Automation, Trade Unions and Atypical Employment•

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Abstract

We study the effect of automation technologies – industrial robots, software and databases – on the incidence of involuntary atypical employment in 13 EU countries between 2006 and 2018. Robots do not affect total employment rate but significantly increase the involuntary atypical employment share, mainly through fixed-term work. Software and databases increase total employment and are neutral for atypical employment. Higher trade union density mitigates the robots' impact on atypical employment, while employment protection legislation plays no role. Using historical decompositions, we attribute 1-2 percentage points of the 15% average atypical employment share in our sample to automation.

Keywords: robots, automation, atypical employment, trade unions

JEL Classification: J23, J51, O33

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1. Introduction

The ongoing technological transformation, characterised by the rapid diffusion of automation and digital technologies, profoundly reshapes labour markets and the nature of work. While technological progress has historically been associated with productivity gains and economic growth, the current wave of automation and digitisation raises concerns about its consequences for employment, job stability and quality (Acemoglu and Restrepo, 2019; Autor, 2015). Evidence suggests that the aggregate labour market effects of automation are more benign in European countries (Bachmann et al., 2024; Battisti et al., 2023; Dauth et al., 2021; Gregory et al., 2022) and Japan (Adachi et al., 2024; Deng et al., 2023) than in the United States (Acemoglu and Restrepo, 2022, 2020; Di Giacomo and Lerch, 2025). Yet, automation continues to create winners and losers across sectors and skill groups.

Automation affects not only the quantity of jobs but also their quality. Workers displaced from routine-intensive occupations often experience occupational downgrading (Autor and Dorn, 2013; Cortes et al., 2020; Goos and Manning, 2007), increased insecurity (Yam et al., 2023), and deteriorating well-being (Nikolova et al., 2024). Those who remain employed can suffer from wage losses (Acemoglu and Restrepo, 2022) and increased work intensity (Antón et al., 2023). As automation may reduce workers' bargaining power and increase firms' demand for flexibility, the rise of atypical employment—involuntary temporary, part-time, or underemployed work—has become a key concern (Doorn and Vliet, 2022). Unlike previous technological waves, this shift coincides with a sustained increase in non-standard employment across high-income countries (ILO, 2016; OECD, 2015).[1] Understanding how automation influences both the incidence and quality of employment has thus become central to the debate on the future of work. An important question is whether automation technologies have contributed to the rise of involuntary atypical employment forms. As these forms tend to reduce workers' health, productivity, and well-being, evaluating automation's impact on their incidence is essential for understanding the multidimensional consequences of automation.[2]

Conceptually, different automation technologies can affect employment and job quality through distinct mechanisms. Industrial robots are labour-saving technologies that substitute for workers in routine manual tasks (Acemoglu and Restrepo, 2020; Bessen et al., 2025; Dauth et al., 2021). Robots rarely augment labour (Acemoglu and Restrepo, 2019), although they may have overall positive employment effects if the productivity gains they bring expand markets (Graetz and Michaels, 2018; Gregory et al., 2022). When firms adopt robots, they may seek additional flexibility by expanding short-term or contingent work arrangements to adjust labour inputs more easily (Fornino and Manera, 2022). Workers affected by automation, especially those engaged in routine tasks, may be hired temporarily to meet the demand volatility in production, and laid off immediately afterwards (Abraham and Taylor, 1996; Bentolila and Saint-Paul, 1994). As a result, robots may have neutral effects on total employment but negative effects on job quality, reflected in higher shares of atypical employment. Software and other information and communication technologies (ICT), however, are more often labour-augmenting: they reduce communication and information processing costs (Calvino and Virgillito, 2018),

[1] We use the terms non-standard employment and atypical employment interchangeably.

[2] Workers in non-standard jobs are more exposed to stress originating from uncertainty concerning employment and income stability (Bender and Theodossiou, 2018). It may particularly affect workers in low-skilled occupations who face a higher risk of displacement and have lower bargaining power.

enhancing productivity in non-routine cognitive and analytical tasks and complementing human skills (Albinowski and Lewandowski, 2024; Almeida et al., 2020; Autor et al., 2003). They may, therefore, increase employment while leaving job quality unaffected (Menon et al., 2020).

Labour market institutions can mediate these dynamics. Trade unions can counteract the erosion of workers' bargaining power by constraining employers' use of precarious contracts, supporting retraining, and redistributing productivity gains (Bryson et al., 2013; Devicienti et al., 2018), improving the outcomes of workers with precarious contracts (Litwin and Shay, 2022; Svarstad, 2024). Additionally, they narrow the gaps between routine and non-routine workers (Kostøl and Svarstad, 2023). Higher union density, therefore, can potentially improve protection of those most vulnerable to automation and mitigate the adverse effects of robots on job quantity and quality. In contrast, stringent employment protection legislation (EPL), while designed to safeguard workers from dismissal, may unintentionally exacerbate dualism by pushing adjustment pressures onto temporary or non-standard workers (Boeri and Garibaldi, 2007). Moreover, a more stringent EPL may discourage layoffs by making them more costly for firms, but its influence on working conditions may be less direct than that of collective bargaining. Thus, institutional capacity—especially collective bargaining— may shape the multifaceted consequences of automation on the labour market.

Against this conceptual backdrop, this paper studies how automation technologies—specifically industrial robots and software and databases—affect the incidence of involuntary atypical employment in 13 European Union countries between 2006 and 2018.[3] We define involuntary atypical employment as the sum of involuntary fixed-term, involuntary part-time, and underemployment forms, drawing on the European Union Labour Force Survey (EU-LFS) microdata. We link these labour outcomes to sectoral measures of technology adoption from the International Federation of Robotics (IFR, 2021) and EU KLEMS, following the task displacement framework of Acemoglu and Restrepo (2022). We use instrumental variables based on sectoral technological frontiers to address potential endogeneity in technology adoption. We use variation across demographic groups within countries for identification (Acemoglu and Restrepo, 2022; Doorley et al., 2023). We categorise workers into 30 demographic groups in each country, defined by age, gender, and education level. We regress changes in involuntary atypical employment share across demographic groups against changes in their exposure to task displacement due to automation technologies. This exposure is adjusted based on each group's sectoral and occupational employment structures, including their specialisation in routine jobs that are more vulnerable to automation. Essentially, our instrument assesses the exposure of demographic groups to automation technologies as if the industries they concentrate in followed the technological frontier.

Our results show that industrial robots increase the share of involuntary atypical employment, mainly through fixed-term contracts, while having no significant effect on the total employment rate. In line with our conceptual framework, the main channel is involuntary fixed-term employment, which firms tend to use to increase the flexibility of hiring. The higher incidence of atypical employment may also reflect a higher labour churn, as

[3] Belgium, the Czech Republic, Germany, Estonia, France, Greece, Hungary, Italy, Lithuania, the Netherlands, Romania, Spain, and Sweden. The country coverage reflects data availability which we discuss in detail in section 2.

temporary contracts may reduce unemployment spells at the cost of lower job stability and quality (Berton and Garibaldi, 2012; Booth et al., 2002).[4]

In contrast, software and databases have positive effects on total employment and neutral effects on the atypical employment share. Moreover, higher trade union density substantially mitigates the impact of robots on atypical work, whereas employment protection legislation has no moderating effect. These findings suggest that the institutional context—particularly collective bargaining—plays a crucial role in shaping how automation affects job quality. Our results are stable across different model specifications and robust to changing the construction of the instrumental variable.

Evaluating the economic significance of automation as a driver of changes in involuntary atypical employment with a counterfactual analysis, we find that its overall contribution was noticeable in some European countries. It amounted to a 1-2 percentage point increase in involuntary atypical employment in countries with the largest technology adoption between 2006 and 2018, namely Central and Eastern European countries, Greece, and the Netherlands. However, it was slightly negative in Germany, Sweden, and Belgium. Without trade unions, the automation-driven increase of the involuntary atypical employment share would have been even larger in the Czech Republic and the Netherlands. In countries with negative contributions, it was primarily due to a strong moderating role of high trade union density.

This paper contributes to three strands of literature. First, it expands research on automation by focusing on involuntary atypical employment, a dimension of job quality often overlooked in studies of automation's aggregate employment and wage effects. Damiani et al. (2023) argued that robots may increase the risk of temporary jobs in industries with low knowledge accumulation. However, they only covered six European countries. This paper covers a larger group of countries, studies robots and digital technologies (software and databases), and comprehensively defines atypical employment. It also complements existing evidence that robots can reduce job quality, as indicated by increased work intensity (Antón et al., 2023) and diminished work meaningfulness and autonomy (Nikolova et al., 2024).

Second, we provide evidence that trade unions can play a crucial role in mitigating automation's adverse labour market effects. The literature has long argued that labour market institutions may shape cross-country differences in automation's impact (Dauth et al., 2021), and collective bargaining was associated with a lower impact of industrial robots on unemployment (Leibrecht et al., 2023). However, causal empirical studies remain scarce. This paper shows that trade unions may be key in mitigating automation-driven increase in involuntary atypical employment. At the same time, we find no such effects for employment protection legislation, opposing theoretical arguments that increasing labour protection (decreasing hiring flexibility) would increase workers' comparative advantage compared to automation (Fornino and Manera, 2022).

Third, we contribute to the literature on factors behind atypical employment growth in Europe. Traditionally, productivity slowdowns (Wasmer, 1999) and asymmetric employment protection reforms conducive to dual

[4] Although non-standard employment is better for workers than unemployment (Borowczyk-Martins and Lalé, 2018), a high presence of atypical contracts harms workers' careers, job quality, and equality (OECD, 2015). Answering if involuntary fixed-term jobs and other forms of atypical employment constitute a bridge between unemployment and full employment is beyond the scope of this paper. The evidence from meta-studies of literature is mixed, but it suggests that they are more often dead ends if unemployment is higher and when forms of contracts are more precarious (Filomena and Picchio, 2022).

labour markets (Boeri and Garibaldi, 2007; Dolado et al., 2002) have been cited as drivers of non-standard employment, especially fixed-term employment. As atypical employment has grown also in countries that did not implement such reforms (Katz and Krueger, 2019; OECD, 2015), globalisation and technological progress have come to the fore as factors undermining workers' bargaining power and working conditions (Autor, 2015; OECD, 2019). However, the empirical literature on technological progress and non-standard employment has been mostly correlational and descriptive. Kahn (2018) argued that high employment protection could fuel labour market polarisation as firms may use temporary workers primarily for manual and routine tasks that are automatable. Doorn and Vliet (2022) showed that middle-skilled workers tend to accept poorer working conditions as they lose a comparative advantage in polarising labour markets. However, they did not quantify the role of technology directly. We show that automation has contributed to the rising incidence of precarious jobs in Europe, although it explains a minor share of atypical employment growth.

The remainder of the paper is structured as follows. Section 2 describes the data and methodology. Section 3 presents results and covers robustness checks. Section 4 concludes and provides policy recommendations.

2. Data and methodology

2.1. Atypical employment definition

Several definitions of atypical employment exist, and most capture job precariousness (Broughton et al., 2016). Many studies have focused on the involuntary forms of atypical employment (Damiani et al., 2023; Doorn and Vliet, 2022; Hyytinen and Rouvinen, 2008), which, by definition, stem from factors other than workers' preferences. This distinction is important as, for instance, part-time employment can reflect individual preferences for balancing care responsibilities with work duties, but it may also result from the inability to find a full-time job (Haines et al., 2018). We focus on the latter. As an undesirable situation, often related to material hardship and uncertainty about future labour outcomes, involuntary atypical employment is inherently depriving (Inanc, 2018). Such manifestations of precarious employment as underemployment, involuntary part-time, and involuntary fixed-term work correlate with distress (Allan et al., 2022). While studying the relationship between involuntary atypical employment and deprivation or job quality is beyond the scope of this paper, there is evidence that involuntary forms of atypical employment systematically exhibit a higher risk of precariousness and deprivation than full-time, open-ended contracts (Broughton et al., 2016).

We assume that technological displacement can influence the incidence of involuntary atypical employment. We acknowledge that technology adoption may also impact preferences and voluntary forms of non-standard employment. However, we focus on involuntary atypical employment, which can be more clearly interpreted in terms of precariousness and deprivation.

We use the EU-LFS for 2006 and 2018, the main cross-country survey in the EU that provides data on employment outcomes, to define involuntary forms of atypical employment. We single out (i) involuntary-part-time employment – individuals who work less than 30 hours[5] per week and state they wanted to work full-time

[5] The EU-LFS distinguishes between usual and actual hours worked. To define the part-time workers, we refer to the usual hours which express the standard schedule of individuals' working hours. However, for individuals, whose working hours vary, we use actual hours, as no information on usual hours is available. Moreover, some workers with positive usual hours declare zero actual hours, probably due to the survey taking place during holidays or paid leaves.

but could not find such a job; (ii) involuntary fixed-term employment – workers on fixed-term contracts who want an open-ended contract; and (iii) underemployment – workers who wish to work more hours than they currently do. To define the outcome, we used the usual reported weekly hours worked. We classify a worker as having an involuntary atypical job if the individual worked in any of these atypical forms. The EU-LFS distinguishes such workers from those who work part-time or on a temporary contract because they wish to. However, it does not single out some atypical forms that are likely involuntary and precarious, such as bogus / spurious self-employment and the so-called zero-hour contracts.

The EU-LFS is a repeated cross-sectional dataset that does not allow studying worker transitions between standard and atypical employment. Therefore, in line with the literature on labour market effects of automation (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Graetz and Michaels, 2018), we focus on long differences – changes in the share of atypical contracts in employment between 2006 and 2018 – that reflect cumulative, long-term impacts of technology adoption. Following Acemoglu and Restrepo (2022) we use the 'demographic group' framework and calculate the relative changes in atypical employment shares by countries and groups defined by education (low – levels 0-2 of the International Standard Classification of Education, ISCED; middle – levels 3-4 of ISCED; and high – level 5 of ISCED), age group (20-29, 30-39, 40-49, 50-59, 60+) and gender (men and women).[6] Therefore, the identifying variation results from differences in atypical employment share changes within demographic groups, which drive the overall change in atypical employment – according to the standard shift-share decomposition, within-group effects contribute 95% of total changes in atypical employment shares in our sample.

2.2. The measurement of technological displacement

We study two key automation technologies that can substitute for human work: industrial robots and information and communication technologies (ICT), specifically software and databases. Robots have been found to deteriorate labour market outcomes, at least for some socio-economic groups, in the US and European countries (Acemoglu and Restrepo, 2020; Albinowski and Lewandowski, 2024; Antón et al., 2023; Dauth et al., 2021; de Vries et al., 2020). ICT, including software, has driven labour market polarization (Almeida et al., 2020; Blanas, 2024; Cnossen, 2025; Jerbashian, 2019). Since Autor et al. (2003), it is common to assume that both these types of technologies tend to be routine-replacing: they substitute people in performing routine tasks but may complement workers performing non-routine tasks. This conceptual framework informs the construction of our exposure variables.

[6] Using variation between local labour markets (Acemoglu and Restrepo, 2020; Anelli et al., 2021; Antón et al., 2023; Dauth et al., 2021), sectors (Aksoy et al., 2021; Albinowski and Lewandowski, 2024; de Vries et al., 2020; Graetz and Michaels, 2018) or occupations (Bachmann et al., 2024) are alternative, common approaches to identifying labour market effects of technology adoption. However, using the variation between demographic groups allows capturing effects resulting from both technology-driven changes between sectors and occupations as well as within them. It also alleviates the issue of worker selection that affects estimates within occupations or industries (Böhm et al., 2022). The local labour market approach has similar advantages, but the regional information in the EU-LFS is too crude to allow precise identification of local labour markets.

We construct the measure of technology adoption on the country-industry level. Following Acemoglu & Restrepo (2020), for each industry *i* in country *c,* we define the adjusted penetration by automation technology (industrial robots, software and databases), $\mathbf{Tech_{i,c}}$, as:

$$\mathrm{AP\_Tech_{i,c}} = \frac{\mathrm{M_{i,c,2018}} - \mathrm{M_{i,c,2006}}}{\mathrm{L_{i,c,2006}}} - \frac{\mathrm{Y_{i,c,2018}} - \mathrm{Y_{i,c,2006}}}{\mathrm{Y_{i,c,2006}}} * \frac{\mathrm{M_{i,c,2006}}}{\mathrm{L_{i,c,2006}}} \quad (1)$$

where:

- $\mathrm{M_{i,c,t}}$ – represents the given technology stock (industrial robots, software and databases) in *industry i* in *country c* in year *t*;
- $\mathrm{L_{i,c,t}}$ – represents employment in the *industry i* in *country c* in year *t*;
- $\mathrm{Y_{i,c,t}}$ – represents the total output of *industry i* in *country c* in year *t*.

This adjusted penetration measure incorporates changes in the sectors' gross output, so adjusted technology penetration is positive if the increase in the technology stock is larger than the increase in the industry's size. This adjustment is essential in our cross-country sample that includes countries with varying growth rates.

We use the International Federation of Robotics (IFR, 2021) data on the operational stock of industrial robots[7] and EU KLEMS data on net capital stock in software and database technology.[8]

We aggregate the adjusted technology penetration to transform the variable from industry to demographic group level. Because of the skewed distribution of technology adoption across sectors, researchers commonly take a (natural) logarithm of technology variables (Acemoglu & Restrepo, 2022). However, the adjusted penetration measure takes non-positive values when the increase in a given technology stock (or value) is below the output growth in that industry.[9] Therefore, we use the inverse hyperbolic sine transformation (IHS) which offers an alternative to a natural logarithm as it works similarly with large values but also applies to non-positive ones (Norton, 2022). The drawback of the IHS transformation is that coefficients cannot be interpreted as either elastic or semi-elasticities.

Next, for each demographic group, *g,* and country, *c*, we calculate the task displacement measure (TDA) for each technology as a weighted exposure of the demographic group to a given technology, namely:

$$\mathrm{TDA_{g,c}} = \sum_{i \in I} \omega_{g,c}^{i} * \frac{\omega_{g,i,c}^{R}}{\omega_{i,c}^{R}} \, \mathrm{IHS(AP\_Tech)_{i,c}} \quad (2)$$

[7] According to the International Organization for Standardization (ISO 8373:201), an industrial robot is an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications".

[8] We use the variables presented in national currencies in 2015 chained prices. Using the Eurostat data on 2015 average annual exchange rates, we re-calculate the capital and output data to Euro.

[9] For example, manufacturing of textiles, wearing apparel, leather and related products in France (Industrial Robots), Arts, entertainment, recreation and other service activities in Spain (Software & Databases).

where:

- $\omega_{g,c}^{i}$ - refers to the share of demographic group *g* employed in sector *i* in country *c*;
- $\frac{\omega_{g,i,c}^{R}}{\omega_{i,c}^{R}}$ – represents the relative share of routine workers of the *g* demographic group in industry *i* among all routine workers in industry *i* in country *c*.

To calculate routine employment shares, we assign 2-digit occupations (according to the International Standard of Occupations, ISCO) into occupational task groups, using the allocation developed by Lewandowski et al. (2020). Following Doorley et al. (2023), we use the EU Structure of Earnings Survey (EU-SES) to calculate detailed sectoral employment structures of demographic groups, $\omega_{g,c}^{i}$.[10] Thus, the variation of task displacement variable across demographic groups reflects differences in industrial employment structures and specialisation in routine occupations within industries.

2.3. Measures of labour market institutions

Institutional factors can shape the labour market effects of macroeconomic factors and shocks (Blanchard and Wolfers, 2000). In the context of technology adoption and atypical employment, we are particularly interested in the potential role of trade unions. Therefore, we aggregate the 2006, 2008 and 2010[11] waves of the European Social Survey (ESS) to the demographic group level and calculate trade union density, namely the shares of unionised workers by demographic group. Neither the EU-LFS nor the EU-SES include information on workers' trade union membership. However, estimating regressions across demographic groups allows the straightforward merging of indicators based on different surveys. Importantly, the ESS provides a within-country variation of union density. We use the country-level data on union density from the OECD/AIS database as a robustness check.

The potential effect of the trade union, however, might serve as a proxy for broader institutional labour protection. Thus, as a robustness check, we also use the Employment Protection Legislation (EPL) indicators provided by the OECD. In particular, the EPL indices cover the strictness of the regulation of open-ended and temporary contracts. We also calculate the difference between the two, which is sometimes used to capture a possible advantage of regular workers in labour protection (Högberg et al., 2019).

Our final sample includes 13 countries covered by all required data: Belgium, the Czech Republic, Germany, Estonia, France, Greece, Hungary, Italy, Lithuania, the Netherlands, Romania, Spain, and Sweden.[12]

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[10] The EU-SES data include 2-digit NACE (Statistical Classification of Economic Activities in the European Community) industry codes, much more granular than 1-digit codes available in the EU-LFS,

[11] This increases sample size and compensates for incomplete country coverage of the 2006 ESS. As trade union density changes rather slowly, the 2008 and 2010 data provide good proxy for 2006 outcomes.

[12] The EU-SES data are unavailable for Austria and Denmark. The EU-KLEMS data are unavailable for Bulgaria, Cyprus, Croatia, Ireland, Luxembourg, Malta, Poland, and Portugal. Slovenia was not covered in the 2006 EU-SES. The data quality for Slovakia drew concern because of outliers regarding technology adoption. For Latvia, the data from IFR is scarce with respect to sectoral division of industrial robots.

2.4. Econometric methodology

We estimate the following equation to assess the impact of technology adoption on the change in atypical employment:

$$\Delta \mathrm{AE}_{g,c} = \beta_{\mathrm{Soft}} * \mathrm{TDA}_{\mathrm{Soft}_{g,c}} + \beta_{\mathrm{Robots}} * \mathrm{TDA}_{\mathrm{Robots}_{g,c}} + \beta_{\mathrm{Robots}_{\mathrm{Union}}} * \mathrm{TDA}_{\mathrm{Robots}_{g,c}} * \mathrm{TradeUnion}_{g,c} + \delta \mathrm{X}_{g,c} + \alpha_{age_{g,c}} + \alpha_{gender_{g,c}} + \alpha_{country_{g,c}} + \varepsilon_{g,c} \quad (3)$$

where $\Delta \mathrm{AE}_{\mathbf{g,c}}$ represents the change in the share of involuntary atypical employment in total employment of a demographic group *g* in the country c between 2006 and 2018. $\mathrm{X}_{\mathbf{g,c}}$ is a matrix of the selected covariates. We use LASSO regularisation as a variable selection model, using Ahrens et al. (2020) method that corrects for the possible omitted variable bias in standard LASSO procedures[13]. We control for country, gender, and age fixed effects in the simplest specification. Based on the LASSO results, we additionally control for the share of migrants, the employment share of small firms (up to 9 employees); the share of manufacturing employment (all in 2006), change in value added per worker between 2008-2016, exposure to the 2008 financial crisis (output change between 2008 and 2009), and the share of workers in trade unions. To contextualise the impacts on atypical employment against the overall labour market effects, we also estimate the effects of automation technologies on employment rate change between 2006 and 2018, using the same specifications as for atypical employment.

Technology adoption may be endogenous to labour market shocks or driven by other, potentially unobserved factors affecting involuntary atypical employment (e.g. exposure to Chinese competition or changes in firms' market power). Thus, the OLS estimates of equation (3) may be biased. To account for the endogeneity bias, we employ GMM-IV estimation. For both types of automation technologies, we follow the state-of-the-art methodology of "technology frontier" instrument previously applied in several studies of automation (Acemoglu and Restrepo, 2020; Albinowski and Lewandowski, 2024; Antón et al., 2023; Bachmann et al., 2024; Damiani et al., 2023; Dauth et al., 2021; Nikolova et al., 2024), slightly modifying its construction. Since Acemoglu and Restrepo (2020), researchers have often used a fixed set of countries to summarise information on technology adoption in high-income countries by industry. However, we apply a more flexible selection: for each sector, we identify the technology leader with the highest level of technology adoption among countries with available data. For example, Japan is the leader in industrial robots applied in computer manufacturing. Appendix Tables A1-A2 present detailed information on the instrument selection. We refer to our instrument as the technological leaders instrument:

$$\mathrm{AP\_Tech}_i^{IV} = \max_{c \in C} \mathrm{AP\_Tech}_{i,c} \quad (4)$$

[13] We employed an IV-LASSO approach to preserve the instrumental variable structure. The candidate variables considered by LASSO included: the share of natives working in the selected demographic group in 2006; the share of employees in small firms (fewer than 20 employees) in 2006; industry shifters; the share of employees in manufacturing; exposure to the 2008 financial crisis; trade union density; and changes in age-, education-, and gender-fixed effects. The final models reported below include only the variables retained in the optimal specification. Details of the LASSO procedure are provided in the Online Appendix.

The instrument variable (max AP_Tech) is reweighted by the same demographic group specialisation in routine tasks as the treatment variable. Supplementary Figure S1 shows a strong and significant correlation between the technology variables and their instruments, sufficient for the relevance assumption. In the case of software and databases, only six out of 21 sectoral technology leaders were out-of-sample, while 10 of 21 of the sectoral leaders were in the Netherlands. For industrial robots, nine out of 16 sectoral technology leaders were out-of-sample, while four were in the Netherlands. Since the overrepresentation of the Netherlands in the instrument can contaminate the results, as a robustness check, we re-estimate our model with an instrument based on a set of out-of-sample European countries (Austria, Denmark, Finland, and Slovenia), which served to construct instruments in other studies (Acemoglu and Restrepo, 2020; Doorley et al., 2023).

Our identification strategy relies on the exogenous shares in routine tasks of particular demographic groups. At the same time, we treat the technology shocks as endogenous and instrument them in line with equation (4). Following Borusyak et al. (2025) recommendations for testing the assumptions behind the shift-share design, we (1) calculate the Rotemberg weights attributed to each industry, (2) report which industries were most decisive in explaining the variance of the endogenous variables, and (3) test the exogeneity of the shares used to construct the shift-share treatment variable.

These tests show that our estimates are robust to shares' exogeneity and that our results are not driven by a selective subset of industries, validating our identification assumptions. The Rotemberg weights for industrial robots, software, and databases (Appendix Tables A4-A5) show that most sectors contribute to the variation in technology adoption.[14] Moreover, technology adoption is generally well-balanced regarding standard demographic group characteristics (Appendix Table A6). However, some significant differences between men and women and less- and more educated individuals emerge, especially for robot exposure. Therefore, we will control for subgroup fixed effects in our regression to minimise the influence of these confounders. Finally, involuntary atypical employment has not changed differently in groups with higher initial specialisation in routine tasks – the correlation between the shares and the change in involuntary atypical employment is statistically insignificant (Appendix Table A7). These tests show we can credibly exploit the reweighted industry-shock variation in technology adoption.

To assess the potential moderating role of trade unions, we interact task displacement variables with the moderator – the demographic group's union density. Our approach is similar to that of Bryson et al. (2013) or Bachmann et al. (2024), though implemented at the demographic group rather than the worker level.

Finally, we calculate a counterfactual scenario to evaluate the economic significance of automation as a driver of atypical employment. Using the GMM-IV estimated coefficients, we calculate the linear prediction of the atypical employment change at a demographic group level (baseline). Then, we predict the same outcome, assuming no technological level change between 2006 and 2018. Comparing this counterfactual scenario – the change in atypical employment if technology adoption remained at the 2006 level – with the baseline scenario isolates the contribution of software, databases, and industrial robots to changes in involuntary atypical employment shares in European countries between 2006 and 2018.

[14] For industrial robots, we can attribute at maximum 20% to manufacturing of machinery equipment. For software and databases, we can attribute at maximum 10% to manufacture of basic metals, fabricated metal products, computer/electronic/optical products, electrical equipment, and machinery.

3. Results

3.1. Descriptive evidence

Table 1 presents descriptive statistics of the variables used. On average, the share of workers in atypical employment increased by 2.05 percentage point (around a 20% increase) between 2006 and 2018. The incidence of involuntary fixed-term contracts and underemployment increased most notably, with fixed-term employment growing by 31.3%. At the same time, the number of involuntary part-time jobs increased by only 2.8%. Regarding the penetration of automation technologies, it was slightly larger and more diverse across demographic groups in the case of robots. The sample is balanced in terms of gender. Most workers are between 40 and 59 years old and have a middle education level.

Table 1. Descriptive Statistics

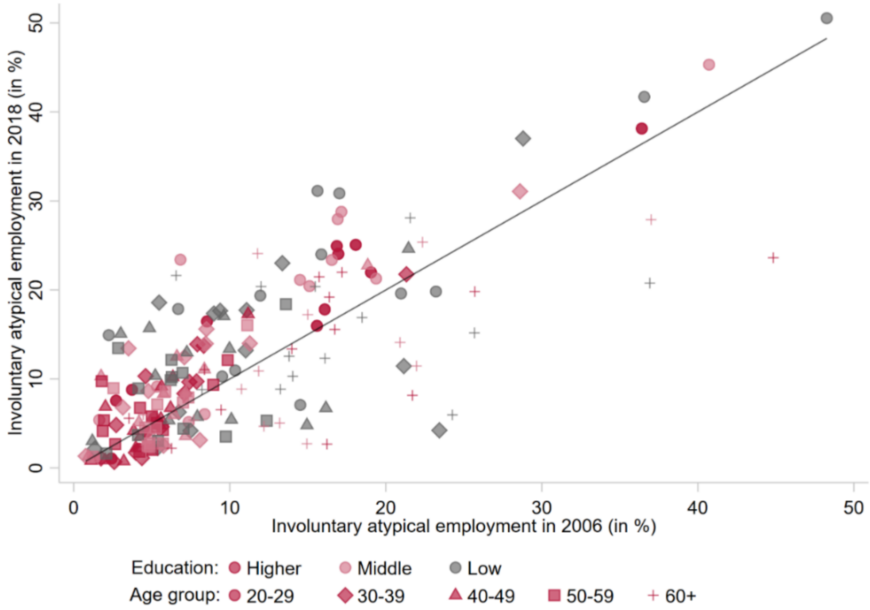
	Mean	Standard Deviation	Change (in %)	Observations
Dependent Variable				
Change in involuntary atypical employment	2.05	5.01	19.2	390
Change in involuntary part-time employment	0.08	2.47	2.80	390
Change in involuntary fixed-time employment	0.78	2.10	31.3	390
Change in underemployment	0.79	4.13	11.3	390
Task Displacement				
Penetration of Industrial Robots	0.17	0.23	-	390
Penetration of Software & Databases	0.12	0.14	-	390
Control Variables				390
Gender: woman	0.46	0.50	-	390
Basic education	0.23	0.42	-	390
Secondary education	0.51	0.50	-	390
Tertiary education	0.26	0.44	-	390
Age: 20-29	0.18	0.38	-	390
Age: 30-39	0.26	0.44	-	390
Age: 40-49	0.29	0.45	-	390
Age: 50-59	0.22	0.41	-	390
Age: 60+	0.06	0.23	-	390
Initial atypical employment	10.73	8.70	-	390
Manufacturing share	27.10	13.40	-	390
Financial crisis exposure	-7.41	5.95	-	390
Trade Union density	16.80	17.80	-	390
Small firms' employees share in 2006	20.40	10.40	-	390
Natives in 2006	91.40	6.90	-	390

Note: *Observations weighted with their within-country employment shares (each country has equal weight in the analysis).*

Source: Own elaboration based on EU-SES, EU-LFS, ESS, EU-KLEMS and IFR data.

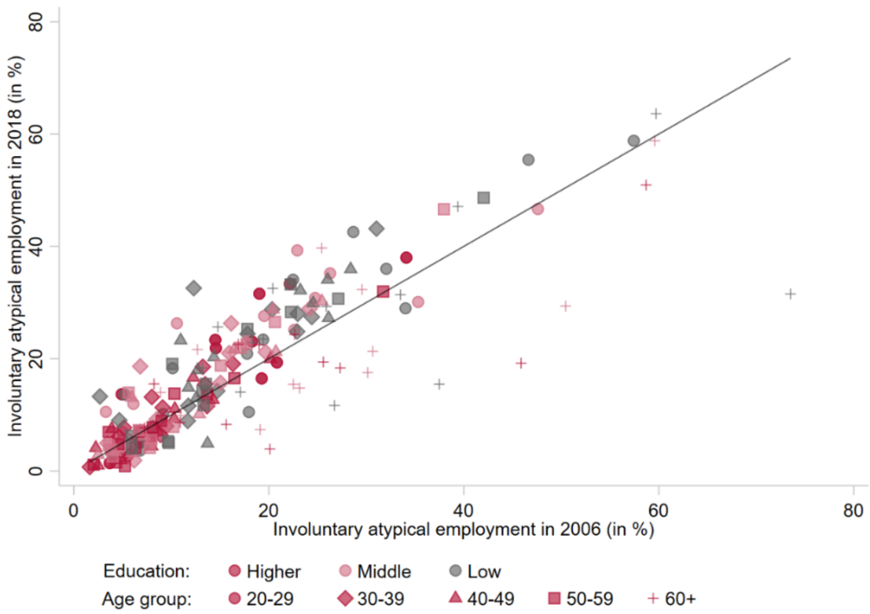
Between 2006 and 2018, involuntary atypical employment increased among most demographic groups. Among men, such an increase was particularly pronounced among those aged 20-29, while among older workers (aged 60 or more), the incidence of atypical employment declined in several countries (Figure 1). Among women, the incidence of atypical employment has increased among most groups, except for women aged 60 or more (Figure 2). For both men and women, education was not a factor clearly distinguishing trends in atypical employment, although higher-educated workers recorded a lower incidence of atypical employment than the other groups (Figures 1-2).

Figure 1. Change in involuntary atypical employment by country and demographic group among men



Source: Own calculations based on EU-LFS data.

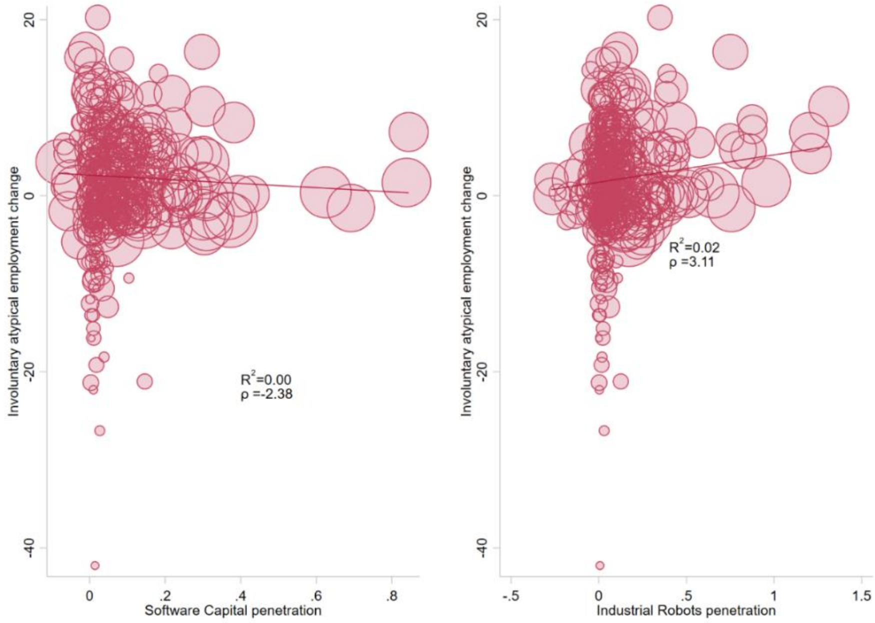
Figure 2. Change in involuntary atypical employment by country and demographic group among women



Source: Own calculations based on EU-LFS data.

Across countries and demographic groups, a positive correlation exists between the change in employees' share in atypical employment and industrial robot penetration and a negative relationship between software and database penetration and change in involuntary atypical employment (Figure 3). However, both correlations are statistically insignificant.

Figure 3. Technology penetration and change in atypical employment



Source: Own elaboration based on EU-LFS data

3.2 The effects of software, databases and industrial robots on atypical and total employment

We start by discussing the OLS results. We find a significant, positive association between task displacement with industrial robots and change in involuntary atypical employment (Table 2). We also find a significant moderating effect of trade unions, as evidenced by the negative coefficient on the interaction between robots and trade union density.[15] At the same time, the association between software and databases and atypical employment is insignificant. We also estimate a model with interaction between software and databases and trade union density, which proved insignificant, so we do not include it for simplicity. These results are available upon request.

As the OLS results might be biased, we focus on the GMM-IV results from now on. For industrial robots, the GMM-IV results are statistically significant and quantitatively similar to the OLS results, albeit slightly smaller (Table 2). The interaction between robots and trade union density is significant at the 10% level (column 5 of Table 2), suggesting that unions could have played a role in mediating the impact of robots on working

[15] We estimated a logistic regression explaining the probability of trade union membership controlling for gender, age, education, size of the firm, migration status and country- industry and occupation fixed effects. It shows significant cross-country differences in the likelihood of trade union membership that cannot be attributed to industrial and occupational structure (Appendix Figure A1).

conditions. The GMM-IV results for software and databases are slightly larger in absolute terms than the OLS results, but noisy and not statistically significant at conventional levels (Table 2). The IHS transformation of technological variables complicates assessing the strength of these estimated effects. Therefore, we discuss the economic significance in subsection 3.4 based on the counterfactual historical analysis.

To locate the effects of automation on atypical employment in the broader pattern of its labour market effects, we re-estimate our models for the employment rate change between 2006 and 2018. Again, the GMM-IV results show contrasting effects of robots, software and databases: the latter increased total employment rates (significantly in most specifications), while the former had no significant impact (Table 2). These patterns are consistent with previous findings that, in European countries, robots had moderate or neutral effects on employment (Bachmann et al., 2024; Dauth et al., 2021; Klenert et al., 2023), contrasting with adverse impacts in the US (Acemoglu and Restrepo, 2020). They are also in line with evidence of ICT's benign effects on labour market outcomes in Europe (Albinowski and Lewandowski, 2024).

Combining our insignificant results for total employment rates and the positive effect on atypical employment share suggests that automation with industrial robots deteriorates job quality, as measured with the incidence of involuntary atypical employment, rather than quantity. Our findings complement previous evidence of robots reducing job quality as measured by work intensity (Antón et al., 2023) and work meaningfulness and autonomy (Nikolova et al., 2024). Trade union density appears to mitigate the effects of robots on the composition of jobs in atypical and typical employment forms, but not on the total employment rate. At the same time, adopting software and databases has more beneficial effects on the labour market as it increases the employment rate while having no impact on atypical employment shares.

Next, we provide additional evidence on the mitigating role of trade unions. Countries with higher trade union density may generally exhibit more stringent labour market institutions, such as employment protection legislation that may discourage firms from hiring workers on non-standard contracts. Therefore, we use alternative measures of labour market institutions and check if they exhibit the same mediating role as trade union density in our baseline specifications. Specifically, we use the OECD Employment Protection Legislation (EPL) index for open-ended contracts (column 2 of Table 3), EPL for temporary contracts (column 3) and the difference between EPL for open-ended and temporary contracts (column 4). We also use country-level trade union density (column 5) instead of demographic-group-level union density calculated with the ESS data. Column 2 of Table 3 repeats our main specification (column 5 of Table 2).[16] Appendix Table A3 compares these indicators for countries studied and shows their cross-country correlations with trade union density based on the ESS.

These additional results show that our findings are specific to trade unions. Using the country-level trade union density (column 2 of Table 3) provides results closely resembling our baseline results. At the same time, we do not find significant results for any of the EPL measures, neither in OLS nor IV regressions (columns 3-5 of Table 3). In line with our conceptual framework, we interpret these findings as suggestive evidence that trade unions can protect workers from the automation-driven increases in involuntary non-standard work arrangements.

[16] We omit Romania due to the missing EPL data.

Table 2. The effect of industrial robots, software and databases on the incidence of atypical jobs and employment, 2006-2018

	(1)	(2)	(3)	(4)	(5)
Atypical employment rate change					
	OLS	OLS	OLS	OLS	OLS
Software and Databases Displacement	-1.13	-0.91	-0.92	-0.97	-3.99
	(2.05)	(2.10)	(2.10)	(2.09)	(2.57)
Industrial Robots Displacement	4.17**	3.58**	3.57**	3.27*	4.46**
	(1.29)	(1.25)	(1.28)	(1.27)	(1.12)
Industrial Robots Displacement x Trade Union density					-0.15*
					(0.05)
	GMM-IV	GMM-IV	GMM-IV	GMM-IV	GMM-IV
Software and Databases Displacement	-2.65	-1.83	-1.85	-3.08	-5.52
	(2.07)	(2.16)	(2.23)	(2.60)	(3.70)
Industrial Robots Displacement	3.87**	3.07*	3.01*	3.14**	4.08***
	(1.25)	(1.26)	(1.21)	(1.05)	(1.13)
Industrial Robots Displacement x Trade Union density					-0.19
					(0.10)
Employment rate change					
	GMM-IV	GMM-IV	GMM-IV	GMM-IV	GMM-IV
Software and Databases Displacement	13.77**	10.43*	9.73*	8.17*	10.51*
	(4.90)	(4.36)	(4.01)	(3.53)	(4.40)
Industrial Robots Displacement	-0.09	1.44	-0.82	-1.19	-2.08
	(2.37)	(2.44)	(2.95)	(2.6)	(2.68)
Industrial Robots Displacement x Trade Union density					0.18*
					(0.09)
Native workers share (2006)	No	Yes	Yes	Yes	Yes
Small firm share (2006)	No	Yes	Yes	Yes	Yes
Industry shifters	No	No	Yes	Yes	Yes
Manufacturing share (2006)	No	No	No	Yes	Yes
Financial crisis	No	No	No	Yes	Yes
Mean of Software and Databases	0.12	0.12	0.12	0.12	0.12
Mean of Industrial Robots	0.17	0.17	0.17	0.17	0.17
Mean of involuntary atypical employment share change	2.05	2.05	2.05	2.05	2.05
Mean of total employment rate change	1.42	1.42	1.42	1.42	1.42
Kleibergen-Paap rk Wald F-statistic	10.23	9.79	9.56	11.00	9.42
Observations	390	390	390	390	390

*Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors (clustered at the country level) in parentheses. We use standardised weights, based on the EU-LFS employment structure in 2018, that give each country equal weight. The first stage F-statistics for software and databases first-stage was 44.41, for industrial robots 164.97 and for interaction between industrial robots and trade union density was 59.02. All models include controls for country, gender, education and age group fixed effects, and trade union density.*

Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

Table 3. The effect of industrial robots and software and databases on the incidence of atypical jobs, with alternative labour protection measures, 2006-2018 (GMM-IV estimates)

	(1)	(2)	(3)	(4)	(5)
`	Baseline (ESS trade union density)	OECD trade union density	EPL for open-ended contracts	EPL for temporary contracts	EPL difference open-ended vs. temporary contracts
Software and Databases Displacement	-4.77	-3.90	-2.27	-3.05	-2.53
	(3.30)	(3.22)	(2.28)	(2.04)	(2.06)
Industrial Robots Displacement	4.76***	3.01*	1.03	2.23	4.17**
	(1.68)	(1.45)	(3.04)	(2.62)	(1.27)
Industrial Robots Displacement x Trade Union Density	-0.17	-0.24**			
	(0.10)	(0.12)			
Industrial Robots Displacement x EPL for open-ended contracts			0.98		
			(0.98)		
Industrial Robots Displacement x EPL for temporary contracts				1.31	
				(1.84)	
Industrial Robots Displacement x EPL difference between open-ended and temporary contracts					-0.16
					(0.69)
First Stage Kleibergen-Paap F-Statistic	9.42	7.48	9.17	7.91	7.78
Mean of outcome	2.35	2.35	2.35	2.35	2.35
Mean of Software and Databases	0.13	0.13	0.13	0.13	0.13
Mean of Industrial Robots	0.17	0.17	0.17	0.17	0.17
Observations	360	360	360	360	360

*Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors (clustered at the country level) in parentheses. We use standardised weights, based on the EU-LFS employment structure in 2018, that give each country equal weight. All models follow the specification of column (5) in Table 2 and include controls for country, gender and age group fixed effects, trade union density, native workers share (2006), small firms workers share (2006), industry shifters, manufacturing share (2006), and financial crisis.*

Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

The Online Appendix presents a range of robustness checks. First, we ran a placebo test with other types of modern capital, specifically, the exposure to net capital stock in brand intellectual property and net capital stock in training. We find no significant effects for these variables (Supplementary Table S1), which suggests that our results are specific to automation. Second, we estimated a battery of leave-one-out regressions omitting one country at a time, finding that our results are generally stable across sub-samples (Supplementary Figure S1). Third, we calculated the instrument using out-of-sample European countries instead of our preferred technological leader approach. The results are robust to this change (Supplementary Table S2). Finally, we verified the correlation between our technological shocks and a potential confounder, migration flows, finding no significant correlation between them (Supplementary Figure S2 and Supplementary Table S3).

3.3 The effects of software, databases and industrial robots on fixed-term, part-time employment and underemployment

To shed more light on the potential channels of automation's impact on involuntary non-standard employment, we re-estimate our models for particular sub-categories of involuntary atypical employment – involuntary fixed-term, involuntary part-time and underemployment. For brevity, we focus on the GMM-IV specifications with interactions between robots and trade union density (as in column 5 of Table 2).

We find only a significant effect on involuntary fixed-term employment (Table 4). The effects of robots on involuntary part-time and underemployment are both positive but insignificant at conventional levels. These results are consistent with our conceptual framework, suggesting that automation might increase the use of atypical contracts that enable firms to adjust labour input more flexibly, such as fixed-term contracts (Caggese and Cuñat, 2008; Fernandes and Ferreira, 2017; Goux et al., 2001). The effects of software and databases on particular categories of non-standard employment are insignificant, in line with the results on the broader category of atypical jobs.

Table 4. Technology exposure and involuntary part-time, fixed-term employment and underemployment, 2006-2018

	Involuntary fixed-term	Involuntary part-time	Underemployment
	GMM-IV	GMM-IV	GMM-IV
Software and Databases Displacement	-2.04	-2.23	-3.48
	(1.53)	(2.39)	(3.10)
Industrial Robots Displacement	2.07*	1.82	1.96
	(0.82)	(1.22)	(1.55)
Industrial Robots Displacement x Trade Union	-0.10**	0.01	-0.08
	(0.04)	(0.03)	(0.05)
First Stage Kleibergen-Paap F-Statistic	39.9	39.9	39.9
Mean of outcome	0.78	0.08	0.79
Mean of Software and Databases	0.12	0.12	0.12
Mean of Industrial Robots	0.17	0.17	0.17
Observations	390	390	390

*Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors (clustered at the country level) in parentheses. We use standardised weights, based on the EU-LFS employment structure in 2018, that give each country equal weight. All models include controls for country, gender, education and age group fixed effects and trade union density, native workers share (2006), small firms workers share (2006), industry shifters, manufacturing share (2006), and financial crisis.*
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

3.4 The contribution of technology to atypical employment change

Next, we use a counterfactual historical decomposition to quantify the economic significance of the estimated effects. First, we use the IV coefficients from column 5 of Table 2 to predict the change in involuntary atypical employment between 2006 and 2018. Second, we calculate an alternative prediction assuming that the penetration with a given type of automation remained at the 2006 level. Since our penetration measures are adjusted for sector-specific growth, it is equivalent to assuming investment levels required to retain the automation capital intensity from 2006. The difference between these two predictions allows for disentangling technology's contribution to changes in atypical employment between 2006 and 2018. Finally, for robots we predict a third scenario assuming that trade union density equals zero in all countries, which allows quantifying the mediating impact of unions. We use estimates for both robots, and software and databases for consistency and completeness, though the latter are insignificant and should be interpreted cautiously.

The total contribution of automation to atypical employment share changes between 2006 and 2018 varies from about a 0.14 percentage point decline in Sweden to more than a 1.50 percentage point increase in Germany and the Czech Republic (Table 5). The contributions are generally larger for robots and in countries that recorded larger growth in robot adoption. The mediating effect of trade union density emerges as an important factor behind the cross-country differences in the contribution of automation to atypical employment. Trade unions have alleviated the impact of robots on atypical employment in most countries, especially in highly unionised countries such as the Netherlands and Belgium, where trade union density is high (Table 5). Comparing the change in atypical employment share that we attribute to automation with the actual change in particular countries between 2006 and 2018 shows that in most countries, the contribution of automation was relatively small.

Table 5. Estimated contribution of technology adoption and trade unions' mitigation effect to the change in the share of workers in atypical employment, 2006-2018

Country	Industrial Robots Contribution	Trade Unions Mitigating Effect	Software & Databases Contribution	Total Contribution of Automation	Recorded Change in Atypical Employment Share
Lithuania	0.91	-0.13	-0.90	-0.12	-2.48
Hungary	1.34	-0.28	-1.33	-0.27	-1.85
Romania	0.96	-0.43	-0.33	0.20	-1.56
Italy	1.29	-0.51	-0.63	0.15	-0.12
Estonia	0.93	-0.15	-0.50	0.29	0.19
Czech Republic	3.00	-0.53	-2.14	0.33	0.50
Sweden	0.71	-1.15	-0.02	-0.46	1.06
Germany	-0.26	0.14	-0.53	-0.65	2.93
Belgium	1.81	-2.21	-0.52	-0.93	3.84
Spain	0.53	-0.06	-0.50	-0.02	3.92
France	1.05	-0.23	-0.89	-0.06	4.66
Netherlands	2.69	-1.21	-0.78	0.70	5.73
Greece	0.85	-0.09	-0.08	0.67	9.87

Note: Countries are sorted by the recorded change in typical employment share between 2006 and 2018.
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

4. Conclusions and policy implications

This paper examined how different types of automation technologies—industrial robots and software and databases—affect employment outcomes and job quality across 13 European countries between 2006 and 2018. Using sectoral data on technology adoption and microdata from the EU Labour Force Survey, we used an instrumental variable approach to evaluate their impact on the incidence of involuntary atypical employment—a proxy for job precariousness. Our approach distinguished between robots as generally labour-saving technologies and software and databases as rather labour-augmenting technologies and explored how labour market institutions mediate their effects.

Consistent with the conceptual framework, we find that software and databases—representing digital, labour-augmenting technologies—have positive employment effects and neutral impacts on atypical work. By enhancing workers' productivity in non-routine and cognitive tasks, software complements rather than substitutes labour, strengthening rather than eroding bargaining power. In contrast, industrial robots—representing labour-saving automation—exert neutral effects on total employment but increase the share of involuntary atypical employment, particularly fixed-term contracts. This asymmetry reflects firms' search for flexibility in adjusting labour inputs under technological change. When robots replace workers in performing routine manual tasks, firms may rely more heavily on temporary contracts to manage production volatility, while workers, facing weakened bargaining power and reduced outside options, increasingly accept precarious work. Thus, in European countries we studied, automation driven by robots affects the quality rather than the quantity of employment. Our findings complement previous evidence that robots can reduce job quality in such dimensions as work intensity (Antón et al., 2023), meaningfulness, and autonomy (Nikolova et al., 2024).

We have also found evidence that institutional factors shape these outcomes. Trade union density significantly mitigates the impact of robots on the atypical employment share, consistent with theories emphasising collective bargaining as a mechanism to defend job quality and distribute technological gains more equitably (Bryson et al., 2013; Devicienti et al., 2018). By contrast, employment protection legislation (EPL) shows no moderating effect, suggesting that legal employment rigidities are less effective in protecting workers from automation-induced precarity. This finding aligns with the evidence that EPL may reinforce dualism by prompting firms to shift adjustment pressures toward temporary workers (Boeri and Garibaldi, 2007).

Our historical decompositions show that robot adoption accounts for an estimated 1-2 percentage point increase in atypical employment between 2006 and 2018 in countries with high automation diffusion, particularly in Central and Eastern Europe, Greece, and the Netherlands. However, these contributions are small compared with the changes recorded in 2006-2018 and with the 2018 atypical employment shares in the countries studied. Hence, while automation contributed to rising precarity, it is not the dominant driver. Notably, without union presence, the adverse impact of robots would have been considerably stronger, underscoring the protective role of collective bargaining. Hence, our results suggest that institutional capacity rooted in collective representation, rather than regulatory strictness, shapes the extent to which automation undermines job quality.

From a policy perspective, these results suggest that strengthening collective bargaining coverage and promoting social dialogue can help workers adjust to technological change while maintaining job quality. In contrast, relying solely on stricter employment protection may fail to address the growing divide between secure and precarious employment. Ensuring that the gains from automation are broadly shared requires policies that reinforce both workers' bargaining power and their capacity to adapt to new technologies.

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Appendix: Additional tables and figures

Table A1. The selection of countries to Software & Databases technological leaders instrument

Country	Industry	Gross Output growth	Software & Databases growth	Employment growth
Denmark*	A	4.7%	142.3%	16.7%
The Netherlands	B	-39.7%	-9.0%	0.0%
Denmark*	C	9.8%	116.5%	-16.6%
The Netherlands	C10-C15	20.9%	95.3%	1.4%
France	C16-C18	-15.5%	40.3%	-33.2%
Denmark*	C19-C23	64.5%	227.8%	9.1%
The Netherlands	C24-C28	25.3%	118.0%	-0.4%
France	C29-C32	7.9%	60.3%	-15.9%
Spain	D	22.4%	225.0%	-8.8%
Spain	D-E	17.2%	159.6%	26.6%
The Netherlands	E	41.9%	211.1%	9.7%
The Netherlands	F	14.9%	99.3%	-19.1%
Austria*	G	16.1%	74.7%	9.6%
Sweden	H_J	44.6%	236.1%	16.6%
The Netherlands	I	16.1%	67.2%	43.1%
Denmark*	K	4.4%	114.1%	-2.5%
The Netherlands	L-N	34.9%	198.9%	22.9%
The Netherlands	O	14.9%	79.8%	7.6%
The Netherlands	P	11.8%	91.9%	6.8%
The Netherlands	Q	31.5%	176.2%	15.0%
Denmark*	R-S	3.7%	113.0%	11.4%

Note: *The countries marked with (*) indicate countries out-of-sample*

Source: Own elaboration based on EU-KLEMS data

Table A2. The selection of countries for the Industrial Robots technological leaders Instrument

Country	Industry	Gross Output growth	Stock of Industrial Robot growth	Employment growth
The Netherlands	A-B	14%	2369%	17%
Sweden	C	18%	2395%	1675%
The Netherlands	C10-C12	23%	17%	-96%
The Netherlands	C10-C15	21%	126%	52%
Denmark*	C13-C15	-20%	296%	1538%
Italy	C16-C18	-21%	571%	-60%
Austria*	C19-C23	51%	109%	722%
Austria*	C24-C25	26%	531%	-80%
Japan*	C26	-3%	317%	-94%
The Netherlands	C27	12%	2650%	-27%
Sweden	C28	-5%	342%	18%
Slovenia*	C29-C30	57%	-[a]	-43%
Slovenia*	D	21%	1717%	-7%
Denmark*	E	-7%	-	-9%
Slovenia*	F	-24%	1200%	-9%
Austria*	P	18%	670%	32%

Note: [a]*The initial value of the operational stock of industrial robots in Slovenia in 2006 equals 0.* The countries marked with (*) indicate countries out-of-sample.

Source: Own elaboration based on EU-KLEMS data.

Table A3. Descriptive statistics on institutional measures of labour protection

Country	Union density (%, ESS)	Union density (%, OECD)	EPL Open-ended contracts (OECD)	EPL Temporary contracts (OECD)
Belgium	43.1	53.6	1.73	2.25
Czech Republic	7.1	17.4	3.26	1.44
Germany	13.5	19.8	2.60	1.13
Estonia	6.6	12.0	1.81	3.00
Spain	7.6	16.4	1.96	2.47
France	6.6	22.6	2.50	3.13
Hungary	7.22	18.0	1.59	1.25
Italy	17.0	34.0	2.93	2.00
Lithuania	5.79	9.3	2.63	2.38
The Netherlands	20.1	19.4	3.24	0.94
Romania	15.9	36.0	-	-
Sweden	58.4	67.0	2.45	0.81
Cross-country correlation with union density based on ESS	*1*	*0.94*	*-0.07*	*-0.42*

Source: Own elaboration based on ESS and OECD data.

Table A4. Shift-share Rotemberg industry weights for industrial robots

Industry	Rotemberg Weight
Manufacture of machinery and equipment n.e.c.	0.202
Manufacture of food products; beverages and tobacco products	0.131
Manufacture of furniture and other manufacturing	0.127
Manufacture of basic metals and fabricated metal products	0.124
Mining and quarrying	0.111
Printing and reproduction of recorded media	0.110
Manufacture of motor vehicles and other transport equipment	0.093
Manufacture of textiles, wearing apparel, leather and related products	0.045
Manufacture of wood and paper products	0.042
Education	0.015

Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS and IFR data.

Table A5. Shift-share Rotemberg industry weights for software & databases

Industry	Rotemberg Weight
Manufacture of basic metals, fabricated metal products, computer/electronic/optical products, electrical equipment, and machinery	0.109
Manufacture of motor vehicles, other transport equipment, furniture, and other manufacturing	0.108
Transportation, storage, information, and communication	0.100
Manufacture of coke, refined petroleum, chemicals, pharmaceuticals, rubber, plastic, and non-metallic mineral products	0.076
Mining and quarrying	0.074
Electricity, gas, steam, air conditioning supply, water supply, sewerage, waste management	0.073
Education	0.066
Human health and social work activities	0.065
Arts, entertainment, recreation, and other service activities	0.064
Real estate, professional/scientific/technical activities, administrative and support services	0.063
Financial and insurance activities	0.045
Construction	0.043
Manufacture of wood and paper products, printing and reproduction of recorded media	0.038
Manufacture of food products, beverages, tobacco, textiles, wearing apparel, and leather products	0.037
Wholesale and retail trade; repair of motor vehicles and motorcycles	0.022
Accommodation and food service activities	0.015

Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS and IFR data.

Table A6. Treatment balance across demographic group characteristics

	Software & Databases Treatment	Industrial Robots Treatment
Gender (Women base category)		
Men	-0.007	-0.102***
	(0.016)	(0.022)
Age (20-29 base category)		
30-39	0.015	0.051
	(0.015)	(0.027)
40-49	0.018	0.050
	(0.015)	(0.027)
50-59	0.018	0.015
	(0.015)	(0.025)
60+	-0.010	-0.022
	(0.016)	(0.026)
Education (Higher Education base category)		
Low Education	-0.074***	0.125***
	(0.017)	(0.030)
Middle Education	-0.016	0.121***
	(0.016)	(0.028)
Controls	Native share (2006), Share of small firms (2006), Industry shifters, Share of demographic group in manufacturing, Financial crisis exposure	

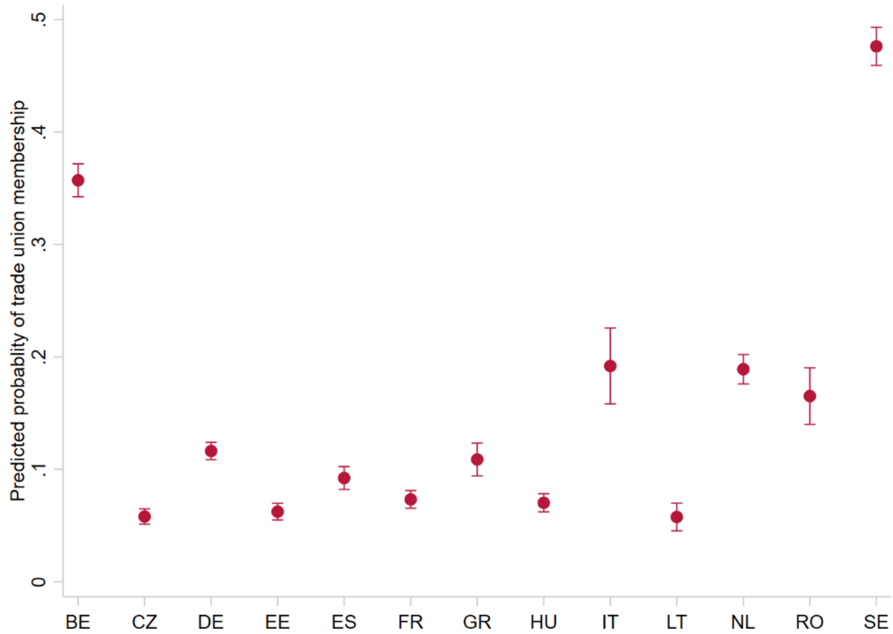
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS and IFR data.

Table A7. Correlation between the outcome and demographic group specialisation in routine tasks shares

	Change in Involuntary atypical employment share	
Routine task specialization	Industrial Robots	Software & Databases
Routine task specialization	5.421	5.222
	(6.291)	(6.862)
Controls	Gender, country, age fixed effects, Native share (2006), Share of small firms (2006), Industry shifters, Share of demographic group in manufacturing, Financial crisis exposure	

Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS and IFR data.

Figure A1 Predicted probability of trade union membership, by country



Notes: controlling for gender, age, education, size of the firm, migration status, and country- industry and occupation fixed effects.

Source: Own calculations based on ESS data

Automation, Trade Unions and Atypical Employment

Supplementary Materials

LASSO Selection Method

A large group of variables may affect the change in involuntary atypical employment change. In this multidimensional setting and small sample, we used IV-LASSO (Instrumental Variables, Least Absolute Shrinkage and Selection Operator), proposed by Ahrens et al. (2020). The first part of obtaining IV-LASSO selection is to set up the list of possible instruments and control variables to be placed in the model. LASSO uses the algorithm, similar to the idea of optimization under constraints – minimize the residual squared errors, conditional on the coefficients sum. In practice, the model values "economic significance model" – variables with little contribution to the model prediction are excluded during the estimation process. Consequently, using LASSO requires standardization of the controls and instruments to obtain coefficient results in the same scaling space.

IV-LASSO first uses LASSO or Post-LASSO to select instruments that are most predictive of the endogenous regressors in the first stage, effectively shrinking the coefficients of weak or irrelevant instruments to zero. This step ensures that only the most relevant instruments are retained. In the second stage, the selected instruments are used in a standard 2SLS framework to obtain consistent and efficient estimates of the structural parameters. We further apply the final selection of variables to the model estimated via GMM.

Robustness checks

Placebo regression with alternative capital measures

Our first robustness check verifies that the results attributed to technologies we focus on – robots, software and databases – are driven by these technologies rather than by general investment levels or modern managerial techniques that may correlate with investments in robots, software and databases. To this end, we use a placebo test. We regress the change in involuntary atypical employment against two different types of capital related to these other trends but not clearly associated with task displacement. Specifically, we use the exposure to net capital stock in brand intellectual property and net capital stock in training. We report only the results of the OLS estimation. Unfortunately, we cannot use the GMM-IV because the "technology-frontier" instrument is implausible for these forms of capital. Yet, it should not be a problem since the OLS and GMM-IV baseline results were highly similar.

We find no statistically significant results for the alternative measures of modern capital (Table 6). This suggests that our key findings are specific to automation, particularly industrial robots, and are not biased by parallel trends in other types of investment.

Table S1. Robustness check – placebo regression

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
	Atypical Employment Share			
Training	-0.78	-0.58	-0.46	0.93
	(1.81)	(1.59)	(1.61)	(1.68)
Brand Intellectual Property	-1.96	-1.23	-1.33	-1.55
	(1.17)	(1.15)	(1.15)	(1.15)
Country, gender, age group fixed effects	Yes	Yes	Yes	Yes
Trade Union density	Yes	Yes	Yes	Yes
Native workers share (2006)	No	Yes	Yes	Yes
Small firms workers share (2006)	No	Yes	Yes	Yes
Industry shifters	No	No	Yes	Yes
Manufacturing share (2006)	No	No	No	Yes
Financial crisis	No	No	No	Yes
Mean of outcome	2.05	2.05	2.05	2.05
Mean of Training	0.01	0.01	0.01	0.01
Mean of Brand Intellectual Property	0.01	0.01	0.01	0.01
Observations	390	390	390	390

*Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors (clustered at the country level) in parentheses. We use standardised weights, based on the EU-LFS employment structure in 2018, that give each country equal weight.*
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

Country leave-one-out regressions

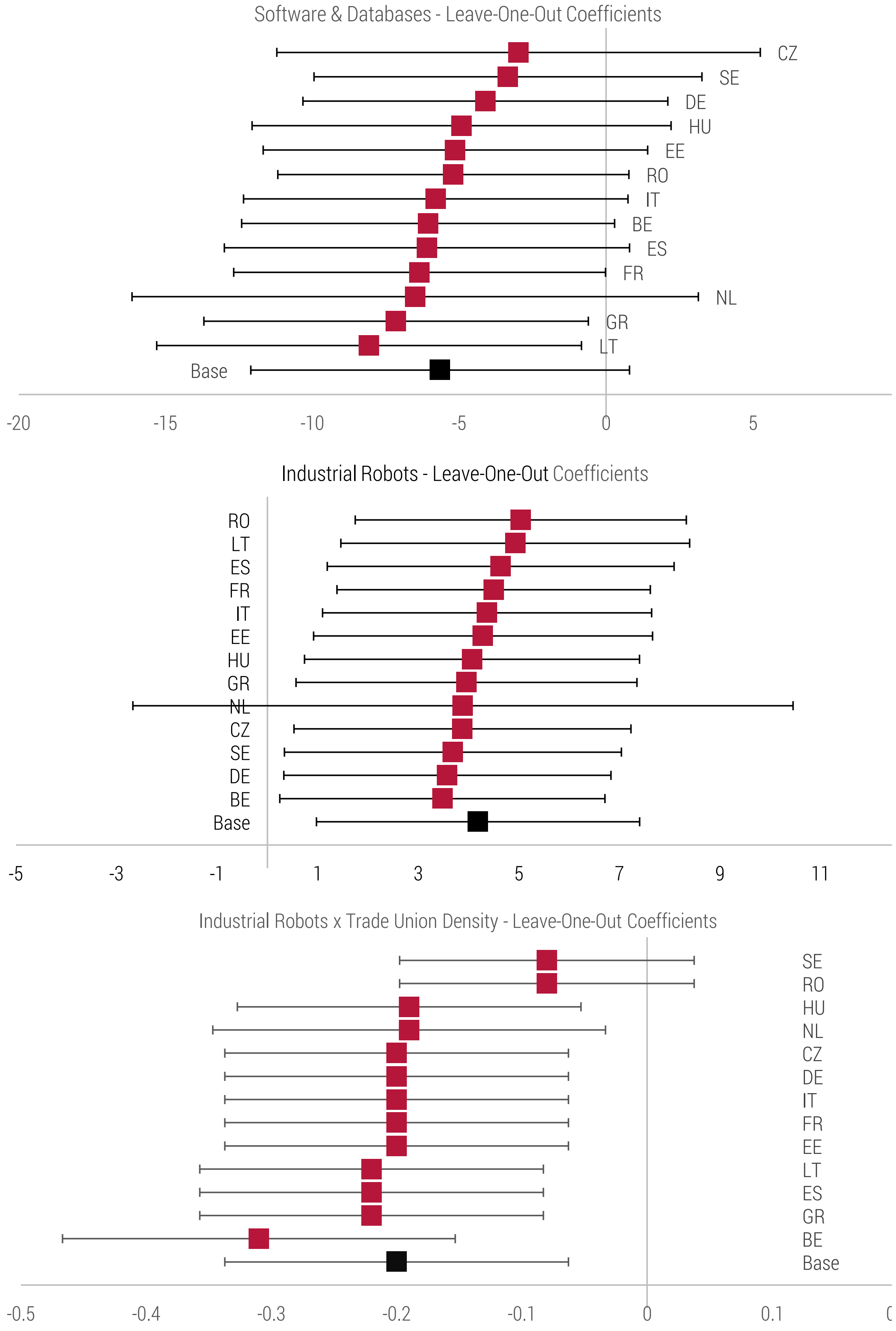
Here, we test the stability of our results to changing the country coverage. To this aim, we run 13 regressions, excluding one country at the time. We report the key GMM-IV coefficients for software and databases, industrial robots' impacts on atypical employment and the trade union moderating effect.

For software and databases, there are no substantial differences between the leave-one-out coefficients and the baseline, insignificant estimate (top panel of Figure 6). However, the coefficient becomes statistically significant at the 5% level in subsamples without Greece or Lithuania.

In the case of industrial robots, there are no significant differences across subsamples (middle panel of Figure 6). However, if we excluded the Netherlands, the coefficient pertaining to the robots would not be statistically significant because of a large standard error.

Finally, we find that the interaction between industrial robots and trade union density is also stable across subsamples, with two exemptions: excluding Sweden or Romania makes the interaction smaller in absolute terms and not statistically significant (bottom panel of Figure 6). These two countries represent the opposite ends of the distribution of trade union density in our sample.

Figure S1. Country Leave-One-Out tests



Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

Out-of-sample European instrument

Next, we change the construction of the instruments for technology measures. Instead of using technological leaders for particular sectors, we use an average for Austria, Denmark, Finland and Slovenia – a set of countries not included in our sample and used in past studies with similar specifications (Acemoglu and Restrepo, 2022; Doorley et al., 2023).

The results are comparable to those using the instrument based on technological leaders (Table 7). We find lower first-stage f-statistics for the models estimated using out-of-sample European instruments. Thus, we prefer our baseline instrument when interpreting the results, as a larger first-stage f-statistic is associated with smaller standard errors of the endogenous variables' parameters. Importantly, changing the instrument does not affect our findings and their interpretation.

Table S2. Robustness check – out-of-sample European countries instrument

	(1)	(2)	(3)	(4)	(5)
	GMM-IV	GMM-IV	GMM-IV	GMM-IV	GMM-IV
Software and Databases Displacement	-1.34	-0.77	-0.85	-2.50	-5.30
	(3.43)	(3.34)	(3.37)	(3.26)	(3.72)
Industrial Robots Displacement	3.95*	2.87	2.80	3.16	4.11*
	(1.71)	(1.73)	(1.76)	(1.76)	(1.81)
Industrial Robots Displacement x Trade Union					-0.20**
					(0.07)
Country, gender, age group fixed effects	Yes	Yes	Yes	Yes	Yes
Trade Union density	Yes	Yes	Yes	Yes	Yes
Native workers share (2006)	Yes	Yes	Yes	Yes	Yes
Small firms workers share (2006)	Yes	Yes	Yes	Yes	Yes
Industry shifters	Yes	Yes	Yes	Yes	Yes
Manufacturing share (2006)	Yes	Yes	Yes	Yes	Yes
Financial crisis	Yes	Yes	Yes	Yes	Yes
First Stage Kleibergen-Paap F-Statistic	37.9	36.3	35.7	44.5	25.5
Mean of outcome	2.05	2.05	2.05	2.05	2.05
Mean of Software and Databases	0.17	0.17	0.17	0.17	0.17
Mean of Industrial Robots	0.20	0.20	0.20	0.20	0.20
Observations	390	390	390	390	390

*Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors (clustered at the country level) in parentheses. We use standardised weights, based on EU-LFS employment structure in 2018, that give each country equal weight.*
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

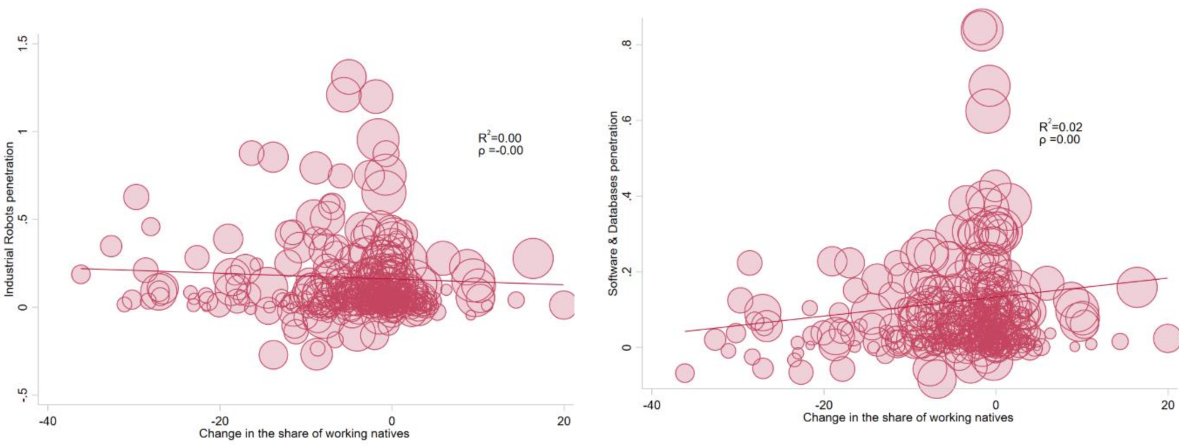
Correlation between migration and technology exposure

Among the parallel phenomena in Europe during the studied period, migration might have acted as a confounder of our analysis. Migrants might be vulnerable in the new markets and take up professions below their skill level, often accepting poorer working conditions. Hence, we correlate the automation exposure measures to see if associated migration patterns could confound the obtained result. We use the change in the share of "natives" in the labour market as a measure of migration exposure.

We find no correlation between the change in the share of native workers and the exposure to technology adoption. The share of variance in the technology exposure measures also indicates little association between migration and technology. Estimating the relationship between these variables, we also find no correlation between technology and migration (Table OA3).

Figure S2. Correlation between technology adoption and migration

industrial robots exposure | software & database exposure



Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

Table S3. The association between adoption of industrial robots and change in migration

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Migration Change	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Country F.E.	Yes	Yes	Yes	Yes
Gender F.E.	Yes	Yes	Yes	Yes
Age group F.E.	Yes	Yes	Yes	Yes
Native workers share (2006)	No	Yes	Yes	Yes
Small firms workers share (2006)	No	Yes	Yes	Yes
Industry shifters	No	No	Yes	Yes
Manufacturing share (2006)	No	No	No	Yes
Financial crisis	No	No	No	Yes
Mean of outcome	2.05	2.05	2.05	2.05
Observations	390	390	390	390

Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.