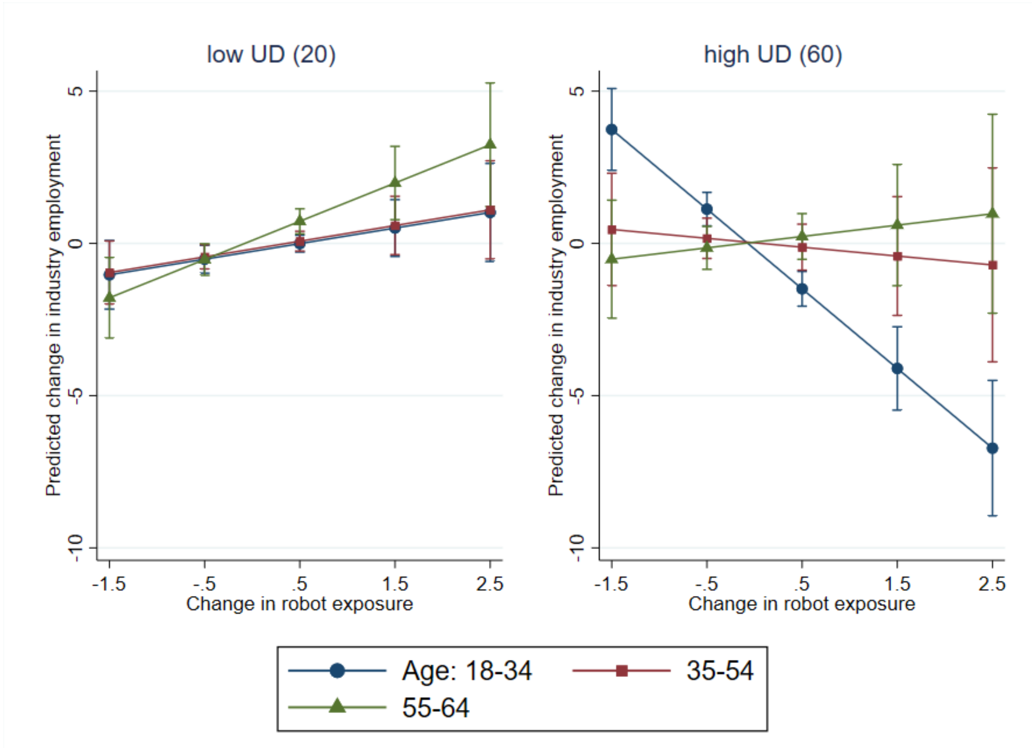


Figure 4. Predicted change in industry employment by robot exposure, union density and age.



So far, the empirical results align with the insider-outsider perspective of unionism: as robotisation changes the nature of industry sector employment, the burden of adjustment falls largely on workers who are 'outside' of the established workplaces to begin with. However, to see the full picture of employment outcomes we need to consider the effect of changes in robotisation not only on *changes* but on *levels* of employment. If countries with strong unions have higher levels of industry employment to start with, then the relatively stronger employment decline in these countries might reflect a process of between-country convergence rather than divergence as robot exposure increases.[4] Indeed, Figure 5 suggests such dynamics are at play for workers with lower secondary education: trending upwards from a starting level of 16% in the weak-union context, and downwards from 21% in the strong-union context, to a similar level around 18-19% at high rates of change in robot exposure. Workers under 35 (Figure 6) are more explicitly facing dualisation, as the predicted level of employment at high rates of change in robot exposure is almost twice as large in the weak-union context as in the strong-union context. The concentration of this negative impact on early-career workers is consistent with previous empirical results from Western European countries (Chiacchio *et al.*, 2018; Dauth *et al.*, 2021).

[4] To test this, we adapt Models 3 and 4 by regressing levels of industry employment on our explanatory variables. Regression tables are available in Online Appendix.

Figure 5. Predicted level of industry employment by robot exposure, union density and education.

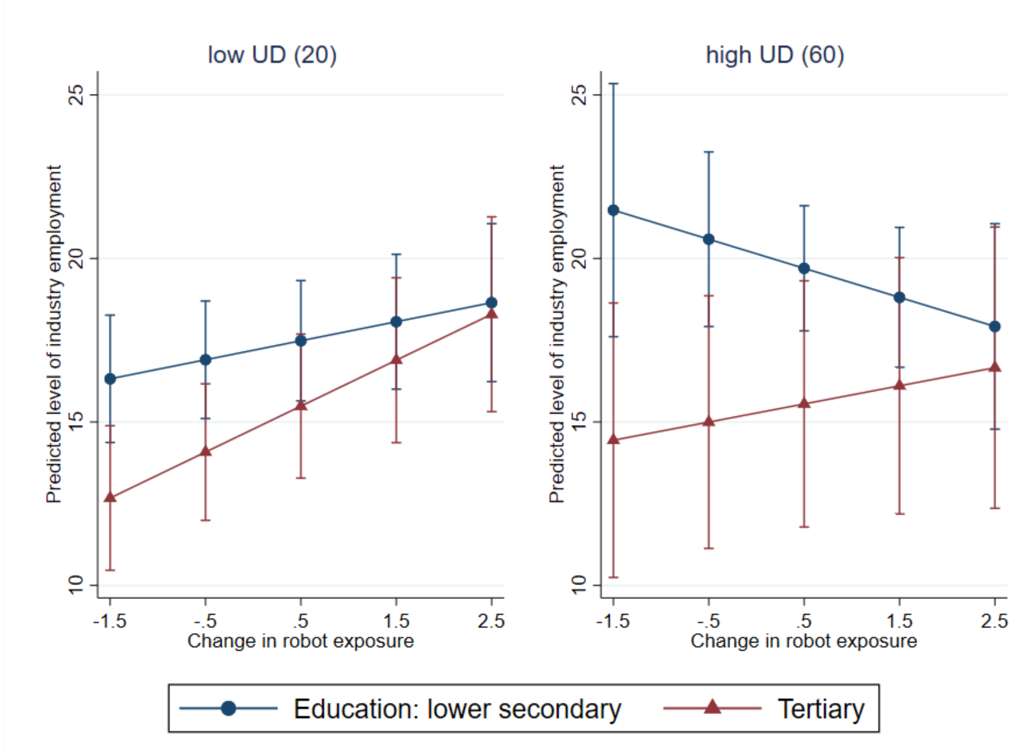
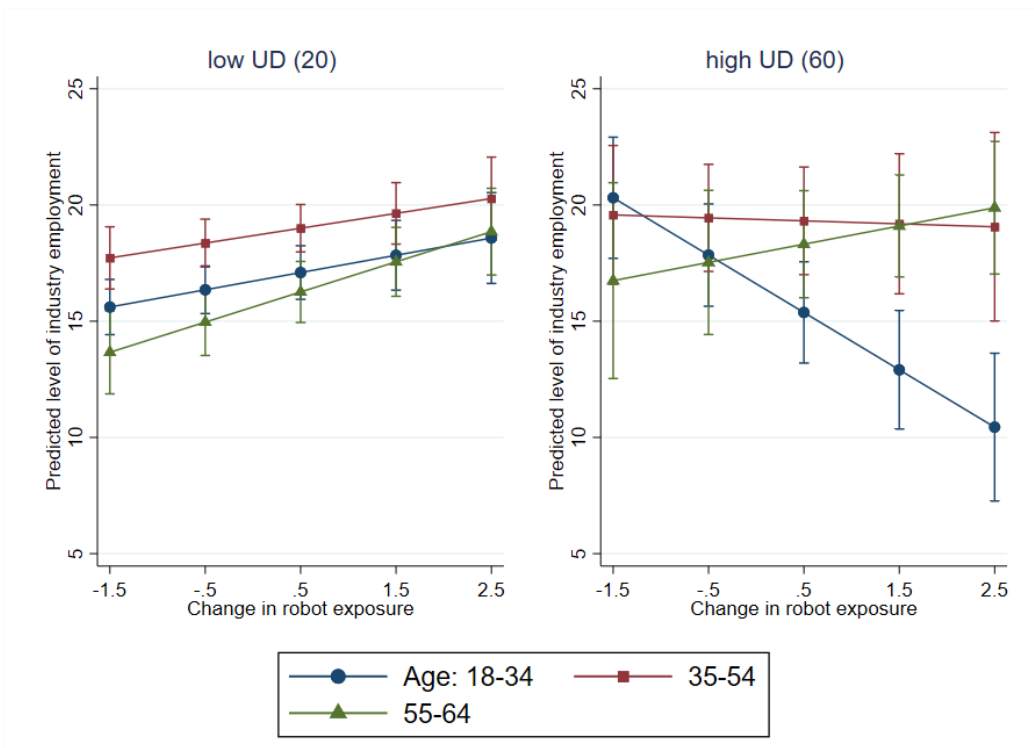


Figure 6. Predicted level of industry employment by robot exposure, union density and age.



Unemployment

The first set of results is largely consistent with the insider-outsider perspective, where stronger unions prioritise the employment trajectories of their current members in the face of technological change. As a second stage in our analysis, we consider whether the exclusion of low-educated and young workers from the industrial sector at high rates of change in robot exposure is reflected in rising unemployment for these groups. This enables us to assess whether unions' insider-outsider behaviour in the industry sector imposes negative externalities on the outsider workers. Notably, Dauth *et al.* (2021) argue that even if young and low-educated people are excluded from the industrial sector, this may result in an overall social gain since these cohorts tend to respond by pursuing further education. At the macro level, the authors conclude that robot exposure has a positive effect on occupational quality and skills upgrading, defined as the share of workers with college degrees.

Past research thus suggests that the displacement effect of robots on industrial employment is not necessarily reflected in a unilateral increase in unemployment rates, as both labour market institutions and welfare state functions such as active labour market policies coordinate the employment transitions of displaced workers (Chiacchio *et al.*, 2018). As employment increasingly rewards abstract skills and higher academic or professional qualifications, trade unions in particular have a vested interest in widening access to education and ensuring that workers possess the skills required by their jobs (Durazzi and Geyer, 2020). How does union strength moderate the effect of robot exposure on unemployment? Recall our two theoretical perspectives: according to PRT, stronger unions reduce unemployment for all groups of workers. According to I-O theory, unions prioritise the protection of old and high-educated workers from unemployment.

Table 2. REWB regressions predicting unemployment: robots, unions, demographics and interactions.

	DV: Change in unemployment			
	(1)	(2)	(3)	(4)
Robot exposure (within-country)	-2.260**	-3.141***	-3.121***	-2.990***
	(0.902)	(0.969)	(0.863)	(0.836)
Robot exposure (between-country)	-0.198***	-0.198***	-0.201***	-0.198***
	(0.065)	(0.064)	(0.064)	(0.064)
Union density (within-country)	0.104	0.127	0.124	0.127
	(0.105)	(0.099)	(0.099)	(0.098)
Union density (between-country)	0.013*	0.011	0.012*	0.011
	(0.008)	(0.007)	(0.007)	(0.007)
Robot exposure (within) * union density (between)		0.038**	0.028	0.036**
		(0.017)	(0.017)	(0.015)
Education (ref: upper secondary)				
Lower secondary	0.137	0.131	0.222	0.126
	(0.083)	(0.082)	(0.159)	(0.085)
Tertiary	-0.256	-0.219	-0.247	-0.209
	(0.210)	(0.211)	(0.220)	(0.215)
Age group (ref: 35-54)				
18-34	0.074	0.062	0.056	-0.033

	(0.064)	(0.063)	(0.064)	(0.101)
55-64	-0.067	-0.064	-0.063	0.036
	(0.047)	(0.047)	(0.048)	(0.075)
Robot exposure (W) * educ (lower secondary)			-0.574	
			(0.950)	
Robot exposure (W) * educ (tertiary)			0.846	
			(0.541)	
Union density (B) * educ (lower secondary)			-0.005	
			(0.003)	
Union density (B) * educ (tertiary)			0.001	
			(0.002)	
Robots (W) * unions (B) * educ (lower secondary)			0.034	
			(0.026)	
Robots (W) * unions (B) * educ (tertiary)			-0.014	
			(0.012)	
Robot exposure (W) * age (18-34)				-0.115
				(0.503)
Robot exposure (W) * age (55-64)				-0.328
				(0.751)
Union density (B) * age (18-34)				0.003
				(0.002)
Union density (B) * age (55-64)				-0.003
				(0.002)
Robots (W) * unions (B) * age (18-34)				0.006
				(0.012)
Robots (W) * unions (B) * age (55-64)				0.002
				(0.013)
Number of cohorts	10,173	10,173	10,173	10,173
Number of countries	28	28	28	28
R-squared	0.257	0.265	0.268	0.265

Notes: Robust standard errors clustered by country are given in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

The results in Table 2 lend some support for an insider-outsider interpretation, but not as strongly as the industry sector results. Firstly, the main effect of robot exposure on within-country changes in unemployment is unilaterally negative, sizeable and strongly significant. In the baseline scenario (Model 1), an increase of one robot per thousand workers is associated with a 2.26 percentage point decline in unemployment, which is more than three times greater than the increase in industry sector employment, suggesting positive spillover effects of robot exposure on employment across sectors. Moreover, the negative between-country effect suggests that countries with higher mean exposure to robots are associated with greater reductions in unemployment. The main effects for union density are positively signed but not statistically significant at conventional levels. In line with the insider-outsider hypothesis, in Model 2 the interaction effect for changes in robot exposure and mean union density is positively signed and significant at the 5% level, suggesting that the robot-induced reduction in unemployment is weaker in countries with greater union density.

In contrast with the results for industry sector employment, however, Models 3 and 4 find only weak evidence of divergent outcomes between education and age groups. The three-way interactions for robot exposure, union density and age come out as effectively zero, suggesting that age is not an explanatory factor for the weaker reduction in unemployment in strong-union contexts. This is confirmed by Figure 7: the predicted change in unemployment depends on union density but not on age group.

The three-way interactions for education, on the other hand, show divergent outcomes although the coefficients fail to reach conventional levels of statistical significance: the different signs for the low- and high-educated suggest that in strong-union contexts, robot exposure is associated with an increase in the share of low-skilled relative to high-skilled unemployment. Empirically, this is reflected in Figure 8 as no change in unemployment for workers with lower secondary education in the strong-union context, whereas tertiary educated workers experience a reduction in unemployment as robot exposure increases.

Figure 7. Predicted change in unemployment by robot exposure, union density and age.

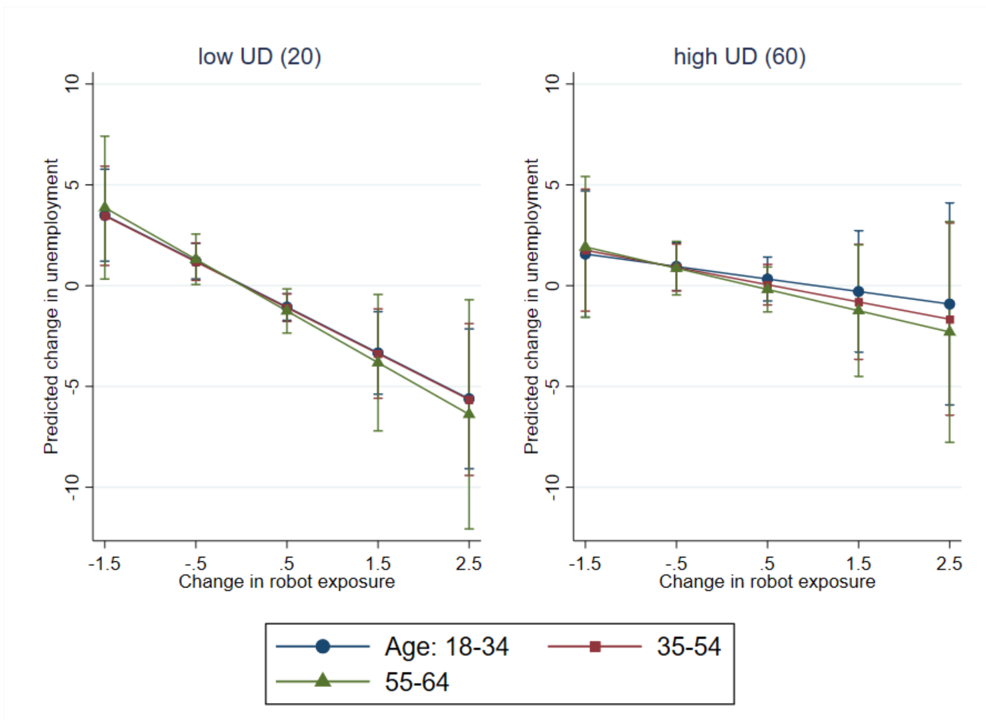
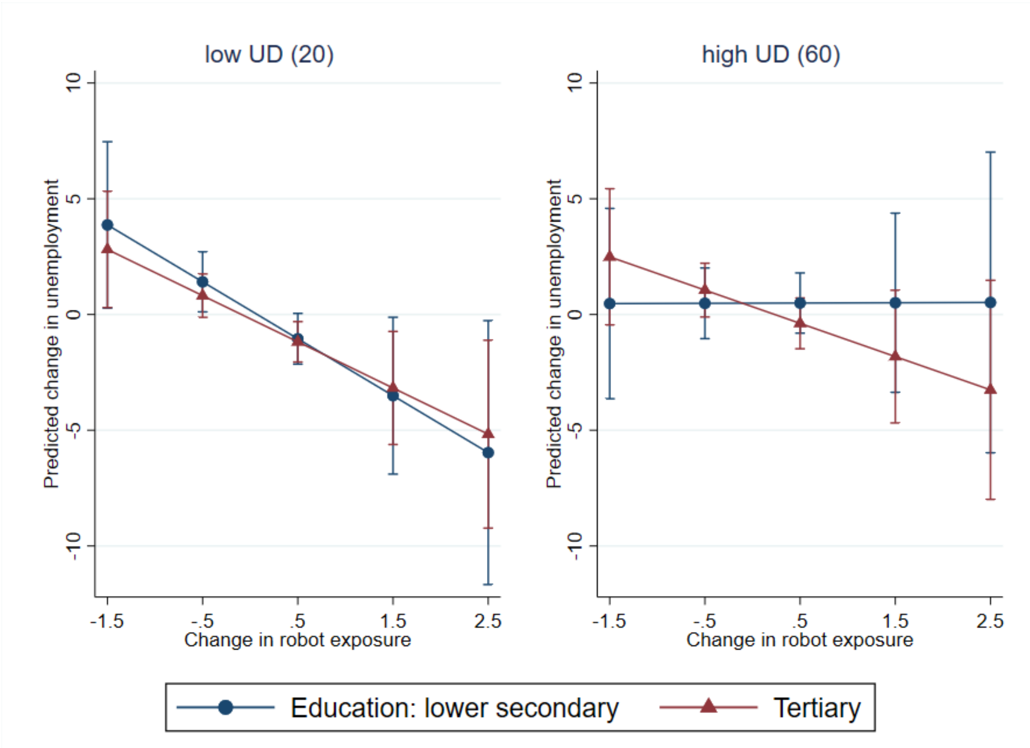


Figure 8. Predicted change in unemployment by robot exposure, union density and education.



The changes-on-levels graphs (Figures 9 and 10) support the interpretations from the changes-on-changes models, while again outlining a process of converging rather than diverging outcomes. Both in terms of age and education, the predicted levels of unemployment at high rates of change in robot exposure look similar in the weak-union and strong-union contexts, whereas at low or negative changes in robot exposure, unemployment is higher in the weak-union context. Therefore the faster rate of unemployment decline in the weak-union context reflects departures from a higher starting level, rather than lower absolute levels of unemployment at higher rates of change in robot exposure. In sum, even if stronger unions fail to reduce low-educated unemployment as exposure to robots increases, they do support the working class since the maximum level of low-educated unemployment in this context remains approximately equal to the minimum level in the weak-union context.

Figure 9. Predicted level of unemployment by robot exposure, union density and age.

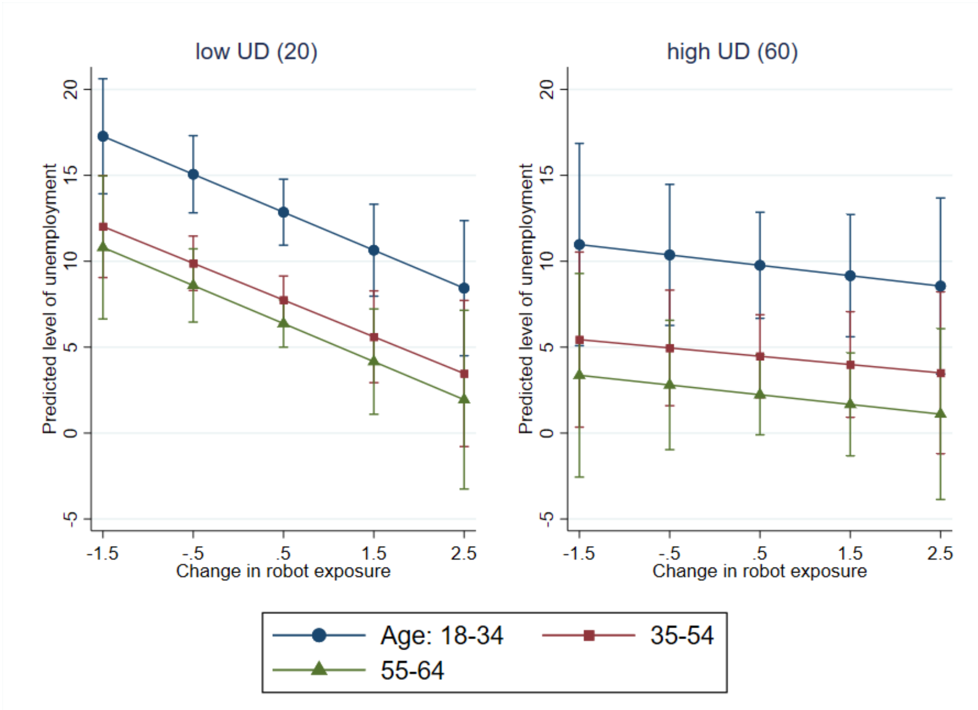
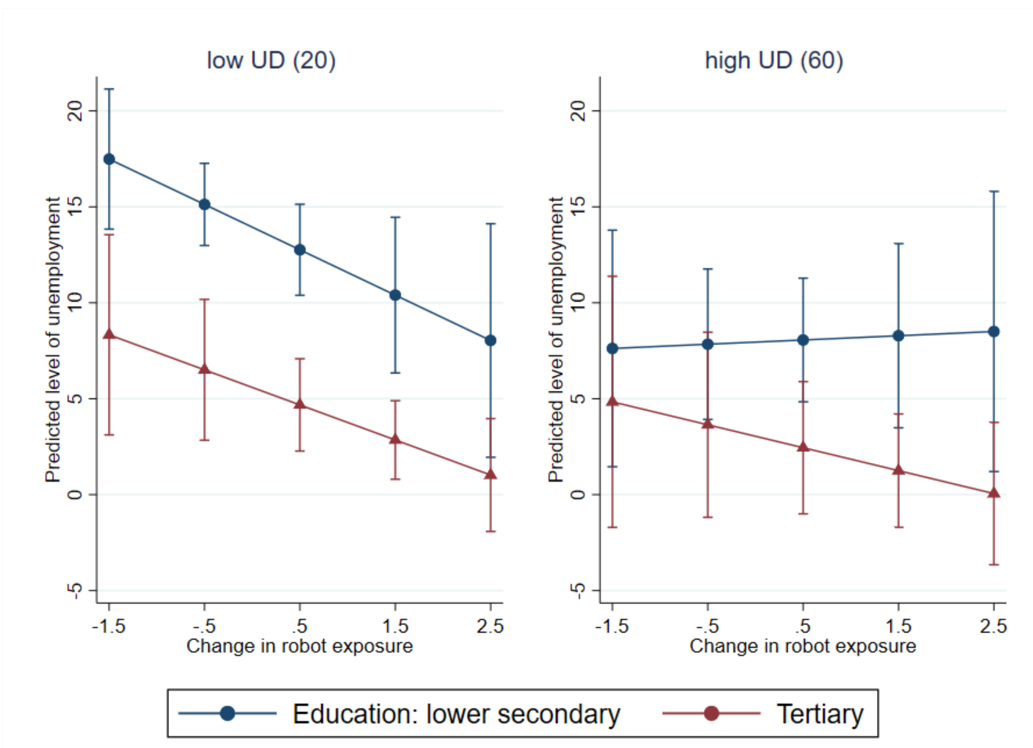


Figure 10. Predicted level of unemployment by robot exposure, union density and education.



In the context of PRT and I-O theory, these results suggest that the strength of unions in a country delivers both universal and group-specific benefits. There is no visible interaction between union density and age – regardless of union strength, workers under 35 are at an elevated risk of unemployment – but all age groups have a lower risk of unemployment when technological change is absent and unions are strong, compared to a context where unions are weak. Interestingly, the greater the rate of change in robot exposure, the more the weak-union and strong-union contexts approach each other in terms of low unemployment rates.

In terms of education, we find some evidence of a three-way interaction, as the gap in unemployment between high- and low-educated workers is the smallest when union density is high and change in robot exposure is zero or negative. This is due to a substantively lower level of low-educated unemployment in the strong-union context, which remains largely constant at varying rates of technological change.

To summarise these dynamics, one could say that stronger unions are good for high-educated workers everywhere, and good for low-educated workers particularly in the absence of technological change. This leads us to accept neither the PRT nor I-O hypotheses at face value – in the domain of unemployment, unions appear to pursue better outcomes for all groups of workers, but whether they succeed in reducing the risk of unemployment depends on the context of technological change. To the extent that robotisation and automation eliminate the demand for low-educated and routine employment, unions are unable to reverse this trend even if they are able to maintain the jobs of current routine workers until retirement (Parolin, 2020; Dauth *et al.,* 2021). Therefore, the reduced ability of unions to counteract low-skilled unemployment at high rates of change in robot exposure is not a sign of unions intentionally seeking dualisation, but rather the consequence of a highly specific 'economic problem load' where labour market returns to skill and education increase with advances in technology (Simoni and Vlandas, 2020). This suggests that in labour markets with insider-outsider dynamics, even unions with an egalitarian mission following the power resources perspective end up promoting insider-outsider outcomes. To contextualise our results, is therefore important to acknowledge that economic forces such as changes in labour demand shape technological unemployment alongside the agency of trade unions.

Robustness checks

To check the robustness of our findings, we replicate the models using alternative definitions for both own-country robot exposure and union strength. We also instrument own-country robot exposure with average robot exposure in a reference group of six countries at a similar level of technological progress, similarly to the "EURO5" group of countries which Acemoglu and Restrepo (2020) select as their instrumental variable. Our main terms of interest, the robots-unions interaction and the three-way interactions with demographic characteristics, maintain the same signs across all alternative specifications but their statistical significance is reduced, particularly in the instrumental variable models. The most robust finding is the exclusion of low-educated and young workers from industry sector jobs in strong-union contexts. The main and interaction effects with regard to unemployment fail to reach statistical significance in the instrumental variable models.

We specify union strength in two alternative ways: first, as an index of ‘inclusive unionism’ consisting of country-specific union density, bargaining centralisation and the Ghent system (Gordon, 2015) and second, by distinguishing five regime types based largely on the above metrics (Garnero, 2020). Results using the Gordon index are consistent with the union density indicator but the estimate size and statistical significance are marginally reduced, particularly for unemployment outcomes. This is because the Gordon index reduces the weight of outlier countries such as France which has very low reported union density compared to the real bargaining power of unions (Gordon, 2015). The regime type models reiterate the main results and offer some country examples: in the industry sector in particular, the returns to education are the strongest in the two most centralised and coordinated bargaining regimes, incorporating the Nordic countries and Austria, Belgium, Germany and the Netherlands. These checks increase our confidence in the main result of insider-outsider dualisation in the industrial sector accelerated by trade unions; whereas in the domain of unemployment, the moderating effect of unions seems marginal at best. Further research is needed to understand the dynamics of cross-sector employment spillovers and the role of trade unions at the sectoral level.

CONCLUSION

Both trade unions and industrial robots are surrounded by a series of conflicting beliefs and misunderstandings. With unions, the main question is whether they are a social good balancing out the weight of worker and employer interests, or an anchor on technological innovation and the flexible application of human resources; with robots, the debate boils down to whether they are going to destroy or preserve jobs in the long run. Still, it is difficult to imagine European and North American industrial sectors without either. Our results add the institutional perspective to the rapidly growing literature on the employment effects of robots, pointing out that automation creates winners and losers, and these distinctions are sharper where only one group is represented by organised labour.

Specifically, we investigate the moderating role of trade unions in shaping the effect of automation on industrial employment shares and unemployment. Applying a series of within-between random effects models on data from 28 high-income countries (27 European countries and the US) over 1998 to 2019, we are able to directly investigate the role of institutional context – in this case, union density as a broad measure of institutionalised worker power – in affecting the employment outcomes that have been at the centre of recent academic research and policy discourse (Acemoglu and Restrepo, 2020; Dauth *et al.*, 2021; Graetz and Michaels, 2018; Im, 2021). Our findings produce several conclusions.

First, we find that stronger unions contribute to a larger gap between high-educated and older ‘insiders’ and low-educated, young ‘outsiders’ in the industrial sector. Specifically, our models suggest a unilateral reduction in the industrial employment of workers under 35 compared to middle-aged and older workers, and a decline in the employment shares of lower secondary educated workers, in countries with high levels of union density and rapidly increasing exposure to industrial robots. To be sure, these divergent outcomes do not necessarily call for pessimism. For several decades, industrial robots and automation have been used to move humans away from dangerous, repetitive, or physically demanding tasks into complex non-manual roles such as production line supervision, logistics planning and management (Ebel, 1986; Fernandez, 2002; Eurofound, 2018). It is hardly in the interests of industrial unions or society at large to maintain jobs that could be performed more safely and efficiently by a robot. Nonetheless, the results clearly point to an exacerbation of the insider-outsider effect with accelerated exposure to industrial robots.

Second, our findings suggest that the exclusion of young and low-educated workers from industrial jobs in countries with strong trade unions does not directly correspond to increasing unemployment for these groups. Rather, we find evidence of union power resources contributing to a persistent working class advantage, as stronger unions are associated with a low and consistent level of low-educated unemployment at all rates of technological change. We also find that exposure to industrial robots by itself tends to reduce rather than increase unemployment across age groups and education levels. This finding, which presents a strong counterpoint against fears of mass technological unemployment, is nonetheless consistent with recent work in labour economics. This literature suggests that the jobs displaced by industrial robots are more or less fully compensated by the creation of new employment in the industry and service sectors, including many jobs directly connected with the new technologies (Blanas *et al.*, 2019; Dauth et al., 2021). Indeed, the burning question appears to be not how to deal with mass unemployment, but how to ensure that the new jobs in the service economy are as good as, or better than, those lost to automation. This is the place for policy and labour market institutions to enforce positive outcomes – widening access to professional training and education for labour market entrants and current workers, to ensure that people's skills are aligned with the demands of a postindustrial economy. 'Collective skill formation systems' as in Germany and Austria, where vocational education and training is designed to align with the demands of the industrial sector, are prime examples of coordinating school and employment policies in light of new technological developments (Durazzi and Geyer, 2020).

In broad terms, our findings point to a need for scholars of automation to incorporate institutional context into their analyses. Single-country studies, largely focused on the US or Germany, have been dominant in recent research on technological change. There are many advantages, of course, to single-country studies, such as more refined data and more in-depth case knowledge. Nonetheless, our findings suggest that neglecting context, such as the labour market institutions present in a country, can obscure a moderating influence with important consequences for interpreting the size and direction of the effect of automation on employment outcomes. The effects of automation on employment, in short, are conditional on the size and agency of organised labour.

We close with several limitations of our study. First, country-level measurements of union density can only approximate the dynamics at the sectoral level, even if this indicator is the most widely available. However, since the industrial sector tends to be one of the most strongly unionised, we are content with the application of country-level indicators. Second, despite controlling for time effects and confounders at the country and individual levels, we cannot fully exclude the possibility of omitted variable bias. Therefore we acknowledge that the models should be not read as direct causal interpretations. Third, in a large-n comparative study it is only possible to approximate the complex theoretical dynamics and the actions taken by different types of unions facing exposure to automation, such as the three modes of acceptance developed in our stylised examples. Future research on the automation-labour interaction could look at case studies at the level of individual countries or manufacturing plants to better sketch out the extent to which the insiders and outsiders have divergent preferences on automation.

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