THE IMPACT OF ICT AND ROBOTS ON LABOUR MARKET OUTCOMES OF DEMOGRAPHIC GROUPS IN EUROPE[•]

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Abstract

We study the age- and gender-specific labour market effects of two key modern technologies, Information and Communication Technologies (ICT) and robots. Our sample includes 14 European countries between 2010 and 2018. We use the variation in technology adoption between industries and apply the instrumental variables strategy proposed by Acemoglu and Restrepo (2020) to identify the causal effects of technology adoption. We find that exposure to ICT and robots increased the shares of young and prime-aged women in employment and in the wage bills of particular sectors. However, it reduced the shares of older women and prime-aged men. We do not detect significant effects of technology adoption on the relative wages of most demographic groups. Between 2010 and 2018, the growth in ICT capital played a larger role than robot adoption in the changes in the within-sector labour market outcomes of demographic groups.

Keywords: technological change, automation, ICT, robots, employment, wages, Europe

JEL: J24, O33, J23

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1. Introduction

The increased use of Information and Communication Technologies (ICT) and robots in workplaces has been changing the world of work. Between 2000 and 2019, the real value of ICT capital per worker in Europe increased by 91%. The robot exposure, measured by the number of industrial robots per 1,000 workers, increased by 140%. These technologies can have aggregate and compositional impacts on labour markets. They can directly reduce employment as machines replace humans in performing certain tasks, resulting in a labour-saving effect. However, they can also increase employment thanks to the scale effect – i.e., an increase in activity thanks to a productivity-enhancing technology – and the demand spillover effect – i.e., demand for other sectors' output resulting from growth in the technology-adopting sector.[1] At the same time, these technologies have reduced the role of routine tasks and increased the role of non-routine tasks, both within and across occupations (Autor et al., 2003; Spitz-Oener, 2006), leading to job polarisation (Goos et al., 2014) and widening wage inequality (Acemoglu and Restrepo, 2022). While a lot of attention has been paid to the winners and losers of technological progress concerning education (Firpo et al., 2011; Gathmann and Schönberg, 2010; Taniguchi and Yamada, 2022), the age and gender dimensions have been less comprehensively studied.

This paper seeks to fill this gap by evaluating the age- and gender-specific labour market effects of two key routine-replacing technologies – ICT and robots – in a large group of European countries. There are two main reasons why the impact of technology adoption on workers can differ depending on whether they are younger or older. First, technological change can compress returns to old skills – i.e., those related to technology that becomes obsolete – and increase returns to new skills – i.e., those related to emerging technology (Barth et al., 2022; Fillmore and Hall, 2021). Older workers tend to be more skilled than young ones in skills complementing older technologies, and their expected time to exploit new skills is shorter (Cavounidis and Lang, 2020). Indeed, older people (aged 55-64) in the OECD countries tend to have lower ICT and analytical skill levels, and are less likely to use information-processing skills at work than younger individuals.[2] Consequently, they may be less mobile in response to asymmetric shocks that increase the returns to new skills at the expense of older skills.

Second, the occupational sorting of younger workers may tilt towards jobs that require new skills. A larger share of younger cohorts may enter growing occupations that often benefit from new technologies, reducing the average skill levels in those occupations (Böhm et al., 2022). At the same time, older workers, especially those with higher skill levels, may increasingly stick to occupations they have specialised in. Such sorting would compress average wage differences between growing and declining occupations (Böhm et al., 2022). Hence, the age differences in responses to new technologies may affect employment structures of demographic groups across occupations and industries, rather than average wages. Indeed, the shift from routine to non-routine work has affected the employment structures of younger workers more than older workers in the US (Autor and Dorn, 2009; Lewandowski et al., 2020), and industrial robots in Germany have reduced the labour market prospects of younger workers in manufacturing (Dauth et al., 2021).

The gender dimension is also relevant. On the one hand, routine-replacing technologies increase returns to social skills, which women tend to have a comparative advantage over men, so they increasingly

[1] Gregory et al. (2022) showed that the latter two effects have been dominant in Europe, leading to an overall positive employment effect of routine-replacing technologies.

[2] Based on the data from the Programme for the International Assessment of Adult Competencies – PIAAC.

select into occupations that require such skills (Cortes et al., 2021; Deming, 2017). Hence, women may benefit from ICT adoption more than men (Black and Spitz-Oener, 2010; Jerbashian, 2019). On the other hand, in Europe, robot-driven productivity improvements have benefited men more than women, widening the gender pay gap (Aksoy et al., 2021). Moreover, fewer women than men have skills that complement new technologies. Women are less likely than men to participate in Science, Technology, Engineering, and Mathematics (STEM) college programmes (Delaney and Devereux, 2019), and they exhibit lower levels of numeracy skills than their male counterparts (Rebollo-Sanz and De la Rica, 2022).

Our first contribution is to disentangle the gender- and age-specific dimensions of the impact of new technologies on European labour markets. We distinguish between the following demographic groups: men and women aged 20-29, 30-49, 50-59, and 60 or older, and focus on three vital outcomes: share in employment, average wage, and share in the total wage bill. We find the age dimension to be of vital importance, both among men and women. This is important as demographic changes will accelerate the ageing of population structures in Europe.

Our second contribution is to distinguish between the effects of two key routine-replacing technologies: ICT and robots.[3] We measure them at a finely disaggregated sector level: ICT capital using Eurostat and EU-KLEMS data and robots using International Federation of Robotics (IFR, 2021) data. We merged these data with the worker-level data of the EU Structure of Earnings Survey (EU-SES), which allows calculating the labour market outcomes of demographic groups. Due to data availability, our sample covers 14 European countries between 2010 and 2018.[4]

To obtain causal effects, we make two methodological choices. First, we estimate models of demographic groups' outcomes within sectors, and thus focus on the direct effects of technology on labour market outcomes.[5] We also control for globalisation, in line with the literature that identifies technological progress as a critical driver of labour market developments and trade as a mediating factor (Gregory et al., 2022). Second, we apply the instrumental variable (IV) methodology. We use exposure to ICT or robots in the same sectors in the US as an instrument. However, technology adoption variables entering the second estimation stage are country-specific because we use country-year fixed effects in both stages. Several papers employed a similar method of instrumenting robot adoption with robotisation in other advanced economies (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Firooz et al., 2023). Our strategy rests on the assumption that sectoral patterns of technology adoption were not correlated with other industry-specific shocks influencing labour market outcomes of particular

[3] The previous literature has focused mainly on robots and their impact on productivity and wages (Graetz and Michaels, 2018), employment (Acemoglu and Restrepo, 2020; Adachi et al., 2022; Dauth et al., 2021; de Vries et al., 2020), wage disparities (Acemoglu and Restrepo, 2022; Aksoy et al., 2021), labour market flows (Bachmann et al., 2022), or multidimensional firm-level adjustments (Acemoglu et al., 2020; Bessen et al., 2023, 2020; Domini et al., 2020; Koch et al., 2021). Studies of ICT often tackled job polarization (Jerbashian, 2019; Michaels et al., 2014). Some studies used broader concepts of routine-replacing technologies and assessed their employment effects (Downey, 2021; Gregory et al., 2022).

[4] Belgium, Czechia, Germany, Estonia, Greece, Spain, Finland, France, Italy, Lithuania, Latvia, the Netherlands, Norway, and Sweden.

[5] Focusing on sectors to assess the causal effects of technology is common. We follow Graetz and Michaels (2018), who used sector regressions to show that robot adoption has increased GDP, labour productivity, and wages; Jerbashian (2019), who studied the within-sector effects of IT technology adoption, and found that it had a negative impact on the share of middle-waged occupations; and Aksoy et al. (2021) who found that robots widened the gender pay gap within industries and occupations in Europe.

demographic groups. Although we are not aware of such a problem in our data, the results should be interpreted with the usual caution.

We find that, between 2010 and 2018, the impact of technology adoption varied between demographic groups. Higher exposure to ICT capital increased the employment shares of young and prime-aged women but lowered the shares of women aged 60 or more. These contrasting effects were concentrated primarily among workers in occupations intensive in non-routine cognitive tasks. This is in line with Cavounidis and Lang (2020) and Fillmore and Hall (2021) arguments that older workers may lack the skills and time horizon to benefit from emerging technologies while younger workers are in a more favourable position to reap the rewards these technologies bring. At the same time, exposure to robots reduced the employment shares of young and prime-aged men in routine manual occupations. In cognitive occupations, it increased the employment shares of young workers, mainly women. Overall, we find that, between 2010 and 2018, the increase in ICT capital played a larger role than robot adoption in driving changes in the shares of demographic groups in sectors' employment and wage bills. We confirm the robustness of our findings by performing placebo tests, using an alternative instrument based on the EU countries, and showing that no particular country drives our results.

Moreover, we find barely any effects of technology on the relative average wages of demographic groups. This result contrasts somehow with previous evidence that the gender wage gap was affected by computerization (Black and Spitz-Oener, 2010) or automation (Acemoglu and Restrepo, 2022; Aksoy et al., 2021; Anelli et al., 2021). However, it is consistent with sorting mechanisms described by Böhm et al. (2022) – the reallocation of workers from declining to growing industries and occupations compresses the average wage differences between these different labour market segments, as the movers tend to earn less than incumbents in both declining and growing segments. Workers switching out of routine occupations may find this transition beneficial (Cortes, 2016). Thus, interpreting the effects on relative wages requires considering the effects on the employment shares.

Our strategy enables identifying the differences in the effects of technology between demographic groups. A positive effect of specific technology on the employment share of a given demographic group suggests that the demographic group has a comparative advantage in utilising this technology. Therefore, technology adoption may increase the employment opportunities for the group in question relative to other demographic groups. However, the limitations of our setup prevent us from directly distinguishing whether the differences in technology's effects on demographic groups stem from the contribution of skill heterogeneity or from differences in workers' sorting patterns.

The rest of the paper is structured as follows. Section 2 introduces our data and presents descriptive evidence on the relationship between technology adoption and labour market outcomes for different demographic groups. In Section 3, we describe our identification strategy and the methodology of our post-estimation analyses to assess the economic significance of the results. In Section 4, we report our results, quantify the impact of technology adoption on the historical changes in the labour market outcomes of demographic groups, and present the robustness checks. In section 5, we present our conclusions.

2. Data and descriptive statistics

2.1 Data and definitions

To measure labour market outcomes, we use worker-level data from the EU Structure of Earnings Survey (EU-SES), the most reliable source of cross-country data on wages in the EU, as firms report these data. Another advantage of using the SES is that the sectoral structure – needed to assign data on technology – Is at the 2-digit NACE level, which is more detailed than in other EU microdata, such as the Labour Force Survey data or the Statistics on Income and Living Conditions data. An important limitation of the EU-SES is that it does not cover firms with fewer than 10 workers. However, we study the labour market effects of automation and ICT capital, which are technologies adopted less often by micro firms than by firms with at least 10 workers. The EU-SES data have previously been used to study the labour market effects of automation, for instance, by Aksoy et al. (2021) and Damiani et al. (2023). The EU-SES data are collected every four years.

We account for the labour market effects of two types of technologies: ICT and industrial robots. Data on both are available at the country x sector level. The data on ICT capital come from Eurostat. We add net stocks of three types of capital: computer hardware, telecommunications equipment, and computer software and databases. We use data expressed in chain-linked volumes to account for the systematic price decline of ICT capital. We use all countries for which sectoral distribution of the ICT capital is available. For Germany, Spain, and the USA, we use data from the EU-KLEMS 2023 release.

The data on robots come from the(International Federation of Robotics (IFR, 2021), which provides annual information on the current stock of industrial robots across countries, broken down by industries.[6] The data are based on consolidated information provided by nearly all industrial robot suppliers. The IFR ensures that the data are reliable and internationally comparable. The International Organization for Standardization (ISO 8373:201) defines an industrial robot as an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". We use Eurostat aggregate employment data to calculate robot and ICT capital exposure.

For reasons of data availability, our study period is 2010-2018. The NACE Rev. 2 classification, used by Eurostat in the EU-SES data from 2010, allows for a fine matching of technology variables. In contrast, the earlier waves of EU-SES used the NACE Rev. 1 classification, which can only be mapped into the NACE Rev. 2 classification at the broad sector level, which does not capture important differences in technology use between finely defined sectors. In particular, major business services sectors in the NACE Rev. 2 classification cannot be retrieved from NACE Rev. 1.[7]

Furthermore, to control for globalisation, we use the OECD Trade in Value Added data to measure the sectors' participation in global value chains. We compute this measure as foreign value added in exports divided by total sectoral output.

Our sample consists of 14 European countries for which all these data are available: Belgium, Czechia, Germany, Estonia, Greece, Spain, Finland, France, Italy, Lithuania, Latvia, the Netherlands, Norway, and

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[6] In the IFR data, some robots are not attributed to specific industries. We assign them to industries based on the observable country-specific structures of robot stocks as provided by the IFR.

[7] For example, NACE rev. 1 category "70 to 73" contains major parts of the four NACE rev. 2 sections: L – Real Estate Activities; N – Administrative and Support Service Activities; J – Information and Communication; and M – Professional, Scientific and Technical Activities.

Sweden. The average number of sectors per country is 21, with some differences arising due to the aggregation schemes in the SES. In the baseline specification, the unit of analysis is a demographic group, which is defined based on age – we distinguish between four age groups (20-29, 30-49, 50-59, 60+) – and gender in a given sector and country. We have 894 country x sector observations for each demographic group. We have dropped groups with fewer than 15 observations in any year. The remaining number of worker-level observations in our sample is 21.2 million. The median number of observations per demographic group per year amounts to 658.

We also estimate regressions separately for four occupation types: non-routine cognitive, routine cognitive, routine manual, and non-routine manual. We use the classification developed by Lewandowski et al. (2020), who adapted the methodology of Acemoglu and Autor (2011) based on the Occupational Information Network (O*NET) data to European data.[8] We use the 2-digit or the 3-digit level of the International Standard Classification of Occupations (ISCO), depending on the availability of the information in the EU-SES data. Table A1 in online Appendix A shows the allocation of occupations to types.

2.2 Descriptive evidence

Table 1 presents descriptive statistics for our sample. In a typical sector, more than half of workers were aged 30-49. The descriptive statistics also show a substantial gender wage gap in all age groups. While ICT exposure displayed significant variation across the entire sample, robots were only present in a select few sectors (primarily manufacturing), leaving 75% of the sectors robot-free.

Demographic groups differed substantially in their occupation structure (Table 2), and consequently in their exposure to task displacement. Men worked much more often than women in manual occupations, and much less often in routine cognitive occupations. For both genders, the share of routine cognitive occupations decreased with age. However, the share of manual occupations increased with age among women, while the share of non-routine cognitive occupations increased with age among men. Notably, there were stark differences in the types of non-routine manual occupations held by men and women – personal services and cleaning jobs dominated among women. In contrast, industrial occupations and drivers dominated among men.

Next, we report correlations between the four-year changes in the stocks of ICT capital (Figure 1) or robots (Figure 2) and in the demographic groups' shares of the sectors' total wage bill. Online Appendix B also reports the correlations for employment shares and relative wages. Changes in labour market outcomes of prime-aged men were negatively correlated with changes in both technologies. In addition, the adoption of ICT was negatively correlated with the outcomes for older women and positively correlated with the outcomes for young and prime-aged women. In the next section, we outline our approach to estimating the causal relationships between technology adoption and labour market outcomes of demographic groups.

[8] de la Rica et al. (2020) and Lewandowski et al. (2022) showed that O*NET data provide a good proxy of task content of occupations in European Union countries.

Table 1. Descriptive statistics

	Mean	p10	p25	p50	p75	p90
Employment share, women 20-29	8.1	2.1	4.2	7.7	11.4	14.3
Employment share, women 30-49	25.1	10.3	17.5	26.0	32.8	38.1
Employment share, women 50-59	11.5	4.0	6.7	9.9	15.8	21.6
Employment share, women 60+	3.9	0.8	1.5	2.7	5.5	8.7
Employment share, men 20-29	8.9	3.0	5.1	8.6	11.8	15.1
Employment share, men 30-49	27.3	10.0	19.7	26.8	34.8	44.3
Employment share, men 50-59	11.6	5.0	7.1	10.4	16.3	20.4
Employment share, men 60+	4.0	1.4	2.2	3.5	5.3	7.3
Relative wages, women 20-29	78.8	65.5	71.6	78.8	85.7	91.4
Relative wages, women 30-49	95.2	88.3	91.4	95.2	98.7	102.0
Relative wages, women 50-59	96.3	83.4	90.3	97.2	102.1	107.1
Relative wages, women 60+	94.9	77.7	85.1	94.6	102.6	112.0
Relative wages, men 20-29	83.5	68.9	75.6	82.2	90.8	100.1
Relative wages, men 30-49	111.7	100.4	103.8	109.4	117.4	127.2
Relative wages, men 50-59	118.7	101.3	109.1	116.7	127.7	139.9
Relative wages, men 60+	121.3	94.9	106.2	117.6	132.3	152.6
ICT capital per worker (thousand EUR)	4.9	0.7	1.2	2.4	4.6	9.0
Robots per thousand employees	1.7	0.0	0.0	0.0	0.1	3.9
GVC participation	4.4	0.0	0.2	1.8	5.3	13.8

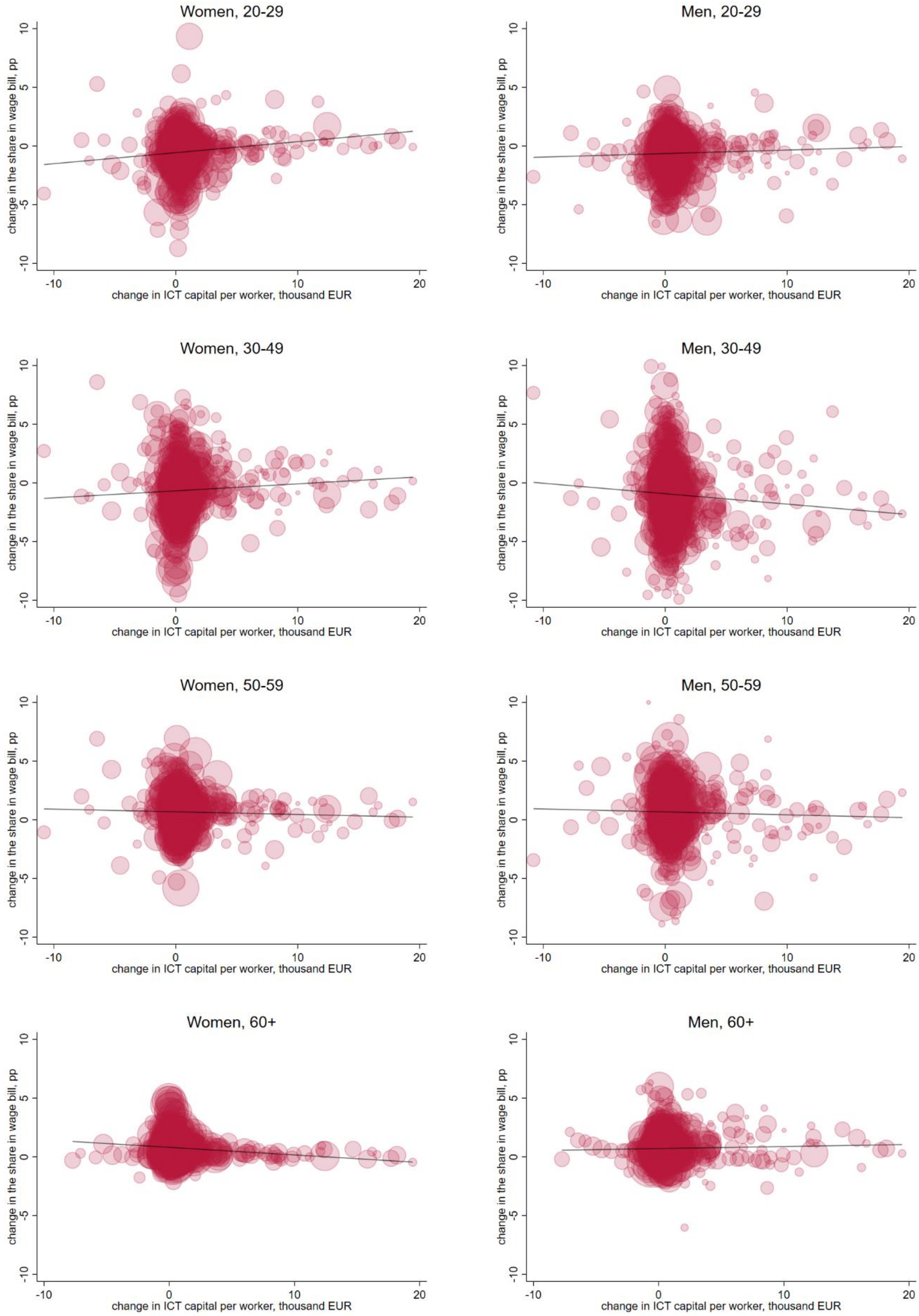
Note: Employment shares of demographic groups sum up to 100 in each country-sector-year cell. Relative wage is the mean hourly wage of a demographic group in a given sector as a % of the mean sectoral hourly wage.

Table 2. Occupational structures of demographic groups' employment, %, 2010

	Non-routine cognitive	Routine cognitive	Routine manual	Non-routine manual	Structure of non-routine manual jobs			
					Services workers	Craft and related trades workers	Drivers and mobile plant operators	Elementary occupations
Women 20-29	27	47	4	21	69	3	1	26
Women 30-49	38	36	5	21	55	3	2	39
Women 50-59	37	30	6	27	48	3	2	48
Women 60+	38	29	4	30	42	1	1	55
Men 20-29	21	27	15	37	18	35	16	30
Men 30-49	35	20	13	31	18	31	28	22
Men 50-59	36	17	13	34	16	31	31	20
Men 60+	42	16	10	33	17	27	30	24

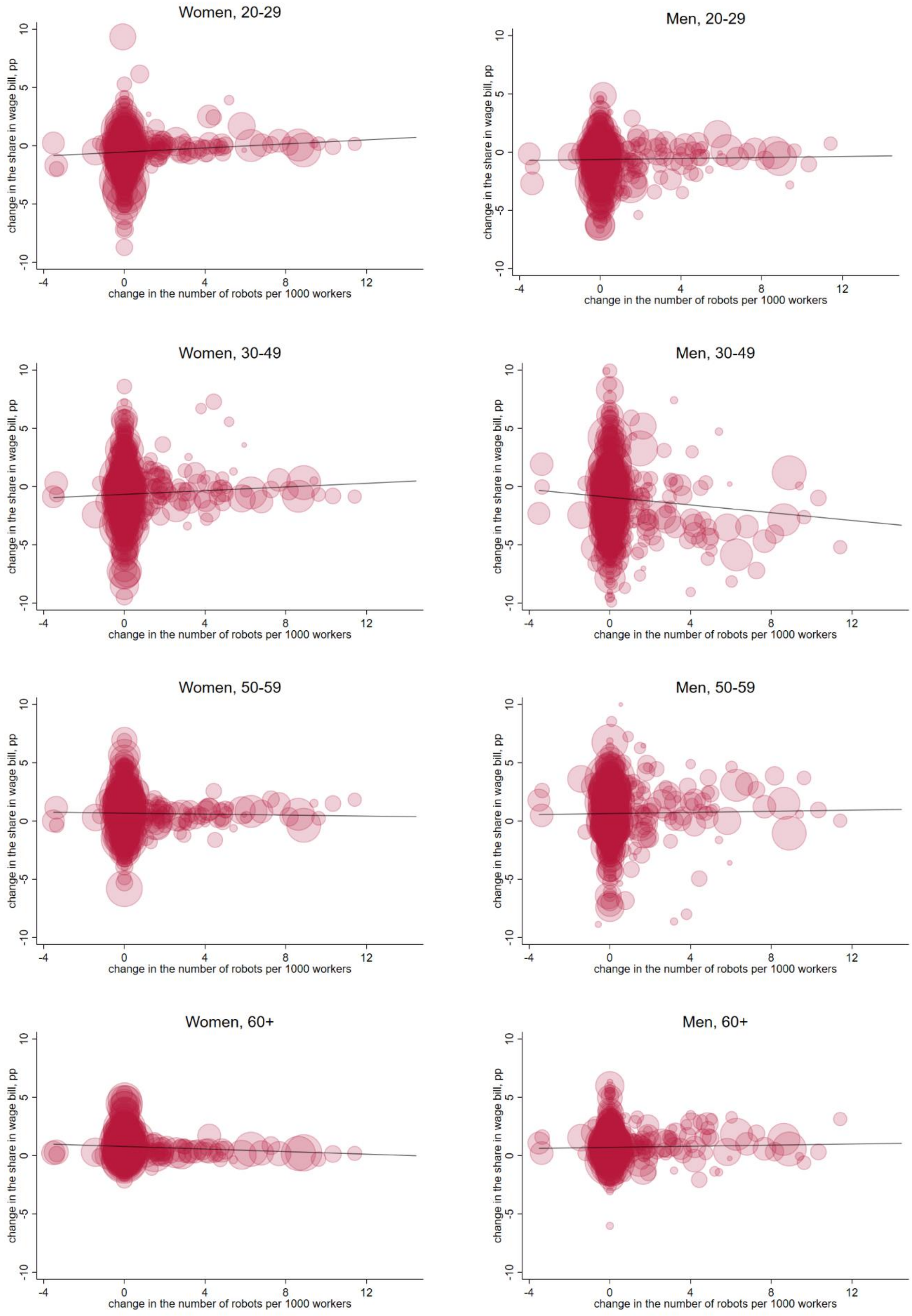
Note: Employment shares as of 2010 are based on the EU-SES data for countries included in the sample, with each country given equal weight.

Figure 1. ICT capital growth and changes in the shares of the wage bill



Source: Own elaboration based on EU-SES, Eurostat, and EU-KLEMS

Figure 2. Growth in robot exposure and changes in the shares of the wage bill



Source: Own elaboration based on EU-SES, Eurostat, and IFR data.

3. Econometric methodology

Here, we outline our estimation framework, the instrumental variable approach to identify causal effects, and the methodology of the post-estimation analyses to quantify their economic significance.

3.1 Estimation framework and instruments

We focus on three key labour market outcomes of demographic groups: share in total sector employment (based on the number of employees), wages relative to the sector's average wage, and share in the sector's wage bill. The third outcome is the product of the former two, and integrates the impact. We study the impact of two technological shocks: exposure to industrial robots and ICT capital. Our identification strategy relies on the variation in technological capital growth across sectors and countries.

Following Graetz and Michaels (2018) and Acemoglu and Restrepo (2020), we calculate robot exposure as the number of robots per thousand workers at the sector level, $(\mathrm{R}_{\mathrm{c,s,t}})$. Analogously, we compute exposure to ICT capital, $(\mathrm{I}_{\mathrm{c,s,t}})$, as the net stock of ICT capital and software expressed in real terms (in 2015 euros) per worker. We use the 2010 employment (the first year of our sample) as a numerator. This ensures that variation in the explanatory variables over time reflects the acquisition of selected assets, and is independent of changes in employment (which could be endogenous to capital growth).

First, we estimate the following ordinary least squares (OLS) regressions for each demographic group *d*:

$$\Delta y_{c,s,d,t} = \beta_1 \Delta I_{c,s,t} + \beta_2 \Delta R_{c,s,t} + \beta_3 \Delta GVC_{c,s,t} + \beta_4 Edu_{c,s,d,t-4} + \rho_{c,t} + \epsilon_{c,s,d,t} \quad (1)$$

where y stands for the share of a demographic group in the total sector wages, its share in total sector employment, or its hourly wages relative to the sector's average in country *c* and sector *s*; $GVC_{c,s,t}$ is the foreign value added in exports divided by total sectoral output; $Edu_{c,s,d,t-1}$ is the lagged share of tertiary educated persons in a demographic group relative to the sectoral average; $\rho_{c,t}$ denotes country-year fixed effects. We use four-year differences and *t* takes two levels: 2014 and 2018.

By including country-year fixed effects, we control for aggregate changes in the labour supply of demographic groups and institutional developments that have a similar impact on the labour market outcomes of specific demographic groups across industries. We also control for sector-specific participation in global value chains, which increased substantially in the analysed period and could have affected labour market outcomes (Goos et al., 2014). Finally, some variation in the labour market outcomes of the demographic groups may be explained by their initial average educational attainment. We control for it in relative terms, using the sector-specific share of tertiary educated workers as a reference point.

Second, we estimate two-stage least squares (2SLS) regressions to account for the fact that our variables of interest – robots and ICT stock – may be endogenous to labour market outcomes, or affected by other trends that can drive labour market outcomes. In particular, sectors facing more severe labour shortages may invest more in labour-saving technologies and retain more incumbent, older workers. For instance, if wages increase in one sector due to a demand shock, it may reduce the influx of young people into other sectors while stimulating investment in automation technologies in those sectors.

To estimate the causal effects of technology in this context, we use the instrumental variable strategy commonly used in the literature on labour market effects of technological progress (Acemoglu and

Restrepo, 2022, 2020; Adachi et al., 2022; Dauth et al., 2021; de Vries et al., 2020). Specifically, we use the "technology frontier" instrument previously applied by Acemoglu and Restrepo (2020) and Dauth et al. (2021). We instrument the growth in robot exposure and in ICT capital with the growth of these types of capital in the same sector in the United States. Notably, the technology variables entering the second stage are country-specific, as the country-average investment in a given type of technology is captured in the first-stage regression by the country-year fixed effects, $\rho_{c,t}$. However, the sectoral patterns of technology adoption are purged of the local shocks that are potentially correlated with the employment shares or relative wages of demographic groups. The relevance of instruments is confirmed by the Stock-Yogo (2005) test for weak instruments.[9]

By studying the within-sector outcomes, we isolate our findings from any correlation between technology adoption and sector growth. A similar strategy has been used by, for example, Aksoy et al. (2021), Graetz and Michaels (2018), and Jerbashian (2019).[10] This approach relies on the assumption that no industry-specific shocks influenced labour market outcomes of specific demographic groups. Such shocks enter our model as a part of an error term, $\epsilon_{c,s,d,t}$. However, to invalidate our identification strategy, such shocks would also need to be systematically correlated with technology adoption. We are not aware of any such confounding factors that could distort our results.

Following Graetz and Michaels (2018) and Lewandowski et al. (2022), we use standardised weights (based on 2010 sectoral employment shares) that give every country in the sample an equal weight. In principle, the weight of a country-sector cell is the same for all demographic groups. However, suppose the number of observed employees in a demographic group is lower than 15 in any year. In that case, we do not include this country-sector cell in the estimation sample for that demographic group. We use alternative weights based on the number of observed employees in a sector as a robustness check.

Finally, we explore the mechanisms behind the results obtained at the level of demographic groups. To this end, we split each demographic group into four subgroups by occupation type, classified according to the most prevalent task: non-routine cognitive, routine cognitive, routine manual, or non-routine manual. We re-estimate our regressions for these sector / demographic group / occupation type cells. This allows us to assess which occupation types drive the overall results found for a given demographic group. For this analysis, we drop outcome variables for cells with fewer than 10 observations. The available sample size prevents us from using more detailed occupation groups.

3.2 Economic significance analysis

We quantify the economic impact of technology adoption on relative labour market outcomes, using the estimated coefficients and actual changes in the exposure to robots and ICT capital. We focus on the shares in employment and in the wage bill. We do not conduct such an analysis for relative wages, as it would be based on statistically insignificant coefficient estimates (see next section).

[9] We use the ivreg2 Stata module developed by Baum et al. (2010).

[10] Our approach differs from Acemoglu and Restrepo (2022), who identified the effect of task displacement technologies using the variance of exposure to these technologies across demographic groups at the country or region level. However, they did not identify any differential effects of technology between younger and older workers. Our approach rests on using the variance in technology adoption between industries to identify potentially varying impacts on various demographic groups, specifically depending on age.

In the first step, we use all the coefficients from the 2SLS estimation (equation 1) and actual values of all variables entering the second stage of the estimation to calculate the predicted changes in the demographic groups' employment / wage bill shares.

In the second step, for each demographic group, we construct two counterfactual employment / wage bill shares, one assuming no changes in the exposure to ICT capital and the other assuming no changes in the exposure to robots. We use the same coefficients as in the first step for that purpose.

In the third step, we sum both the model-predicted and counterfactual employment (wage bill) shares of demographic groups at the country level. Here, we use time-varying sectors' weights based on the actual number of employees in each year. By doing so, we combine our results with the information on structural changes in each country. However, using time-varying sector weights does not alter our results substantially.

In the fourth step, we express the effects of each technology as the percentage point difference in employment / wage bill shares between the model-predicted and the counterfactual scenario. This allows assessing the relative contribution of robots and ICT capital to changes in labour market outcomes across demographic groups, as implied by within-sector effects that are the focal point of this paper.

4. Results

In this section, we present our econometric results and assess the economic significance of the estimated effects of technology on the labour market outcomes of demographic groups.

4.1 The impact of technology adoption on labour market outcomes

First, we report the effects of technology adoption on the demographic groups' employment shares, focusing on the 2SLS results (Table 3). We find that adopting both types of technology positively affected the employment share of young women (aged 20-29) and negatively affected the employment share of women aged 60 or more. Growth in ICT capital of one thousand EUR per worker[11] increased the employment share of young women by 0.13 pp (*p-value* = 0.051) and reduced the employment share of older women by 0.11 pp. Each additional robot per one thousand workers[12] increased the employment share of young women by 0.20 pp and decreased the employment share of older women by 0.13 pp. We also find positive effects of growth in ICT capital for the employment share of prime-aged women. These differential effects of technology adoption, varying with respect to age among women, align with the hypothesis that technological change can benefit labour market entrants while making the skills of some of the older incumbents obsolete (Fillmore and Hall, 2021). Adult skill surveys confirm that ICT and analytical skills decrease with age. According to the PIAAC data, nearly 50% of people aged 25-34 are among the best performers (Level 2 or 3) in problem-solving in a technology-rich environment, compared with 24% of those aged 45-54 and only 12% of those aged 55-65 (OECD, 2013).

[11] In our sample, a weighted average four-year change in the ICT capital per worker amounted to EUR 718.

[12] Among sectors that invested in robots, a weighted average four-year increase in the number of robots per one thousand workers amounted to 1.29.

For prime-aged men, one additional robot per 1,000 workers reduced the employment share of men aged 30-49 by 0.20 pp. In contrast, for men aged 50-59, one additional robot increased the employment share by 0.11 pp.

Our 2SLS estimates are generally larger in absolute terms than the OLS ones (Table 3). This may mean that some unobserved shocks are negatively correlated with changes in exposure to task displacement technologies and bias downward the OLS estimates of the coefficients on robots and ICT. Also, the initial selection of younger / older and male / female workers into different sectors could introduce a negative correlation between errors in the demographic groups' labour market outcomes and exposure to robots and ICT.

Table 3. The effects of technological change on the employment shares of demographic groups

	Women, OLS	Women, 2SLS	Men, OLS	Men, 2SLS
A: Age 20-29				
Δ ICT capital	0.065***	0.129*	0.010	0.009
	(0.021)	(0.066)	(0.039)	(0.090)
Δ Robots	0.079***	0.201***	0.004	-0.008
	(0.019)	(0.060)	(0.045)	(0.113)
Kleibergen-Paap rk Wald F statistic		35.3		33.7
No. of Observations	558	558	582	582
B: Age 30-49				
Δ ICT capital	0.053	0.156**	0.008	-0.13
	(0.032)	(0.066)	(0.042)	(0.101)
Δ Robots	0.041	0.015	-0.105*	-0.202**
	(0.027)	(0.052)	(0.060)	(0.091)
Kleibergen-Paap rk Wald F statistic		34.7		37.4
No. of Observations	590	590	596	596
C: Age 50-59				
Δ ICT capital	-0.019	-0.022	-0.073**	-0.031
	(0.027)	(0.033)	(0.034)	(0.031)
Δ Robots	-0.012	-0.025	0.006	0.109**
	(0.025)	(0.056)	(0.020)	(0.054)
Kleibergen-Paap rk Wald F statistic		33.6		46.6
No. of Observations	580	580	592	592
D: Age 60+				
Δ ICT capital	-0.047***	-0.105***	-0.004	0.026
	(0.016)	(0.041)	(0.008)	(0.033)
Δ Robots	-0.046***	-0.125***	0.010	0.025
	(0.014)	(0.039)	(0.012)	(0.046)
Kleibergen-Paap rk Wald F statistic		40.9		29.0
No. of Observations	496	496	562	562

*Note: The table presents the estimated coefficients of the OLS and 2SLS regressions. Standard errors (in brackets) are clustered at the sector-year level. The dependent variable is a four-year change in the demographic group's share (in %) in total sector employment. Δ ICT capital is a four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is a four-year change in the number of industrial robots per 1000 workers, where employment is fixed in 2010. Country-year fixed effects are included. We also control for the change in the GVC participation and for the lagged share of tertiary-educated workers in the demographic group relative to the sector's average (coefficients reported in Table C1 in online Appendix). For 2SLS, Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in the United States. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. *** p<0.01, ** p<0.05, * p<0.1.*

Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

In online Appendix D, we report the estimated effects on the demographic groups' shares in total hours worked. However, these are similar to the previously discussed effects on the employment shares as the impact of technology on the average hours worked was negligible, with some small positive effects detected only for prime-aged men (Table D1).

Contrasting with significant effects on employment shares, we do not find any statistically significant IV effects of technology adoption on the average relative wages of demographic groups (columns with 2SLS results in Table 4). The findings from past research focus on gender gaps and are mixed. The early waves of computerization reduced the gender wage gap within industries in Germany (Black and Spitz-Oener, 2010). Robots widened the gender pay gap in European countries, as they brought productivity gains that benefited mainly men in high- and middle-skilled occupations (Aksoy et al., 2021). However, in the US, automation reduced the gender pay gap (Acemoglu and Restrepo, 2022; Anelli et al., 2021).

Finally, we discuss the impacts on the demographic groups' shares in the wage bill (Table 5). As the product of employment share and wage effects, these impacts follow the patterns discussed for employment shares but are weaker (see Table 3 for results based on employed persons and Table D2 for those based on work hours). Specifically, for young and prime-aged women and prime-aged men, the wage effects operated opposite to the employment effects. This is consistent with the selection mechanism, in which workers entering growing occupations tend to be less skilled than the incumbent employees (Böhm et al., 2022). According to our estimates, the growth in the ICT capital of one thousand EUR per worker increased the wage bill share of young and prime-aged women by 0.08 pp and 0.14 pp, respectively. In contrast, it decreased the wage bill share of older women by 0.09 pp (Table 5). Furthermore, one additional robot per thousand workers increased the wage bill share of young women by 0.14 pp and decreased the share of older women by 0.11 pp. Importantly, the effects of robot adoption on wage bill shares are insignificant for men, with wage effects counterbalancing employment effects and suggesting stronger selection mechanism than among women.

Table 4. The effects of technological change on the relative wages of demographic groups

	Women, OLS	Women, 2SLS	Men, OLS	Men, 2SLS
A: Age 20-29				
Δ ICT capital	0.033	0.001	0.025	0.007
	(0.061)	(0.123)	(0.059)	(0.155)
Δ Robots	0.039	0.049	-0.059	0.043
	(0.160)	(0.211)	(0.081)	(0.193)
Kleibergen-Paap rk Wald F statistic		35.3		33.7
No. of Observations	558	558	582	582
B: Age 30-49wo				
Δ ICT capital	0.014	-0.077	0.005	-0.036
	(0.056)	(0.148)	(0.052)	(0.196)
Δ Robots	0.102*	-0.129	0.137**	0.233
	(0.058)	(0.159)	(0.059)	(0.211)
Kleibergen-Paap rk Wald F statistic		34.7		37.4
No. of Observations	590	590	596	596
C: Age 50-59				
Δ ICT capital	0.282**	0.165	0.187	-0.014
	(0.127)	(0.103)	(0.158)	(0.113)
Δ Robots	0.007	-0.063	-0.012	-0.114
	(0.088)	(0.202)	(0.143)	(0.420)
Kleibergen-Paap rk Wald F statistic		33.6		46.6
No. of Observations	580	580	592	592
D: Age 60+				
Δ ICT capital	0.300	0.201	0.117	0.254
	(0.181)	(0.218)	(0.185)	(0.221)
Δ Robots	0.117	0.347	-0.139	0.235
	(0.180)	(0.348)	(0.195)	(0.402)
Kleibergen-Paap rk Wald F statistic		40.9		29.0
No. of Observations	496	496	562	562

*Note: The table presents the estimated coefficients of the OLS and 2SLS regressions. Standard errors (in brackets) are clustered at the sector-year level. The dependent variable is a four-year change in the demographic group's average hourly wage as % of the sector's average. Δ ICT capital is a four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is a four-year change in the number of industrial robots per 1000 workers, where employment is fixed in 2010. Country-year fixed effects are included. We also control for the change in the GVC participation and for the lagged share of tertiary-educated workers in the demographic group relative to the sector's average (coefficients reported in Table C2 in online Appendix). For 2SLS, Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in the United States. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. *** p<0.01, ** p<0.05, * p<0.1.*

Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

Table 5. The effects of technological change on the shares of demographic groups in the wage bill

	Women, OLS	Women, 2SLS	Men, OLS	Men, 2SLS
A: Age 20-29				
Δ ICT capital	0.045***	0.084**	0.002	0.012
	(0.013)	(0.039)	(0.031)	(0.081)
Δ Robots	0.050***	0.135***	-0.013	-0.016
	(0.014)	(0.034)	(0.031)	(0.109)
Kleibergen-Paap rk Wald F statistic		35.3		33.7
No. of Observations	558	558	582	582
B: Age 30-49				
Δ ICT capital	0.055*	0.136*	-0.001	-0.148
	(0.032)	(0.077)	(0.039)	(0.099)
Δ Robots	0.046*	-0.011	-0.077	-0.140
	(0.027)	(0.071)	(0.055)	(0.132)
Kleibergen-Paap rk Wald F statistic		34.7		37.4
No. of Observations	590	590	596	596
C: Age 50-59				
Δ ICT capital	-0.001	0.005	-0.060*	-0.013
	(0.029)	(0.037)	(0.034)	(0.041)
Δ Robots	-0.013	-0.028	0.010	0.097
	(0.023)	(0.051)	(0.031)	(0.087)
Kleibergen-Paap rk Wald F statistic		33.6		46.6
No. of Observations	580	580	592	592
D: Age 60+				
Δ ICT capital	-0.040**	-0.090**	-0.001	0.045
	(0.016)	(0.040)	(0.011)	(0.037)
Δ Robots	-0.044***	-0.113***	0.008	0.037
	(0.015)	(0.041)	(0.013)	(0.050)
Kleibergen-Paap rk Wald F statistic		40.9		29.0
No. of Observations	496	496	562	562

*Note: The table presents the estimated coefficients of the OLS and 2SLS regressions. Standard errors (in brackets) are clustered at the sector-year level. The dependent variable is a four-year change in the demographic group's share (in %) in total sector wages. Δ ICT capital is a four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is a four-year change in the number of industrial robots per 1000 workers, where employment is fixed in 2010. Country-year fixed effects are included. We also control for the change in the GVC participation and for the lagged share of tertiary-educated workers in the demographic group relative to the sector's average (coefficients reported in Table C3 in online Appendix). For 2SLS, Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in the United States. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. *** p<0.01, ** p<0.05, * p<0.1.*
Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

4.2 The effects of technology adoption within occupation types and potential mechanism

In this subsection, we explore the potential mechanisms behind the differential effects of technology adoption on demographic groups. We report the effects of technology adoption for four major occupation types: non-routine cognitive, routine cognitive, routine manual, and non-routine manual. On the one hand, the difference between demographic groups in the overall effects of technology adoption could reflect differences in the shares of occupation types that vary in vulnerability to task displacement technologies. In this case, we would expect to find the coefficient signs for a given occupation type to be the same for different demographic groups. On the other hand, the impact of technology on a given occupation type might be age-or gender-specific, e.g., due to skill profiles. In that case, the coefficient signs for a given occupation type would vary between the demographic groups. In online Appendix E, we also report the effects of technology on the aggregate labour market outcomes of the occupation types without considering the demographic dimension.

Overall, we find important differences between demographic groups within particular occupation types. This suggests that the age- and gender-specific effects of technology adoption drove the different impacts of robot and ICT exposure on younger and older men and women, rather than the occupational composition of the jobs held by various demographic groups.

First, our results show that robot exposure substantially and significantly reduced the employment shares of young (aged 20-29) and prime-aged (30-49) men in routine manual occupations and increased the employment shares of men aged 50 or older in routine manual occupations (Table 6). By contrast, robotisation had much weaker effects on workers in non-routine manual occupations (either men or women, Table 6). These findings are consistent with theories that automation technologies can substitute human labour mainly in structured and repetitive tasks. Furthermore, robotisation contributes to routine manual occupations getting older, in line with the evidence presented by Autor and Dorn (2009) for the US and Lewandowski et al. (2020) for European countries. A potential explanation could be that younger workers increasingly select into growing rather than shrinking occupations (Böhm et al., 2022) as automation reduces new hires (Dauth et al., 2021). Our estimates for women in routine manual jobs are less reliable due to small sample sizes and the resulting weakness of instruments.

Second, we find that robotisation (indirectly) affected workers in occupations that demand primarily cognitive tasks. This result suggests complementarities between adopting automation technologies and cognitive skills. Notably, the effects differ between demographic groups. We find that robots reduced cognitive occupations' employment shares of women aged 50 or older and increased the employment shares of young women and young men (Table 6). The wage impacts of robots provide additional evidence of this complementarity. Robots negatively affected the earnings of women aged 30-59 in non-routine cognitive occupations but positively influenced the earnings of men aged 60 or older within the same occupational category (Table 7).

Third, we find varying effects of ICT capital among non-routine cognitive workers. It increased employment shares of women aged 20-49, while there were no effects for men in this age group. This finding aligns with arguments suggesting that ICT adoption increases returns to social skills, in which women tend to have a comparative advantage (Deming, 2017). Relatedly, Cortes et al. (2021) showed for the US that women increasingly sort into high-paying occupations due to the increasing importance of social tasks.

Table 6. The effects of technological change on the employment shares by occupational task groups (2SLS estimates)

	Women				Men			
	Non-Routine Cognitive	Routine Cognitive	Routine Manual	Non-Routine Manual	Non-Routine Cognitive	Routine Cognitive	Routine Manual	Non-Routine Manual
A: Age 20-29								
Δ ICT capital	0.068***	0.035	0.149	0.003	-0.027	0.002	0.208	0.016
	(0.019)	(0.054)	(0.122)	(0.078)	(0.050)	(0.024)	(0.229)	(0.032)
Δ Robots	0.038**	0.135**	-0.073*	0.062	0.040	0.057**	-0.218**	0.057
	(0.016)	(0.059)	(0.044)	(0.039)	(0.053)	(0.024)	(0.091)	(0.043)
K-P F statistic	49.4	36.2	6.0	5.1	34.1	48.6	6.9	33.0
Observations	516	518	254	390	540	480	386	510
B: Age 30-49								
Δ ICT capital	0.107*	-0.037	0.273	0.082*	-0.022	-0.035	-0.092	-0.023
	(0.065)	(0.044)	(0.259)	(0.042)	(0.123)	(0.029)	(0.087)	(0.045)
Δ Robots	0.024	0.058	-0.165	0.061*	0.047	0.005	-0.252**	0.013
	(0.038)	(0.052)	(0.128)	(0.035)	(0.079)	(0.047)	(0.112)	(0.089)
K-P F statistic	33.9	34.8	6.4	12.2	34.8	30.0	11.6	21.6
Observations	580	580	370	506	592	538	464	572
C: Age 50-59								
Δ ICT capital	0.026	-0.043*	-0.125	-0.011	0.068	-0.020	-0.105	-0.037
	(0.028)	(0.022)	(0.079)	(0.056)	(0.042)	(0.024)	(0.078)	(0.027)
Δ Robots	0.014	-0.051*	0.025	0.010	0.063*	0.005	0.076**	-0.005
	(0.024)	(0.027)	(0.034)	(0.017)	(0.033)	(0.031)	(0.032)	(0.041)
K-P F statistic	39.7	27.4	7.2	9.6	41.9	42.4	6.8	18.2
Observations	534	548	322	464	584	478	426	556
D: Age 60+								
Δ ICT capital	-0.044	-0.015	-0.264***	0.011	0.052***	0.007	-0.065	0.023
	(0.029)	(0.012)	(0.080)	(0.082)	(0.019)	(0.006)	(0.045)	(0.057)
Δ Robots	-0.074***	-0.058***	0.089***	-0.047**	0.027	-0.011*	0.090***	-0.085***
	(0.028)	(0.016)	(0.031)	(0.022)	(0.022)	(0.006)	(0.033)	(0.030)
K-P F statistic	14.5	48.7	5.8	6.5	45.1	38.0	6.0	6.3
Observations	390	424	194	348	518	372	308	478

*Note: The table presents the estimated coefficients of the 2SLS regressions. Standard errors (in brackets) are clustered at the sector-year level. The dependent variable is a four-year change in the group's share (in %) in total sector employment. Δ ICT capital is a four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is a four-year change in the number of industrial robots per 1000 workers, where employment is fixed in 2010. Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in the United States. Country-year fixed effects are included. We also control for the change in the GVC participation and for the lagged share of tertiary-educated workers in the group relative to the sector's average. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. *** p<0.01, ** p<0.05, * p<0.1.*

Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

Table 7. The effects of technological change on the relative wages by occupational task groups (2SLS estimates)

	Women				Men			
	Non-Routine Cognitive	Routine Cognitive	Routine Manual	Non-Routine Manual	Non-Routine Cognitive	Routine Cognitive	Routine Manual	Non-Routine Manual
A: Age 20-29								
Δ ICT capital	-0.010	-0.129	2.066	1.365	-0.362	-0.111	1.114	0.143
	(0.207)	(0.227)	(1.815)	(1.052)	(0.396)	(0.264)	(1.026)	(0.232)
Δ Robots	-0.212	-0.043	-0.342	0.170	0.001	-0.024	-0.502	0.225
	(0.474)	(0.531)	(0.612)	(0.393)	(0.507)	(0.495)	(0.361)	(0.151)
K-P F statistic	49.4	36.2	6.0	5.1	34.1	48.6	6.9	33.0
Observations	516	518	254	390	540	480	386	510
B: Age 30-49								
Δ ICT capital	-0.048	-0.206**	3.503*	-0.327	0.225	-0.361	0.865	-0.522***
	(0.254)	(0.098)	(1.839)	(0.291)	(0.273)	(0.282)	(0.957)	(0.168)
Δ Robots	-0.925*	-0.022	-1.232*	0.606***	-0.069	0.257	0.281	-0.119
	(0.491)	(0.390)	(0.671)	(0.229)	(0.674)	(0.375)	(0.323)	(0.166)
K-P F statistic	33.9	34.8	6.4	12.2	34.8	30.0	11.6	21.6
Observations	580	580	370	506	592	538	464	572
C: Age 50-59								
Δ ICT capital	0.024	-0.395	1.036	-0.270	-0.507	0.515*	0.227	-0.073
	(0.352)	(0.243)	(0.789)	(0.453)	(0.367)	(0.280)	(0.971)	(0.538)
Δ Robots	-1.006**	0.248	-0.319	-0.287	0.136	0.085	-0.007	-0.296
	(0.473)	(0.209)	(0.306)	(0.199)	(0.905)	(0.551)	(0.371)	(0.224)
K-P F statistic	39.7	27.4	7.2	9.6	41.9	42.4	6.8	18.2
Observations	534	548	322	464	584	478	426	556
D: Age 60+								
Δ ICT capital	-0.158	0.207	0.803	0.150	-0.087	0.839	-1.060	0.492
	(0.441)	(0.289)	(2.081)	(0.716)	(0.638)	(0.612)	(1.125)	(0.810)
Δ Robots	-0.162	0.240	0.182	0.204	2.299**	-0.599	0.024	-0.032
	(0.628)	(0.340)	(0.734)	(0.181)	(1.102)	(0.827)	(0.394)	(0.284)
K-P F statistic	14.5	48.7	5.8	6.5	45.1	38.0	6.0	6.3
Observations	390	424	194	348	518	372	308	478

*Note: The table presents the estimated coefficients of the 2SLS regressions. Standard errors (in brackets) are clustered at the sector-year level. The dependent variable is a four-year change in the group's average hourly wage as % of the sector's average. Δ ICT capital is a four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is a four-year change in the number of industrial robots per 1000 workers, where employment is fixed in 2010. Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in the United States. Country-year fixed effects are included. We also control for the change in the GVC participation and for the lagged share of tertiary-educated workers in the group relative to the sector's average. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. *** p<0.01, ** p<0.05, * p<0.1.*

Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

Table 8. The effects of technological change on the wage bill shares by task groups (2SLS estimates)

	Women				Men			
	Non-Routine Cognitive	Routine Cognitive	Routine Manual	Non-Routine Manual	Non-Routine Cognitive	Routine Cognitive	Routine Manual	Non-Routine Manual
A: Age 20-29								
Δ ICT capital	0.046**	0.015	0.130	-0.005	-0.029	0.003	0.185	0.013
	(0.018)	(0.026)	(0.081)	(0.053)	(0.054)	(0.010)	(0.237)	(0.024)
Δ Robots	0.028	0.082**	-0.054**	0.044	0.032	0.030**	-0.165*	0.042
	(0.018)	(0.034)	(0.026)	(0.028)	(0.051)	(0.013)	(0.093)	(0.035)
K-P F statistic	49.4	36.2	6.0	5.1	34.1	48.6	6.9	33.0
Observations	516	518	254	390	540	480	386	510
B: Age 30-49								
Δ ICT capital	0.105	-0.023	0.210	0.056	-0.020	-0.049	-0.083	-0.029
	(0.082)	(0.036)	(0.156)	(0.036)	(0.108)	(0.033)	(0.097)	(0.045)
Δ Robots	-0.04	0.052*	-0.116*	0.056*	-0.005	0.037	-0.192	0.040
	(0.055)	(0.027)	(0.070)	(0.033)	(0.060)	(0.055)	(0.117)	(0.081)
K-P F statistic	33.9	34.8	6.4	12.2	34.8	30.0	11.6	21.6
Observations	580	580	370	506	592	538	464	572
C: Age 50-59								
Δ ICT capital	0.045	-0.038**	-0.108	-0.011	0.099*	-0.023	-0.094	-0.031
	(0.032)	(0.018)	(0.088)	(0.048)	(0.059)	(0.027)	(0.071)	(0.027)
Δ Robots	0.002	-0.045*	0.022	0.009	0.083	0.004	0.060**	-0.010
	(0.025)	(0.023)	(0.025)	(0.017)	(0.075)	(0.032)	(0.028)	(0.031)
K-P F statistic	39.7	27.4	7.2	9.6	41.9	42.4	6.8	18.2
Observations	534	548	322	464	584	478	426	556
D: Age 60+								
Δ ICT capital	-0.054	-0.015*	-0.158***	-0.003	0.060**	0.011	-0.050	0.019
	(0.033)	(0.009)	(0.059)	(0.056)	(0.024)	(0.007)	(0.046)	(0.048)
Δ Robots	-0.094***	-0.043***	0.053**	-0.025	0.058*	-0.012*	0.075***	-0.077***
	(0.034)	(0.010)	(0.024)	(0.015)	(0.032)	(0.006)	(0.026)	(0.025)
K-P F statistic	14.5	48.7	5.8	6.5	45.1	38.0	6.0	6.3
Observations	390	424	194	348	518	372	308	478

*Note: The table presents the estimated coefficients of the 2SLS regressions. Standard errors (in brackets) are clustered at the sector-year level. The dependent variable is a four-year change in the group's share (in %) in total sector wages. Δ ICT capital is a four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is a four-year change in the number of industrial robots per 1000 workers, where employment is fixed in 2010. Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in the United States. Country-year fixed effects are included. We also control for the change in the GVC participation and for the lagged share of tertiary-educated workers in the group relative to the sector's average. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. *** p<0.01, ** p<0.05, * p<0.1.*
Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

4.3 Economic significance of the estimated effects

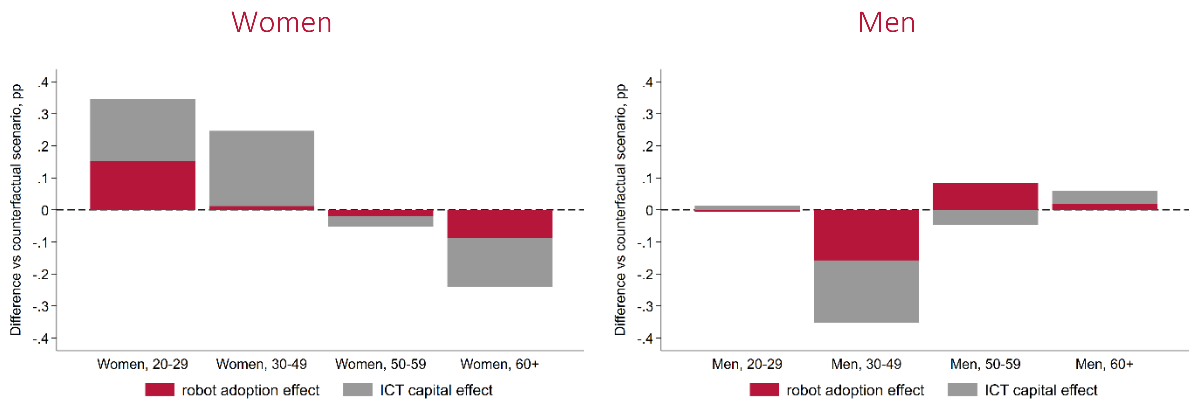
In this subsection, we quantify the economic significance of our findings. In the period covered in our analysis, the population and employment shares of people aged 50 or older increased notably. Other factors potentially contributing to these increases include changes in the population structure or retirement system reforms. We control for them with country-year fixed effects.

For older women, technology adoption slowed down the trend of rising employment shares. On average, the employment shares of older women in 2018 were 0.24 pp lower than they would have been in the counterfactual scenario of no technology adoption in 2010-2018 (Figure 3). We attribute the dominant part of this outcome (-0.15 pp) to ICT capital. The economic significance of this effect is noticeable, as the average employment share of older women in our sample was 4.7% in 2018 (with technology remaining at the 2010 level, it might have reached 4.9%). In contrast, for men aged 60 or older, technology adoption contributed positively to the overall rising trend, as the employment share of this group was, on average, 0.06 pp higher in 2018 than it would have been if ICT capital and robot exposure remained at the 2010 levels (employment share of older men in 2018 amounted to 4.7%, equal to that of older women).

For younger women, the contribution of technology adoption is also substantial. On average, their 2018 employment shares were 0.35 pp higher than they would have been in the counterfactual scenario (Figure 3). The employment share of this group decreased by 1.3 pp, from 8.8% in 2010 to 7.5% in 2018, so without rising technology levels, that decline would have been 25% stronger. In contrast, the contribution of technology to changes among young men is close to zero. It is also relatively small for prime-aged women and prime-aged men (0.25 pp and -0.35 pp, respectively) compared to their overall employment shares in 2018 (24.5% and 26.5%, respectively).

Overall, we attribute most changes in the employment shares in 2010-2018 to ICT capital growth, with a smaller contribution of robot adoption (Figure 3). The effects on the share in total wages are somewhat weaker than the employment effects. We report them in online Appendix F. Previous research showed that automation increases job separations among incumbent workers, while computerisation does not (Bessen et al., 2023). Hence, the larger impact of ICT capital growth on the employment shares of demographic groups could have materialised through young and prime-aged women sorting into sectors investing heavily in ICT. Fro instance, there is evidence that ICT improves relative opportunities for high-educated workers with low-educated parents (Arntz et al., 2023).

Figure 3. The contribution of ICT and robots to changes in demographic groups' employment shares, pp



Note: The differences in the employment shares of demographic groups in the historical and counterfactual scenarios of no increase in ICT and robot exposure in 2010-2018.
Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

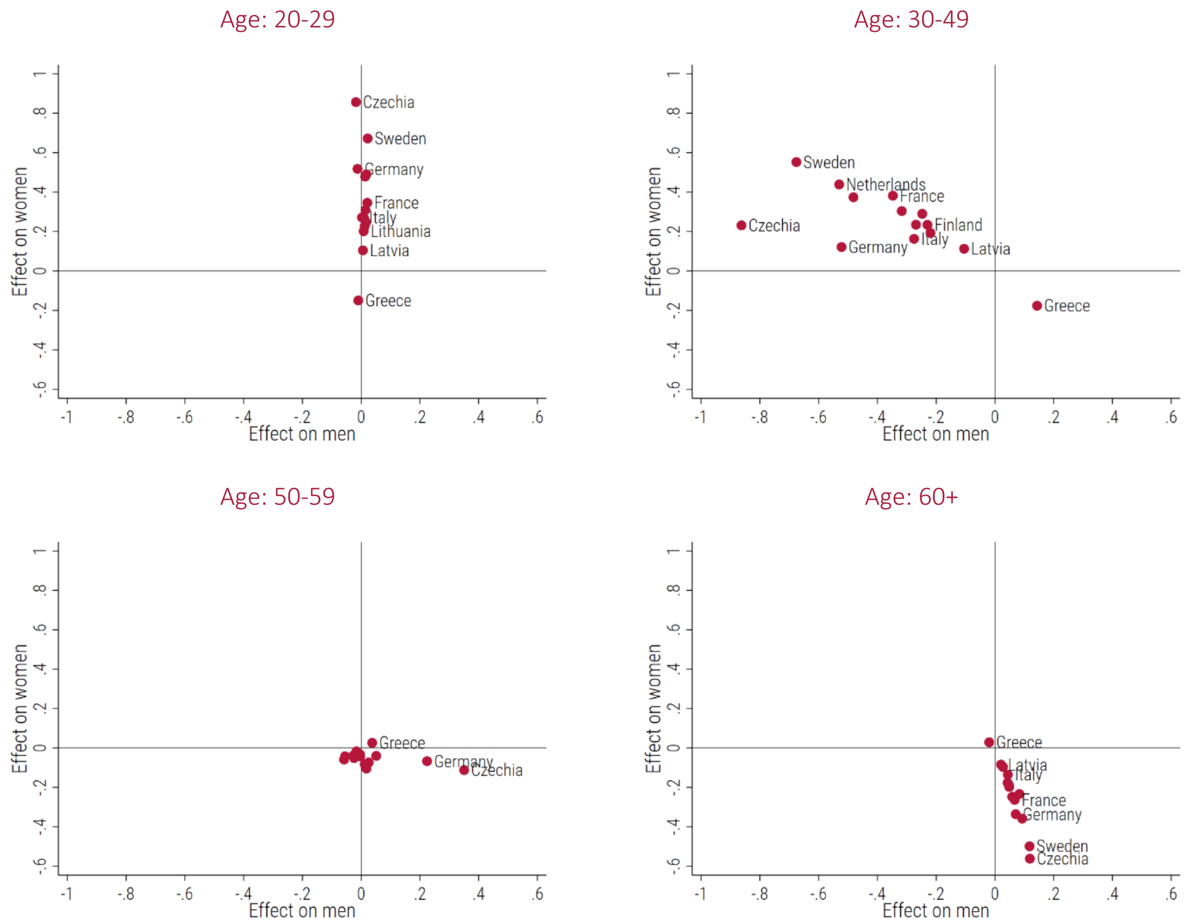
Finally, we quantify the contribution of technology adoption to changes in demographic groups' labour market outcomes in each country (Figure 4). The variation across countries stems from differences in: i) the country-specific growth in ICT and robot exposures (captured in the first stage regressions by country-year fixed effects) and ii) countries' sectoral structures.[13] Our results imply that the quantitative effects of technology adoption were heterogeneous across countries. Notably, Czechia and Germany, which made substantial investments in robots, record noticeable contributions of this technology to

[13] The full results for specific countries are available upon request.

changes in relative labour market outcomes of demographic groups (Figure 4). For all other countries studied, however, the growth in ICT capital plays a more prominent role. Sweden stands out with the largest ICT capital growth, contributing considerably to changes in women's employment shares. Greece, in turn, is an outlier with negative ICT investment and shifts in demographic groups' outcomes, which contrast with other countries in the sample.

Among prime-aged and older workers, adopting technology shifts the balance of gender employment shares. Larger employment gains for prime-aged women accompany the corresponding decreases in employment shares of prime-aged men (Figure 4). The opposite patterns emerge for workers aged 60 or older.

Figure 4. The contribution of ICT and robots to changes in demographic groups' employment shares, by countries, pp



Note: Each dot represents the difference in the employment shares of demographic groups in the historical and counterfactual scenarios of no increase in ICT and robot exposure in one country in 2010-2018.

4.4 Robustness analysis

As an initial robustness check, we conduct placebo tests, replacing ICT capital and robots with other types of capital. Here, we use transport equipment and a broad category of machinery, excluding transport equipment and ICT capital. Thus, we verify whether ICT capital and robots uniquely shape the labour market outcomes of demographic groups or whether we can detect similar effects for other types of capital. However, the "technology frontier" instrument is invalid for the assets considered in this placebo test.[14] In consequence, we report only the OLS results. Notably, in our baseline results, the OLS results align with most of the 2SLS findings about the significant employment effects of ICT capital and robots (Table 3).

The employment shares of demographic groups were unrelated to the changes in the other types of capital (Table 9). These results starkly contrast with the significant effects of ICT capital and robots. The placebo tests for relative wages and shares in the wage bill also support our identification strategy (reported in online Appendix G).

Table 9. Placebo tests results for the employment shares of demographic groups

	Age 20-29	Age 30-49	Age 50-59	Age 60+
A: Women				
Δ Transport equipment	-0.010	0.005	-0.001	-0.002
	(0.023)	(0.041)	(0.020)	(0.010)
Δ Machinery capital	0.002	0.003	0.004	-0.003
	(0.004)	(0.006)	(0.004)	(0.002)
No. of Observations	556	588	578	494
B: Men				
Δ Transport equipment	-0.013	0.035	-0.001	-0.017
	(0.030)	(0.035)	(0.024)	(0.014)
Δ Machinery capital	0.002	-0.005	-0.005	0.002
	(0.004)	(0.009)	(0.005)	(0.003)
No. of Observations	580	594	590	560

*Note: The table presents the estimated coefficients of the OLS regressions. Standard errors (in brackets) are clustered at the sector-year level. The dependent variable is a four-year change in the demographic group's share (in %) in total sector employment. Δ Transport equipment is a four-year change in the transport equipment stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Machinery capital is a four-year change in the other machinery capital stock (code "N11ON", in thousand EUR, constant prices) divided by employment as of 2010. Country-year fixed effects are included. We also control for the change in the GVC participation and for the lagged share of tertiary-educated workers in the demographic group relative to the sector's average. *** p<0.01, ** p<0.05, * p<0.1.*
Source: Authors' calculations based on the EU-SES, Eurostat, OECD TiVA, and EU-KLEMS data.

Next, we conduct a range of robustness checks to ensure that our results are not sensitive to regression weights or the model specification and are not driven by outliers. First, instead of equal weights for each country, we compute weights as the square root of the number of observed employees in a sector. The qualitative interpretation of all results remains the same, with the impact of robot adoption being quantitatively lower (Table 10).

Second, we verify that our findings do not hinge on the choice of control variables. We report the results from a specification without controls for GVC participation or the average educational attainment. This modification has a minor impact on the results. Without these controls, we would detect a smaller impact of ICT capital on the employment of women aged 20-49.

Third, we show that our findings are robust to the change in the instrument. Instead of the US technology adoption, we use an instrument based on other EU countries, similar to the instrument used by Anelli et al. (2019), Dauth et al. (2021), and Damiani et al. (2023). For each country-sector cell, we construct a leave-one-out instrument for ICT capital and robots. The results are very similar to the ones obtained with the instrument using the US technology adoption.

[14] The instrumental variables constructed according to equation (2) are not statistically significant in the first-stage regressions explaining actual changes in transport equipment or other machinery capital.

Table 10. Robustness analysis of the estimated employment effects

	Women				Men			
	Baseline	Alternative weights	No controls	EU-based IV	Baseline	Alternative weights	No controls	EU-based IV
A: Age 20-29								
Δ ICT capital	0.129*	0.117***	0.097	0.158**	0.009	0.034	0.042	0.000
	(0.066)	(0.045)	(0.070)	(0.067)	(0.090)	(0.057)	(0.090)	(0.098)
Δ Robots	0.201***	0.120***	0.236***	0.230***	-0.008	-0.007	0.012	-0.095
	(0.060)	(0.035)	(0.067)	(0.074)	(0.113)	(0.069)	(0.102)	(0.085)
K-P F statistic	35.3	78.5	35.2	92.1	33.7	72.7	35.2	100.1
Observations	558	558	558	558	582	582	582	582
B: Age 30-49								
Δ ICT capital	0.156**	0.098***	0.119*	0.151**	-0.130	-0.082	-0.127	-0.093
	(0.066)	(0.033)	(0.070)	(0.063)	(0.101)	(0.075)	(0.105)	(0.118)
Δ Robots	0.015	0.019	-0.001	0.063	-0.202**	-0.099**	-0.219***	-0.276**
	(0.052)	(0.034)	(0.059)	(0.087)	(0.091)	(0.049)	(0.064)	(0.117)
K-P F statistic	34.7	78.9	35.4	107.4	37.4	79.7	35.4	94.1
Observations	590	590	590	590	596	596	596	596
C: Age 50-59								
Δ ICT capital	-0.022	-0.021	-0.031	-0.008	-0.031	-0.026	-0.026	-0.057
	(0.033)	(0.021)	(0.029)	(0.045)	(0.031)	(0.036)	(0.032)	(0.049)
Δ Robots	-0.025	-0.025	-0.073	-0.025	0.109**	0.060*	0.125***	0.123
	(0.056)	(0.045)	(0.059)	(0.074)	(0.054)	(0.036)	(0.039)	(0.093)
K-P F statistic	33.6	80.0	35.2	91.4	46.6	79.9	35.2	89.9
Observations	580	580	580	580	592	592	592	592
D: Age 60+								
Δ ICT capital	-0.105***	-0.095***	-0.094**	-0.139***	0.026	-0.005	0.043	0.016
	(0.041)	(0.029)	(0.041)	(0.053)	(0.033)	(0.022)	(0.039)	(0.025)
Δ Robots	-0.125***	-0.094***	-0.128***	-0.147***	0.025	0.015	0.042	0.035
	(0.039)	(0.026)	(0.037)	(0.053)	(0.046)	(0.023)	(0.049)	(0.048)
K-P F statistic	40.9	54.4	31.6	56.1	29.0	72.1	29.1	94.7
Observations	496	496	496	496	562	562	562	562

*Note: The table presents the robustness analysis of the baseline 2SLS employment regressions reported in Table 3. We provide the baseline results for each demographic group in the first column. For the regression reported in the second column, we use the square root of the number of observed employees as a weight of a country-sector cell. In the third column, we report the results of regressions that do not control for the change in the GVC participation and for the lagged share of tertiary-educated workers. For the regression reported in the fourth column, the instrument variable is based on all countries from the sample, except for the country for which the endogenous variable is instrumented. Standard errors (in brackets) are clustered at the sector-year level. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. *** p<0.01, ** p<0.05, * p<0.1.*
Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

Fourth, we verify the sensitivity of the results to the adjustment dynamics assumed in the specification (1). To this aim, we use an 8-year difference instead of the baseline approach of two 4-year differences per country-sector cell. In Table 11, we report estimation results for the pooled sample and for occupational task groups. The qualitative interpretation of the results remains mostly the same. In the pooled sample, the exceptions are a reduced impact of ICT capital on the employment of young women and significant effects of both types of technology on the employment shares of young men, not detected in the baseline setup. However, for young women and men, the effects within occupational task groups are similar to the baseline results. For young men, the effects on the employment shares of non-routine cognitive workers become more sizable, though the direction of the effect matches that of the baseline specification. This suggests that a stronger effect on employment shares of young workers in the pooled sample probably reflects workers' sorting, which manifests to a larger extent over a longer period (compared to four-year spans). When considering the eight-year differences, we also detect more positive effects of ICT capital on the shares of men aged 30-59 working in non-routine cognitive occupations.

Finally, we rule out that any particular country drives our results. To this end, we re-estimate our baseline 2SLS regressions while excluding one country from the sample each time. In Figures G1 and G2 in online Appendix G, we report the results for the employment effects of ICT capital and robot adoption, respectively. The results confirm that developments in single countries do not drive our findings. Excluding individual countries had only a minor impact on the estimated coefficients, with one exception being perhaps Czechia – excluding it increases, in an absolute sense, the estimated effects of robot adoption. During the period studied, Czechia experienced rapid growth in the value added in manufacturing, which limited the potential for the adverse employment effects of robot adoption (Cséfalvay, 2020).

In online Appendix G, we report analogous robustness checks for the effects on the relative wages and the shares in the wage bill. They also show the stability of our results.

Table 11. The effects of technological change on the employment shares using 8-year differences (2SLS estimates)

	Women					Men				
	All	Non-Routine Cognitive	Routine Cognitive	Routine Manual	Non-Routine Manual	All	Non-Routine Cognitive	Routine Cognitive	Routine Manual	Non-Routine Manual
A: Age 20-29										
Δ ICT capital	0.081	0.054***	0.002	0.190	-0.001	-0.078**	-0.065***	-0.018	0.102	0.028
	(0.067)	(0.018)	(0.054)	(0.134)	(0.070)	(0.035)	(0.019)	(0.018)	(0.094)	(0.043)
Δ Robots	0.175***	0.006	0.138***	-0.067	0.033	0.112***	0.080***	0.042*	-0.145***	0.059
	(0.031)	(0.020)	(0.052)	(0.046)	(0.024)	(0.043)	(0.030)	(0.024)	(0.051)	(0.039)
K-P F statistic	42.2	43.3	37.6	3.8	2.7	35.0	40.0	42.6	4.0	28.0
Observations	279	258	259	127	195	291	270	240	193	255
B: Age 30-49										
Δ ICT capital	0.215**	0.185**	-0.069	0.329	0.081	-0.060	0.096**	-0.052	-0.096	-0.015
	(0.086)	(0.094)	(0.052)	(0.217)	(0.055)	(0.076)	(0.040)	(0.037)	(0.122)	(0.054)
Δ Robots	-0.026	-0.019	0.090**	-0.160***	0.043	-0.210***	0.098	0.039	-0.292***	-0.039
	(0.066)	(0.055)	(0.045)	(0.056)	(0.046)	(0.062)	(0.069)	(0.042)	(0.087)	(0.034)
K-P F statistic	36.9	38.3	39.2	3.1	33.9	38.3	38.4	41.7	11.1	35.2
Observations	295	290	290	185	253	298	296	269	232	286
C: Age 50-59										
Δ ICT capital	-0.021	0.056	-0.052**	-0.214**	-0.015	-0.030	0.114***	-0.041	-0.134	-0.053
	(0.027)	(0.041)	(0.026)	(0.098)	(0.038)	(0.036)	(0.028)	(0.029)	(0.097)	(0.033)
Δ Robots	-0.033	0.018	-0.061	0.029	0.015	0.084	0.101***	-0.019	0.061	-0.04
	(0.058)	(0.031)	(0.043)	(0.035)	(0.027)	(0.079)	(0.033)	(0.046)	(0.041)	(0.053)
K-P F statistic	34.9	36.8	38.4	4.1	4.9	41.6	37.8	36.7	3.5	36.9
Observations	290	267	274	161	232	296	292	239	213	278
D: Age 60+										
Δ ICT capital	-0.110***	-0.036	-0.012	-0.299***	0.007	0.023	0.054***	0.003	-0.074	0.026
	(0.043)	(0.034)	(0.015)	(0.075)	(0.099)	(0.045)	(0.019)	(0.009)	(0.047)	(0.083)
Δ Robots	-0.085	-0.051	-0.048**	0.071	-0.024	0.044	0.055***	-0.018**	0.108***	-0.114**
	(0.053)	(0.035)	(0.022)	(0.055)	(0.028)	(0.046)	(0.013)	(0.009)	(0.025)	(0.048)
K-P F statistic	43.8	41.4	56.4	3.5	4.2	36.1	29.5	45.5	2.9	22.4
Observations	248	195	212	97	174	281	259	186	154	239

*Note: The estimated coefficients of the 2SLS regressions using 8-year differences. Standard errors (in brackets) are clustered at the sector-year level. The dependent variable is an eight-year change in the group's share (in %) in total sector employment. Δ ICT capital is an eight-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is an eight-year change in the number of industrial robots per 1000 workers, where employment is fixed in 2010. Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in the United States. Country fixed effects are included. We also control for the change in the GVC participation and for the lagged share of tertiary-educated workers in the group relative to the sector's average. *** p<0.01, ** p<0.05, * p<0.1.*

Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

5. Conclusions

In this paper, we study the impact of exposure to two key modern technologies – ICT and robots – on the labour market outcomes of different demographic groups – men and women of different ages. We focus on the within-sector outcomes – employment shares, average hourly wages, and shares in total wages. We use the between-sector variance in technology adoption and the instrumental variable approach to identify causal effects. Our sample covers 14 European countries in 2010-2018.

We found that across the demographic groups, the effects of technology adoption on employment shares are noticeable, while the effects on relative wages are minor. Technology adoption increases the employment shares of young and prime-aged women but decreases the shares of older women and prime-aged men. These effects could be only partly attributed to the different occupational exposures of the demographic groups to task displacement by technology, as we found gender- and age-specific effects within particular occupation types. In particular, our results show that the labour-replacing effects of robot adoption concentrate among young and prime-aged men in routine manual occupations. For ICT, we find positive effects on employment shares of young and prime-aged women in non-routine cognitive occupations and slightly adverse effects on employment shares of older women in cognitive occupations. This suggests that intergenerational differences in ICT-related and interpersonal skills may have contributed to the age divide in the effects of technology. We also find that in the 2010s, ICT capital was a more critical driver of labour market outcomes than robots.

Our study has limitations. We identify the effects of technology adoption on labour market outcomes within sectors. The overall effects of technology may also involve between-sector effects, i.e. the changes in the relative size of sectors. As studying the impact of ICT and robot adoption on the economy's structure is not feasible within our framework, we do not attempt to analyse this issue in the present investigation. Moreover, our framework does not allow evaluating the relative roles of skill differences and worker sorting for heterogeneous effects of technology on different demographic groups. Lastly, our results should be interpreted with the usual caution, as our instrumental variables strategy may not necessarily identify the pure effects of technology adoption.

The emergence of new digital technologies, such as artificial intelligence, will probably expand the range of tasks that technology can perform toward less routine-intensive tasks (Eloundou et al., 2023). As population ageing will increase the share of older workers, an increasing group of workers may be left behind. Workers' sorting partly drives the differences identified in our study, but these mechanisms are interconnected. Public policy can help to bridge the gap between the evolving demand for skills and the skill supply of affected older workers by reducing costs or increasing private returns to lifelong learning. Identifying and promoting best practices in lifelong learning, increasing public spending on such programs, and encouraging workers to participate already in their prime age are potential policy responses to these challenges.

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