Labour and product market regulations and vulnerability

Piotr Lewandowski (IBS, IZA, RWI), Fabrizio Pompei & Cristiano Perugini (UNIPG), Wojciech Szymczak (IBS)

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Abstract

This research analyses the potential moderating impact of employment protection legislation (EPL) and product market regulation (PMR) on the relationship between automation technologies and employment rates of different demographic groups based on age, gender, and education in 12 EU economies from 2006 to 2018. The study makes three contributions to the literature on technological transformation, labour markets, and institutions. First, when considering other megatrends as controls, we introduce, along with indicators for globalisation, a proxy for green technology to account for the ecological transition. Second, we investigate the impacts of robot and ICT exposure on the most vulnerable workers, specifically those aged between 20-29 and 60+. Finally, we calculate a specific measure for group exposure to the EPL of the country, according to the importance of the demographic group in industries with different 'natural' propensity to dismiss workers. We have devised a similar metric to gauge the extent of a group's exposure to the sector and country-level PMR.

After controlling for endogeneity, increased exposure to robots resulted in a 1.6 percentage point decrease in employment rates. This result suggests that in the EU-12, displacement effects slightly exceeded reinstatement effects on human labour tasks, in line with part of the previous research. We did not find a significant moderating effect of EPL on the relationship between automation technologies and employment. The negative moderating effect of EPL on both robot and ICT exposure was observed only among workers aged 20-29. It is important to note that young workers often transition from education to employment. These individuals are at a higher risk of being affected by the increasing prevalence of robots under a stricter EPL regime because the latter induces expectations of rising dismissal costs for employers. As a result, their chances of being hired may be reduced.

1. Introduction

There has been a growing concern in recent years about the potential negative impact of the latest wave of automation technologies on employment. Along with this, concerns related to other megatrends such as globalisation, demographics, and climate change have increased demand for research in these areas. The transition to a digital and ecological economy should be accompanied by a 'just transition', defined by the International Labour Organization as 'Greening the economy in a way that is as fair and inclusive as possible to everyone concerned, creating decent work opportunities and leaving no one behind.'[1] In the European Union (EU), the Action Plan for the European Pillar of Social Rights set the target of a 78% employment rate to be reached by 2030 (European Commission, 2021). Most international organisations now agree that the impact of megatrends on employment and inequality can be milder and mitigated by various active policies and institutional reforms (UN, 2020). Indeed, the available empirical studies focusing on those countries that experienced a massive introduction of robots and ICT technologies, show very different results in terms of employment losses, depending on the production specialisation and institutional context of the country analysed. Acemoglu and Restrepo (2020; 2022) find a clear negative effect of automation technologies on employment and wages at the local labour market and demographic group level in the US. Using a different methodology, Graetz and Michaels (2018) find no significant effects of robots on hours worked in 17 EU countries, particularly for high-skilled workers. Chiacchio *et al.* (2018), by adopting a methodology similar to Acemoglu and Restrepo's, find more apparent but milder negative effects of robots on the employment of demographic groups residing in NUTS2 regions of six EU countries. After performing their analysis, Chiacchio *et al.* (2018) suggest that differences in labour market policies and other institutional factors could account for the variation in the negative impact of automation on employment between Europe and the US.

Although there has been a significant amount of literature in the past thirty years on the impact of employment protection legislation (EPL) stringency on employment and penalisation of vulnerable groups of workers (see the comprehensive reviews by OECD in 2020 and Boeri and Van Our in 2014), the potential moderating effect of these labour market institutions after the implementation

1 See https://climatepromise.undp.org/news-and-stories/what-just-transition-and-why-it-important.

of automation technologies has not been explored as much (Traverso *et al.*, 2022). Likewise, anticompetitive laws and product market regulation (PMR) have been analysed for their direct impact on labour market outcomes (Bassanini and Duval, 2006; Amable *et al.*, 2006; Denk, 2016) or their complementarity with employment protection legislation (Boeri *et al.*, 2000; Amable *et al.*, 2011). However, the effect of stringent product market regulation working as a moderator on the relationship between automation technologies and employment still needs to be explored[2].

This research aims to fill this gap by analysing the role of EPL and PMR as moderators of the relationship between automation technologies and employment rate between 2006 and 2018 in twelve EU economies. We follow the methodology that Doorley *et al.* (2023) have borrowed from Acemoglu and Restrepo (2020; 2022) and applied to European countries. Hence, we investigate how exposure to robots and ICT affects the employment rate of different demographic groups (based on age, education and gender)[3] while controlling for globalisation-related variables. We differentiate our analysis from that of Doorley *et al.* (2023) in three aspects.

First, to consider the ecological transition, we control for a proxy of green technology, the change in environment-related patents filed by inventors residing in the countries under analysis. This is because numerous studies have found a significant positive correlation between green innovations and employment (Pfeiffer and Rennings, 2001; Horbach, 2010; Licht and Peters, 2013; Gagliardi *et al.*, 2016; Albrizio *et al.*, 2017). Aldieri *et al.* (2019) conducted a study on the impact of patent activity in waste recycling on employment in the EU, Japan, and the US during the years surrounding the Global crisis (2002-2010). They discovered a significant positive effect of these green innovations on employment. All of these studies indicate that failing to include a control for this factor may lead to biased coefficients for automation technologies.

Second, we investigate the impacts of robot and ICT exposure on the most vulnerable workers, specifically those aged between 20-29 and 60+. Third, we calculate a specific measure to determine the exposure of demographic groups to the country-level EPL, as further explained in the following sections. This will be achieved by taking into account the importance of the demographic group in

2 Di Mauro *et al.*, (2023) pointed out that stringent market product regulation also reflects on higher power that firms can exert on the input markets, such as the labour market, by depressing wages and employment (https://cepr.org/voxeu/columns/sources-large-firms-market-power-and-why-it-matters).

3 Henceforth, 'group exposure' refers to the exposure of demographic groups to changes in automation technologies, institutions, and other megatrends captured by control variables.

the industries and the fact that employment protection may be more or less binding depending on the tendency of different industries to layoff workers. Likewise, we calculated a measure for the exposure of demographic groups to the industry-level PMR.

Identifying workers' vulnerability with specific age groups (such as most young and old workers) becomes particularly important when the analysis focuses on automation technologies and the moderating effects of labour and product market institutions[4]. The adoption and convergence of new automation technologies are happening faster than previous industrial revolutions. This change mainly affects young individuals transitioning from education to work, as they often have poor occupation-specific or firm-specific skills that complement those of new machinery (ILO, 2020; European Commission, 2021). As discussed in the next section, the education-to-work transition also makes young individuals more susceptible to EPL and PMR due to reduced employment inflows and labour market participation under specific regimes of these institutions. At the same time, workers aged 60+, despite being more protected under stricter EPL regimes, potentially experience a higher risk of early retirement as automation rapidly causes the obsolescence of their jobs or skills (Aisa *et al.*, 2023). These considerations lead us to mainly explore the heterogeneity of automation technology's effects, and the moderating role of institutions, across age groups.

Combining several datasets necessitated the selection of twelve EU countries only (Belgium, Czech Republic, Estonia, Germany, France, Greece, Lithuania, Latvia, Italy, Spain, The Netherlands, and Sweden) so as not to lose information on key variables. However, by doing so we have included the largest economies of the EU-27 in our sample. In 2018, these twelve countries (EU-12) accounted for 85% of the total robots and over 70% of the ICT net capital stock implemented in the EU-27. This guarantees that we are analysing a representative sample of the EU economy regarding the subject under scrutiny.

Figure 1 illustrates some stylised facts about the megatrends that have taken place in the EU-12. The employment rate for the population aged 20-64 increased from 69% in 2006 to 72% in 2018 (it reached 74% in 2022). It may be challenging to achieve the 78% target set in the Action Plan for

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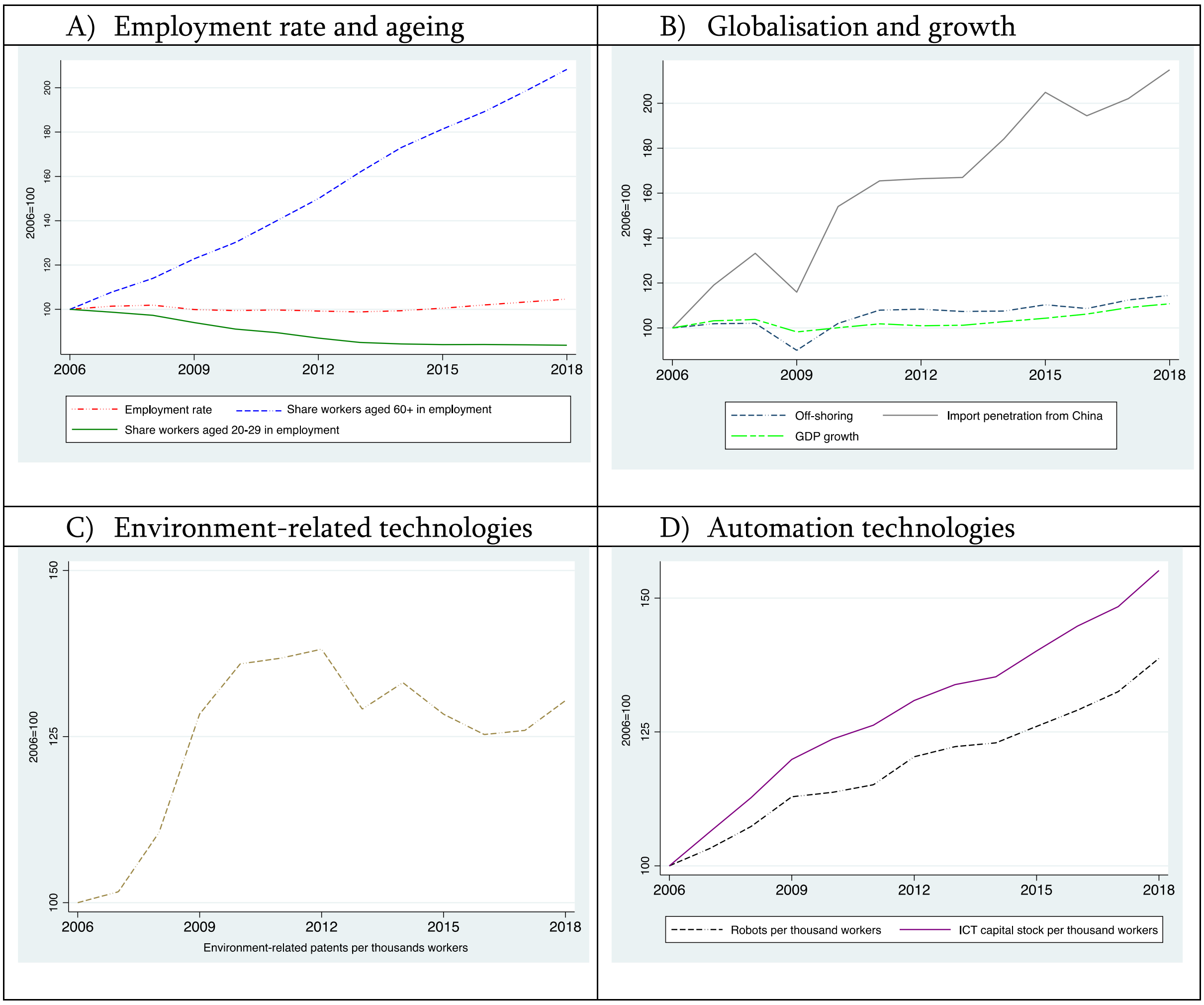
[4] In this context, we only discuss the economic reasons behind vulnerability. A significant argument, revolving around the equal treatment principle and how age-based discrimination affects younger and older workers simultaneously, has been taking place in comparative law studies of both EU and non-EU Anglo-Saxon countries (Blackhalm, 2019).

the European Pillar of Social Rights, given the current performance. Moreover, employment in the EU-12 underwent significant age composition changes, alongside the slow growth in the overall employment rate. The proportion of employed workers aged 60+ has increased, while the percentage of young workers aged 20-29 has decreased (Figure 1, Panel A).

Figure 1. Megatrends in 12 selected European countries (2006-2018)



Source: Eurostat, OECD, EUKLEMS, IFR. Note: all indicators are calculated as weighted averages from Belgium, Czech Republic, Estonia, France, Germany, Greece, Italy, Latvia, Lithuania, the Netherlands, Spain, and Sweden. Employment rate and shares of older workers are calculated on individuals aged 20-64. The indexes for automation technologies are calculated from number of robots (IFR) and net ICT capital stock (EUKLEMS) per thousand workers. Environment-related patents per thousand workers are from OECD. Import penetration from China is the ratio of imports from this country and the sum of gross output plus imports minus exports. Off-shoring is measured as foreign value added to gross output.

Changes in the overall employment rate and workforce demographics may be associated with other relevant phenomena. The impact of globalisation, diffusion of automation and environment-related technologies on the employment rate is complex. From Figure 1 (Panels B, C and D), we learn that all these forces remarkably increased over the analysed years. However, due to the slow employment rate growth, it can be deduced that, if present, the influence might have gone in opposite directions.

To find out if the spread of automation technologies has affected employment rates, after considering globalisation, the advancement of green technology, and the moderating role of labour and product market institutions, the rest of this study develops as follows. Section 2 contains a literature-based conceptual framework. Sections 3 and 4 present data sources, variables and descriptive statistics. Econometric methodology and results are discussed in sections 5 and 6, respectively. Section 7 provides conclusions.

2. Literature-based conceptual framework

In their extensive literature review on automation technologies and employment, Filippi *et al.* (2023) identified more than one hundred papers published between 2014 and 2021. A critical outcome of this review is that once controlling for globalisation and demographic change, the effect of interest varies significantly in size and direction depending on the level and unit of analysis adopted and the countries investigated.

From a theoretical perspective, Acemoglu and Restrepo (2019) documented a complex relationship between technology and employment. On the one hand, automation always generates a productivity effect, and the resulting increase in value-added may raise labour demand for non-automated tasks. Depending on the relationship between technology and tasks, robots may reallocate to capital tasks previously performed by labour, such that a *displacement* effect dominates. Alternatively, several new tasks, or a refinement of former tasks about labour complementing the robot's task may give rise to *reinstatement* effects. Hence, *displacement* and *reinstatement* effects can have ambiguous effects on employment. As for the empirical analysis, Acemoglu and Restrepo (2020) build a Bartik-like measure of robot exposure for the US, where the industry variation of robots is weighted by the baseline employment share of a given industry i in a commuting zone c (that is, a local labour market). The authors repeated this analysis for the US economy, using demographic groups instead of commuting zones (Acemoglu and Restrepo, 2022).

This measure of robot exposure captures general effects in the demographic group (local labour market), where changes in the employment rate may be due to the reallocation of employment across industries after the introduction of automation technologies. The authors have found an aggregate negative influence of robot adoption on employment in the US local labour markets and at the demographic group level. Introducing robots reduces the price of tradable goods and benefits the rest of local labour markets (demographic groups) less exposed to robot adoption. However, this result is counterbalanced by reduced employment and wages in the commuting zones (demographic groups) more exposed to robots, which negatively affects the demand for non-tradable goods and reduces employment in construction, retail, and personal services. The effect of ICT on employment is weaker (even positive) when they use the usual measure of ICT capital (Acemoglu and Restrepo, 2020) and negative when they isolate a specific component of ICT investments strictly related to automation (Acemoglu and Restrepo, 2022).

The results concerning the EU countries are less conclusive. Graetz and Michaels (2018) use a different methodology from that illustrated above and found no significant effects of robot implementation on overall hours worked in 17 EU countries between 1993 and 2007. Likewise, Klenert *et al.* (2023) use industry-country level data and find positive or no significant effects of both robots and ICT capital on total employment for 15 EU countries (1995-2017). Chiacchio *et al.* (2018), instead, use a methodology partially similar to Acemoglu and Restrepo's; they investigate the effects of robot and ICT exposure at the demographic group level, across NUTS2 regions and six EU countries between 1995 and 2007. They identify a clear displacement effect of robots on employment, where youth and workers with medium education drive this general result. These authors, based on their comparison with US results, conjecture in the conclusions of their study that the less severe impact of robots in Europe may be due to different labour market policies.

The results for EU countries were only partially confirmed by Doorley *et al.* (2023), who also used Acemoglu and Restrepo's methodology. Doorley *et al.* (2023) analysed the effect of robot exposure on wages and employment rates of demographic groups in fourteen EU countries between 2006 and 2018. They found a negative impact of automation technologies on wages, but the impact on employment was still negative, albeit weaker. Likewise, Albinowski and Lewandowski (2023) find that ICT exposure reduces the employment of older women, while robots substitute for prime-aged men. Additional studies focussing on single countries and exploring the impact of robots and ICT on firm-level employment are also worth mentioning. Dauth *et al.* (2021) used matched employer-employee data for Germany. They found that, after implementing robots, companies allocated tasks complementary to automation to workers with longer job tenures, thus improving both the stability and the quality of their jobs. The authors also show that the negative effect of automation on manufacturing employment between 1994 and 2014 was driven by smaller inflows of younger workers. However, these displacement effects in manufacturing are fully offset by new jobs for younger workers in services. Bessen *et al.* (2019) found that in The Netherlands companies introducing robots show higher firing rates among workers with long tenures, while no significant displacement effects emerged for younger workers with shorter average tenures (less than three years). These authors also report that robot adoption turns out to be more labour-displacing than increasing the use of ICT.

Based on the evidence above and considering we are using the Bartik-like measure of robot and ICT exposure at the demographic group level (Acemoglu and Restrepo, 2022; Doorley et al., 2023;

Chiacchio et al.,2018), we expect general negative effects of automation technologies on employment rate. If we disregard the role of institutions, this effect should have a lesser impact on younger individuals who are transitioning from education to employment, since they can easily move from industries that have higher exposure to automation technologies to those that have less exposure (Dauth et al., 2021; Bessen et al., 2019).

Besides the effects of automation on total employment, the question addressing the potential moderating role that employment protection legislation (EPL) and product market regulation (PMR) may exert on the effects of automation technologies on employment remains largely unanswered.

As for EPL, apart from the consolidated literature on the effects of regulation on employment, productivity and wages (Bassanini *et al.*, 2009; Cingano *et al.*, 2010; Damiani *et al.*, 2016; Pompei and Perugini, 2017; OECD, 2020), we find more studies from the perspective of EPL inhibiting robot adoption than investigations upon the mitigating role of labour market institutions on the adverse effects of automation technologies (Traverso *et al.*, 2022). On the one hand, strict dismissal regulation tends to reduce layoffs which is a direct result of its intended effect to raise the costs of dismissals. On the other hand, it also tends to reduce hiring, as firms factor in the higher costs for a potential dismissal already at the time of hiring (OECD, 2020). Combining these considerations on EPL with those on the effects of automation technologies on employment, as measured by the Acemoglu and Restrepo methodology, we can conclude that strict dismissal regulations alone do not hurt the overall employment rate. However, if measuring robot and ICT exposure at the demographic level also captures the reallocation of employment across industries (i.e., from those with high- to those with low-content of routinary jobs), increasing stringency may hinder the job inflows. This might only affect young workers who are transitioning from education to work, and not all categories of workers. The conjecture is supported by the results of Dauth *et al.* (2021), where the smaller inflows of younger workers in industries highly exposed to robots are fully offset by new jobs for younger workers in services. This labour reallocation could be inhibited with increasing dismissal regulation.

For PMR, we find literature on its direct impact on employment while the role of market regulation as moderator of the automation technology-employment relationship has yet to be explored. Anti-competitive markets (especially in energy, communications, transport and professional services) give rise to monopolistic and monopsonistic behaviour by large companies. This means these companies reduce wages below the reservation wage and limit employment opportunities for certain groups. ‘at the margin’ of the labour market (Bassanini and Duval, 2006; Amable *et al.*, 2006; Amable *et al.*, 2016). Similar behaviour may be observed for companies operating in downstream industries: depending on the intensity of the input-output relations with non-competitive market services, these companies are affected by knock-on effects (Conway and Nicoletti, 2006). Due to the increase in input prices, such as energy and professional services, companies may apply a wage markdown in any sector.

However, the opposite evidence is offered by other studies only focussing on network industries (energy, transport and communication), where higher profits are shared with workers and guarantee higher wage premia and employment stability relative to similar workers in other industries (Denk, 2016).

Due to this mixed evidence, the moderating role of PMR on the employment rate affected by automation technologies is an open question. Suppose the knock-on effect on all industries dominates. In that case, companies apply a markdown on wages and inhibit labour market participation of the most vulnerable workers, such as those aged 20-29. Consequently, we should expect increasing stringency in product market regulation (or modest deregulation) to aggravate the negative effect of automation technologies. By contrast, if rent-sharing practices for non-routine occupations in network industries protected by anti-competitive laws become prevalent in the economy, increasing PMR or modest deregulation may promote the reassignment of labour across industries, specifically from the manufacturing sector to these network industries.

To summarise, expectations concerning the moderating role of labour and product market institutions on the effects of automation technologies are different.

In general, EPL may hinder labour mobility across industries after automation implementation, this effect could be even more severe for workers aged 20-29 transitioning from education to work.

Opposing forces come into play in the case of PMR. Network industries benefitting anti-competitive laws may devolve part of their profits to ensure higher wages and stable employment. This can offset the negative effects of wage markdowns applied by companies in other industries affected by anti-competitive laws. Determining which force dominates is an empirical question.

3. Data sources and variables

The empirical analysis is conducted at the demographic group level and different datasets have been merged[5]. First, demographic groups are defined as in Doorley *et al.* (2023) and combine five age classes (20-29; 30-39; 40-49; 50-59 and 60+); three classes for the highest level of education attained by individuals (primary, secondary and tertiary education) and two classes reporting gender (men and women). A repeated cross-section of about 1.62 million individuals in 2006 and 2018 was the original size of the LFS sample from which we collected individuals to map into the 360 demographic groups (30 groups x 12 countries). The minimum and maximum size of these groups, depending on the country size, are 37 and around 97,000 people, respectively.

3.1. Dependent variables

The dependent variable used is the change in the employment rate $\Delta Employment\ rate_{c,g}$) at the demographic group level (g) and across countries (c) between 2006 and 2018. This employment rate measure covers all industries in the economy and is based on the Eurostat Labour Force Survey.

3.2. Key explanatory variables

The key explanatory variables proxying automation technologies are robot and ICT exposure proposed by Acemoglu and Restrepo (2022) and used by Doorley et al. (2023). Robot data are derived from IFR database while information on ICT has been drawn from EUKLEMS[6]. These variables measure task displacement due to robots and ICT as follows:

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[5] Eurostat microdata on the structure of earnings survey (SES) and labour force survey (LFS), industrial robots from International Federation of Robotics (IFR), ICT capital stock from EUKLEMS (release February 2023), green patents from Orbis and OECD, employment protection legislation (EPL), product market regulation (PMR) indicators and proxies for off-shoring and import penetration from China are from OECD statistics while value-added data for industry shifters come from Eurostat macrodata.

[6] We used the 2023 release of EUKLEMS, provided by the Lab of European Economics (LUISS). The variables we used, namely net capital stock in computing equipment (IT), communications equipment (CT), computer software, databases (SoftDB), and gross output, were obtained in the form of chained linked volumes (2015). We used the final net capital stock in information and communication technology as the sum of net capital stock in IT, CT and SoftDB. To provide a meaningful cross-country comparison, we recalculated variables derived from EUKLEMS, using the 2015 data EUROSTAT, to the same currency – the euro. In addition, we extracted information from EUKLEMS on the number of employees in individual industries to limit the number of sources used. We calculated the indicator describing demographic group exposure to the ICT net capital stock penetration based on the abovementioned variables.

$$TD_{c,g} = \sum_{i \epsilon I} [\omega_{c,g}^{i} \cdot \left(\frac{\omega_{c,g,i}^{R}}{\omega_{c,i}^{R}}\right) \cdot AP_{i,c}] \qquad (1.a)$$

where *c*=12 countries, *g*= 30 demographic groups; *i*= 14 industries[7]; $TD_{c,g}$ is robot exposure (Δ Robots) and ICT exposure (Δ ICT) for country *c* and demographic group *g;* $\omega_{c,g}^{i}$ is the group exposure to different industries, that is the share of industry *i* in total earnings of workers in group g in country c; the ratio $\frac{\omega_{c,g,i}^{R}}{\omega_{c,i}^{R}}$ identifies the relative specialisation of group g in the industry *i* routine occupations[8] (where displacement is assumed to take place); $AP_{i,c}$ is the adjusted penetration of robots (ICT) in industry i and country c.

$AP_{i,c}$ is in turn calculated as follows:

$$AP_{i,c} = \frac{A_{i,c,2018} - A_{i,c,2006}}{L_{i,c,2006}} - \frac{Y_{i,c,2018} - Y_{i,c,2006}}{L_{i,c,2006}} \cdot \frac{A_{i,c,2006}}{L_{i,c,2006}} \qquad (1.b)$$

where $AP_{i,c,t}$ represents the current stock of robots or net capital stock of ICT in the industry *i*, country c and years 2018 and 2006; this difference is normalised by the initial level of employment ($L_{i,c,2006}$) and adjusted by the overall change in the industry output $\frac{Y_{i,c,2018} - Y_{i,c,2006}}{L_{i,c,2006}} \cdot \frac{A_{i,c,2006}}{L_{i,c,2006}}$ to take into account the secular decline of some industries.

These measures of automation exposure can be endogenous to changes in the employment rate. As we will see in the descriptive statistics, the ageing of workers has been important over the years under scrutiny. This can anticipate investments in automation technologies and a reverse causality problem emerges. To address this problem, we follow Acemoglu and Restrepo (2020) and Doorley *et al.* (2023), by defining instruments for the adjusted penetration measures $AP_{i,c}$ based on the average variation of Robots and ICT occurred in countries not included in our main sample. We

[7] Robot and ICT exposures are defined on 14 SES industries for which robot data are available, adjusting for their different level of aggregation across countries: 1) Agriculture; 2) Mining and Quarrying; 3) Manufacture of food, beverages, tobacco; 4) Manufacture of textile, wearing apparel, and footwear; 5) Manufacture of wood and paper, and printing; 6) Manufacture of refined petroleum, chemical, pharmaceutical, plastic and non-metallic mineral products; 7) Manufacture of basic metal and metal products; 8) Manufacture of computer and optical product; 9) Manufacture of electrical equipment; 10) Manufacture of machinery; 11) Manufacture of motor vehicles and other transport equipment; 12) Energy and waste management; 13) Construction; 14) Education.

[8] The EU-SES is used to calculate shares of workers in routine jobs by demographic group and country. We apply the typology of Lewandowski *et al.* (2020), based on the Occupational Information Network (O*NET) data, to define routine occupations at the 2-digit level of the International Standard Classification of Occupations (ISCO).

singled out four small EU countries, Slovenia, Austria, Denmark and Finland. The original instrument in Acemoglu and Restrepo (2020) comprised Denmark, Finland, France, Italy, and Sweden. Since three of these countries are included in our sample (France, Italy and Sweden), we must modify the original instrument. Therefore, the instrument we are using in our analysis includes four countries: Slovenia, Austria, Denmark, and Finland. These countries were selected due to their high levels of robot penetration (see Figure A.1 in the Appendix), which may reflect their greater willingness to adopt the latest automation technologies compared to the EU-12. As a result, they may have played a role in promoting and reinforcing robot and ICT adoption in the EU-12. Other studies that use technology adoption in peer countries as an instrument for European economies include Anelli *et al.* (2021), Bachmann *et al.* (2022), Damiani *et al.* (2023), Doorley *et al.*, 2023), Matysiak *et al.* (2023), and Nikolova *et al.* (2022).

The key explanatory variables capturing the mediating effect of labour and product market institutions are from OECD statistics. As for employment protection legislation (EPL), we use the summary country-level indicator for individual and collective dismissals for regular workers (version 1998-2019). We borrow the idea proposed in the empirical literature on the effects of labour institutions on labour productivity (Bassanini *et al.*, 2009; Cingano *et al.*, 2010; Damiani *et al.*, 2016 and 2020; Jerbashian, 2019), and apply it to map into industries the country-level stringency of employment protection. Next, we introduce this derived variable in a Bartik-like indicator to measure the exposure to EPL change at the demographic group level.

$$\Delta \mathrm{EPL}_{c,g} = \sum_{i \in I} \left[\omega_{c,g}^{i,empl} * (\mathrm{layoffs}_{i,empl,\mathrm{UK}} * (\mathrm{EPL}_{c,2018} - \mathrm{EPL}_{c,2006}))_{i,empl,c} \right] \quad (2)$$

where $\mathrm{layoffs}_{\mathrm{i,UK}}$ are redundancy rates by industry (average of the available years, from 2009 to 2018) reported by the Office for National Statistics in the UK (see Figure A.2 in the Appendix); $(\mathrm{EPL}_{c,2018} - \mathrm{EPL}_{c,2006})$ is the percentage change in the stringency of employment protection between 2006 and 2018, and $\omega_{c,g}^{i,empl}$ is group's *g* exposure to different industries given by the share of industry *i*[9] in total working age population (LFS micro-data) in the group *g* in country *c*. In the

[9] $\omega_{c,g}^{i,empl}$ is different from $\omega_{c,g}^{i}$, as the former has been defined on 14 LFS industries with different level of aggregation: 1) Agriculture; 2) Mining and Quarrying; 3) Manufacturing; 4) Energy and waste management; 5) Construction; 6) Wholesale and retail trade; 7) Transport, storage and telecommunications; 8) Accommodation and food services; 9) Financial and Insurance Activities; 10) Real estate, business, admin. and support Services); 11) Public administration; 12) Education; 13) Health; 14) Arts, entert. and other services.

spirits of Rajan and Zingales (1998) and its extension to the labour economics empirical studies (Bassanini et al., 2009; Damiani et al., 2016; 2020; Jerbashian, 2019), we assume that the effect of country-level institutions on employment outcomes will be more binding for those industries with higher 'natural' propensity to dismiss workers. Industries that independently of protection legislation show a 'natural' propensity to dismiss workers can be proxied by those in the country with the lowest level of regulation and showing an economic environment closer to the *laissez faire*. The UK is not only the European country with the lowest level of EPL but also one for which annual statistics on redundancies (with industry-level breakdown) are available. Thus, we created, first, an industry-level variable for the EPL of countries in our sample and then retrieved the same information at the demographic-group level to obtain the group's g exposure to the EPL of the country, according to the importance of the demographic group in industries with different 'natural' propensity to dismiss workers.

Our measure for PMR change is based on the OECD Regulatory Impact Indicator (2018 extended version), which measures the impact of regulatory barriers to competition in seven network industries (electricity, gas, telecom, post, and air, rail and road transports) on all industries (36 ISIC Rev.3 Industries, see Egert and Wanner 2016). We first mapped this industry-country indicator to the 14 industries and countries of LFS microdata[10]. Next, we use the following equation to retrieve this information at the demographic-group level for any country.

$$\Delta \mathrm{PMR}_{c,g} = \sum_{i \in I} \left[\omega_{c,g}^{i,empl} * \left(\mathrm{PMR}_{i,empl,c,2018} - \mathrm{PMR}_{i,empl,c,2006} \right) \right] \qquad (3)$$

Where $(\mathrm{PMR}_{c,2018} - \mathrm{PMR}_{c,2006})$ is the percentage change in the regulatory impact indicator measuring the barriers to competition between 2006 and 2018, and $\omega_{c,g}^{i,empl}$ is the same weight already used in equation 2 to obtain a Bartik-like measure for demographic groups. As for the EPL change, we assume that PMR change can affect demographic groups with different intensities depending on the group's g exposure to different industries, given by the share of industry i in total working age population (LFS micro-data) in the group g in country c.

[10] Different from the EPL, the OECD regulatory impact indicator we use is available at the industry-country level.

3.3. Control variables

3.3.1. Green Technologies

We build a measure to control the progress of green technologies based on publications of green patents reported by the OECD. Although patent publications in green technologies, as well as in other technological fields, have limitations, they do offer a way to measure innovative activities that are closely related to research and development expenditures, as well as downstream innovations (Oltra *et al.*, 2010)[11]. Nevertheless, patent publications provide valuable insights into the level of innovation happening within a specific field. Since the statistics on environment-related patents released by OECD are only available at the country level, we defined industry-level weights based on the Orbis_Intellectual_Property database to map the OECD patents into country-industry. For the 12 countries in our sample, we selected from OrbisIP a sample of companies that applied for environment-related patents according to the OECD methodology (IPC technological classes including green technologies, see OECD, 2011, Annex B[12]). From company-level information in the OrbisIP database we retrieved the green patent applications at the NACE rev.2 industry level by calculating the sum of green patent applications over the years (2006-2018) and firms within the same industry. Next, we calculated weights for green patent applications at the industry level, for each country in our sample using this information. We used these weights to reallocate country-level OECD green patents to the industries and countries in our sample. The OECD green patents are more reliable because they refer to patents that have been filed by priority date in at least two IP offices worldwide, one of which among the Five IP offices (namely the European Patent Office, the Japan Patent Office, the Korean Intellectual Property Office, the US Patent and Trademark Office and the State Intellectual Property Office of the People Republic of China). Further, the number of country-level green patent applications from OECD is much higher than that we observe in the OrbisIP database. To avoid measurement errors related to the Orbis sample, we opted for the

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[11] It's important to note that an invention is different from an innovation, and not all innovations are patented. However, patent publications are often preferred over patent grants, this is because the latter may show a significant delay and do not reflect the innovative effort that has been made much earlier.

[12] The main technology fields from which we selected more than fifty 6_digits IPC classes are: i) Air pollution abatement; ii) Water pollution abatement; iii) Solid waste management and recycling; iv) Improved engine design technologies; v) Fuel characteristics that improve combustion; vi) Improved vehicle design technologies; vii) Alternative fuel vehicle technologies.

OECD patents and used the Orbis database only to calculate country-industry level weights for green patents. Eventually, we calculated a proxy of exposure to green technology at the demographic group level as follows:

$$\Delta \text{ Green Patents}_{c,g} = \sum_{i \in I} \left[\omega_{c,g}^{i,empl} * \frac{(\text{Green Patents}_{i,empl,c,2018} - \text{Green Patents}_{i,empl,c,2006})}{L_{i,empl,c,2006}} \right] \quad (4)$$

where, the first term is identical to that already used in equations 2 and 3, and the second term reports the difference between the patents filed by priority date over the years 2006-2018 normalised by the level of employment at the initial year. This variable gives us an idea about what occurred at the employment rate for demographic groups that, depending on their importance in specific industries, have been exposed to the invention of green technologies with different intensities. Unlike the automation exposure variables, we do not have a reliable measure for the industry green job specialisation that parallels the coefficient $\frac{\omega_{c,g,i}^{R}}{\omega_{c,i}^{R}}$ in the equation 1.a. In addition, we lack an appropriate instrument to control for the potential endogeneity between green patent exposure and employment rate. For these reasons, we only retain green patent changes as a control variable and do not directly treat it as a key explanatory variable by contrasting it to automation exposure.

3.3.2. Globalisation and industry shocks

Again, in line with Acemoglu and Restrepo (2022) and Doorley *et al.* (2023), we define three additional control variables to take into account the rest of the megatrends that can affect labour market outcomes, i.e., asymmetries among industries concerning the economic growth and globalisation.

Based on Eurostat macro data, we use a measure for industry shifters, that is, the group exposure to change in log value added between 2006 and 2018. In addition, we draw from OECD TiVA statistics measures for off-shoring and import penetration from China. More in detail, off-shoring is defined as the difference in the group exposure to the foreign value added in gross output (2006-2018), while import penetration from China has been calculated as the change in import from China (2006-2018) divided by initial absorption (industry outputs plus industry imports minus industry exports). We first calculate these variables at the industry-country level and then map them into the demographic groups as follows:

$$\Delta Var_{c,g} = \sum_{i \in I} \left[\omega_{c,g}^{i,empl} * (\mathrm{Var}_{i,empl,c,2018} - \mathrm{Var}_{i,empl,c,2006}) \right] \quad (5)$$

where $\omega_{c,g}^{i,empl}$ is the usual weight already discussed above and Var stands for value added, off-shoring and China imports, alternatively.

4. Descriptive statistics

Table 1 shows summary statistics for variables used in the econometric analysis. Between 2006 and 2018 the employment rate at the demographic group level increased by 2.6 percentage points. An increase in exposure to automation technologies accompanies this modest increase. Robot and ICT capital, calculated as in equations 1.a and 1.b, increased by 0.11 units and 0.281 million Euros per thousand workers, respectively. The average exposure to green technology increased by 0.015 patents per thousand workers. Over the same period, the stringency of labour and product market regulation decreased on average by 16% and 11%, respectively.

Table 1. Summary statistics

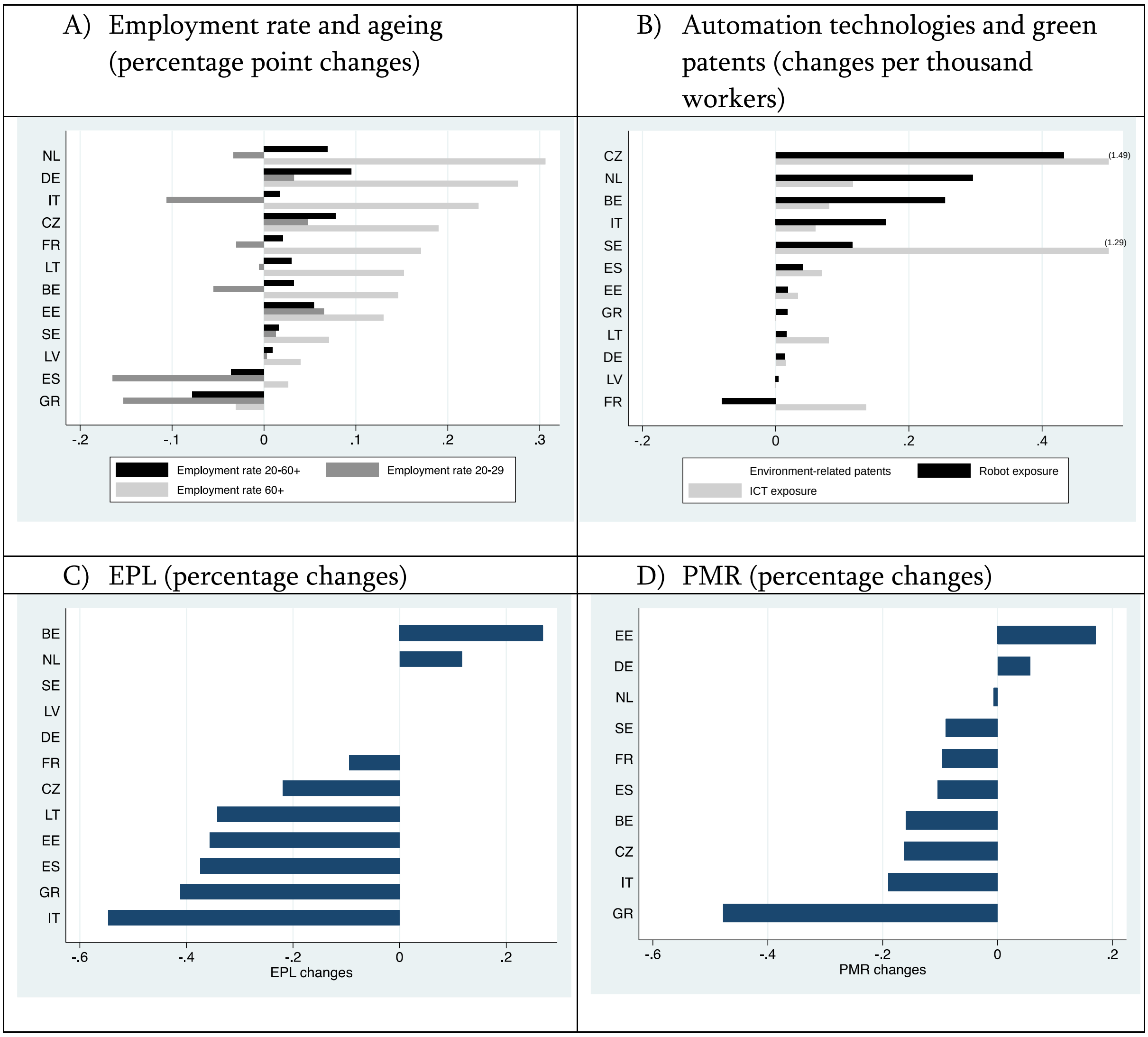
Dependent variables	Observations	Mean	SD
Δ employment rate	360	0.026	0.106
Key explanatory variables			
Δ Robots	360	0.108	0.333
Δ ICT	360	0.281	0.925
Δ EPL	360	-0.163	0.336
Δ PMR	300	-0.106	0.164
Control variables			
Δ Green Patents	360	0.015	0.030
Industry Shifter	360	0.120	0.364
Δ OffShoring	360	0.012	0.068
Δ Imports_CN	360	0.014	0.013
Employment rate 2006	360	0.69	0.23

Source: Eurostat, OECD, EUKLEMS, IFR. Note: all variables refer to the demographic groups and are reported as changes 2006-2018 (see Table A.1 in the Appendix for details). The employment rate is the percentage point changes for all demographic groups including individuals aged 20-60+. DRobots and DICT are Robot and ICT exposures calculated as in equations 1.a & 1.b, the number of robots and million Euros of ICT per thousand workers, weighted for the groups' exposure to different industries and the group's relative specialisation in the industry routine's occupation. DEPL and DPMR are percentage changes in labour and product market regulation weighted for the groups' exposure to different industries. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania. For the definition of control variables see Table A.1 in the Appendix.

Beyond these aggregate figures, significant heterogeneity is observed across countries (Figure 2, and Figure A.3 in the Appendix), age, education, and gender groups (Figures A.4, A.5. and A.6 in the

Appendix). Except for Greece and Spain, all other countries experienced increased employment rates, although some remain far from the 78% target established in the European Pillar of Social Rights. Italy, Belgium and France are included in this group (Figure A.3 in the Appendix). The increase in the majority of countries can be attributed to the ageing of workers, as individuals above 60 years old had a higher employment rate growth compared to other categories of workers. Institutional changes such as the pension reforms launched in the 2000s, which gradually increased the normal retirement age contribute to explaining this improved performance for older workers (Gabriele *et al.*, 2018, Fehr *et al.*, 2012).

Figure 2. Employment rate, ageing, automation and environment-related technologies across countries (changes between 2006 and 2018)



Source: Eurostat, OECD, EUKLEMS, IFR. Note: all variables refer to the demographic groups and are reported as changes 2006-2018 (see Tables 1 above and A.1 in the Appendix for details).

Figure 2 also shows that high robot exposure is associated with a reduction in the youth employment share in countries that significantly increased (Belgium and the Netherlands) or reduced (Italy and Spain) the stringency in employment protection. Overall, seven out of twelve countries eased the restrictions on protection for individual and collective dismissals of regular workers in the aftermath of the global financial crisis. Belgium and the Netherlands were the only two countries that did the opposite. The OECD (2020) explained these changes as a coordinated effort to realign protection levels for different categories of workers and reduce the dualism in the labour market. Out of twelve countries, the relaxation of PMR occurred in ten. Exceptions were Germany and Estonia. According to Vitale *et al.* (2018), over the last few years, there has been an effort to reach a regulatory stance closer to competition-friendly product markets.

Regarding the age, education, and gender profiles of workers, exposure to robots and ICT was important for younger individuals (aged 20-29), women, and those with intermediate education. On the other hand, exposure to green technology was more significant for older individuals (aged 60+) and male workers with tertiary education (Figures A.4, A.5., and A.6 in the Appendix). According to our measure of exposure to institutional changes, the relaxation of EPL impacted younger workers (aged 20-29) more than older workers (aged 60+), particularly those with lower levels of education. We observe a similar pattern for the PMR relaxation, with the only exception of women being more affected than men.

5. Methodology

In the first step of the econometric analysis, we run a baseline OLS regression where we explain the changes in the employment rate with the measure of robot and ICT exposure illustrated in equations 1.a and 1.b.

$$\Delta Empl_{c,g} = \beta TD_{c,g} + \vartheta \Delta INST_{c,g} + \gamma \Delta X_{c,g} + \alpha_{educ(g,c)} + \kappa_{gender(g,c)} + \eta_{country(g,c)} + \varepsilon_{(c,g)} \quad (6)$$

where c=1,..12 countries; g=1,...30 demographic groups; $TD_{c,g}$ is robot exposure (ΔRobots) and ICT exposure (ΔICT) for country c and demographic group g; $\Delta INST_{c,g}$ stands for our measures of demographic group exposure to institutional changes, it includes $\Delta \text{EPL}_{c,g}$ and $\Delta \text{PMR}_{c,g}$ calculated according to equations 2 and 3; $\Delta X_{c,g}$ is a vector of control variables containing the exposure of demographic groups to i) green technologies, proxied by the change in environment-related patents (equation 4), ii) import penetration from China, and iii) off-shoring, to take into account for globalisation, and iv) a measure for industry shifter to take into account the groups' exposure to the industry-level growth (all these three measures are described by equation 5). We also control for country-, gender- and education-specific effects to take into account idiosyncratic factors associated with these different dimensions.

In the second step, we follow the usual practice reported in the literature (Acemoglu and Restrepo, 2020; Doorley *et al.*, 2023) to control for potential endogeneity of TD. We use an average measure of adjusted penetration for robot and ICT ($AP_{i,c}$ in equation 1.b) which have been adopted in four countries not in our sample (Slovenia, Austria, Denmark and Finland). The idea is that the exogenous adoption of automation technology (in countries not in our sample), stimulates the diffusion of robots and ICT in the countries of interest, without directly affecting their labour markets.

Next, we augment the IV specification discussed above with an interaction to study the moderating effect of these institutions on the relationship between automation technologies and employment rate. More in detail, we run the following regression:

$$\Delta EMPL_{c,g} = \beta^{INST}(TD_{c,g} \text{x}\, \Delta INST_{c,g}) + \vartheta \Delta INST_{c,g} + \theta TD_{c,g} + \gamma \Delta X_{c,g} + \alpha_{educ(g,c)} + \kappa_{gender(g,c)} + \eta_{country(g,c)} + \varepsilon_{(c,g)} \quad (7)$$

where all variables have already been discussed in equation (6).

Finally, we investigate the potential heterogeneity across the most vulnerable workers defined in terms of age (younger and older workers versus the rest). We first run regressions implementing an interaction term ($TD_{c,g}$x $Age_{c,g}$) where $Age_{c,g}$ is a binary variable equalling 1 for workers aged 20-29 (or for workers aged 60+) and zero otherwise. Secondly, we introduce a triple interaction ($TD_{c,g}$x $\Delta INST_{c,g}$ x $Age_{c,g}$) to identify potential heterogeneity of the moderating effect of institutions across vulnerable workers.

It is worth noting that all regressions reported in equations 6 and 7 are weighted by the group's share of the country's employment.

6. Results

Table 2 shows OLS baseline estimates for the employment rate change 2006-2018 at the demographic group level[13]. In line with the empirical literature using the measure of exposure to automation technologies proposed by Acemoglu and Restrepo (Chiacchio *et al.*, 2018; Doorley *et al.*, 2023) we find a negative and significant association between robot exposure and employment rate (Table 2, columns 1, 2 and 3), while no correlation has been detected for ICT (columns 4, 5 and 6). We postpone a more detailed discussion of our key variables to the IV regressions presented in the following Tables. It is noteworthy, however, from this baseline OLS regression that the effect of the EPL change on the employment rate is non-negative (even weakly positive in these first results), as suggested by the literature reported in section 2. At the same time, no association is observed for product market regulation.

[13] According to Acemoglu and Restrepo (2022) and Doorley *et al.* (2023), in order to alleviate problem of skewness in the distributions we transform our key variables in ln(1+ Δ Robots) and ln(1+ Δ ICT). A similar treatment has been applied to Green Patents.

Table 2. Employment rate change: exposure to automation technologies, labour and product market institutions between 2006 and 2018 (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var.	Δ Employment rate					
Δ Robots	-0.034** (0.017)	-0.040** (0.017)	-0.037* (0.019)			
Δ ICT				-0.013 (0.020)	-0.018 (0.017)	-0.016 (0.018)
Δ EPL		0.038* (0.021)			0.039* (0.021)	
Δ PMR			0.007 (0.005)			0.007 (0.005)
Δ Green Patents		0.010*** (0.002)	0.026*** (0.010)		0.010*** (0.002)	0.027*** (0.010)
Industry Shifter		0.001 (0.001)	0.001 (0.001)		0.001 (0.001)	0.001 (0.001)
Δ OffShoring		-0.001* (0.001)	-0.001 (0.001)		-0.001 (0.001)	-0.000 (0.001)
Δ Imports_CN		0.002 (0.005)	-0.001 (0.004)		0.003 (0.005)	-0.001 (0.004)
Country, gender, and education fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	360	360	300	360	360	300
R2	0.312	0.358	0.377	0.306	0.352	0.372

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change between 2006 and 2018 in employment share at the country and demographic group level. All explanatory variables capture the group exposure to the specific phenomenon between 2006 and 2018. Robots, ICTs and Green Patents are taken in log. All regressions are weighted by the group's share of the country's employment. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania.

Source: LFS, IFR robotics, OECD, Orbis.

It is also important to mention that exposure to green technology works as a good control, as it is always positive and highly significant, even though modest in magnitude. Therefore, green innovations behave differently from automation technologies, as their diffusion benefits employment[14].

These preliminary OLS results are confirmed even when we test their sensitivity to different specifications, as in Table A.2 in the Appendix.

Instrumental variable regressions are reported in Table 3, where robot and ICT exposure (ΔRobots and ΔICT) have been regressed in the first stage on adjusted penetration of robot and ICT occurred in four countries not in our sample (Slovenia, Austria, Denmark, and Finland). To enhance the readability of this table and the following tables, only the coefficients of interest and the *weak instrument identification test* of the first stage (F statistics) will be displayed[15]. As for specifications shown in Table 3, the value of the F statistics signals that the correlations between the endogenous regressors and the excluded instruments are not weak (Baum *et al.*, 2007).

After controlling for endogeneity, the analysis confirms the negative and significant influence of robot exposure on employment rates, finding, instead, a negative but insignificant effect of ICT exposure. If we take the specification with all control variables and EPL change (Table 3, column 2) and stick to the variability of robot exposure in our sample, one standard deviation[16] higher in robot exposure lowers the employment rate by 1.6 percentage points (p.p.). The magnitude of this effect is not so far from 2 and 4.4 p.p., found by Doorley *et al.* (2023) in the EU countries, and Acemoglu and Restrepo (2022) in the US, respectively. Results from Table 3 concerning changes in the institutions confirm that EPL has a positive and weak influence on the employment rate, while PMR does not. Interestingly, the control for green technology retains its positive impact, even if modest in magnitude.

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[14] This outcome deserves further research in the future. Hopefully this additional research will allow us to treat green technology exposure as a key explanatory variable. Indeed, we currently lack adequate measures to describe specialisation in green jobs comparable to those used for routine job specialisation in automation technologies.

[15] Results for control variables and other first-stage statistics are available upon request.

[16] The standard deviation for ln (1+Δrobots) is 0.197.

Table 3. Employment rate change: exposure to automation technologies, labour and product market institutions between 2006 and 2018 (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var.	Δ Employment rate					
Δ Robots	-0.069** (0.028)	-0.081** (0.032)	-0.093** (0.044)			
Δ ICT				-0.060 (0.038)	-0.075 (0.059)	-0.117 (0.081)
Δ EPL		0.037* (0.021)			0.041** (0.021)	
Δ PMR			0.007 (0.005)			0.006 (0.005)
Δ Green Patents		0.010*** (0.002)	0.020** (0.010)		0.009*** (0.002)	0.016 (0.015)
Other control variables	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Country, gender, and education fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	360	360	300	360	360	300
Kleibergen-Paap rk Wald F statistic	31.16	21.43	14.60	30.20	15.02	10.89

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change between 2006 and 2018 in employment share at the country and demographic group level. All explanatory variables capture the group exposure to the specific phenomenon between 2006 and 2008. Other control variables include Ind.Shifter, Δ OffShoring, Δ Imports_CN, already included in estimations shown in Table 1. Δ Robots and Δ ICT have been instrumented with robot and ICT exposure observed in 4 countries not included in our sample (Slovenia, Austria, Denmark and Finland). All regressions are weighted by the group's share of the country's employment. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania.
Source: LFS, IFR robotics, OECD, Orbis

Overall, workers aged 20-29 have been penalised regarding employment rate after the global crisis. This is evident from Figure A.4 (panel A) and emerges from regressions shown in Table 4, where the employment of young workers has decreased by 4 to 5 percentage points compared to other workers (see coefficient of dummy Young). Introducing this control for vulnerable workers does not affect the main results for robot exposure while slightly improving the statistical significance of ICT which shows a weak negative impact on the employment rate[17].

[17] As expected, a dummy for workers aged 60+ shows a positive and strongly significant sign meaning that older individuals have seen an improvement in terms of employment compared to the rest of workers (see Table A.4 in the Appendix). A weaker negative effect of robot exposure is observed in this case, as its coefficient is no longer significant. This result deserves more investigation in the future.

Table 4. Employment rate change: exposure to automation technologies, labour and product market institutions between 2006 and 2018. Control for young workers (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var.	**Δ Employment rate**					
Δ Robots	-0.069**	-0.076**	-0.097*			
	(0.034)	(0.038)	(0.054)			
Δ ICT				-0.077**	-0.084	-0.149*
				(0.037)	(0.059)	(0.082)
Young (20-29)	-0.045***	-0.046***	-0.054***	-0.046***	-0.043***	-0.049***
	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
Δ EPL		0.038*			0.042**	
		(0.020)			(0.020)	
Δ PMR			0.004			0.004
			(0.004)			(0.004)
Control variables	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Country, gender, and education fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	360	360	300	360	360	300
Kleibergen-Paap rk Wald F statistic	32.92	21.97	14.53	33.67	16.03	11.32

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change between 2006 and 2018 in employment share at the country and demographic group level. All explanatory variables capture the group exposure to the specific phenomenon between 2006 and 2008. Control variables include Δ Green Patents, Ind.Shifter, Δ OffShoring, Δ Imports_CN, already included in estimations shown in Table 1. Δ Robots and Δ ICT have been instrumented with robot and ICT exposure observed in 4 countries not included in our sample (Slovenia, Austria, Denmark and Finland). All regressions are weighted by the group's share of the country's employment. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania.

Source: LFS, IFR robotics, OECD, Orbis.

In line with our literature-based expectations (Bessen *et al.*, 2019; Dauth *et al.*, 2021), young workers have not been penalised by robots and ICT exposure (Table 5, columns 2 and 4). This may be because it is easier for workers in this category, in transition from education to work, to be hired in industries that are less exposed to robots and ICT, provided that there are not other obstacles. Table 5 (columns from 5 to 8) shows an opposite sign for older workers, even though all interactions between automation technologies and older workers lack statistical significance.

Table 5. Employment rate change: exposure to automation technologies by age of workers (IV)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var.	Δ Employment rate							
Δ Robots x Young	0.075 (0.049)	0.134** (0.064)						
Δ ICT x Young			0.086 (0.053)	0.091* (0.047)				
Δ Robots	-0.121** (0.051)	-0.193** (0.084)			-0.042 (0.029)	-0.055 (0.037)		
Δ ICT			-0.113* (0.068)	-0.195** (0.097)			0.039 (0.060)	0.019 (0.073)
Young	-0.058*** (0.013)	-0.081*** (0.017)	-0.064*** (0.013)	-0.075*** (0.016)				
Δ EPL	0.040** (0.020)		0.050** (0.020)		0.028 (0.019)		0.027 (0.020)	
Δ PMR		0.004 (0.004)		0.003 (0.004)		0.008** (0.004)		0.009** (0.004)
Δ Robots x Old					-0.383 (0.609)	-0.113 (0.869)		
Δ ICT x Old							-0.023 (0.121)	-0.074 (0.104)
Old					0.125*** (0.019)	0.140*** (0.024)	0.125*** (0.019)	0.150*** (0.022)
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Country, gender, and education fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	360	300	360	300	360	300	360	300
Kleibergen-Paap rk Wald F statistic	6.60	19.34	12.67	7.34	2.20	7.21	7.59	5.50

Note: Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable is the change between 2006 and 2018 in employment share at the country and demographic group level. All explanatory variables capture the group exposure to the specific phenomenon between 2006 and 2008. Control variables include Δ Green Patents, Ind.Shifter, Δ OffShoring, Δ Imports_CN, already included in estimations shown in Table 1. Δ Robots and Δ ICT have been instrumented with robot and ICT exposure observed in 4 countries not included in our sample (Slovenia, Austria, Denmark and Finland). All regressions are weighted by the group's share of the country's employment. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania.

Source: LFS, IFR robotics, OECD, Orbis.

The weak but overall positive effect of stringent employment protection on the employment rate deserves further investigation and discussion. This is because the theoretical predictions in section 2 suggest that increased stringency has substantially negative effects on labour mobility but no effects on the overall employment rate. We have found two tentative explanations for our positive outcome. First, in the period under analysis (2006-2018) the majority of countries in the sample experienced significant deregulation (Italy, Greece and Spain) or no changes in employment protection (Germany and Sweden, among others). The minor increases implemented in the Netherlands and Belgium were meant to realign the protection levels between regular and temporary contracts (see Figure A.1 in the Appendix). Therefore, we can interpret our result as a positive effect of no change or a mild increase in the EPL. In the PMR case, we should contrast strong versus mild deregulation since all countries underwent a relaxation of regulatory stances during the analysed period. Secondly, we create a metric of demographic group exposure to the EPL change capturing different impacts compared to the traditional EPL indicator at the country (or industry-country) level. In our case, the EPL indicator provided by the OECD, has a different effect for the demographic groups of the same country, depending on the importance of the group on those industries with a higher 'natural' propensity to lay off, that is, an exogenous characteristic measured in the country with the lowest employment protection level and not considered in our sample (UK).

However, we find no moderating role for EPL in the impact of robot exposure on employment (see Table 6). Based on the literature discussed in section 2, we expect robot exposure to hurt employment because, even in the case of labour reallocation across industries, the displacement effects prevail on the productivity and reinstatement effects. At the same time, in line with the theoretical predictions for a negative effect of EPL on labour mobility, we should expect higher stringency in EPL aggravating the impact of robot exposure. The coefficient of the interaction term *ΔRobots x ΔEPL* (Table 6, columns 1 and 2) has the expected negative sign yet is not statistically significant.

By contrast, a positive PMR change (i.e., a modest deregulation in product markets) plays a role in worsening the negative impact of ICT on the employment rate (Table 5, columns 7 and 8). In the event of a slow repeal of anti-competitive laws, higher input costs such as those for energy and business services, may cause companies to implement a wage cut, discouraging certain groups of workers from participating in the labour market. This process could interfere with labour reallocation among industries due to increasing ICT exposure. Therefore, the negative impact of the interaction term *ΔICT x ΔPMR* adds to that shown by *Δ*ICT as a stand-alone term (Table 5, columns 7 and 8).

Table 6. Employment rate change: the moderating effects of labour and product market regulation on the exposure to automation technologies (IV)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var.	**Δ Employment rate**							
Δ Robots x Δ EPL	-0.075 (0.065)	-0.070 (0.074)						
Δ ICT x Δ EPL			-0.088 (0.124)	-0.108 (0.112)				
Δ Robots	-0.087** (0.035)	-0.098** (0.038)			-0.278 (0.171)	-0.316 (0.210)		
Δ ICT			-0.082 (0.060)	-0.091 (0.061)			-0.476** (0.231)	-0.529* (0.278)
Δ EPL	0.047** (0.019)	0.043** (0.020)	0.050* (0.030)	0.047** (0.021)				
Δ Robots x Δ PMR					-0.012 (0.009)	-0.013 (0.010)		
Δ ICT x Δ PMR							-0.029* (0.015)	-0.032** (0.016)
Δ PMR					0.008 (0.005)	0.008 (0.005)	0.009 (0.006)	0.010* (0.006)
Control Variables	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Country, gender, and education fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	360	360	360	360	300	300	300	300
Kleibergen-Paap rk Wald F statistic	12.74	10.92	12.67	7.99	7.33	4.39	14.46	7.54

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change between 2006 and 2018 in employment share at the country and demographic group level. All explanatory variables capture the group exposure to the specific phenomenon between 2006 and 2008. Control variables include Δ Green Patents, Ind.Shifter, Δ OffShoring, Δ Imports_CN, already included in estimations shown in Table 1. Δ Robots and Δ ICT have been instrumented with robot and ICT exposure observed in 4 countries not included in our sample (Slovenia, Austria, Denmark and Finland). All regressions are weighted by the group's share of the country's employment. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania.

Source: LFS, IFR robotics, OECD, Orbis.

Finally, we want to focus on potential heterogeneities emerging in the moderating role of EPL when workers are grouped by age. Table 7 only reports some preferred specifications which have been singled out from a larger array of models (see the full Table A.4 in the Appendix).

We only concentrate on younger workers due to the non-significant results for older workers.

We find EPL having a negative and significant influence (even though only at the 10% level of significance) on the relationship between automation technologies and the employment rate of young workers. This effect is reported by the coefficients attached to triple interactions (Δ Robots x ΔEPL x Young) and (ΔICT x ΔEPL x Young). Interestingly, and in line with previous results, robots, ICT and the *young* dummy, as standing-alone terms, negatively affect changes in the employment rate. In contrast, the opposite holds for the EPL effect.

Their interactions instead result in negative coefficients and indicate that greater robot (or ICT) exposure becomes particularly harmful for young people under increasing restrictions of EPL.

Table 7. Employment rate change: the moderating effects of labour market regulation and age of workers on the exposure to automation technologies (IV)

Dep.Var.	Δ Employment rate	
	(1)	(2)
Δ Robots x Δ EPL x Young	**-0.201***	
	(0.105)	
Δ Robots x Δ EPL	-0.076	
	(0.073)	
Δ EPL x Young	-0.003	0.034
	(0.040)	(0.038)
Δ Robots	-0.143***	
	(0.052)	
Δ EPL	0.044**	0.051**
	(0.019)	(0.021)
Young	-0.054***	-0.050***
	(0.013)	(0.012)
Δ ICT x Δ EPL x Young		**-0.229***
		(0.120)
Δ ICT x Δ EPL		-0.109
		(0.118)
Δ ICT		-0.142*
		(0.075)
Control Variables	*Yes*	*Yes*
Country, gender, and education fixed effects	*Yes*	*Yes*
Observations	360	360
Kleibergen-Paap rk Wald F statistic	27.90	8.64

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. This table is an excerpt; the full table is available in the Appendix (Table A.3). The dependent variable is the change between 2006 and 2018 in employment share at the country and demographic group levels. All explanatory variables capture the group exposure to the specific phenomenon between 2006 and 2008. Control variables include Δ Green Patents, Ind.Shifter, Δ OffShoring, Δ Imports_CN, already included in estimations shown in Table 1. Δ Robots and Δ ICT have been instrumented with robot and ICT exposure observed in 4 countries not included in our sample (Slovenia, Austria, Denmark and Finland). All regressions are weighted by the group's share of the country's employment. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania.

Source: LFS, IFR robotics, OECD, Orbis.

To better understand the coefficients associated with the triple interaction, we can examine the potential outcome means of changes in employment rates for two groups of workers: those aged 20-29 and those aged 30-60+, under varying levels of exposure to robots (or ICT) and changes in EPL.

Table 8 illustrates estimates on the potential outcome means of changes in employment rate under different values of robot (ICT) exposure and EPL changes. These values are 10th, median and 90th percentiles of robot, ICT and EPL distributions in our sample. In the case of robot exposure (Table 8, panel A), we observe that with an increase in EPL, the negative effects on employment rate change increased from 2.4 to 6.3 percentage points as robot exposure intensified from 0 to 0.25 log points (i.e., from the 10th to the 90th percentile)[18]. The impact of high EPL change and robot exposure differs among age groups. The negative effect is more pronounced for younger workers, with a decrease of 6.3 percentage points. In contrast, the effect is not statistically significant for the rest of the workers, with a decrease of only 0.9 percentage points. A tentative explanation for these results aligns with Dauth *et al.*'s (2021) findings for the German case: high exposure to robots does not harm senior workers because the more stringent EPL regime protects them. This stricter regulation could prompt companies to initiate training programmes for senior workers, upgrading their skills and finding new complementary tasks to robots. By contrast, young workers transitioning from education to work, face more difficulties in being hired in sectors less exposed to automation technologies when the stringency in EPL increases. This is because employers are less willing to hire under these circumstances due to negative expectations of higher dismissal costs.

It is interesting to note that for young workers exposed to high levels of robots, there is a non-linear effect on the change in EPL (Table 8, Panel A, last column). When there is a moderate EPL change (mild deregulation), the negative impact on the employment rate change of young workers is at its lowest (-3 p.p.). This is in comparison to a decrease of -6.3 p.p. under increasing EPL or -3.7 p.p. under strong EPL deregulation.

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[18] Figure A.7 in the Appendix complements Table 8 and shows the full pattern of predictive margins for the employment rate change and for three different values of EPL change as a robot (ICT) exposure intensifies.

Table 8. Predictive margins on employment rate changes for different intensities of Robot and ICT exposure and EPL changes

	Panel A: Robot Exposure		
	Workers aged 20-29		
	Low Rob Exposure	Med Rob Exposure	High Rob exposure
Low EPL change	0.000 (0.015)	-0.003 (0.014)	-0.037*** (0.014)
Med EPL change	0.007 (0.016)	0.004 (0.016)	-0.030** (0.015)
High EPL change	-0.024* (0.015)	-0.027* (0.014)	-0.063*** (0.014)
	Workers aged 30-60+		
Low EPL change	0.054*** (0.011)	0.051*** (0.010)	0.017** (0.007)
Med EPL change	0.061*** (0.013)	0.058*** (0.012)	0.024*** (0.009)
High EPL change	0.030** (0.012)	0.027** (0.012)	-0.009 (0.010)
	Panel B: ICT Exposure		
	Workers aged 20-29		
	Low ICT Exposure	Med ICT Exposure	High ICT exposure
Low EPL change	0.019 (0.023)	0.012 (0.020)	-0.032 (0.013)
Med EPL change	0.027 (0.025)	0.020 (0.021)	-0.024** (0.015)
High EPL change	-0.009 (0.022)	-0.016 (0.019)	-0.060*** (0.015)
	Workers aged 30-60+		
Low EPL change	0.069*** (0.022)	0.062*** (0.018)	0.018 (0.008)
Med EPL change	0.078*** (0.023)	0.071*** (0.020)	0.071 (0.020)
High EPL change	0.042* (0.021)	0.035* (0.018)	-0.010 (0.012)

Note: Predictive margins are potential outcome means calculated from models in Table 7 at different values of robot and ICT exposure, EPL changes and dummy young (1 young worker (20-29); 0 senior worker (30-60+)). Low, Med and High robot exposure are 10th percentile (-0.001), median (0.015) and 90th percentile (0.250). Low, Med and High ICT exposure are 10th percentile (0), median (0.045) and 90th percentile (0.354). Low, Med and High EPL change are 10th percentile (-0.600), median (-0.060) and 90th percentile (0.113). Standard errors calculated with the delta method in parentheses *** p<0.01, ** p<0.05, * p<0.1.

7. Conclusions

This research examined the relationship between employment rates and automation technologies in twelve EU economies between 2006 and 2018, moderated by labour and product market institutions. Special attention has been given to the moderating effects across workers grouped by age, with a focus on identifying the most vulnerable age groups, particularly the younger (20-29) and older (60+) workers.

In the descriptive analysis, we have discussed the diffusion of automation technologies as one of the major trends, along with globalisation, workforce ageing, and the spread of green technologies driven by climate change. These factors have likely contributed to the modest increase in the employment rate.

In the econometric analysis, we rely on Acemoglu and Restrepo (2020; 2022) and Doorley *et al.* (2023) to develop a methodology for creating a Bartik-like measure of exposure to robots and ICT. We then investigated the impact of these automation technologies on employment rates at the demographic group level, which was defined by age, gender, and education.

To explore the relation between employment rate and automation, we control for the other megatrends and study the interaction between specific indicators of institutional change at the demographic group level and indicators of automation technologies.

The study makes three contributions to the literature on technological transformation, labour markets, and institutions.

First, we introduced a variable capturing exposure to the invention of green technologies, along with variables controlling for globalisation, which provided a good control. Despite the marginal role played in the current study, the diffusion of green innovations as a technological trend alternative to that based on automation deserves further research in the future. This is because, unlike automation technologies, we have found a significant positive effect of green technology on employment.

Second, we introduce two new measures in our analysis to evaluate the exposure of demographic groups to changes in employment protection and product market regulation, which exploit the relative importance of the demographic groups in the industries where the legislation is more binding.

Third, we analyse the moderating effects of both measures on automation technologies, as well as their specific impact on vulnerable groups like young and older workers.

Regarding the main results, we find that in the period 2006-2018, the modest increase in the employment rate in the EU-12 (from 69% to 72%) was driven by a notable increase of the older workers (60+) in the workforce, while a reduction has been registered for the youth employment rate.

Overall, increasing robot exposure reduced employment rates by 1.6 p.p., while ICT exposure had no significant impact on labour performance as a standing-alone term. Although we have to be cautious about these results, which need additional investigation on methods to control the endogeneity of automation technologies, we may claim that they are in line with the cited literature.

In particular, our results suggest that in the EU-12, displacement effects slightly exceeded reinstatement effects on human labour tasks. Our measure for robot exposure considers the shift of labour across industries within a particular demographic group. Therefore, in line with the theoretical predictions on EPL, we expected that increasing its stringency would aggravate the negative impact of robot exposure on employment. However, we did not find a significant overall moderating effect of EPL on the relationship between robot exposure and employment rate. The negative moderating effect of EPL on both robot and ICT exposure was only observed among workers aged 20-29. This category of workers has shown a poor employment rate over the analysed period, but they have not been penalised by higher robot exposure *per se*. Our findings indicate that young workers are only negatively affected by exposure to robots in situations where employment protection legislation is becoming more restrictive. It is important to note that young workers often transition from education to employment. These individuals are at a higher risk of being affected by the increasing robot exposure under a stricter EPL regime because the latter induces expectations of rising dismissal costs for employers. As a result, their chances of being hired may be reduced. Interestingly, our analysis shows non-linear effects of EPL changes with intensive robot exposure. The best way to protect youth from the harmful effects of robot exposure is to implement an intermediate regime of employment protection instead of strong deregulation or regulation.

APPENDIX

Table A.1 Variable Descriptions

Variables	Description	Source
Dependent variables		
Δ employment rate	Percentage point changes for all demographic groups including individuals aged 20-60+	LFS
Key explanatory variables		
Δ Robots	Difference in group exposure to robots (robots per 1,000 workers 2006-2018, see equations 1.a & 1.b)	IFR/SES
Δ ICT	Difference in group exposure to ICT (Million Euros per 1,000 workers 2006-2018, see equations 1.a & 1.b)	EUKLEMS/SES
Δ EPL	Difference in group exposure to EPL (percentage changes 2006-2018, see equation 2)	OECD
Δ PMR	Difference in group exposure to PMR (percentage changes 2006-2018, see equation 3)	OECD
Control variables		
Δ Green Patents	Difference in group exposure to green patents (patents per 1,000 workers 2006-2018, see equation 4)	OECD/TiVA
Δ Offshoring	Difference in the group exposure to offshoring measured as foreign value added in gross output (2006-2018), see equation 5	OECD/TiVA
Δ Imports_CN	Difference in the group exposure to the Chinese import penetration following Acemoglu et al. (2016): change in import from China (2006-2018) divided by initial absorption (industry outputs plus industry imports minus industry exports), see equation 5	
Industry Shifter	Group exposure to change in log value added (2006-2018), see equation 5	Eurostat
Employment rate 2006	Initial level of employment rate	LFS
Definition of demographic groups (characteristics)		
Gender	Binary variables describing worker's gender	LFS/SES
Education	A categorical variable describing worker's highest level of education completed, three categories: basic education (ISCED 0-2), secondary education (ISCED 3-4), and tertiary education (ISCED 5-8)	LFS/SES
Age group	A categorical variable describing worker's age, five categories: 20-29, 30-39, 40-49, 50-59, 60 or more (60+)	LFS/SES

Table A.2 Employment rate change: exposure to automation technologies, labour and product market institutions between 2006 and 2018 (different model specifications, OLS)

Dep.Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Δ Robots	-0.034**		-0.031*		-0.035**		0.015		-0.033*		-0.003		-0.039	-0.046**
	(0.017)		(0.017)		(0.018)		(0.017)		(0.019)		(0.016)		(0.024)	(0.023)
Δ ICT		-0.013		-0.008		-0.008		0.001		-0.011		-0.010	0.001	0.017
		(0.020)		(0.020)		(0.020)		(0.021)		(0.017)		(0.017)	(0.020)	(0.019)
Δ EPL			0.040**	0.041**	0.039*	0.041**	0.045***	0.034*	0.029	0.029	0.043***	0.034	0.053*	-0.010
			(0.018)	(0.018)	(0.020)	(0.020)	(0.013)	(0.020)	(0.021)	(0.021)	(0.016)	(0.022)	(0.028)	(0.023)
Δ PMR					0.007	0.007	0.002***	0.008	0.007	0.008	0.001**	0.007	0.007	0.006**
					(0.005)	(0.005)	(0.000)	(0.005)	(0.005)	(0.005)	(0.000)	(0.005)	(0.005)	(0.003)
Δ Green Patents							0.005	0.028***	0.024**	0.026***	0.005	0.026***	0.025***	0.019***
							(0.004)	(0.009)	(0.009)	(0.009)	(0.004)	(0.009)	(0.009)	(0.006)
Industry Shifter									0.001	0.001	0.001*	0.001	0.001	0.000
									(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Δ OffShoring											-0.000	-0.001	-0.002	0.000
											(0.001)	(0.001)	(0.001)	(0.001)
Δ Imports_CN													0.006	0.017***
													(0.006)	(0.004)
Employment rate 2006														-0.374***
														(0.032)
Country, gender, and education fixed effects														
Observations	360	360	360	360	300	300	300	300	300	300	300	300	300	300
R2	0.312	0.306	0.322	0.316	0.359	0.352	0.257	0.372	0.381	0.376	0.276	0.377	0.386	0.620

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change between 2006 and 2018 in employment share at the country and demographic group level. All explanatory variables capture the group exposure to the specific phenomenon between 2006 and 2018. Robots, ICTs and Green Patents are taken in log. All regressions are weighted by the group's share of the country's employment. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania.

Source: LFS, IFR robotics, OECD, Orbis

Table A.3 Employment rate change: exposure to automation technologies, labour and product market institutions between 2006 and 2018. Control for old workers (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var.	Δ Employment rate					
Δ Robots	-0.015 (0.028)	-0.040 (0.029)	-0.054 (0.037)			
Δ ICT				0.043 (0.039)	0.039 (0.060)	0.018 (0.073)
Old (60+)	0.121*** (0.013)	0.119*** (0.014)	0.138*** (0.018)	0.132*** (0.015)	0.123*** (0.014)	0.140*** (0.017)
Δ EPL		0.028 (0.019)			0.027 (0.020)	
Δ PMR			0.008** (0.004)			0.008** (0.004)
Other control variables	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Country, gender, and education fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	360	360	300	360	360	300
Kleibergen-Paap rk Wald F statistic	29.91	21.47	14.72	26.09	15.15	11.00

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change between 2006 and 2018 in employment share at the country and demographic group level. All explanatory variables capture the group exposure to the specific phenomenon between 2006 and 2008. Control variables include Δ Green Patents, Ind.Shifter, Δ OffShoring, Δ Imports_CN, already included in estimations shown in Table 1. Δ Robots and Δ ICT have been instrumented with robot and ICT exposure observed in 4 countries not included in our sample (Slovenia, Austria, Denmark and Finland). All regressions are weighted by the group's share of the country's employment. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania.

Source: LFS, IFR robotics, OECD, Orbis.

Table A.4 Employment rate change: the moderating effects of labour, product market regulation and age of workers on the exposure to automation technologies (IV)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var.	Δ Employment rate							
Δ Robots x Δ EPL x Young	-0.201* (0.105)							
Δ Robots x DEPL	-0.076 (0.073)				0.024 (0.069)			
Δ EPL x Young	-0.003 (0.040)	0.034 (0.038)						
Δ Robots	-0.143*** (0.052)		-0.439 (0.291)		-0.034 (0.032)		-0.038 (0.173)	
Δ EPL	0.044** (0.019)	0.051** (0.021)			0.028 (0.020)	0.025 (0.021)		
Young	-0.054*** (0.013)	-0.050*** (0.012)	-0.046** (0.020)	-0.019 (0.016)				
Δ ICT x Δ EPL x Young		-0.229* (0.120)						
Δ ICT x Δ EPL		-0.109 (0.118)				0.078 (0.113)		
Δ ICT		-0.142* (0.075)		-0.585** (0.274)		0.058 (0.064)		-0.103 (0.266)
Δ Robots x Δ PMR x Young			-0.006 (0.004)					
Δ ICT x Δ PMR x Young				0.002 (0.003)				
Δ Robots x ΔPMR		-0.015 (0.012)				0.001 (0.009)		
Δ ICT x DPMR			-0.034** (0.015)				-0.008 (0.015)	
Δ PMR x Young		0.003*** (0.001)	0.002*** (0.001)					
Δ PMR			0.004 (0.004)	0.007 (0.004)			0.008* (0.004)	0.009** (0.005)
Δ Robots x Δ EPL x Old					1.887 (9.543)			

Table A.4 Employment rate change: the moderating effects of labour, product market regulation and age of workers on the exposure to automation technologies (IV) (continued)

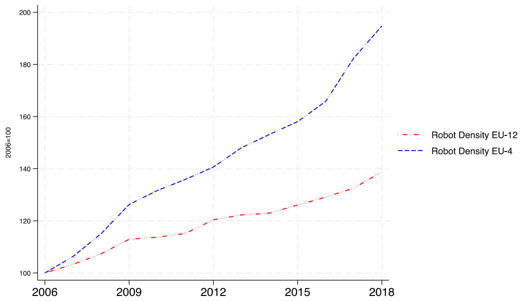
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var.	Δ Employment rate							
Δ Robots x Δ PMR x Old							-0.044 (0.067)	
Δ ICT x Δ EPL x Old						-0.632 (4.313)		
Δ ICT x Δ PMR x Old								-0.010 (0.012)
Δ EPL x Old					0.096 (0.139)	0.166 (0.182)		
Δ PMR x Old							0.002* (0.001)	0.001 (0.001)
Old					0.125*** (0.017)	0.137*** (0.021)	0.143*** (0.022)	0.121*** (0.029)
Δ Green Patents	0.008*** (0.002)	0.008*** (0.003)	0.010 (0.012)	0.014 (0.012)	0.006*** (0.002)	0.005** (0.002)	0.006 (0.010)	0.016 (0.012)
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Country, gender, and education fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	360	360	300	300	360	360	300	300
Kleibergen-Paap rk Wald F statistic	27.90	8.64	3.64	5.14	7.10	5.12	2.70	3.60

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the change between 2006 and 2018 in employment share at the country and demographic group level. All explanatory variables capture the group exposure to the specific phenomenon between 2006 and 2008. Control variables include Δ Green Patents, Ind.Shifter, Δ OffShoring, Δ Imports_CN, already included in estimations shown in Table 1. Δ Robots and Δ ICT have been instrumented with robot and ICT exposure observed in 4 countries not included in our sample (Slovenia, Austria, Denmark and Finland). All regressions are weighted by the group's share of the country's employment. Observations reduce to 300 in the specification with PMR due to the missing information on this variable for Latvia and Lithuania.

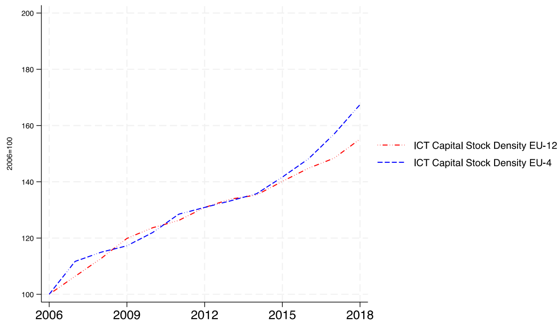
Source: LFS, IFR robotics, OECD, Orbis.

Figure A.1 Evolution of automation technologies in the EU-12 and Austria, Denmark, Finland and Slovenia (EU-4)

Robots per thousand workers

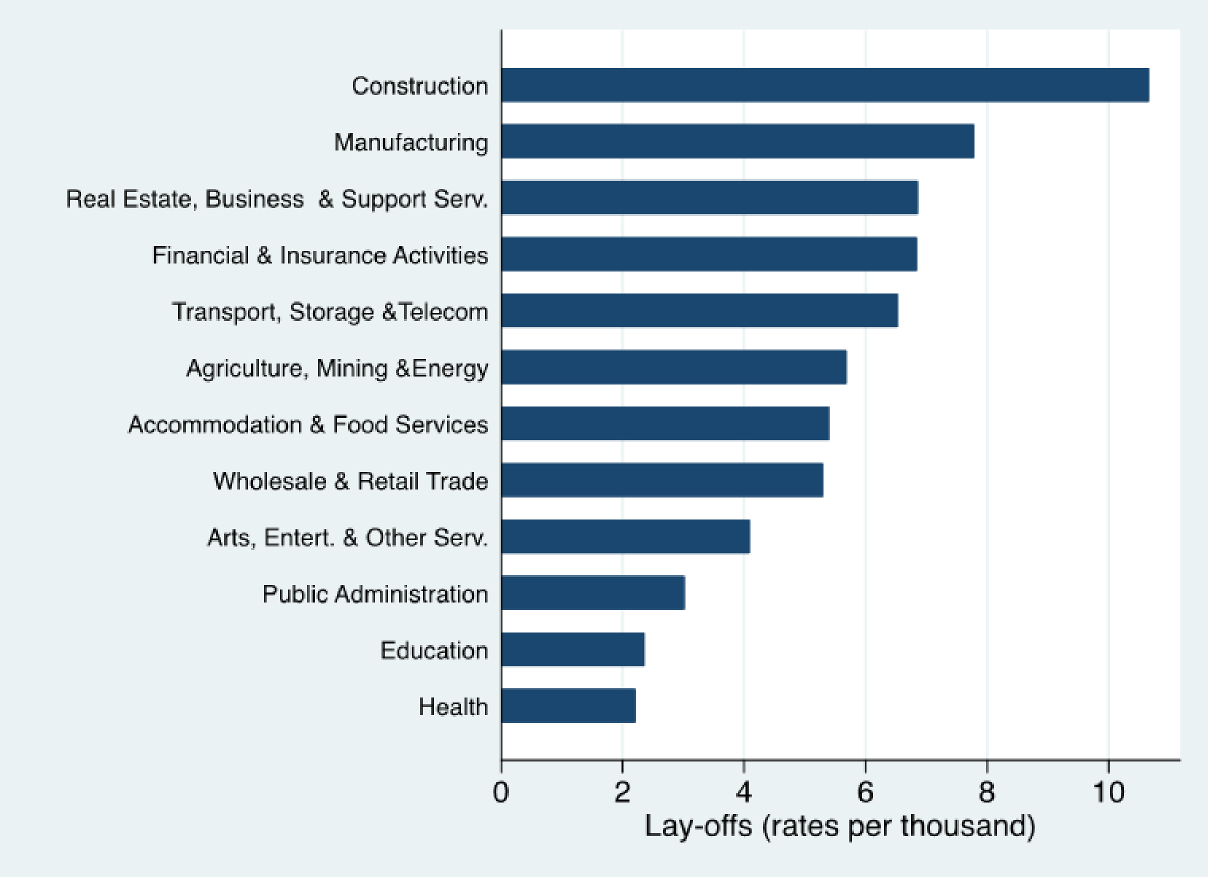


ICT net capital stock per thousand workers



Source: Eurostat, EUKLEMS, IFR. Note: Robot and ICT density for EU-12 are weighted averages of Robots/employment and ICT/employment from Belgium, the Czech Republic, Estonia, France, Germany, Greece, Italy, Latvia, Lithuania, the Netherlands, Spain, and Sweden. Similar weighted averages have been calculated for Austria, Denmark, Finland and Slovenia (EU-4). The adjusted penetrations of robots and ICT (see equation 1.b) in the EU-4 have been used as instruments for adjusted penetration of robots and ICT in the EU-12

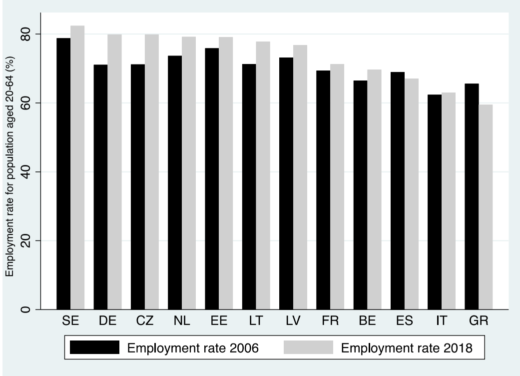
Figure A.2 Lay-off rates in the UK (average 2009-2018)



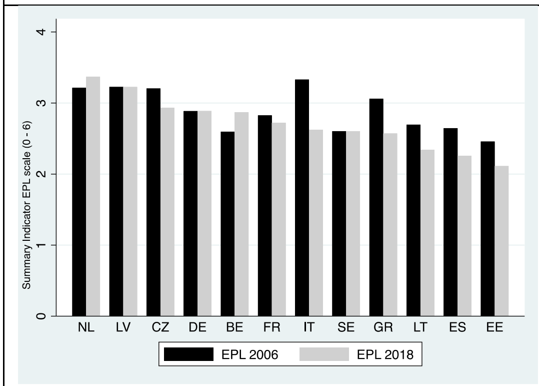
Source: Office for National Statistics in the UK

Figure A.3 Employment rate, EPL and PMR, levels in 2006 and 2018

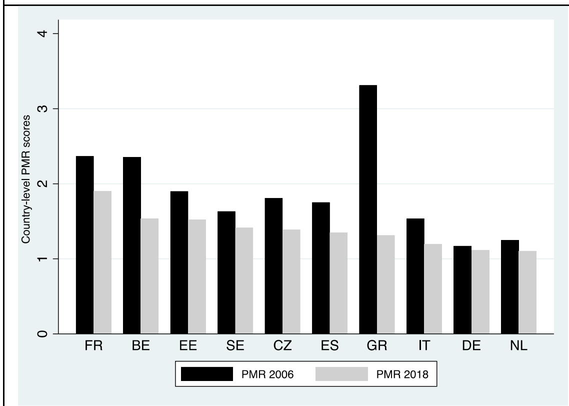
Employment rates (20-64)



EPL



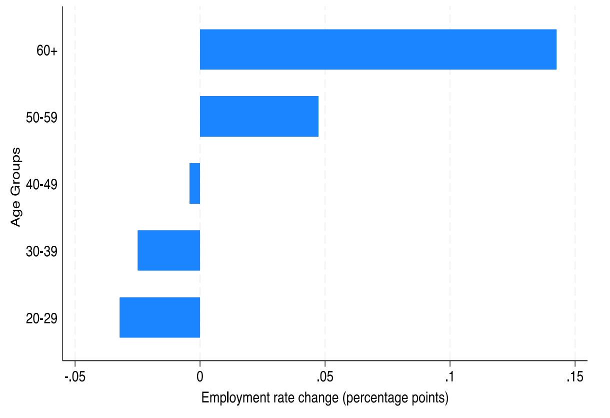
PMR



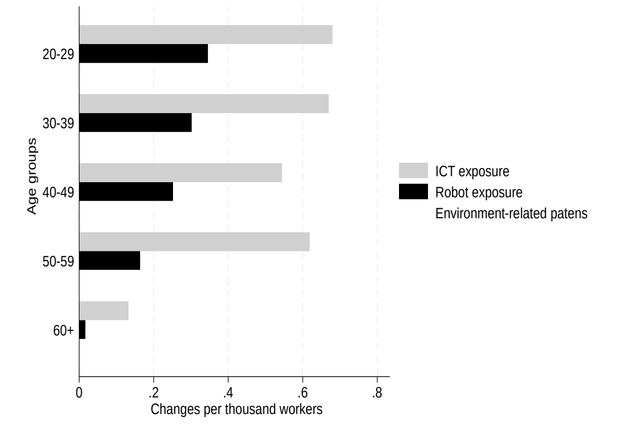
Source: Eurostat (LFS); OECD

Figure A.4 Employment rate, automation and environment-related technologies across age groups (changes between 2006 and 2018)

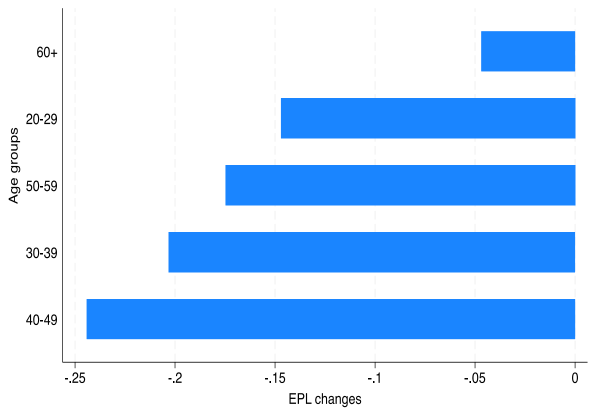
A) Employment rate (percentage point changes)



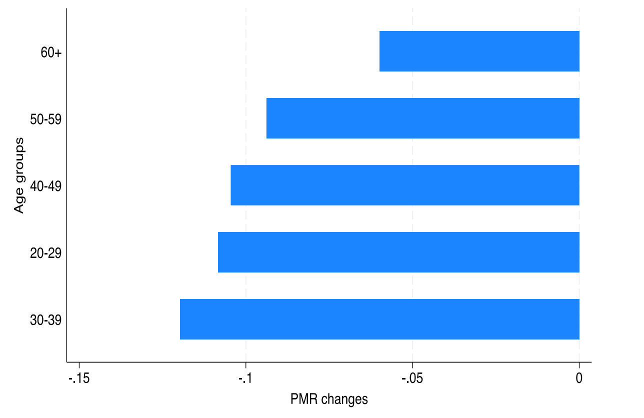
B) Automation technologies and green patents (changes per thousand workers)



C) EPL (percentage changes)



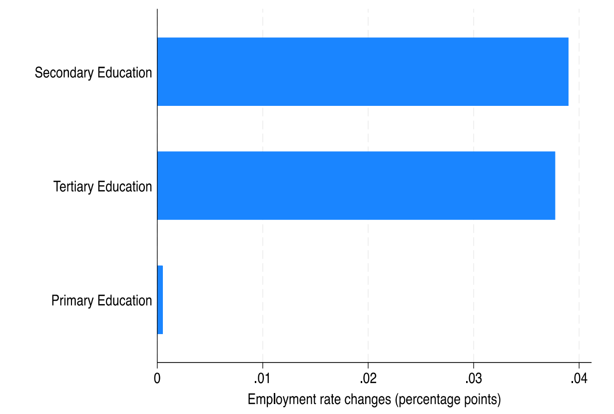
D) PMR (percentage changes)



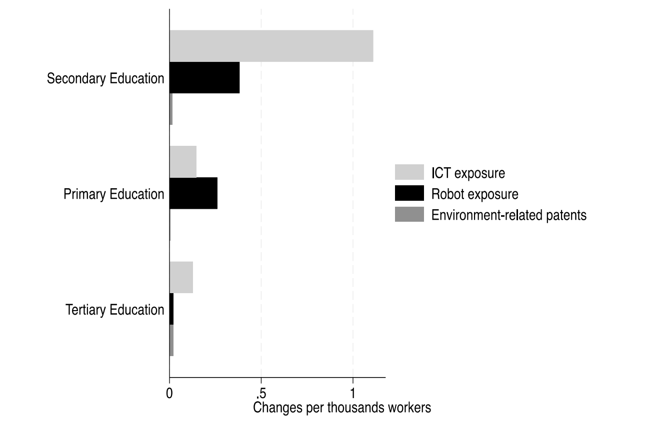
Source: Eurostat, OECD, EUKLEMS, IFR. Note: all variables refer to the demographic groups and are reported as changes 2006-2018 (see Tables 1 above and A.1 in the Appendix for details).

Figure A.5 Employment rate, automation and environment-related technologies across education groups (changes between 2006 and 2018)

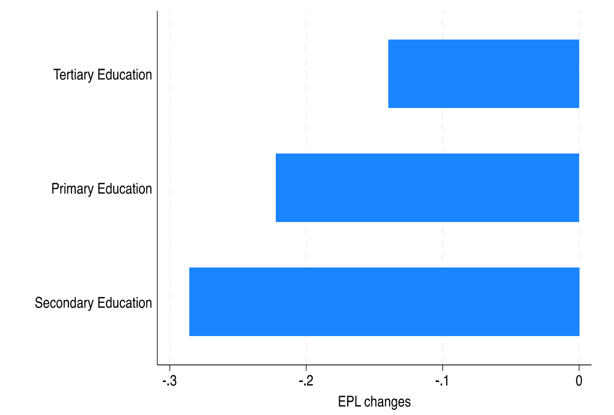
A) Employment rate (percentage point changes)



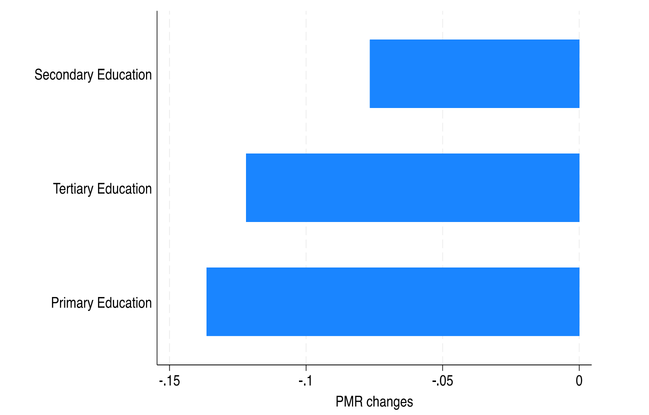
B) Automation technologies and green patents (changes per thousand workers)



C) EPL (percentage changes)



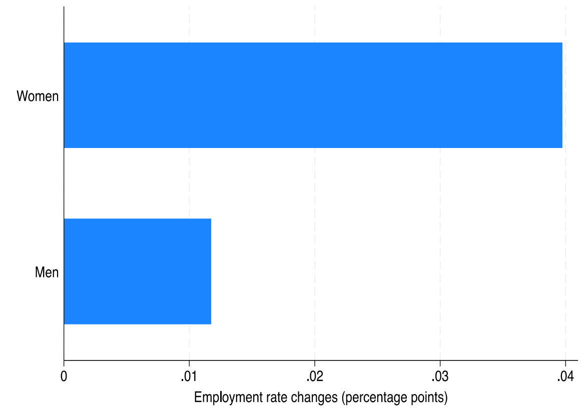
D) PMR (percentage changes)



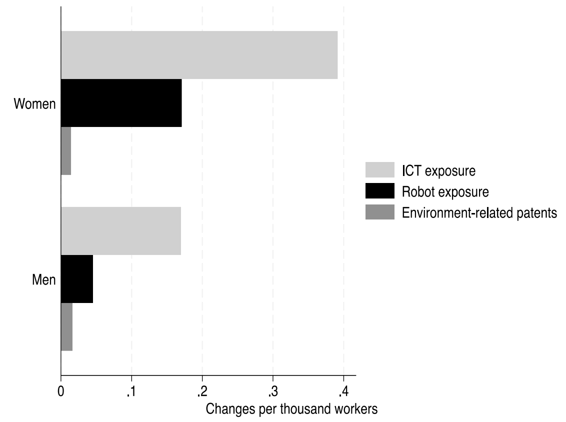
Source: Eurostat, OECD, EUKLEMS, IFR. Note: all variables refer to the demographic groups and are reported as changes 2006-2018 (see Tables 1 above and A.1 in the Appendix for details).

Figure A.6 Employment rate, automation and environment-related technologies by gender (changes between 2006 and 2018)

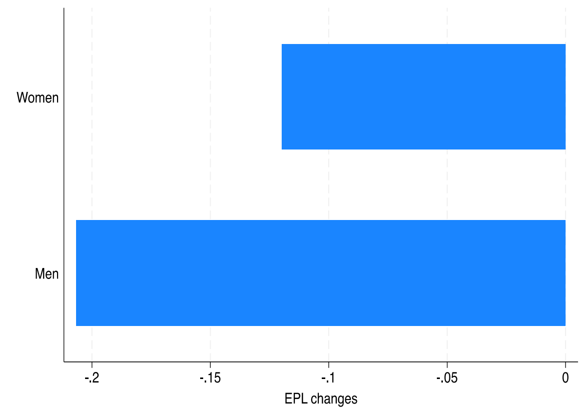
A) Employment rate (percentage point changes)



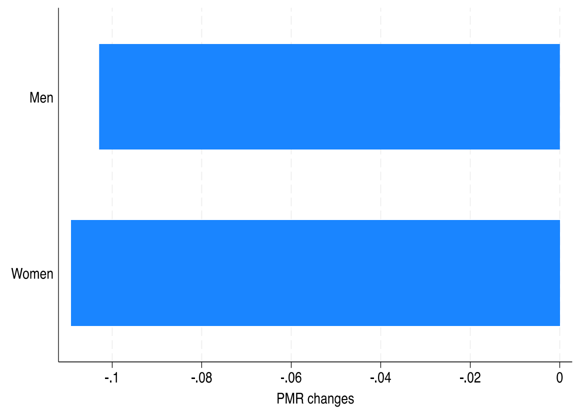
B) Automation technologies and green patents (changes per thousand workers)



C) EPL (percentage changes)



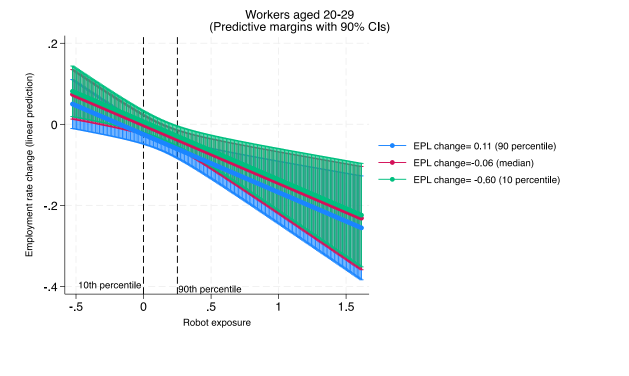
D) PMR (percentage changes)



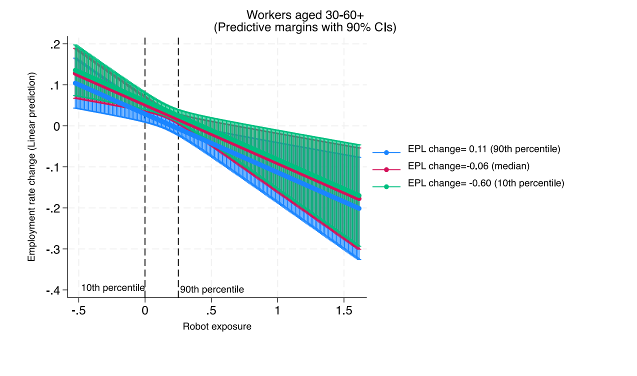
Source: Eurostat, OECD, EUKLEMS, IFR. Note: all variables refer to the demographic groups and are reported as changes 2006-2018 (see Tables 1 above and A.1 in the Appendix for details).

Figure A.7 Predictive margins of robot and ICT exposure for different values of EPL changes

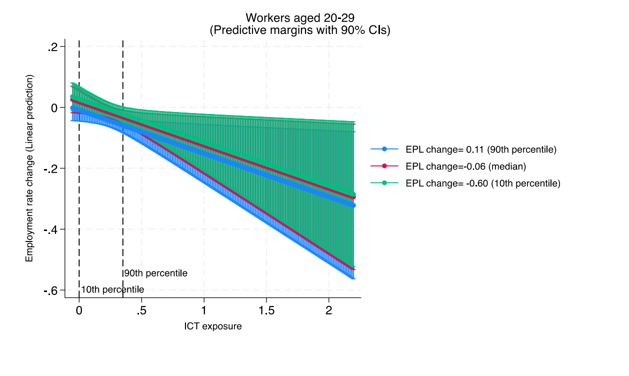
A) Robot exposure and young workers



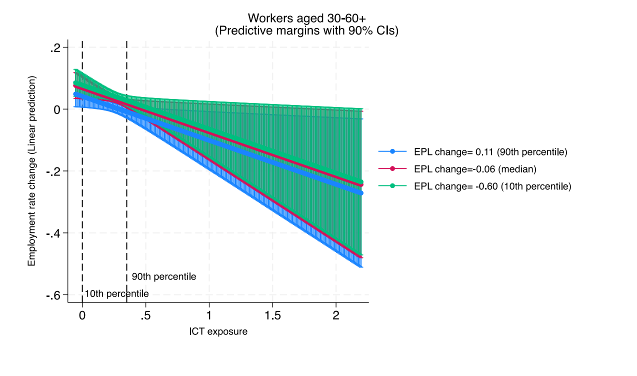
B) Robot exposure and senior workers



C) ICT exposure and young workers



D) ICT exposure and senior workers



Note: Predictive margins are potential outcome means calculated from models in Table 7 at different values of robot and ICT exposure, EPL changes and dummy young (1 young worker (20-29); 0 senior worker (30-60+)). Robot and ICT exposure are measured as ln(1+robot exposure) and ln(1+ICT exposure), respectively. The x-axis scale reports minimum and maximum values for robot and ICT exposure. Robot exposure percentiles 10th and 90th are -0.001 and 0.250. ICT exposure percentiles 10th and 90th are 0 and 0.354. Predictive margins have been calculated with 90% confidence intervals.

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WeLaR is Horizon Europe research project examining the impact of digitalisation, globalisation, climate change and demographic shifts on labour markets and welfare states in Europe. It aims to improve the understanding of the individual and combined effects of these trends and to develop policy proposals fostering economic growth that is distributed fairly across society and generates opportunities for all.

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