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DISCUSSION PAPER SERIES

IZA DP No. 17544

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ABSTRACT

Automation, Trade Unions and Atypical Employment*

We study the effect of the adoption of automation technologies – industrial robots, and software and databases – on the incidence of atypical employment in 13 EU countries between 2006 and 2018. We find that industrial robots significantly increase atypical employment share, mostly through involuntary part-time and involuntary fixed-term work. We find no robust effect of software and databases. We also show that the higher trade union density mitigates the robots' impact on atypical employment, while employment protection legislation appears to play no role. Using historical decompositions, we attribute about 1-2 percentage points of atypical employment shares to rising robot exposure.

JEL Classification: J23, J51, O33

Keywords: robots, automation, atypical employment, trade unions

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1. Introduction

The ongoing technological transformation, characterised by increasing automation and digitisation across industries, 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 important questions about its implications for workers, particularly in terms of job displacement, changing skill requirements, and deteriorating working conditions (Acemoglu and Restrepo, 2019; Autor, 2015). The aggregate labour market effects of automation appear to be harmful in the US (Acemoglu and Restrepo, 2020) but more benign in European countries (Bachmann et al., 2024; Battisti et al., 2023; Dauth et al., 2021; Gregory et al., 2022) and in Japan (Adachi et al., 2024; Deng et al., 2023). However, automation creates winners and losers, often benefiting higher-skilled workers but hurting middle- and low-skilled workers, especially those performing routine-intensive jobs (Acemoglu and Restrepo, 2019; de Vries et al., 2020) who often experience occupational downgrading (Autor and Dorn, 2013; Cortes et al., 2020; Goos and Manning, 2007). This may increase work intensity (Antón et al., 2023; Bryson et al., 2013) and job insecurity (Yam et al., 2023), and reduce work meaningfulness (Nikolova et al., 2024), mental health and job satisfaction (Liu, 2023). As a labour-saving technology, automation can reduce workers' bargaining power, contributing to the proliferation of atypical employment forms, especially those that workers accept involuntarily (Doorn and Vliet, 2022). Indeed, non-standard employment forms have grown across high-income countries (OECD, 2015).[1] An important question is whether automation technologies have contributed to the rise of atypical employment, especially since the increasing incidence of non-standard work is a novel phenomenon absent during previous automation waves (ILO, 2016).

In this paper, we study the effect of two key automation technologies – industrial robots, and software and databases – on the incidence of atypical employment in 13 EU countries between 2006 and 2018.[2] We hypothesise that automation may increase atypical employment because of decreased workers' bargaining power and firms' demand for short-term employment flexibility. We draw on theories suggesting that firms can adapt employment more flexibly than capital or technology. As robots become relatively more productive, firms may increasingly hire workers to achieve flexibility in responding to shocks (Fornino and Manera, 2022). The potential threat of automation may further decrease workers' bargaining power (Arnoud, 2018). Instead of displacing workers, firms may therefore provide atypical contracts to enhance their ability to adjust labour inputs in response to shocks, while diminished bargaining power may leave workers with little choice but to accept such contracts. As non-standard employment forms tend to affect workers' health, productivity, and well-being, evaluating automation's impact on the incidence of atypical contracts is essential for understanding the multidimensional consequences of automation.[3]

[1] Throughout the paper, we use the terms non-standard employment and atypical employment interchangeably.

[2] 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.

[3] 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 tend to face higher risk of displacement and have lower bargaining power. Self-employment also can negatively impact on an individual's mental health because of wage uncertainty and employment instability (Bogan et al., 2022).

We define atypical employment as a sum of forms that undoubtedly constitute deprivation, namely involuntary fixed-term work, involuntary part-time work, and underemployment. We use the EU Labour Force Survey (EU-LFS) microdata to measure its incidence. We quantify automation technologies with the International Federation of Robotics (IFR, 2021) data on industrial robots and the EU-KLEMS data on software and database stock available at the sector level. To estimate the impact of automation technologies on atypical employment, we follow the approach proposed by Acemoglu and Restrepo (2022) and adopted to European data by Doorley et al. (2023). We regress changes in 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. We categorise workers into 30 demographic groups in each country, defined by age, gender, and education level. Given that the adoption of robots may be influenced by labour demand and other factors that also affect labour market outcomes, we employ an instrumental variable approach. Specifically, we leverage plausibly exogenous variation in robot penetration derived from trends in technology adoption in countries that are technology leaders in particular sectors. We then interact these trends with the initial employment structures of the demographic groups. Essentially, our instrument assesses the exposure of demographic groups to automation technologies as if the industries they concentrate in followed the technological frontier.

We find that task displacement with industrial robots increases atypical employment. On average, the effect amounts to 1.21 pp nonstandard employment share (GMM-IV). In line with our bargaining power hypothesis, the main channel is through involuntary fixed-term employment which firms tend to use to increase the flexibility of hiring, followed by involuntary part-time work. At the same time, software and databases do not show any significant effect on atypical employment. Our results are stable across different model specifications and robust to changing the construction of the instrumental variable.

As workers' bargaining power might differ between countries and industries with different institutional settings, we test if trade unions mitigate the impact of automation on atypical employment. Interacting task displacement with demographic groups' trade union density, we find that higher unionisation significantly reduces robots' impact on atypical employment. However, we do not find any significant effect for other labour market institutions, particularly for the stringency of employment protection legislation. This suggests that collective bargaining may play a particularly relevant role in shaping the labour market impacts of automation.

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

We make three contributions to the literature.

First, we enrich the literature on labour market effects of automation technologies by studying the impacts on non-standard employment forms that are a key challenge in Europe as they often provide lower job quality than open-ended employment (OECD, 2015). Literature on the labour market effects of automation has primarily focused on overall employment and wage effects while impacts on atypical jobs remain underresearched. Antón et al. (2023) showed that automation amplifies work intensity, stress, and anxiety in Europe. Damiani et al. (2023) argued that robots might reduce the risk of temporary jobs among high-skilled workers in industries with high knowledge accumulation but increase it more broadly 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 defines atypical employment more comprehensively. In line with our conceptual framework that stresses bargaining power, we find that fixed-term contracts constitute the main channel of automation-driven increase in atypical employment.

Second, we provide evidence that trade unions can play a crucial role in mitigating the adverse effects of technological advancements on non-standard work arrangements. The literature on automation has long argued that labour market institutions may shape cross-country differences in automation's impact (Dauth et al., 2021), but causal empirical studies remain scarce. Trade unions can help counteract wage declines associated with atypical employment, and collective bargaining is linked to a reduced impact of industrial robots on unemployment (Leibrecht et al., 2023). By leveraging their bargaining power, trade unions can improve outcomes of workers with precarious contracts (Litwin and Shay, 2022; Svarstad, 2024), potentially offering protection to those most vulnerable to automation. Additionally, they tend to narrow the gaps between routine and non-routine workers (Kostøl and Svarstad, 2023). This paper presents evidence that trade unions may play a key role in mitigating automation's influence on the shift toward atypical employment. At the same time, we find no such effects for employment protection legislation, opposing theoretical arguments that increasing labour protection (consequently decreasing workers' flexibility) would affect labour comparative advantage compared to automation capital (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 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 in countries that did not implement such reforms (Katz and Krueger, 2019; OECD, 2015), globalisation and technological progress have come to 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 can fuel labour market polarisation as firms may use temporary workers mostly for manual and routine tasks that are automatable. Doorn and Vliet (2022) argued that middle-skilled workers tend to accept poorer working conditions as they lose comparative advantage in polarising labour markets. However, they did not quantify the role of technology directly.

The remainder of the paper is structured as follows. Section 2 describes the data and methodology. Section 3 presents results, and Section 4 covers robustness checks. Section 6 concludes and provides policy recommendations.

2. Data and methodology

2.1. Atypical employment definition

Several definitions of atypical employment exist, usually aimed at capturing job precariousness (Broughton et al., 2016). Recently, many studies have focused on the involuntary forms of atypical employment (Cuccu et al., 2023; Damiani et al., 2023; Doorn and Vliet, 2022; Hyytinen and Rouvinen, 2008) which, by definition, are driven by factors other than preferences. This is an important distinction as, for instance, part-time employment can reflect individual preferences for balancing care responsibilities with work duties or the inability to find a full-time job (Haines et al., 2018). This paper assumes that technological displacement can influence the incidence of involuntary atypical employment. We acknowledge that increased 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 Labour Force Survey (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[4] per week and state they wanted to work full-time 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 currently they do. To define the outcome, we used the usual reported weekly hours worked.[5] The EU-LFS allows distinguishing these forms from others which are more likely a choice, such as voluntary part-time or self-employment. However, it does not identify some atypical forms that are likely involuntary and precarious, such as bogus / spurious self-employment and the so-called zero-hour contracts (Table 1). We identify a worker as an involuntary atypical employee if the individual worked in any of these atypical forms of employment.

Table 1. Atypical Employment definitions and data availability

Atypical Employment		
Involuntary	Preference-based (at least partly)	Unavailable in the EU-LFS data
• Involuntary-part-time • Fixed-term work • Underemployment	• Temporary agency work • Voluntary part-time • Marginal part-time • Self-employment	• Bogus self-employment/ Freelancing • Zero hour contracts

Note: *We follow atypical employment definitions based on the European Parliament's Committee on Employment and Social Affairs policy report on work precariousness and atypical employment (Broughton et al., 2016)*
Source: Own elaboration

[4] The SU-LFS distinguishes between usual and actual hours worked. To define the part-time workers we refer to the usual hours as these 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.

[5] We focus on usual hours because a fraction of employees states zero actual working hours, probably because of the survey taking place during holidays and paid leaves.

The EU-LFS is a repeated cross-section and does not allow a direct study of worker transitions from typical to atypical employment. Therefore, we use the 'demographic group' framework – we calculate the incidence of atypical employment in groups defined by education (Higher, Middle, Low), age group (20-29, 30-39, 40-49, 50-59, 60+) and gender (M, F) (Acemoglu and Restrepo, 2022; Doorley et al., 2023). In line with the literature on automation (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Graetz and Michaels, 2018), we focus on long-differences that better reflect cumulative, long-term impacts of technology adoption: the percentage point change in the share of involuntary non-standard workers among all workers between 2006 and 2018.

Our sample includes the following 13 countries: Belgium, the Czech Republic, Germany, Estonia, France, Greece, Hungary, Italy, Lithuania, the Netherlands, Romania, Spain, and Sweden. This reflects the availability of EU-LFS and other data, which we discuss below.

2.2. The measure of technological displacement

We study two types of key automation technologies that can substitute for human work: industrial robots that have been found to affect labour market outcomes around the world (Acemoglu and Restrepo, 2020; Adachi et al., 2024; Albinowski and Lewandowski, 2024; Antón et al., 2023; Dauth et al., 2021), as well as software and databases, which among the ICT technologies were found to shift workers from abstract to more routine tasks (Almeida et al., 2020; Gregory et al., 2022). We distinguish these two technologies as their impact does not have to be uniform, especially among low- and middle-skiled groups (Blanas, 2024).

We use the International Federation of Robotics (IFR, 2021) data on the operational stock of industrial robots[6] and EU KLEMS data on net capital stock in software and database technology.[7]

We construct the measure of technology adoption on the country-industry level. Following Acemoglu & Restrepo (2020), for each industry sector *i* in country *c,* we define the adjusted penetration by automation technology (industrial robots, and 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, and 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*.

[6] 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".

[7] We use the variables presented in national currencies in 2015 chained prices. We use Eurostat data on 2015 average annual stock exchange and re-calculate the capital and output data to euros.

In contrast to standard measures assessing technological penetration, such as the quantity change in the robots per worker, we also incorporate changes in the sectors' gross output. By doing so, we measure the change in technology stock within the specified sector, compared to the increase in technology stock associated with output change. The positive values of adjusted technology penetration show a larger increase in the technology stock compared to the industry's size. This adjustment is essential in our cross-country sample that includes countries with varying growth rates.

We aggregate the adjusted technology penetration to transform the variable from industry- to demographic group level. 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:

$$\mathrm{TDA_{g,c}} = \sum_{i \in I} \omega_{g,c}^{i} * \frac{\omega_{g,i,c}^{R}}{\omega_{i,c}^{R}} \ \mathrm{IHS(AP\_Tech)}^{8}{}_{\mathrm{i,c}} \ (2)$$

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 the industry *i* in relation to all routine workers in the industry *i* in a 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). Finally, following Doorley et al. (2023), we use the EU Structure of Earnings Survey (EU-SES) to calculate detailed sectoral employment structures of demographic groups, $\omega_{g,c}^{i}$.[9] 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 (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[10] waves of the European Social Survey (ESS) to the demographic group level and calculate the shares of unionised workers. Neither the EU-LFS nor the EU-SES include information on workers' trade union membership. However, estimating regressions across demographic groups allows straightforward merging of indicators based on different surevys.

[8] Because of the negative values of the technological treatment, we apply inverse hyperbolic sine transformation (IHS). When the transformed variable is relatively large, the IHS transformation can be interpreted in the same manner as the logarithm.

[9] 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,

[10] We aggregate ESS waves to increase sample size and compensate 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.

Importantly, this approach allows for 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 individual regulation for workers on regular contracts (EPL-REG) and the strictness of temporary contracts (EPL-TEMP). These indices often serve as proxies for employment protection. In particular, the difference in the EPL-REG and EPL-TEMP is sometimes used to account for the possible advantage of regular workers in labour protection (Högberg et al., 2019).

2.4. Econometric methodology

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

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

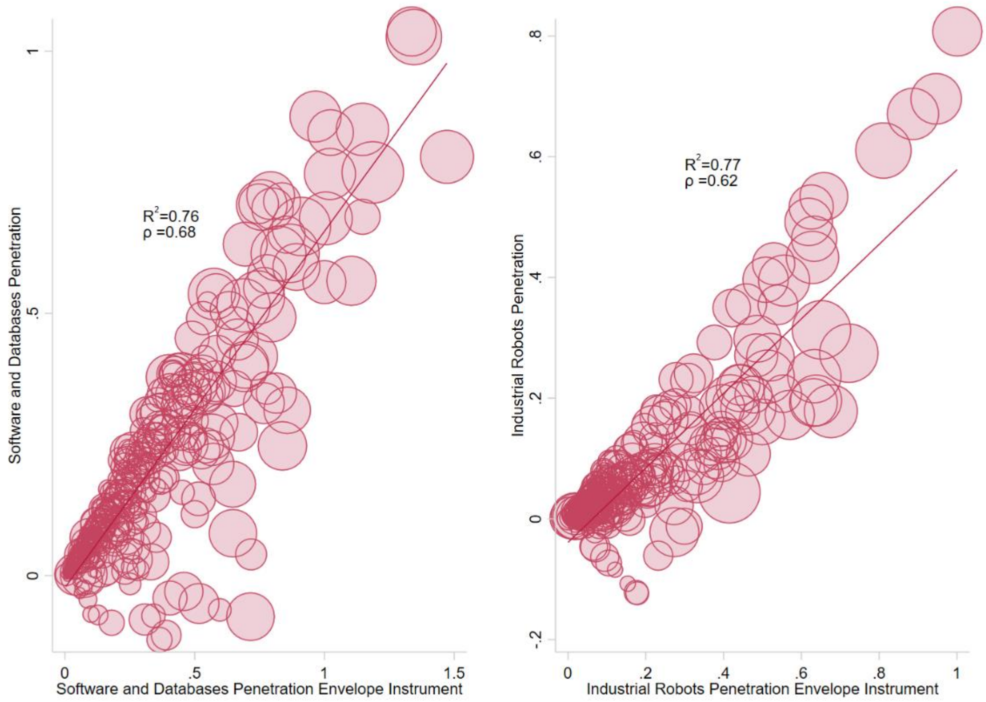
where $\Delta \mathrm{A.E.}_{\mathrm{g,c}}$ represents the change in the share of employees in (any) involuntary atypical employment of a demographic group *g* in the country c between 2006 and 2018. $\mathrm{X}_{\mathrm{g,c}}$ is a matrix of the selected covariates. We use LASSO regularisation as a variable selection model, using Ahrens et al. (2020) method that corrects for the possible omitted variable bias in standard LASSO procedures. We control for country, gender, age fixed effects in the simplest specification. We addtionaly control for the share of migrants, employment share of small firms (up to 9 employees); share of manufacturing employment (all in 2006), change in value added per worker between 2008-2016, exposure to financial crisis (output change between 2008 and 2009), and the share of all and atypical workers in trade unions.

Technology adoption may be endogenous to labour market shocks or driven by other, potentially unobserved factors that also affect 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 generalise the "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). However, instead of choosing a fixed set of countries, we identify the technological leader for each sector – a country with the highest penetration of a given technology, industrial robots, and software and databases. Such instrument proxies for technological frontier – adoption driven by technological progress rather than other factors – and mimics the behaviour of firms adopting the given technology based on the technological leaders (Table A1 in the Appendix depicts the industries and countries used). We refer to the applied instrument as the technological leaders instrument.

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

Plotting the relationship between the endogenous variables and their instruments (Figure 1), we find strong and significant correlation between them, 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, we also estimate a 2SLS model with a set of out-of-sample European countries (Austria, Denmark, Finland, Slovenia) which were used as instruments in past studies (Acemoglu and Restrepo, 2020; Doorley et al., 2023).

Figure 1. First-stage relationships – technological leaders instrument



Notes: Marker sizes indicate the within-country employment shares of demographic groups.
Source: Own elaboration based on EU-LFS and IFR data.

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 worker level.

Finally, we calculate a counterfactual scenario to evaluate the economic significance of automation as a driver of atypical employment. Using the 2SLS estimated coefficients, we calculate the linear prediction of the atypical employment change at a demographic group level (baseline). Then, we predict the same outcome, but assuming no change in technology level between 2006 and 2018. Comparing this counterfactual scenario – what would be the change in atypical employment if there was no change in technology adoption – 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.

3. Results

3.1. Descriptive evidence

Table 2 presents descriptive statistics of the variables used in the regression. On average, the share of workers in atypical employment increased by 2.05 pp (around a 20% increase) between 2006 and 2018. The incidence of involuntary fixed-term contracts and underemployment increased most notably, with fixed-term employment noting a 31.3% increase. 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.

Most demographic groups recorded small increases in non-standard atypical employment between 2006 and 2018 (Table 2). Young workers (aged 20-29) experienced the largest changes – from, on average across countries studied, 15.6% in 2006 20.1% in 2018. Regarding education, the incidence of non-standard employment increased the most among workers with primary or vocational education (4.01 p.p), followed by those with secondary (1.62 p.p) and with tertiary education (1.19 p.p). The changes were similar among men and women (Figures A1-A2 ain appendix). However, as men were less exposed to atypical employment in 2006, they experienced a larger relative change.

Table 2. Descriptive Statistics

	Mean	Standard Deviation	% change	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	2.8%	390
Change in involuntary fixed-time employment	0.78	2.1	31.3%	390
Change in underemployment	0.79	4.13	11.3%	390
Task Displacement[11]				
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	8.7	-	390
Manufacturing share	27.1	13.4	-	390
Financial crisis exposure	-7.41	5.95	-	390
Trade Union density	16.8	17.8	-	390
Small firms employees share in 2006	20.4	10.4	-	390
Natives in 2006	91.4	6.9	-	390

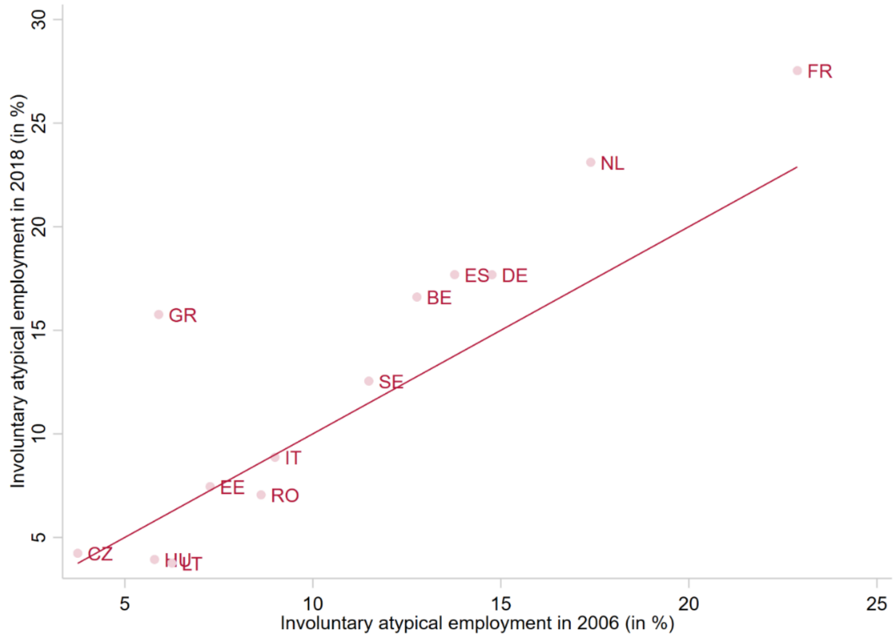
Note: *This table presents weighted means, standard deviations and the number of observations for selected variables. We weigh observations by their within-country employment shares (each country has equal weight in the analysis).*

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

The evolution of atypical employment shares differs between EU countries (Figure 1). The largest increases occurred in Greece, Belgium and the Netherlands, where atypical employment grew by more than 30% from 2006 to 2018. In contrast, in most Central-Eastern European countries, the share of atypical employment declined, the most in Lithuania and Hungary.

[11] The technological displacement adjustments are presented after IHS transformation. While interpreting the results of the regression we refer to standard deviations of the variables before transformation, which is a standard mechanism when using logarithmic transformation.

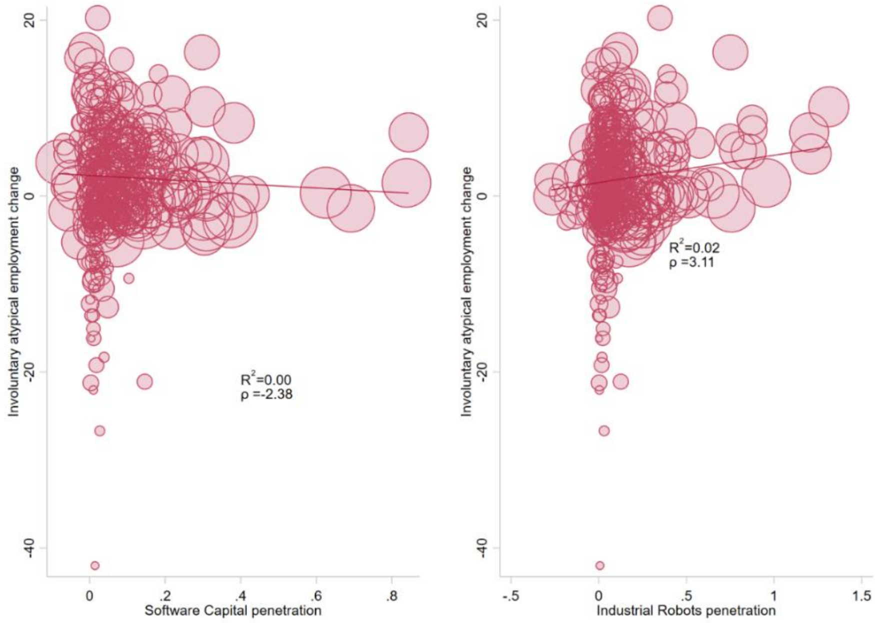
Figure 2. Change in involuntary atypical employment by country



Source: Own elaboration based on EU-LFS data

Across countries and demographic groups, there is a positive correlation 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 2). Both correlations are statistically insignificant though.

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 involuntary atypical employment

We start with discussing the OLS results. We find a significant, positive association between the penetration of industrial robots and change in involuntary atypical employment (Table 3). We also find a significant moderating effect of trade unions,[12] which can contribute to alleviating the impact of industrial robots. At the same time, the association between software and databases and atypical employment is not significant at a 5% level. We have also estimated 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. For industrial robots, the GMM-IV results are statistically significant and quantitatively similar to the OLS results, albeit slightly smaller (Table 3). The interaction between robots and trade union density is also significant (column 5 of Table 3), confirming that unions might have played a role in mediating the impact of robots on working 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 3). The IHS transformation of technological variables complicates assessing the strenght of these estimated effects. Therefore, we will discuss the economic significance in subsection 4.3. based on the counterfactual historical analysis.

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 used in our baseline specifications. Specifically, we use the Employment Protection Legislation Index (EPL) of the OECD. We compare our main specification (column 2 of Table 4)[13] to three models using EPL for regular contracts (column 2), EPL for temporary contracts (column 3) and the difference between EPL for regular and temporary contracts (column 4). In addition, we also use country-level trade union density (column 5) instead of demographic-group level union density based on the ESS data. Table A3 in Appendix compares these indicators for country studied and shows their cross-country correlation with trade union density based on the ESS.

These additional results suggest that trade unions may indeed moderate the automation's impact on atypical employment. We do not find any significant results for any of the EPL measures, neither in OLS nor in IV regressions (Table 4). However, the result based on the OECD Trade Union density (column 5 of Table 4) resemble baseline results. We interpret these findings as suggestive evidence that trade unions indeed can protect workers from the automation-driven increases in non-standard work arrangements.

[12] We run 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 that attributed to industrial and occupational structure (Appendix, Figure A3).

[13] Specification in column 2 in Table 4 is the same as in column 5 of Table 3 but we omit Romania due to missing EPL data.

Table 3. Automation exposure and the incidence of atypical jobs, 2006-2018

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Software and Databases Displacement	-1.19	-0.96	-0.98	-1.03	-4.24
	(2.07)	(2.11)	(2.11)	(2.10)	(2.40)
Industrial Robots Displacement	4.68***	3.78**	3.74**	3.45**	4.62***
	(1.30)	(1.28)	(1.30)	(1.30)	(1.36)
Industrial Robots Displacement x Trade Unions					-0.16**
					(0.05)
	GMM-IV	GMM-IV	GMM-IV	GMM-IV	GMM-IV
Software and Databases Displacement	-2.23	-1.66	-1.69	-2.89	-5.65
	(3.05)	(2.97)	(2.98)	(2.91)	(3.29)
Industrial Robots Displacement	4.31**	3.23*	3.14	3.26*	4.19*
	(1.61)	(1.61)	(1.64)	(1.64)	(1.64)
Industrial Robots Displacement x Trade Union					-0.20**
					(0.07)
Country F.E.	Yes	Yes	Yes	Yes	Yes
Gender F.E.	Yes	Yes	Yes	Yes	Yes
Age group F.E.	Yes	Yes	Yes	Yes	Yes
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
First Stage Kleibergen-Paap F-Statistic	62.2	59.5	58.7	66.9	39.9
Mean of outcome	2.05	2.05	2.05	2.05	2.05
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
Observations	390	390	390	390	390

*Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors 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.

Table 4. Automation exposure and the incidence of atypical jobs with alternative labour protection measures, 2006-2018

	(1)	(2)	(3)	(4)	(5)
	Baseline	EPL-REG	EPL-TEMP	EPL-DIFF	OECD Trade Union
	OLS	OLS	OLS	OLS	OLS
Software and Databases Displacement	-4.17	1.21	-1.28	-1.03	-3.58
	(2.43)	(2.21)	(2.00)	(2.09)	(2.48)
Industrial Robots Displacement	5.48***	2.01	3.26	4.38**	4.93**
	(1.41)	(3.30)	(2.55)	(1.43)	(1.53)
Industrial Robots Displacement x Trade Union	0.15**				-0.17*
	(0.05)				(0.07)
Industrial Robots Displacement x EPL-REG		0.82			
		(1.22)			
Industrial Robots Displacement x EPL-TEMP			0.86		
			(1.44)		
Industrial Robots Displacement x EPL-DIFF				-0.02	
				(0.74)	
	2SLS	2SLS	2SLS	2SLS	2SLS
Software and Databases Displacement	-5.20	-2.03	-2.96	-2.32	-3.79
	(3.05)	(2.67)	(2.67)	(2.60)	(3.22)
Industrial Robots Displacement	5.04**	0.40	2.10	4.31*	3.11
	(1.68)	(3.85)	(2.68)	(2.07)	(1.72)
Industrial Robots Displacement x Trade Union	-0.21**				-0.25**
	(0.07)				(0.08)
Industrial Robots Displacement x EPL-REG		1.25			
		(1.31)			
Industrial Robots Displacement x EPL-TEMP			1.53		
			(1.69)		
Industrial Robots Displacement x EPL-DIFF				-0.15	
				(0.85)	
Country F.E.	Yes	Yes	Yes	Yes	Yes
Gender F.E.	Yes	Yes	Yes	Yes	Yes
Age group F.E.	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	57.17	55.7	50.3	48.04	45.0
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 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.

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 non-standard employment, we re-estimate our models for particular sub-categories on involuntary atypical employment – involuntary part-time, fixed-term, and underemployment. For brevity, we focus on specifications with interactions between robots and trade union density (as in column 5 of Table 3)

Table 5. Technology exposure and involuntary part-time, fixed-term employment and underemployment, 2006-2018, with trade unions interactions

	Involuntary part-time	Involuntary fixed-term	Underemployment
	OLS	OLS	OLS
Software and Databases Displacement	-1.24	0.66	-4.55*
	(1.35)	(1.41)	(1.86)
Industrial Robots Displacement	2.28**	1.77**	1.88
	(0.87)	(0.68)	(1.14)
Industrial Robots Displacement x Trade Union	0.02	-0.07*	-0.09*
	(0.03)	(0.03)	(0.04)
	GMM-IV	GMM-IV	GMM-IV
Software and Databases Displacement	-2.23	-2.04	-3.48
	(2.39)	(1.53)	(3.10)
Industrial Robots Displacement	1.82	2.07*	1.96
	(1.22)	(0.82)	(1.55)
Industrial Robots Displacement x Trade Union	0.01	-0.10**	-0.08
	(0.03)	(0.04)	(0.05)
Country F.E.	Yes	Yes	Yes
Gender F.E.	Yes	Yes	Yes
Age group F.E.	Yes	Yes	Yes
Native workers share (2006)	No	Yes	Yes
Small firm share (2006)	No	Yes	Yes
Industry shifters	No	No	Yes
Manufacturing share (2006)	No	No	No
Financial crisis	No	No	No
First Stage Kleibergen-Paap F-Statistic	39.9	39.9	39.9
Mean of outcome	0.08	0.78	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 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.

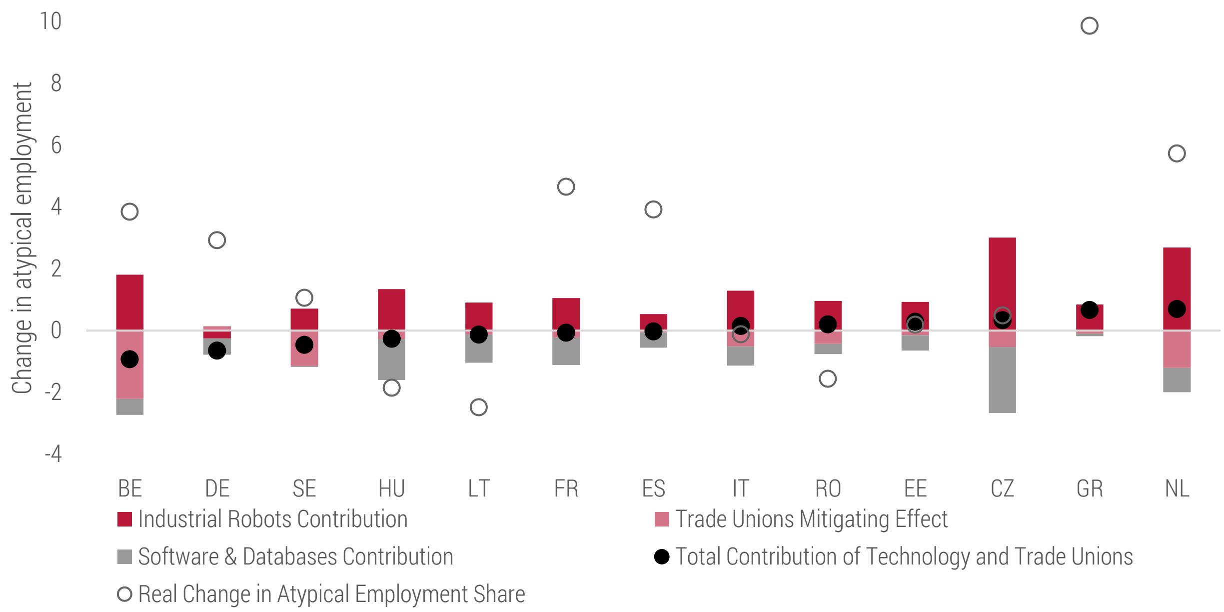
The OLS results show significant association between robots and both involuntary fixed-term and part-time jobs, but the IV results indicate only a significant effect on fixed-term employment (Table 5). The relationship between robots and underemployment is positive, but insignificant at conventional 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, which fixed-term contracts indeed do (Caggese and Cuñat, 2008; Fernandes and Ferreira, 2017; Goux et al., 2001). The effects of software and databases on particular categories of nonstandard employment are insignificant, in line with the pooled results.

3.4 The contribution of technology to atypical employment change

Next, we use a counterfactual analysis to quantify the contribution of automation to the change in atypical employment from 2006 to 2018. First, we use the IV coefficients presented in column 5 of Table 3 to predict the change in involuntary atypical employment between 2006 and 2018. Second, we make an alternative prediction assuming that the penetration with automation technology did not change over time. As we adjusted the penetration measures for sector-specific growth, this is equivalent to assuming that the only investments occurred to compensate for depreciation and retain the automation capital intensity from 2006. The difference between these two predictions allow disentangling the role of technology for changes in atypical employment between 2006 and 2018 in particular countries in our sample.

The total effect of technology varies from about 0.5 pp decline of atypical employment share in Belgium, Germany and Sweden, up to more than 0.6 pp increase in the Netherlands and Greece (Figure 3). The effect is generally larger in countries that recorded larger growth in robot adoption. However, 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. We calculate one more prediction, additionaly assuming that trade union density equals zero in all countries. It shows that trade unions have alleviated the impact of robots on atypical employment in most countries, especially in the Netherlands, Belgium or Sweden, where trade union density is high. 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 the role of automation was relatively small. Using a covariance-based variance decomposition (Morduch and Sicular, 2002), we can attribute only about 4% of the cross-country variation in changes in atypical employment to automation.

Figure 4. Contribution of technology adoption to increase in the share of workers in atypical employment between 2006 and 2018



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

4 Robustness Checks

4.1. Placebo regression with alternative capital measures

Our first robustnees check is aim at verifying that the results attributed technologies we focus on – robots, and software and databases – are driven by these technologies rather than general investment levels or modern managerial techniques that which may be correlated with investments in robots, software and databases. To this end, we use placebo test. We regress the change in involuntary atypical employment against two different types of capital which are related to these other trends but are 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 of "technology-frontier" instrument is implausible for these types of capital. Yet, it should not be a problem since the OLS and 2SLS 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 6. 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 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)	Yes	Yes	Yes	Yes
Small firms workers share (2006)	Yes	Yes	Yes	Yes
Industry shifters	Yes	Yes	Yes	Yes
Manufacturing share (2006)	Yes	Yes	Yes	Yes
Financial crisis	Yes	Yes	Yes	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 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.

4.2 Country leave-one-out regressions

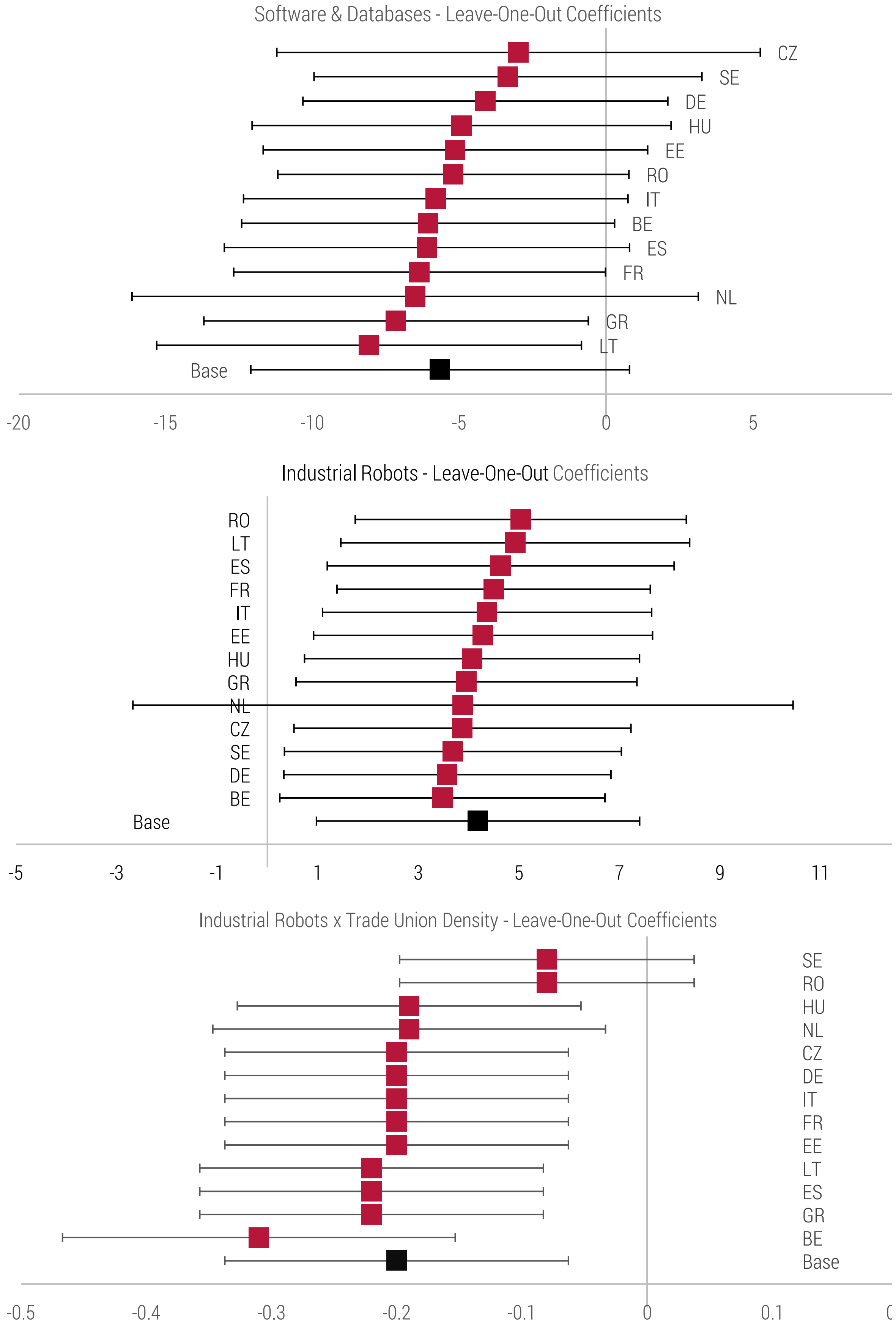
Here, we test the stability of our results to changing the country coverage. To this aim, we run 13 regressions, excluding one country at the time. We report the key 2SLS coefficients for software and databases, industrial robots' impacts on atypical employment and for the trade union moderating effect.

There are no substantial differences between the leave-one-out coefficients and the baseline, insignificant coefficient for software and databases (top panel of Figure 4). However, the coefficient becomes statistically significant at the 5% level in subsamples without Greece or Lithuania.

In case of industrial robots, there are no significant differences across subsamples (middle panel of Figure 4). However, if we excluded the Netherlands, the coefficient pertaining to the robots would not be statistically significant because of large standard error.

Finally, we find that the interaction between industrial robots and trade union density is also rather 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 4). These two countries represent the opposite ends of the distribution of trade union density in our sample.

Figure 5 Country Leave-One-Out tests



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

4.3 Out-of-sample European instrument

Next, we run a robustness check of changing the instrument. Instead of using technological leaders for particular sectors, we use an average the technological task displacement in 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 7. Robustness check – out-of-sample European instrument

	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
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 F.E.	Yes	Yes	Yes	Yes	Yes
Gender F.E.	Yes	Yes	Yes	Yes	Yes
Age group F.E.	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 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.

4.4 Correlation between migration and technology exposure

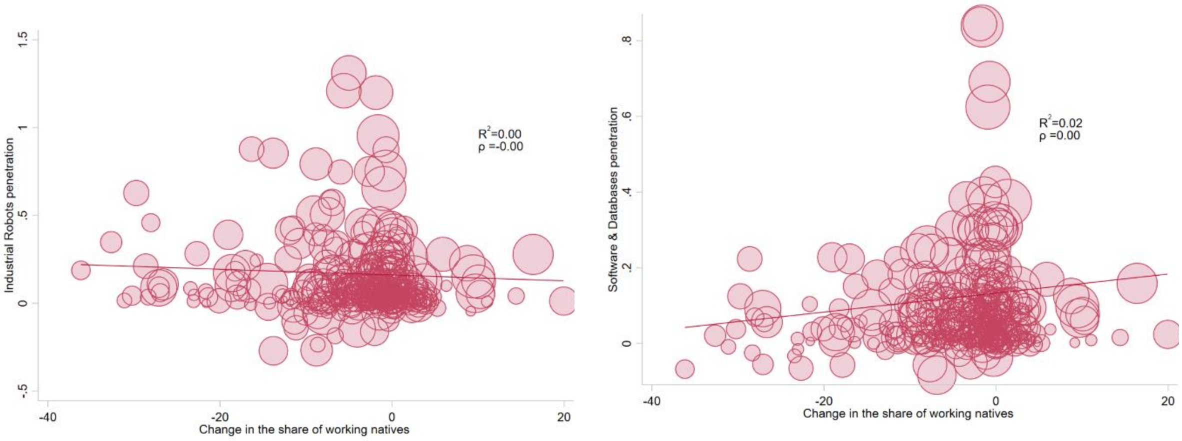
Among the parallel phenomena taking place in Europe during the studied period, migration might have served as a confounder of our analysis. Migrants might be vulnerable to the new markets and take up professions below their skill level, often accepting poorer working conditions. Hence, we correlate the automation exposure measures to see if the obtained result could be confounded by associated migration patterns. 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 (Figure 5). The share of variance in the technology exposure measures also indicates little association between migration and technology. We also run the regression and find no correlation between technology and migration (Table A4 in Appendix).

Figure 6. 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.

5 Conclusions and policy implications

We have studied the impact of automation technologies on the incidence of atypical employment in 13 European countries between 2006-2018. Assessing these impacts is important to understand the welfare consequences of automation. 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). We have combined survey microdata with sectoral data on technology usage and utlised variation in technologoical exposures across demographic groups, employing instrumental variables estimation. Our findings reveal that industrial robots significantly increased the share of atypical employment, primarily through involuntary part-time and fixed-term work. However, we found no significant effect from software and databases. Additionally, our results indicate that higher trade union density mitigated the impact of robots on atypical employment, while the stringency of employment protection legislation had no such effect. Historical decompositions suggest that increased exposure to robots accounts for 1-2 pp of atypical employment share by 2018, particularly in Central and Eastern European countries with low unionisation rates.

Workers' bargaining power is a likely mechanism explaining our findings. Automation may reduce it, increasing workers' acceptance of atypical, more precarious contracts, while higher unionisation can boost it. However, as shown by Kostøl and Svarstad (2023), unions can help to compress wage differences between routine and non-routine workers, but it can also incentivise investments in routine-replacing technologies, potentially reducing demand for routine workers in longer term. In this context, policymakers might focus on policies that simultaneously target increasing employment and decreasing non-standard employment share – providing flexible learning opportunities and targeting middle-educated workers.

Adult education that updates workers' skills in response to technological progress can increase their bargaining power and consequently tame the increase of atypical employment (Doorn and Vliet, 2022). Training itself is more effective than providing employment opportunities, as these encourage workers to accept any job, including part-time jobs. Yet, in Europe, the active labour market policies fail to target low- and middle-educated workers, as it is the highly educated who usually participate in training the most. As of 2022, only 25% of low- and 41.5% of middle-skilled population participated at least once in training, compared to 65.7% among high-skilled individuals. What is more, workers exposed to automation not only learn less but also often train themselves in skills that do not improve chances of a job transition (Heß et al., 2023). This challenge is especially evident in Eastern Europe[14], where the share of highly skilled individuals participating in training is, on average, almost 3.8 times larger than those with low education. In comparison, the ratio is 3.5 in Southern Europe[15], 2.7 in Western Europe[16], and 1.8 in Northern Europe[17]. Thus, especially the Eastern European countries should prioritise investment in training to converge towards Western Europe and increase technology penetration without precarisation of the labour market.

[14] Estonia, Bulgaria, Czech Republic, Slovakia, Latvia, Slovenia, Lithuania, Hungary, Poland, Croatia and Romania.

[15] Spain, Malta, Portugal, Cyprus, Italy and Greece

[16] The Netherlands, France, Germany, Belgium, Austria

[17] Sweden, Finland, Denmark and Norway

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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 to 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%	-[18]	-43%
Slovenia*	D	21%	1717%	-7%
Denmark*	E	-7%	-	-9%
Slovenia*	F	-24%	1200%	-9%
Austria*	P	18%	670%	32%

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

Source: Own elaboration based on EU-KLEMS data.

Table A3 Descriptive statistics on instiutional measures of labour protection

Country	Union density (%, ESS)	Union density (%, OECD)	EPL Regular 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.

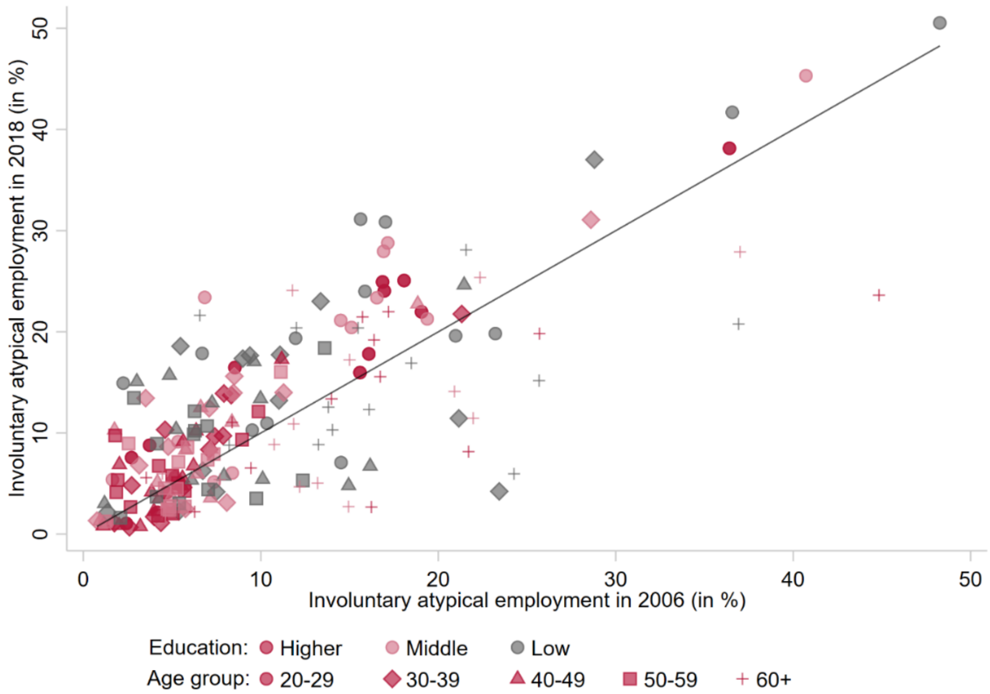
[18] Initial value of the operational stock of industrial robots in 2006 equal to 0.

Table A4 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
Adjusted R-squared				
Mean of outcome	2.05	2.05	2.05	2.05
Mean of Migration				
Observations	390	390	390	390

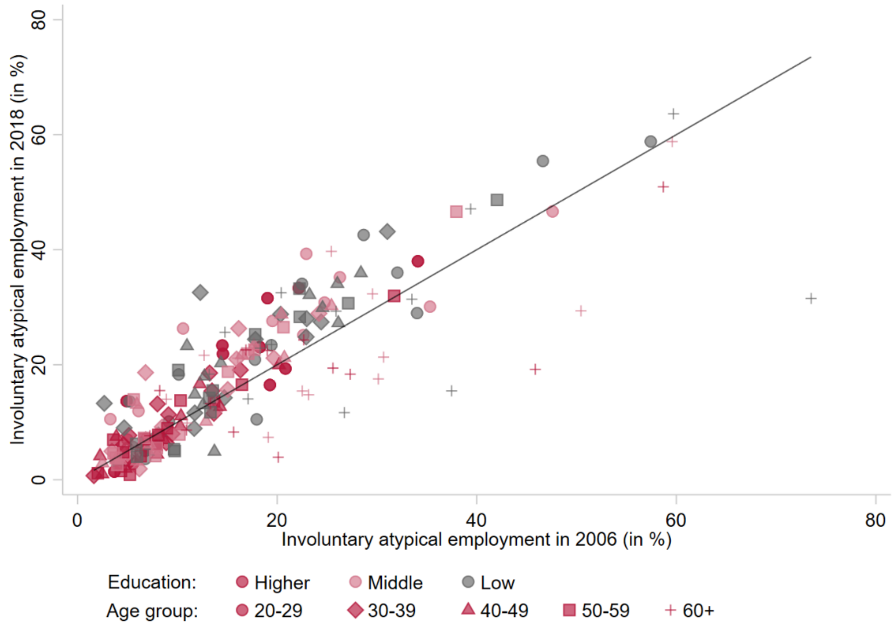
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

Figure A1 Change in involuntary atypical employment - Men



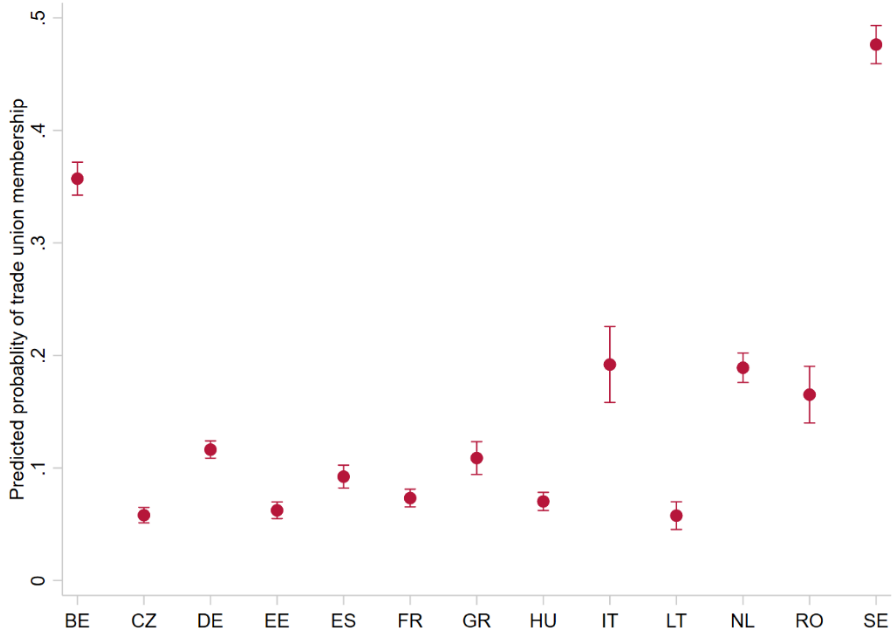
Source: Own elaboration based on EU-LFS

Figure A2 Change in involuntary atypical employment - Women



Source: Own elaboration based on EU-LFS.

Figure A3 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 elaboration based on European Social Survey