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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, in 14 European countries between 2010 and 2018. To identify the causal effects of technology adoption, we utilise the variation in technology adoption between industries and apply the instrumental variables strategy proposed by Acemoglu and Restrepo (2020). We find that the adoption of ICT and robots increased the shares of young and prime-aged women in employment and the wage bills of particular sectors, but reduced the shares of older women and prime-aged men. The negative effects were particularly pronounced for older women in cognitive occupations, who had relatively low ICT-related skills; and for young men in routine manual occupations, who experienced substitution by robots. Between 2010 and 2018, the growth in ICT capital played a much larger role than robot adoption in the changes in the labour market outcomes of demographic groups.

Keywords: technological change, automation, labour market outcomes, 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 in the last few decades. Between 2000 and 2019, the real value of ICT capital per worker in Europe has increased by 91%, while the robot exposure, measured by the number of industrial robots per 1,000 workers, has increased by 140%. Robots and other labour-saving technologies can have important aggregate and compositional labour market effects. They can directly reduce employment as machines replace humans in performing certain tasks, resulting in a labour-saving effect. However, the product demand 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 higher product and incomes in the technology-adopting sector – can increase employment. Gregory, Salomons, and Zierahn (2021) showed that the latter two effects have been dominant in Europe, leading to an overall positive employment effect of routine-replacing technologies. However, computers and other digital technologies have changed the structure of jobs tasks performed by humans, reducing the role of routine tasks and increasing the role of non-routine tasks, both within and across occupations (Autor, Levy, and Murnane 2003; Spitz-Oener 2006). These developments have led to job and wage polarisation in developed countries (Goos, Manning, and Salomons 2014). The hollowing out of the middle-paid jobs has created winners and losers of technological progress. While a lot of attention has been paid to differences associated with education (Firpo, Fortin, and Lemieux 2011; Gathmann and Schönberg 2010), the age and gender dimensions of exposure to new technologies have not been comprehensively studied.

In this paper, we seek to fill this gap by evaluating the age- and gender-specific labour market effects of two key modern technologies – ICT and robots – in a large group of European countries. There are two main reasons why the effects 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 (Fillmore and Hall 2021; Barth et al. 2022). As older workers tend to have skills that complement older technologies, and their expected returns from an investment in new skills are lower than those of younger workers, older workers can be more affected by technological change than younger workers. 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.1 Second, older workers are more likely to benefit from insider power. As such, they may be more protected from changes than younger workers, who are often outsiders or labour market entrants. Indeed, there is evidence that the shift away from routine towards non-routine work in Europe has affected younger workers more than older workers (Lewandowski et al. 2020), and that industrial robots in Germany have reduced the labour market prospects of younger workers (W. Dauth et al. 2021). The gender dimension is also relevant. On the one hand, as routine-replacing technologies increase returns to social skills, which tend be higher among women than among men (Deming 2017), women may benefit from ICT adoption more than men (Jerbashian 2019). On the other hand, smaller shares of women than of men have skills that complement new technologies, as 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 numeracy skills than their male counterparts (Rebollo-Sanz and De la Rica 2020).

Our first contribution in this paper is to disentangle both the gender- and the age-specific effects in the labour market impact of new technologies. We focus on three key labour market outcomes of demographic

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

groups: share in employment, average wage, and share in the wage bill. This approach enables us to identify the key consequences of technology adoption for particular demographic groups: men and women aged 20-29, 30-49, 50-59, and 60 or older.

Our second contribution is to distinguish between the effects of two key types of routine-replacing technologies: ICT and robots.[2] We measure ICT capital using Eurostat data, and robots using International Federation of Robotics (IFR, 2017) data. Both types of technology are measured at a finely disaggregated sector level. We merged these data with the worker-level data of the EU Structure of Earnings Survey (EU-SES), which allows us to calculate the labour market outcomes of demographic groups. For reasons of data availability, our sample covers 14 European countries between 2010 and 2018.[3] 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.[4] Second, we apply the instrumental variable (IV) methodology. As an instrument, we use the average exposure to ICT or robots in comparable countries. This method has been previously applied to measure the effects of robots by, e.g., Acemoglu and Restrepo (2020), Dauth et al. (2021), and Bachmann et al. (2022). We also control for globalization, in line with the literature that has identified technological progress as a key driver of labour market changes, and trade as a mediating factor (Gregory, Salomons, and Zierahn 2021).

We find that, between 2010 and 2018, the impact of technology adoption varied across demographic groups. Increased exposure to ICT capital was beneficial for the labour market outcomes of women aged 20-49, but detrimental for the labour market outcomes of women aged 60 or older and men aged 30-59. These effects were concentrated among workers in occupations intensive in non-routine manual tasks, which suggests that some basic level of ICT-related skills may be required even in jobs that generally require less advanced skills. Moreover, among women aged 60 or older, the adoption of ICT capital led to a deterioration in the labour market outcomes of workers in cognitive occupations. Meanwhile, the adoption of robots harmed the labour market outcomes of men aged 20-49, and particularly of those in occupations intensive in routine manual tasks. In contrast, men aged 50 or older were shielded from negative effects, in line with arguments that older workers have stronger insider power that may protect them from shocks. Overall, we find that, between 2010 and 2018, the increase in ICT capital played a much larger role than robot adoption in driving changes in labour market outcomes in Europe, and that both types of technology affected the employment shares of demographic groups rather than their relative earnings.

We identify the causal effects of technology adoption on labour market outcomes within sectors, while bearing in mind that the overall changes in the employment and the earnings of demographic groups may also be influenced by the changes in the relative sizes of sectors. As studying the impact of ICT and robot

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[2] The previous literature has largely been focused on the aggregate effects of ICT and robots. While these routine-replacing technologies have had a direct negative effect on employment in Europe (substitution), once the demand and spillover effects are accounted for, the total effect has been positive (Gregory, Salomons, and Zierahn 2021). Robots reduced aggregate employment in the US (Acemoglu and Restrepo 2020), which fuelled fears that automation would lead to mass joblessness. In Europe, however, the labour market effects of robots have been benign: robot adoption reduced employment in manufacturing at the expense of higher employment in services, but had a neutral effect on total employment in Germany (W. Dauth et al. 2021). Robot adoption has reduced the risk of job loss and improved the chances of finding a job in Eastern and Southern European countries, but has had minimal effects on labour market flows in Western European countries (Bachmann et al. 2022).

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

[4] 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; and 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.

adoption on the structure of the economy is not feasible within our framework, we do not attempt to analyse this issue in the present investigation.

The rest of the paper is structured as follows. In Section 2, we introduce our dataset and present 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 the regression results and the robustness checks, and quantify the impact of technology adoption on the historical changes in the labour market outcomes of different demographic groups. In section 5, we discuss the policy options for mitigating the negative effects of technology adoption on the most vulnerable groups. In section 6, 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), which is the most reliable source of cross-country data on wages in the EU, as these data are reported by firms. 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 Labour Force Survey data. An important limitation of the EU-SES is that it does not cover firms with fewer than 10 workers. However, we are studying the effects on workers of automation and ICT capital, and thus of technologies that are 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, Özcan, and Philipp (2021). 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 are obtained 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 the ICT capital. We use all countries for which sectoral distribution of the ICT capital is available. For Germany and Spain, we use data from the EU-KLEMS 2019 release.[5]

The data on robots come from the International Federation of Robotics (IFR, 2017), which provides annual information on the current stock of industrial robots across countries, broken down by industries. 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 exposure to both robots and ICT capital.

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

[5] KLEMS data end in 2017 for Germany and in 2016 for Spain. We impute values for 2018 using aggregate growth of ICT capital from Eurostat.

between finely defined sectors. In particular, major business services sectors that are present in the NACE Rev. 2 classification cannot be retrieved from NACE Rev. 1.[6]

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

Our sample of countries for which all these data are available consists of 14 European countries: Belgium, Czechia, Germany, Estonia, Greece, Spain, Finland, France, Italy, Lithuania, Latvia, the Netherlands, Norway, and Sweden. The average number of sectors per country is 22, 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. In total, we have 936 country x sector observations for each demographic group. We have dropped groups with fewer than 15 observations. The remaining number of worker-level observations in our sample is 21.2 million. On average, a demographic group contains 2934 observations.

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. 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. The allocation of occupations to types is shown in Table A1 in Appendix A.

2.2 Descriptive evidence

Table 1 presents descriptive statistics for our sample. Typically, more than half of the workers employed at the sector level were aged 30-49. The descriptive statistics also tend to confirm that there was a substantial gender wage gap in all age groups. ICT exposure varied significantly across the whole sample, while robots were concentrated in selected sectors only (mostly manufacturing).

The demographic groups differed substantially in their occupation structure (Table 2), and thus in their exposure to task displacement. Men were much more likely than woman to be employed in manual jobs, while women were more likely than men to be performing routine cognitive tasks. For both women and men, the share of routine cognitive occupations decreased with age. While the share of manual occupations increased with age among women, the share of non-routine cognitive occupations increased with age among men. Importantly, there were stark differences in the kinds of non-routine manual occupations held by men and women. For women, these were mostly associated with personal services and cleaning jobs, while the majority of men in this group worked as industrial workers or drivers.

Next, we report correlations between the four-year changes in the stocks of ICT capital (Figure 1) or robots (Figure 2) and the four-year changes in the demographic groups' shares of the sectors' total wage bill. In Appendix B, we also report the correlations for other outcome variables. We find that the labour market outcomes of prime-aged men were negatively correlated to both types of technology. In addition, we observe that the adoption of ICT technology was negatively correlated with the outcomes for older women and

[6] 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.

positively correlated with the outcomes for young and prime-aged women. However, as these findings do not account for various types of endogeneity, they cannot be interpreted in causal terms.

Table 1. Descriptive statistics

	Mean	p10	p25	p50	p75	p90
Employment share, women 20-29	8.1	2.1	4.2	7.6	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	6.6	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	27.2	10.0	19.7	26.7	35.0	44.3
Employment share, men 50-59	11.6	4.9	7.1	10.5	16.3	20.4
Employment share, men 60+	4.0	1.4	2.2	3.5	5.3	7.4
Relative wages, women 20-29	78.8	65.3	71.6	78.8	85.7	91.4
Relative wages, women 30-49	95.2	88.1	91.4	95.3	98.7	102.0
Relative wages, women 50-59	96.4	83.1	90.3	97.3	102.2	107.3
Relative wages, women 60+	94.9	77.5	85.1	94.5	102.4	112.5
Relative wages, men 20-29	83.5	68.8	75.6	82.2	90.8	100.1
Relative wages, men 30-49	95.2	88.1	91.4	95.3	98.7	102.0
Relative wages, men 50-59	96.4	83.1	90.3	97.3	102.2	107.3
Relative wages, men 60+	121.3	94.9	106.0	117.6	132.3	152.6
ICT capital per worker (thousand EUR)	5.1	0.7	1.2	2.4	4.9	9.4
Robots per thousand employees	1.5	0.0	0.0	0.0	0.0	2.8
GVC participation	4.5	0.0	0.2	1.8	5.3	13.8

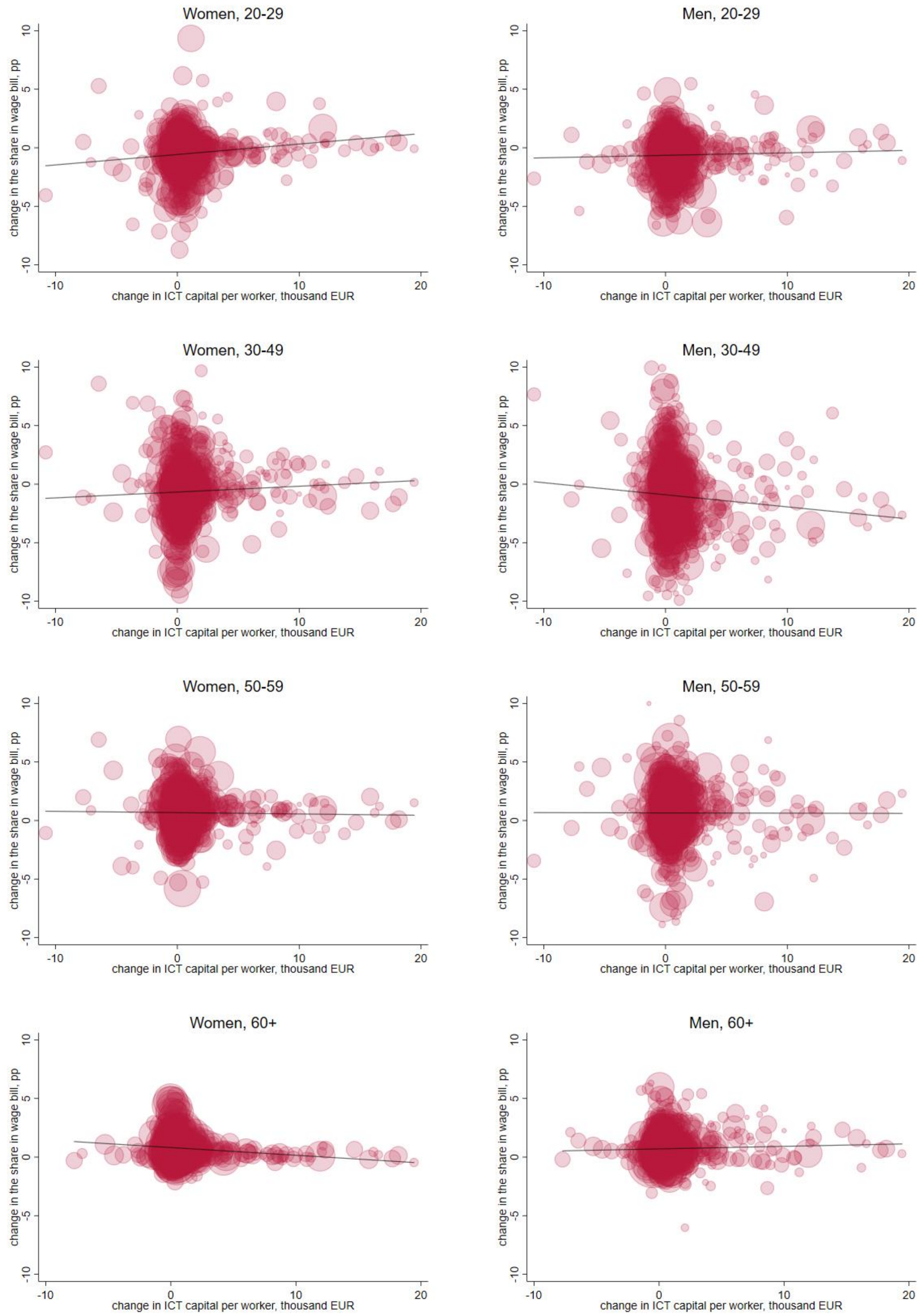
Note: Employment shares of all demographic groups sum up to 100 in each country-sector-year cell. Relative wage is the mean hourly wage of a demographic group in a given sector as a % of the mean sectoral hourly wage.

Table 2. Occupation structures of demographic groups, %, 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

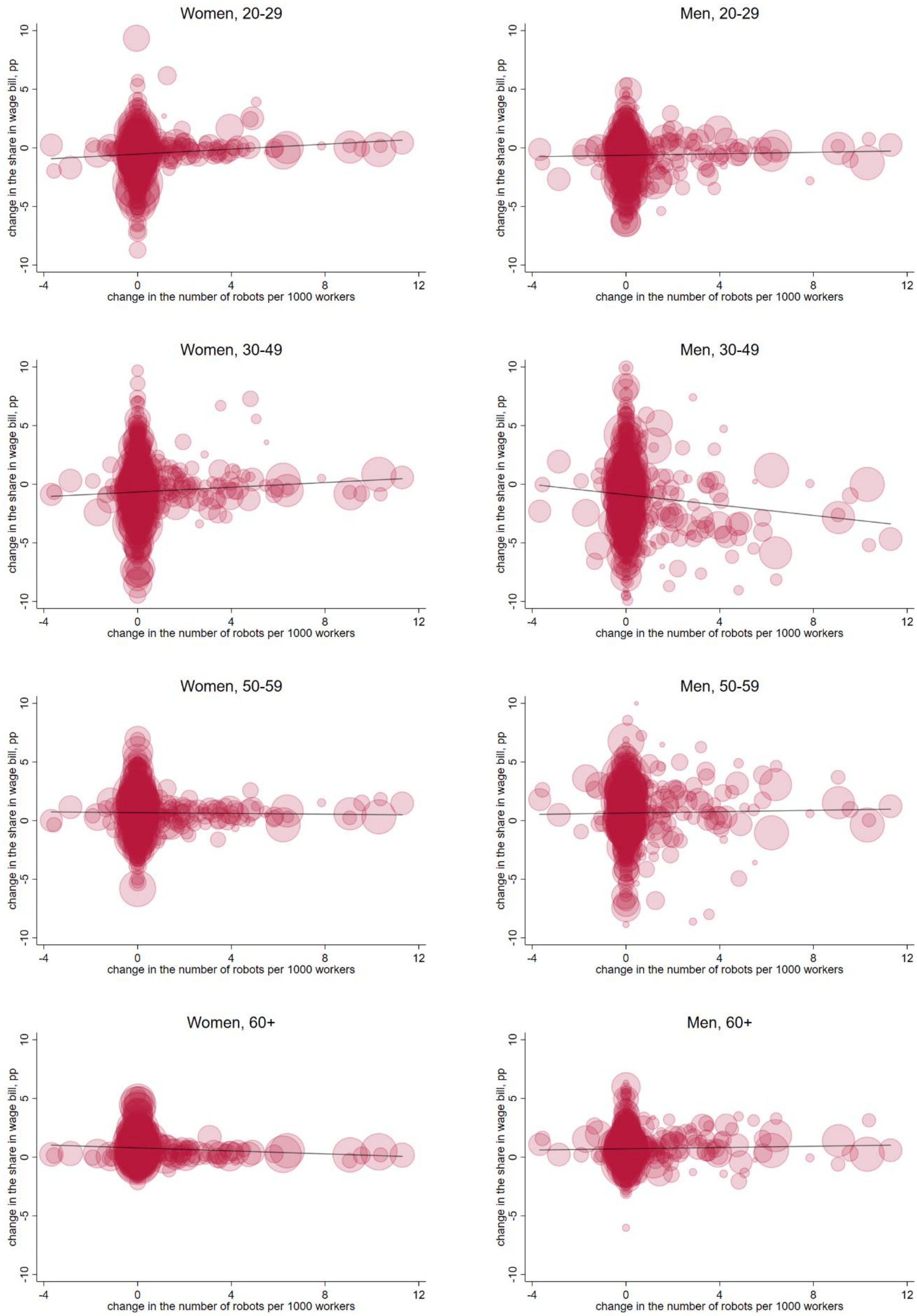
Note: Employment shares as of 2010 are based on the EU-SES data for countries included in the sample, with each country given equal weight.

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



Source: Own elaboration based on EU-SES and Eurostat

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



Source: Own elaboration based on EU-SES and IFR

3. Econometric methodology

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

3.1 Estimation framework and instruments

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

Following Graetz and Michaels (2018) and Acemoglu and Restrepo (2019), we calculate robot exposure as the number of robots per thousand workers at the sector level, ($\mathrm{R_{c,s,t}}$). Analogously, we compute exposure to ICT capital, ($\mathrm{I_{c,s,t}}$), 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 OLS regressions for each demographic group *d*:

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

where y stands for the share of a demographic group in the total wage bill, its share in employment, or its relative wages; $GVC_{c,s,t}$ 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; t takes two levels: 2014 and 2018, with 2010 serving as the initial reference period.

By including country-year fixed effects, we control for all aggregate changes in the labour supply of the demographic groups, as well as for institutional developments that may affect the labour market outcomes. We also control for sector-specific participation in global value chains, which increased substantially in the analysed period. Some variation in the labour market outcomes of the demographic groups may be explained by their initial average educational attainment. We express it in relative terms, as the average percentage of tertiary educated people is sector-specific. We use standardised weights (based on 2010 employment structures) that give every country in the sample an equal weight.

As the explanatory variables of interest might be endogenous to the labour market outcomes,[7] we apply the instrumental variable method to obtain the causal effects of technology. We instrument exposure to both robots and ICT capital. In each case, we follow Bachmann et al. (2022), and generalise the "technology frontier" instrument previously applied by (Acemoglu and Restrepo 2020) and Dauth et al. (2021). We instrument the robot (ICT) exposure in sector s, country c, and year t with the average robot (ICT) exposure in other European countries. For example, instrument for robot adoption, $R^{iv}_{c,s,t}$, is given by:

[7] In particular, firms' decisions to invest in technology may depend on the availability of workers, labour costs, etc.

$$R^{iv}_{c,s,t} = \sum_{k,k\neq c}^{K} \frac{ROB_{k,s,t}}{EMP_{k,s,t_0}} \tag{2}$$

where $ROB_{k,s,t}$ is the stock of industrial robots in country *k*, sector *s,* and year *t*, and EMP_{k,s,t_0} is employment level in thousands in country k, and sector s in 2010. We re-estimate equation (1) using two-stage least squares (2SLS). The relevance of instruments is confirmed by the Stock-Yogo (2005) test for weak instruments.[8]

Furthermore, 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 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 size of the sample prevents us from using more detailed occupation groups.

3.2 Counterfactual analysis

To assess the economic impact of technology adoption on relative labour market outcomes, we conduct a counterfactual historical analysis. We focus on the shares in employment and in the wage bill. We do not conduct a counterfactual analysis for relative wages, as it would be based on statistically insignificant estimates. In the counterfactual scenario, we keep the ICT and robot exposures in each country and sector constant after 2010.

In the first step, we use 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 employment / wage bill shares of the demographic groups. In the second step, we predict for each demographic group 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. For that purpose, we use the same coefficients as in the first step. In the third step, we express the effects of each technology as the percentage point difference in the employment / wage bill shares between the model-predicted and the counterfactual employment. As in the regression analysis, each country is given equal weight.

4. Results

In this section, we present our econometric results, followed by the results of a counterfactual analysis used to 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 (Table 3). We find that the adoption of both types of technology had positive effects on the employment share of young women and negative effects on the employment share of women aged 60 or older. Growth in ICT

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

capital of one thousand EUR per worker[9] increased the employment share of young women by 0.13 pp (*p-value* = 0.051), and reduced the employment share of older women by 0.21 pp. Each additional robot per one thousand workers[10] increased the employment share of young women by 0.25 pp and decreased the employment share of older women by 0.17 pp. We also find positive effects of growth in ICT capital for prime-aged women. For prime-aged men, we find a significant negative effect of robot adoption, as one additional robot per thousand workers reduced the employment share of men aged 30-49 by 0.31 pp. In contrast, for men aged 50-59, robots had a positive (but less precisely estimated) employment effect.

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	0.066***	0.130*	0.010	0.007
	(0.022)	(0.067)	(0.026)	(0.077)
Δ Robots	0.101***	0.250***	0.020	-0.113
	(0.025)	(0.085)	(0.034)	(0.077)
Kleibergen-Paap rk Wald F statistic		11.4		10.7
No. of Observations	584	584	608	608
B: Age 30-49				
Δ ICT capital	0.048*	0.196*	0.003	-0.116
	(0.028)	(0.106)	(0.056)	(0.119)
Δ Robots	0.057	0.095	-0.147**	-0.310**
	(0.035)	(0.089)	(0.072)	(0.156)
Kleibergen-Paap rk Wald F statistic		12.0		12.1
No. of Observations	616	616	622	622
C: Age 50-59				
Δ ICT capital	-0.019	-0.004	-0.063	-0.105
	(0.022)	(0.066)	(0.045)	(0.089)
Δ Robots	-0.017	-0.036	-0.009	0.148
	(0.020)	(0.055)	(0.037)	(0.093)
Kleibergen-Paap rk Wald F statistic		11.3		11.4
No. of Observations	606	606	618	618
D: Age 60+				
Δ ICT capital	-0.047***	-0.208***	-0.003	0.074
	(0.012)	(0.055)	(0.009)	(0.046)
Δ Robots	-0.053**	-0.168**	0.015	0.042
	(0.022)	(0.075)	(0.014)	(0.041)
Kleibergen-Paap rk Wald F statistic		9.5		11.2
No. of Observations	520	520	586	586

*Note: The table presents the estimated coefficients of the OLS and 2SLS regressions. Standard errors (in brackets) are clustered at the country-sector level. The dependent variable is a four-year change in the demographic group's share (in %) in total sector employment. Δ ICT capital is the four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is the 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. For 2SLS, Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in other European countries. 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.*

[9] In our sample, a weighted average four-year change in the ICT capital per worker amounted to EUR 315.
[10] Among sectors that invested in robots, a weighted average four-year increase in the number of robots per one thousand workers amounted to 1.09.

We do not find any statistically significant (at a 5% level) causal effects of technology adoption on relative wages (columns with 2SLS results in Table 4). For prime-aged men, robot adoption had a small positive impact on wages (*p-value* = 0.061), with an additional robot per one thousand workers increasing relative wages by 0.36 pp. However, this wage effect may result from compositional changes if negative employment effects (see Table 3) materialise among low-paid workers, which would increase the average wage.

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	0.042	0.192	0.020	-0.089
	(0.068)	(0.260)	(0.053)	(0.189)
Δ Robots	0.053	0.117	-0.029	0.022
	(0.070)	(0.231)	(0.072)	(0.221)
Kleibergen-Paap rk Wald F statistic		11.4		10.7
No. of Observations	584	584	608	608
B: Age 30-49				
Δ ICT capital	0.006	0.192	0.006	-0.219
	(0.045)	(0.197)	(0.035)	(0.190)
Δ Robots	0.117*	0.047	0.178**	0.355*
	(0.060)	(0.190)	(0.069)	(0.190)
Kleibergen-Paap rk Wald F statistic		12.0		12.1
No. of Observations	616	616	622	622
C: Age 50-59				
Δ ICT capital	0.298***	0.245	0.192	-0.275
	(0.104)	(0.163)	(0.171)	(0.249)
Δ Robots	0.008	-0.067	0.035	-0.229
	(0.078)	(0.199)	(0.135)	(0.259)
Kleibergen-Paap rk Wald F statistic		11.3		11.4
No. of Observations	606	606	618	618
D: Age 60+				
Δ ICT capital	0.240	0.422	0.169	0.298
	(0.167)	(0.414)	(0.211)	(0.404)
Δ Robots	0.104	0.286	-0.229	0.388
	(0.196)	(0.508)	(0.225)	(0.517)
Kleibergen-Paap rk Wald F statistic		9.5		11.2
No. of Observations	520	520	586	586

*Note: The table presents the estimated coefficients of the OLS and 2SLS regressions. Standard errors (in brackets) are clustered at the country-sector 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 the four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is the 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. For 2SLS, Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in other European countries. 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.*

Now, we turn to the effects of technology on the demographic groups' shares in the wage bill (Table 5). This outcome variable is a result of the two previously discussed ones, but it also accounts for changes in the average hours worked by the different demographic groups. However, as is reported in Appendix C, the impact of technology on the hours worked was negligible, with some small positive effects detected only for prime-aged men (Table C1).

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	0.047***	0.115**	0.001	0.020
	(0.017)	(0.054)	(0.022)	(0.063)
Δ Robots	0.068***	0.166***	0.002	-0.120
	(0.020)	(0.060)	(0.030)	(0.076)
Kleibergen-Paap rk Wald F statistic		11.4		10.7
No. of Observations	584	584	608	608
B: Age 30-49				
Δ ICT capital	0.048*	0.212**	-0.007	-0.148
	(0.026)	(0.105)	(0.054)	(0.141)
Δ Robots	0.057*	0.097	-0.109	-0.224
	(0.032)	(0.088)	(0.068)	(0.165)
Kleibergen-Paap rk Wald F statistic		12.0		12.1
No. of Observations	616	616	622	622
C: Age 50-59				
Δ ICT capital	0.000	0.032	-0.049	-0.120
	(0.022)	(0.065)	(0.045)	(0.109)
Δ Robots	-0.019	-0.046	-0.001	0.117
	(0.020)	(0.057)	(0.041)	(0.098)
Kleibergen-Paap rk Wald F statistic		11.3		11.4
No. of Observations	606	606	618	618
D: Age 60+				
Δ ICT capital	-0.041***	-0.180***	0.000	0.096*
	(0.012)	(0.050)	(0.011)	(0.051)
Δ Robots	-0.051**	-0.154**	0.011	0.053
	(0.020)	(0.071)	(0.017)	(0.048)
Kleibergen-Paap rk Wald F statistic		9.5		11.2
No. of Observations	520	520	586	586

*Note: The table presents the estimated coefficients of the OLS and 2SLS regressions. Standard errors (in brackets) are clustered at the country-sector level. The dependent variable is a four-year change in the demographic group's share (in %) in total sector wages. Δ ICT capital is the four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is the four-year change in the number of industrial robots per 1000 workers, where employment is fixed in 2010. Country-year fixed are effects 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. For 2SLS, Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in other European countries. 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.

As in the case of employment effects, both ICT capital and robots had a positive impact on the labour market outcomes of young women and a negative impact on the labour market outcomes of women aged 60 or older (Table 5). However, we also find that the overall effect of ICT capital was significantly positive for prime-aged women and for men aged 60 or older. Growth in ICT capital of one thousand EUR per worker increased the wage bill share of young and prime-aged women by 0.12 pp and 0.21 pp, respectively; while it decreased the wage bill share of older women by 0.18 pp. Another important result is that robot adoption had a negative (though insignificant) effect on the share in the total wage bill of prime-aged men. Thus, for this group, the positive effects on average hourly wages (Table 4) did not compensate for the negative employment effects of robot adoption (Table 3).

4.2 Robustness analysis

In this subsection, we conduct a range of robustness checks to ensure that our results are not sensitive to the model specification, and are not driven by outliers. First, we verify that our findings do not hinge on the choice of control variables. In Table 6, we report the results from a specification that does not include controls for GVC participation or the average educational attainment. This modification has a minor impact on the interpretation of the results. Without these control variables, we would detect a slightly smaller impact of ICT capital on the employment of women aged 20-49, while some other coefficients of interest would be statistically more significant (the effects of robot adoption on employment among people aged 50-59, and the effects of growth in ICT capital on employment among older men).

Second, we verify the sensitivity of the results to the adjustment dynamics assumed in the specification (1). Here we use one 8-year difference instead of the baseline approach of two 4-year differences per country-sector cell. The qualitative interpretation of the results remains mostly the same, except for the much-reduced impact of ICT capital on the employment of young women.

Table 6. Robustness analysis of the estimated employment effects

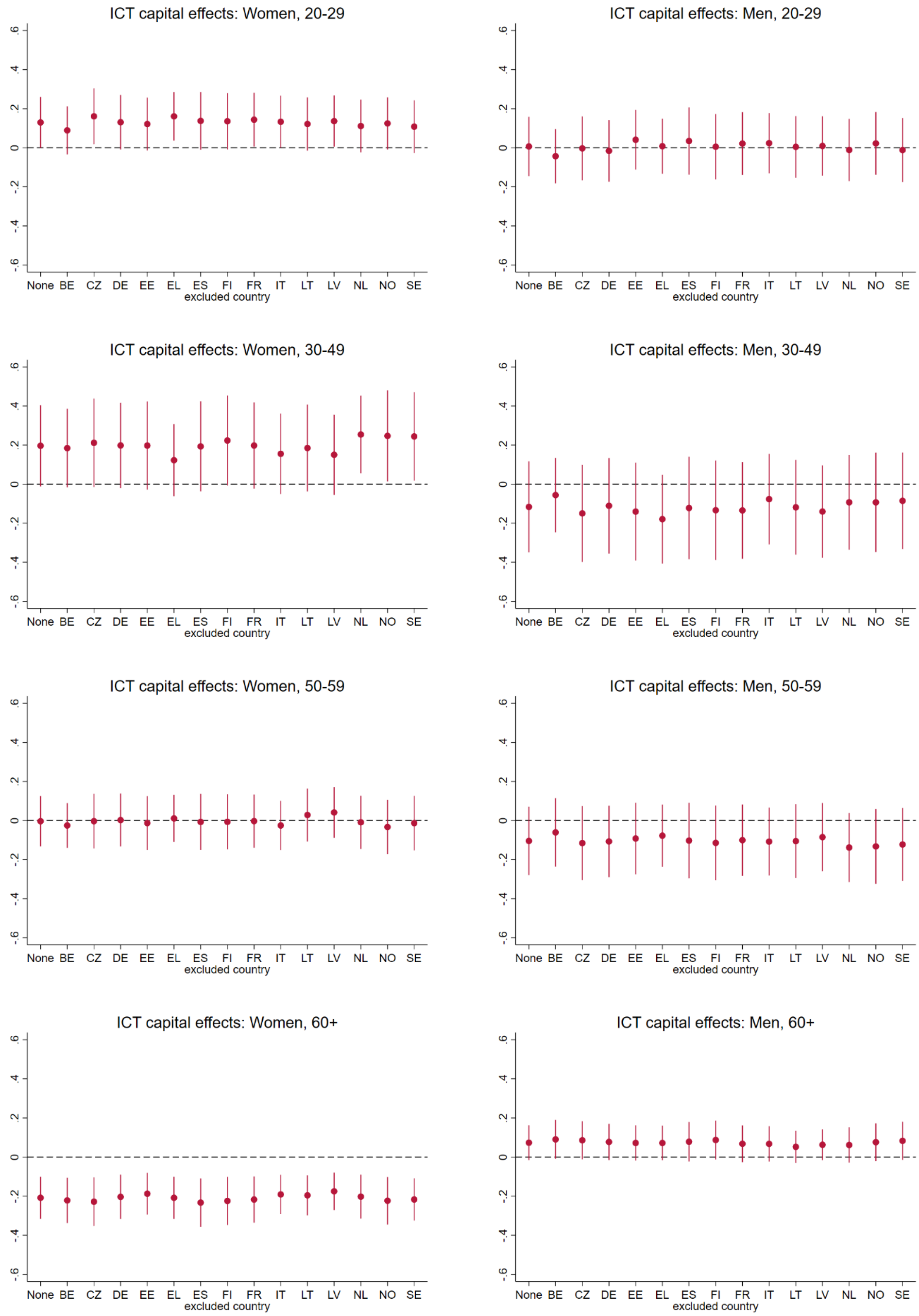
	Women			Men		
	Baseline	No controls	8-year diff.	Baseline	No controls	8-year diff.
A: Age 20-29						
Δ ICT capital	0.130* (0.067)	0.112* (0.068)	0.031 (0.065)	0.007 (0.077)	0.065 (0.075)	-0.072 (0.067)
Δ Robots	0.250*** (0.085)	0.331*** (0.094)	0.196*** (0.073)	-0.113 (0.077)	-0.078 (0.068)	0.062 (0.084)
K-P F statistic	11.4	11.7	10.9	10.7	11.8	10.9
Observations	584	584	292	608	608	304
B: Age 30-49						
Δ ICT capital	0.196* (0.106)	0.170 (0.104)	0.315*** (0.114)	-0.116 (0.119)	-0.111 (0.117)	-0.107 (0.101)
Δ Robots	0.095 (0.089)	0.089 (0.094)	0.065 (0.105)	-0.310** (0.156)	-0.330** (0.136)	-0.352** (0.168)
K-P F statistic	12.0	12.3	11.3	12.1	12.3	11.3
Observations	616	616	308	622	622	311
C: Age 50-59						
Δ ICT capital	-0.004 (0.066)	-0.014 (0.065)	-0.006 (0.049)	-0.105 (0.089)	-0.087 (0.085)	-0.135 (0.083)
Δ Robots	-0.036 (0.055)	-0.094* (0.055)	-0.080 (0.070)	0.148 (0.093)	0.175** (0.086)	0.106 (0.113)
K-P F statistic	11.3	11.8	10.8	11.4	11.8	11.0
Observations	606	606	303	618	618	309
D: Age 60+						
Δ ICT capital	-0.208*** (0.055)	-0.188*** (0.050)	-0.197*** (0.059)	0.074 (0.046)	0.095** (0.045)	0.084* (0.049)
Δ Robots	-0.168** (0.075)	-0.159** (0.072)	-0.170* (0.090)	0.042 (0.041)	0.049 (0.042)	0.098* (0.059)
K-P F statistic	9.5	10.2	8.5	11.2	12.1	10.3
Observations	520	520	260	586	586	293

*Note: The table presents the robustness analysis of the baseline 2SLS employment regressions reported in Table 3. For each demographic group, we provide the baseline results in the first column. In the second column, we report the results of regressions that do not control for the change in e GVC participation and for the lagged share of tertiary-educated workers. The results of the regression using 8-year differences are presented in the third column. Standard errors (in brackets) are clustered at the country-sector 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.*

Third, we test whether our results are driven by any particular countries. To this end, we re-estimate our baseline 2SLS regressions, while excluding one country from the sample each time. In Figures 3 and 4, we report the results of our robustness checks for the employment effects of ICT capital and robot adoption, respectively. The results assure us that our findings are not driven by developments in single countries. Excluding individual countries had only a minor impact on the estimated coefficients. We observe some quantitative variation in the estimated effects of robot adoption for prime-aged men. In particular, after excluding Czechia or Estonia from the sample, the negative effect increased from 0.31 pp to 0.45 pp or 0.43 pp. During the analysed period, these Eastern European countries experienced rapid growth in the value added in manufacturing, which limited the potential for the adverse employment effects of robot adoption.

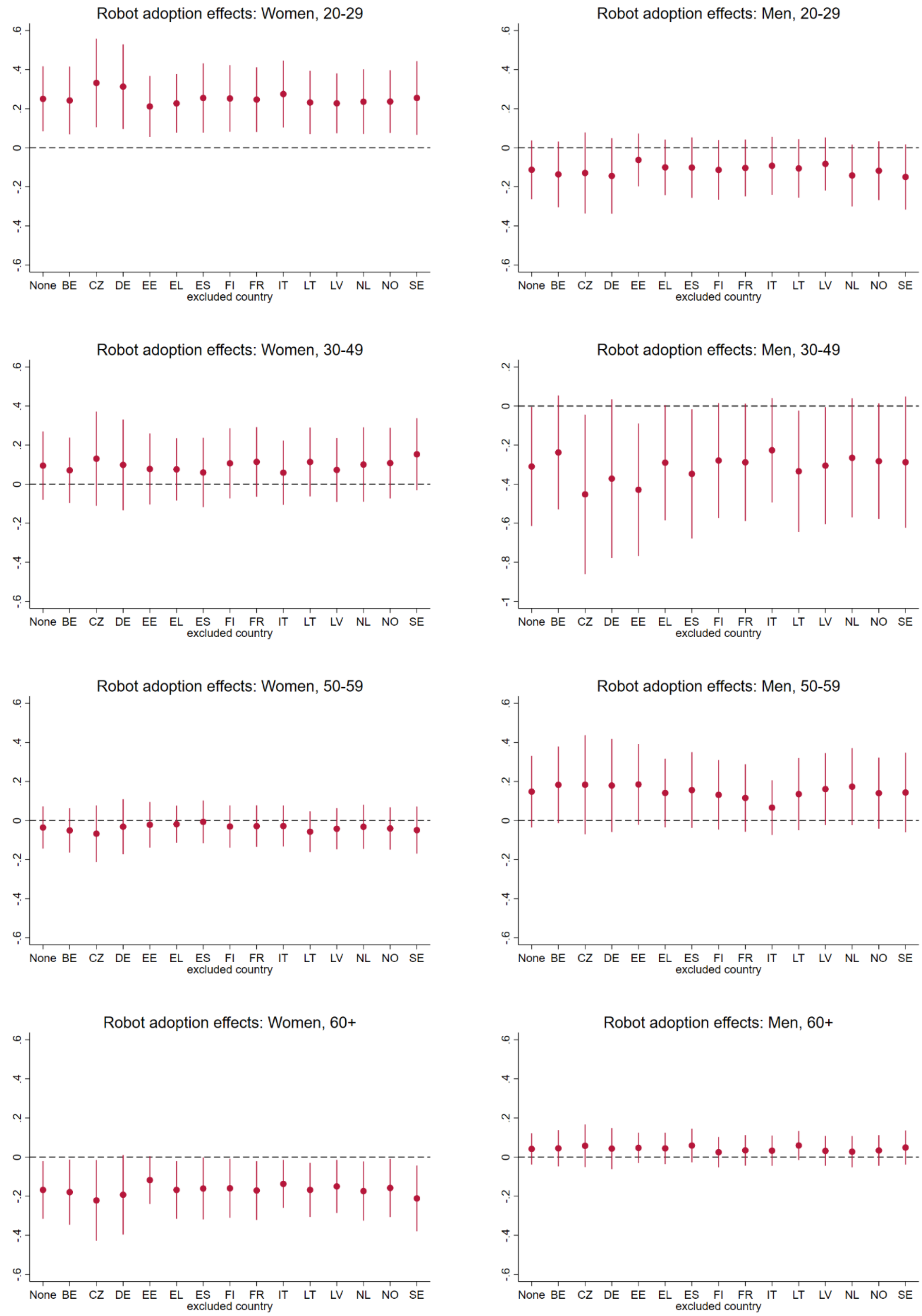
In Appendix D, we report analogous robustness checks for the effects on the relative wages and the shares in the wage bill. They also show the stability of our results.

Figure 3. Robustness of the estimated employment effects of ICT capital



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

Figure 4. Robustness of the estimated employment effects of robot adoption



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

4.3 The effects of technology adoption within occupation types

In this subsection, we explore the potential mechanisms behind the differences in the effects of technology adoption between the demographic groups. We report the effects of technology adoption while focusing on four major occupation types: non-routine cognitive, routine cognitive, routine manual, and non-routine manual. On the one hand, the overall effects could reflect different shares of occupation types among different demographic groups. If this were the 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 demographic-specific; e.g., due to skill profiles or institutional features that benefit certain groups. In that case, the coefficient signs would vary between the demographic groups. In 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 effects of robot and ICT exposure on younger and older workers and on men and women, rather than the occupational composition of the jobs held by various demographic groups.

First, our results show that robotisation had strong and significant negative effects on the employment shares of young and prime-aged men (aged 20-49) in routine manual occupations (Table 7). By contrast, robotisation had no significant effects on workers in non-routine manual occupations (either men or women, Table 7), and no significant wage effects (Table 8). These findings are consistent with theories that stress that automation technologies can substitute human labour mainly in structured and repetitive tasks. Our observation that robotisation had slightly positive effects on the employment of men aged 50 or older in routine manual occupations suggests that the negative effects of robotisation led to a reduction in new hires, rather to an increase in job separations. These results are consistent with those of Bachmann et al. (2022), who found that robotisation had positive effects on the employment stability of older workers, and, in some countries, negative effects on job findings. At the same time, we observe no significant effects for women in routine manual jobs; however, these estimates are less reliable due to small sample sizes and resulting weak instruments.

Second, we find that robotisation had indirect effects on workers performing cognitive tasks (Table 7). This result suggests that there are complementarities between the adoption of automation technologies and cognitive skills. Importantly, the age dimension was again relevant, as these effects were large and positive for younger workers, and especially for women (in terms of both employment shares, Table 7, and wage bill shares, Table 9), but were negative for women aged 50 or older. Moreover, we also find significant negative effects of ICT capital adoption on the employment shares of older women (Table 7). These differential effects are in line with the hypothesis that technological change benefits labour market entrants, while making the skills of some of the older incumbents obsolete (Fillmore and Hall 2021). OECD (2013) confirmed that ICT and analytical skills decrease with age. Nearly 50% of adults aged 25-34 were among the best performers (Level 2 or 3) in PIAAC tests of problem-solving in technology-rich environment, compared with 24% of adults aged 45-54, and only 12% for the age group 55-65.

Third, we find that ICT adoption had significant effects that were concentrated among young and prime-aged workers in non-routine manual occupations, and that differed between men and women. These effects were positive for young and prime-aged women, while they were negative for men aged 30-59. These findings are in line with arguments that ICT adoption increases returns to social skills, and that women tend to have a comparative advantage in these skills (Deming 2017).[11] Moreover, we find further evidence that modern technologies benefited younger workers more than older workers, as these effects were positive among young workers, but were negative among older workers, and especially among women (Table 7).

Table 7. The effects of technological change on the employment shares by task groups

	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	0.026	-0.023	0.174**	-0.014	0.011	0.052	0.029
	(0.045)	(0.041)	(0.126)	(0.075)	(0.054)	(0.031)	(0.090)	(0.037)
Δ Robots	0.054*	0.159**	-0.032	0.059	0.029	0.066**	-0.324***	0.082**
	(0.032)	(0.064)	(0.048)	(0.045)	(0.030)	(0.027)	(0.081)	(0.041)
K-P F statistic	11.7	10.7	1.7	6.2	11.0	8.9	5.2	10.4
Observations	542	544	256	396	566	498	390	520
B: Age 30-49								
Δ ICT capital	0.174	-0.030	-0.050	0.110**	0.137	-0.044	-0.109	-0.172*
	(0.148)	(0.158)	(0.097)	(0.049)	(0.142)	(0.120)	(0.123)	(0.091)
Δ Robots	0.087	0.044	-0.085	0.093*	0.095	-0.050	-0.382***	0.029
	(0.063)	(0.050)	(0.054)	(0.055)	(0.126)	(0.045)	(0.148)	(0.082)
K-P F statistic	11.3	11.9	4.4	8.7	11.8	11.3	11.1	11.1
Observations	606	606	378	522	618	558	478	594
C: Age 50-59								
Δ ICT capital	0.092	-0.070	-0.165*	-0.010	0.138	-0.078	-0.049	-0.117***
	(0.074)	(0.051)	(0.085)	(0.042)	(0.088)	(0.070)	(0.094)	(0.043)
Δ Robots	0.017	-0.067**	0.067*	-0.002	0.089	-0.009	0.078	0.025
	(0.039)	(0.032)	(0.037)	(0.026)	(0.054)	(0.030)	(0.063)	(0.041)
K-P F statistic	10.9	11.6	4.0	6.8	11.3	9.4	7.1	10.8
Observations	558	574	326	478	610	496	434	570
D: Age 60+								
Δ ICT capital	-0.099**	-0.063***	-0.223	-0.071	0.091***	-0.007	0.025	0.030
	(0.046)	(0.024)	(0.149)	(0.057)	(0.034)	(0.022)	(0.046)	(0.039)
Δ Robots	-0.113**	-0.066**	0.112*	-0.044	0.021	-0.018	0.110***	-0.104***
	(0.052)	(0.030)	(0.068)	(0.031)	(0.025)	(0.011)	(0.035)	(0.038)
K-P F statistic	6.9	6.9	2.9	2.9	11.7	7.2	5.3	7.8
Observations	402	442	190	358	542	384	306	484

*Note: The table presents the estimated coefficients of the 2SLS regressions. Standard errors (in brackets) are clustered at the country-sector level. The dependent variable is a four-year change in the group's share (in %) in total sector employment. Δ ICT capital is the four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is the 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 other European countries. 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.*

[11] This difference is partly reflected in the different occupational structures among men and women employed in non-routine manual jobs, with women being more heavily represented in occupations that require social skills, like service occupations (Table 2).

Table 8. The effects of technological change on the relative wages by task groups

	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	-0.040	-0.078	3.350	-0.337	-0.756*	0.076	0.245	-0.424
	(0.359)	(0.184)	(2.277)	(0.635)	(0.453)	(0.237)	(0.581)	(0.377)
Δ Robots	-0.087	0.262	-0.861	1.001	0.043	-0.110	-0.352	0.416
	(0.504)	(0.298)	(0.993)	(0.697)	(0.516)	(0.329)	(0.352)	(0.358)
K-P F statistic	11.7	10.7	1.7	6.2	11.0	8.9	5.2	10.4
Observations	542	544	256	396	566	498	390	520
B: Age 30-49								
Δ ICT capital	-0.175	-0.110	-0.001	-0.110	-0.218	-0.233	0.210	-0.431
	(0.346)	(0.202)	(0.894)	(0.390)	(0.448)	(0.274)	(0.396)	(0.387)
Δ Robots	-0.661	0.298	-0.427	0.618	0.265	-0.180	0.506	-0.240
	(0.407)	(0.269)	(0.625)	(0.408)	(0.406)	(0.313)	(0.372)	(0.263)
K-P F statistic	11.3	11.9	4.4	8.7	11.8	11.3	11.1	11.1
Observations	606	606	378	522	618	558	478	594
C: Age 50-59								
Δ ICT capital	-0.289	-0.279	-0.291	-1.166*	-1.362	0.753*	-0.205	-0.217
	(0.487)	(0.204)	(0.791)	(0.599)	(0.830)	(0.429)	(0.477)	(0.558)
Δ Robots	-1.131	0.261	0.326	-0.084	-0.091	-0.257	0.152	-0.442
	(0.711)	(0.350)	(0.395)	(0.423)	(0.820)	(0.489)	(0.371)	(0.332)
K-P F statistic	10.9	11.6	4.0	6.8	11.3	9.4	7.1	10.8
Observations	558	574	326	478	610	496	434	570
D: Age 60+								
Δ ICT capital	-1.279*	0.183	1.705	0.302	0.367	0.164	1.199	0.400
	(0.768)	(0.505)	(1.481)	(0.767)	(0.732)	(0.719)	(0.891)	(0.404)
Δ Robots	0.598	0.717	-0.086	0.227	1.942	0.473	-0.579	0.120
	(0.872)	(0.637)	(0.671)	(0.372)	(1.434)	(0.889)	(0.567)	(0.504)
K-P F statistic	6.9	6.9	2.9	2.9	11.7	7.2	5.3	7.8
Observations	402	442	190	358	542	384	306	484

*Note: The table presents the estimated coefficients of the 2SLS regressions. Standard errors (in brackets) are clustered at the country-sector 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 the four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is the 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 other European countries. 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 9. The effects of technological change on the wage bill shares by task groups

	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	0.047	0.027	0.039	0.090*	-0.020	0.017	0.061	0.011
	(0.041)	(0.024)	(0.088)	(0.047)	(0.047)	(0.018)	(0.076)	(0.030)
Δ Robots	0.043	0.104**	-0.039	0.050*	0.018	0.035*	-0.266***	0.070*
	(0.032)	(0.045)	(0.033)	(0.028)	(0.031)	(0.020)	(0.073)	(0.036)
K-P F statistic	11.7	10.7	1.7	6.2	11.0	8.9	5.2	10.4
Observations	542	544	256	396	566	498	390	520
B: Age 30-49								
Δ ICT capital	0.169	0.004	-0.002	0.075**	0.114	-0.075	-0.098	-0.161*
	(0.134)	(0.132)	(0.068)	(0.037)	(0.165)	(0.121)	(0.118)	(0.093)
Δ Robots	0.056	0.056	-0.074*	0.075*	0.058	-0.024	-0.320**	0.073
	(0.069)	(0.048)	(0.039)	(0.044)	(0.148)	(0.045)	(0.146)	(0.081)
K-P F statistic	11.3	11.9	4.4	8.7	11.8	11.3	11.1	11.1
Observations	606	606	378	522	618	558	478	594
C: Age 50-59								
Δ ICT capital	0.101	-0.055	-0.126**	-0.015	0.169	-0.090	-0.040	-0.120***
	(0.079)	(0.044)	(0.062)	(0.035)	(0.113)	(0.076)	(0.081)	(0.044)
Δ Robots	0.000	-0.058**	0.053*	-0.002	0.111	-0.011	0.057	0.008
	(0.047)	(0.025)	(0.030)	(0.022)	(0.076)	(0.033)	(0.056)	(0.039)
K-P F statistic	10.9	11.6	4.0	6.8	11.3	9.4	7.1	10.8
Observations	558	574	326	478	610	496	434	570
D: Age 60+								
Δ ICT capital	-0.142**	-0.049***	-0.140	-0.044	0.111**	-0.002	0.033	0.019
	(0.060)	(0.017)	(0.097)	(0.031)	(0.045)	(0.023)	(0.041)	(0.028)
Δ Robots	-0.129**	-0.052**	0.073*	-0.026	0.047	-0.019*	0.095***	-0.096***
	(0.065)	(0.022)	(0.044)	(0.021)	(0.035)	(0.011)	(0.030)	(0.034)
K-P F statistic	6.9	6.9	2.9	2.9	11.7	7.2	5.3	7.8
Observations	402	442	190	358	542	384	306	484

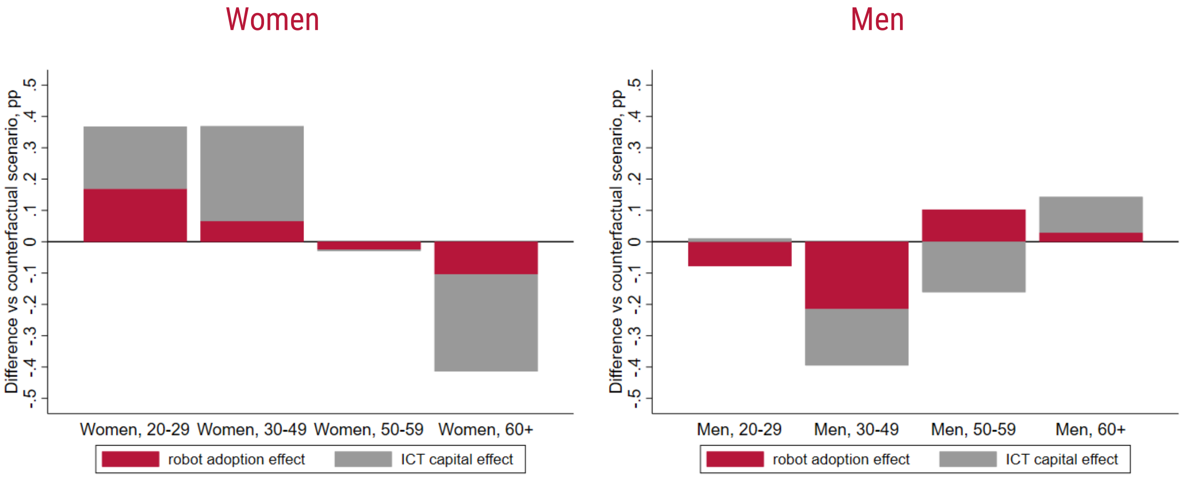
*Note: The table presents the estimated coefficients of the 2SLS regressions. Standard errors (in brackets) are clustered at the country-sector level. The dependent variable is a four-year change in the group's share (in %) in total sector wages. Δ ICT capital is the four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is the 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 other European countries. 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.*

4.4 Counterfactual analysis of the labour market outcomes

In this subsection, we show the economic significance of our findings. In the period covered in our analysis, there were significant increases in the employment shares of people aged 50 or older, representing a continuation of an earlier trend. The major factors that contributed to these increases, such as changes in the population structure or retirement system reforms, are controlled for in our regressions with the country-year fixed effects.

For older women, technology adoption acted in opposition to the overall trend. On average, the employment shares of older women in 2018 were 0.41 pp lower than they were in the counterfactual scenario of no technology adoption in the 2010-2018 period (Figure 5). The major part of this outcome (-0.31 pp) can be attributed to the adoption of ICT capital. The economic significance of this effect was large, as the average employment share of older women in 2018 in our data was 4.9%. In contrast, for men aged 60 or older, technology adoption had positive effects that were supportive of the overall trend, as their employment shares were 0.14 pp higher in 2018 than they would be in the counterfactual scenario.

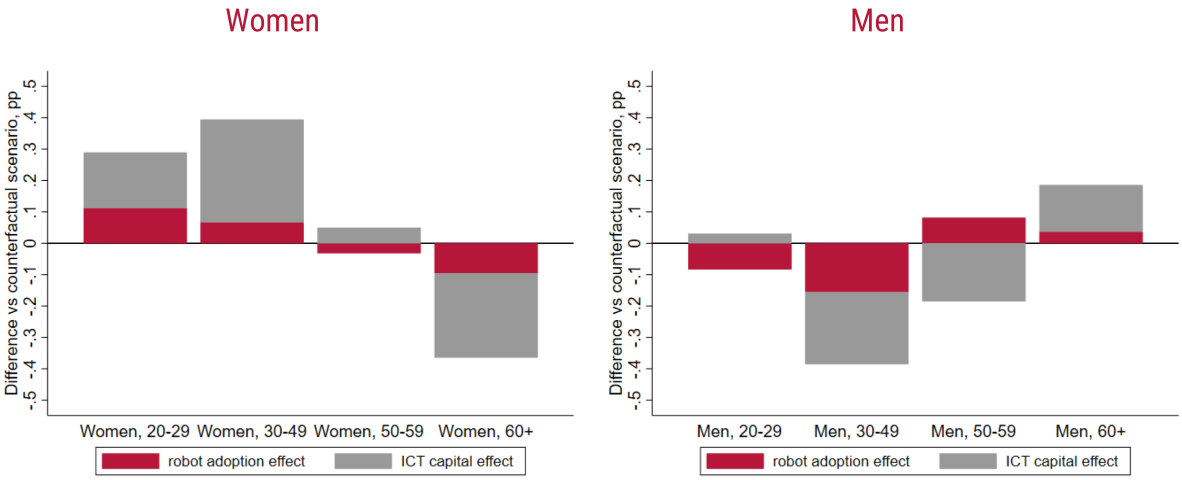
Figure 5. The effects of technology adoption on employment shares, pp



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

On average, the employment shares of young women were 0.37 pp higher in 2018 than in the counterfactual scenario. The relative effects were quite large, as the average employment share of this group decreased from 8.8% to 7.3% in 2018. In contrast, the effects for young men were small (-0.07 pp). For prime-aged women and prime-aged men, the effects of technology adoption were relatively small (0.37 pp and -0.40 pp, respectively) in relation to their overall employment shares in 2018 (24.3% and 26.7%, respectively). Lastly, for people aged 50-59, the overall effects were insignificant.

Figure 6. The effects of technology adoption on shares in the wage bill, pp



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

The effects on the share in total wages differed only slightly with respect to the employment effects, with the largest difference observed for young women. Due to technology adoption, the share in the wage bill increased by 0.29 pp for young women, by 0.39 pp for prime-aged women (Figure 6), and by 0.19 pp for older men. If not for technology adoption, the share in the wage bill would have been 0.39 pp larger for prime-aged men and 0.36 pp larger for older women. In the period of our analysis, the majority of changes in the labour market outcomes were attributable to ICT capital growth, with robot adoption having a smaller impact.

In the appendix, we report the results of counterfactual analyses conducted for each country separately (the employment effects are reported in Appendix F, and the effects on the shares in total wages are reported in Appendix G). The variation in the results across countries stems from two factors: i) the country-specific average growth in ICT and robot exposures (captured in the first stage regressions by country-year fixed effects), and ii) the differences in the sectoral structures of the economies. Czechia and Germany were the most affected by robot adoption; while in France, Finland, and Norway, almost all of the effects of technology adoption on the demographic groups were due to increased exposure to ICT capital. The sizes of the effects also varied substantially across countries.

5. Discussion of policy options to mitigate the age- and gender-specific effects of automation and ICT

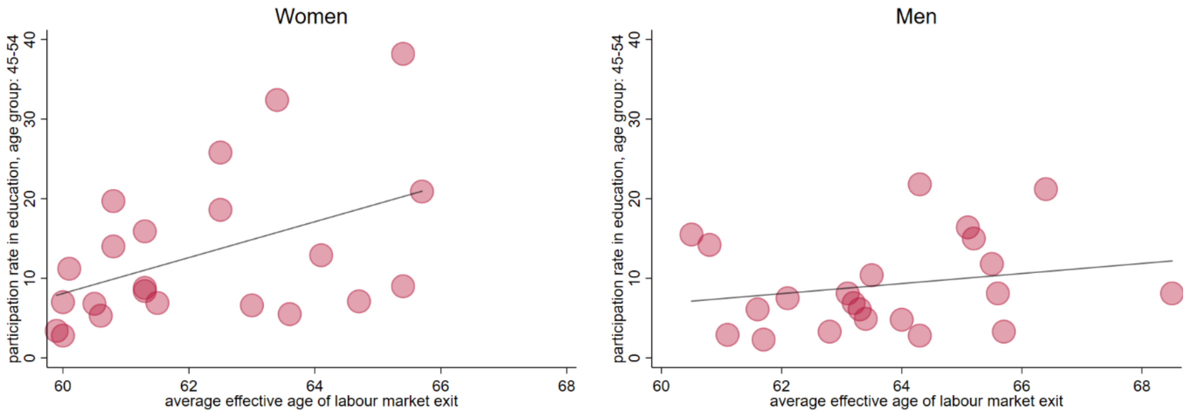
Our findings indicate that women aged 60 or older are the group most negatively affected by technology adoption in Europe. This effect can most likely be attributed to shortages of skills that complement new technologies. Indeed, surveys of adult skills have shown that, compared to men with similar observable characteristics or younger people, women aged 45-64 are much less likely to have high skill levels in problem-solving in a technology-rich environment (OECD 2013).

Public policy can help to bridge the gap between the needs of the market and the skills of older women and other groups left behind by technological progress by increasing private returns to lifelong learning. First, governments may subsidise adult education by channelling targeted funds to either employers or individuals. In some cases, public employment services may organise training on their own, such as training for unemployed individuals. Second, the social security system should promote the extension of working life, because the longer the period of time people work after receiving training, the higher the return on investment in education (Ben-Porath 1967). Early retirement options interact with the impact of technology adoption by decreasing the expected return on investment in the new skills that complement modern technologies. Generous unemployment benefits reduce the employment rates of older workers who are exposed to digital technologies (Yashiro et al., 2022). Indeed, across the EU countries, there is a positive correlation between participation in adult education and the average effective age of labour market exit (Figure 7). The correlation is much stronger among women (0.46) than among men (0.22). While we cannot make claims regarding the direction of causality, we can state that a higher incidence of lifelong learning is empirically consistent with longer working lives.

In the countries covered by our study, participation in adult education increased between 2010 and 2018. Still, the propensity to participate in education decreased sharply with age. In 2018, the share of women who had participated in formal or non-formal education within the last four weeks was 17.1% for those aged 35-44, and was only 10.2% for those aged 55-64.[12] Moreover, non-formal education is rarely aimed at improving skills related to new technologies. Among people aged 55-64, only 0.6% participated in training within the fields of ICT or engineering.

[12] Based on the EU-LFS data. We report unweighted averages for 14 countries included in our sample.

Figure 7. Effective age of labour market exit vs participation in adult education in European countries, 2018



Note: Circles represent 22 EU countries. Bulgaria, Cyprus, Croatia, Malta, and Romania are omitted due to missing data.
Source: Authors' calculations based on the OECD (2019) and Eurostat data.

The majority of evaluation studies in Western European countries have found that adult education has positive employment effects (Hällsten 2012; Fouarge, Schils, and de Grip 2013; Picchio and van Ours 2013; Dauth and Toomet 2016; Card, Kluve, and Weber 2018; Midtsundstad and Nielsen 2019). However, voucher-financed education (governments subsidise courses chosen by individuals) appears to be an exception. Evaluations of such programmes have generally found no positive employment effects, at least in the short term (Schwerdt et al. 2012; Hidalgo, Oosterbeek, and Webbink 2014; Görlitz and Tamm 2016). From a policy-making perspective, the overall cost-benefit balance needs to be positive to justify an intervention. Even with significantly positive employment effects, the measurable benefits may not outweigh the costs of public interventions (Dauth 2020). Therefore, pilot projects should precede the introduction of full-scale programmes subsidising lifelong learning.

In the 1990s, early retirement schemes were widely promoted to reduce unemployment. But in the 21st century, European governments reversed their priorities and focused on extending working life (Ogg and Rašticová 2020). The remaining objective of early retirement is to insure older workers against the risk of poor labour outcomes, which may occur due to changes in labour demand or individual factors such as health problems. In this context, early retirement benefits should be understood broadly as all social transfers that can serve as a long-term source of income for people of pre-retirement age. Various forms of early retirement are frequently used in the 14 countries covered by our study. In 2010, only 25.8% of women aged 61-65 were employed, while 57.0% were jobless and received social transfers such as unemployment benefits, old-age benefits, survivor benefits, or disability benefits.[13] By 2018, the employment rate among this demographic group increased to 41.1%, while the share of jobless benefit recipients decreased to 43.7%. In the period of our study, European countries continued to implement reforms of their social safety nets aimed at incentivising longer employment. In particular, 10 out of 14 analysed countries raised the statutory retirement age. Still, in seven EU countries, the statutory retirement age remains lower for women than for men, which may discourage from investing in skills, and could contribute to the adverse effects of technology adoption on the labour market outcomes of older women. Efforts to prolong working lives should be combined with policies aimed at increasing access and funding for life-long learning, and ensuring access to safety nets for older workers.

[13] Based on the EU-SILC data. We report unweighted averages for 14 countries included in our sample.

6. Conclusions

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

We found that across the various demographic groups, the differences in the effects of technology adoption on employment shares were noticeable, while the differences in the effects on relative wages were statistically insignificant. While technology adoption led to an improvement in the labour market outcomes of young and prime-aged women, it led to a deterioration in the outcomes 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, we observed that the negative effects of robot adoption were concentrated among men in routine manual occupations. For ICT, we found positive effects on employment for young and prime-aged women in non-routine manual occupations, and negative effects on employment for older women in cognitive occupations. This suggests that intergenerational differences in ICT-related skills and interpersonal skills may have contributed to the age divide in the effects of technology. Overall, we also found that in the 2010s, ICT capital was a more important driver of labour market outcomes than robots.

Our results help to shed light on the future of demographic-specific challenges, such as extending working life, preventing youth unemployment, and minimising the gender wage gap. As technology adoption is bound to continue, we may expect to observe trends similar to those we reported in our study over the near term. Our findings give support to arguments that the role of lifelong learning should be increased and the retirement age should be the same for men and women.

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Appendices

Appendix A. Classification of Occupations

In Table A1, we report the allocation of occupations to task groups used for the econometric analysis reported in Section 4.3.

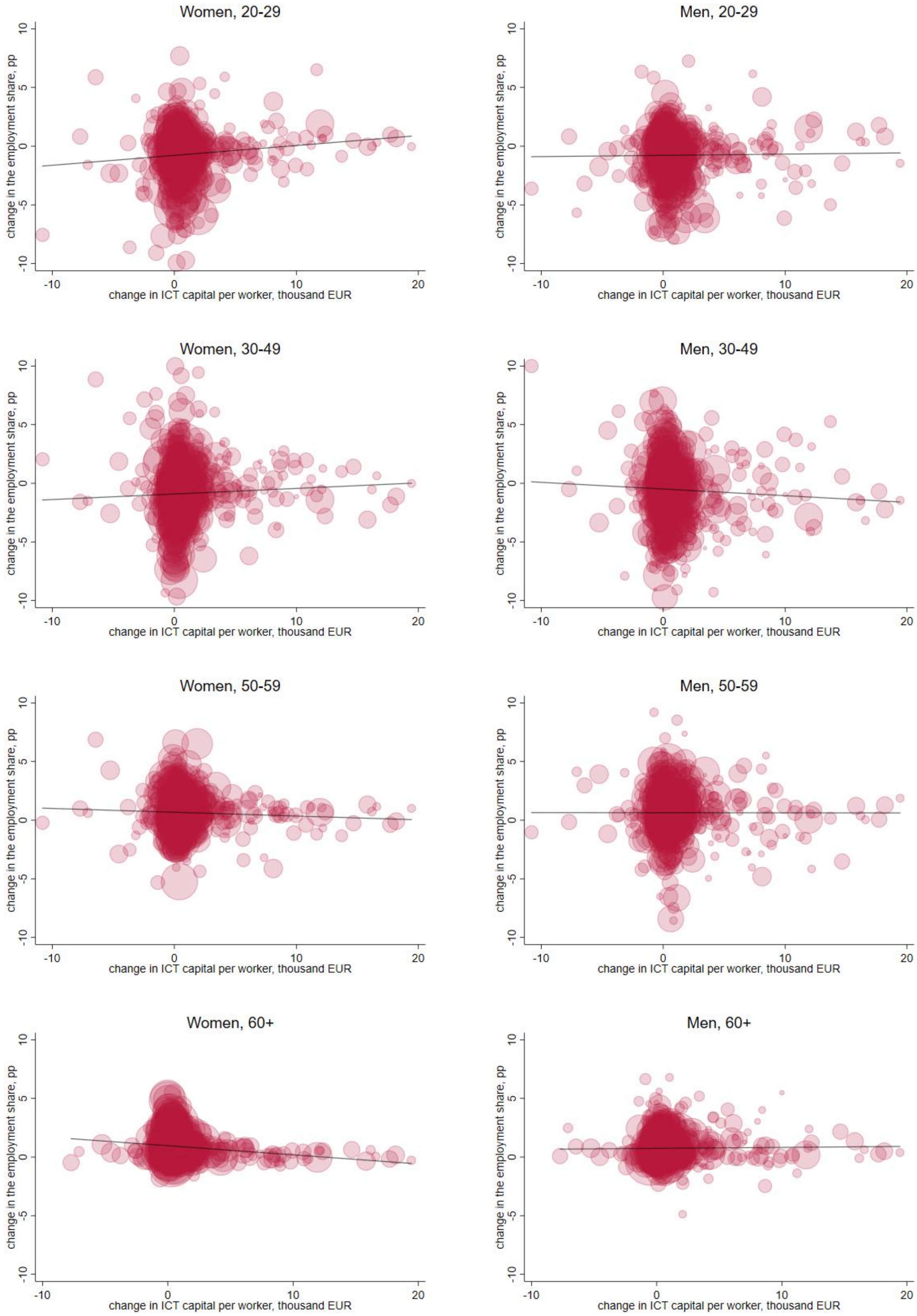
Table A1. The allocation of occupations to task groups in the ISCO-08 classification

Task group	ISCO-08 code	Occupation
Non-routine cognitive	11	Chief Executives, Senior Officials, and Legislators
	12	Administrative and Commercial Managers
	13	Production and Specialised Services Managers
	14	Hospitality, Retail and Other Services Managers
	21	Science and Engineering Professionals
	22	Health Professionals
	23	Teaching Professionals
	24	Business and Administration Professionals
	25	Information and Communications Technology Professionals
	26	Legal, Social, and Cultural Professionals
	31	Science and Engineering Associate Professionals
	32	Health Associate Professionals
	35	Information and Communications Technicians
Routine cognitive	33	Business and Administration Associate Professionals
	34	Legal, Social, Cultural, and Related Associate Professionals
	41	General and Keyboard Clerks
	42	Customer Services Clerks
	43	Numerical and Material Recording Clerks
	44	Other Clerical Support Workers
	52	Sales Workers
Routine manual	72	Metal, Machinery, and Related Trades Workers
	73	Handicraft and Printing Workers
	75	Food Processing, Woodworking, Garment, and Other Craft and Related Trades Workers
	81	Stationary Plant and Machine Operators
	82	Assemblers
	94	Food Preparation Assistants
Non-routine manual	51	Personal Services Workers
	53	Personal Care Workers
	54	Protective Services Workers
	61	Market-oriented Skilled Agricultural Workers
	62	Market-oriented Skilled Forestry, Fishery, and Hunting Workers
	63	Subsistence Farmers, Fishers, Hunters, and Gatherers
	71	Building and Related Trades Workers (excluding Electricians)
	74	Electrical and Electronic Trades Workers
	83	Drivers and Mobile Plant Operators
	91	Cleaners and Helpers
	92	Agricultural, Forestry, and Fishery Labourers
	93	Labourers in Mining, Construction, Manufacturing, and Transport
	95	Street and Related Sales and Services Workers
	96	Refuse Workers and Other Elementary Workers

*Source: Authors' elaboration based on Lewandowski et al. (2020), O*NET, and EU-LFS data.*

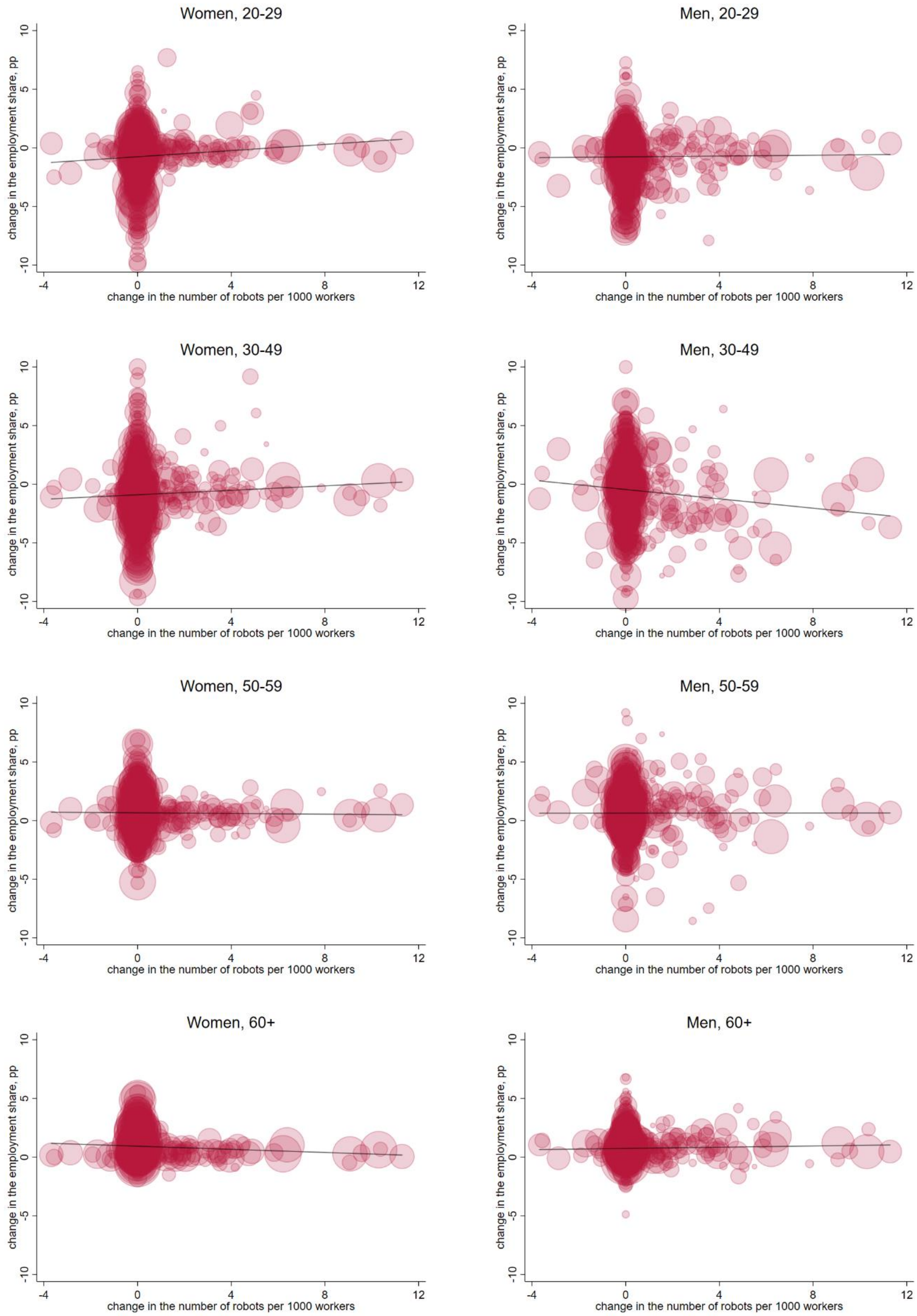
Appendix B. Descriptive evidence

Figure B1. ICT capital growth and changes in the employment shares



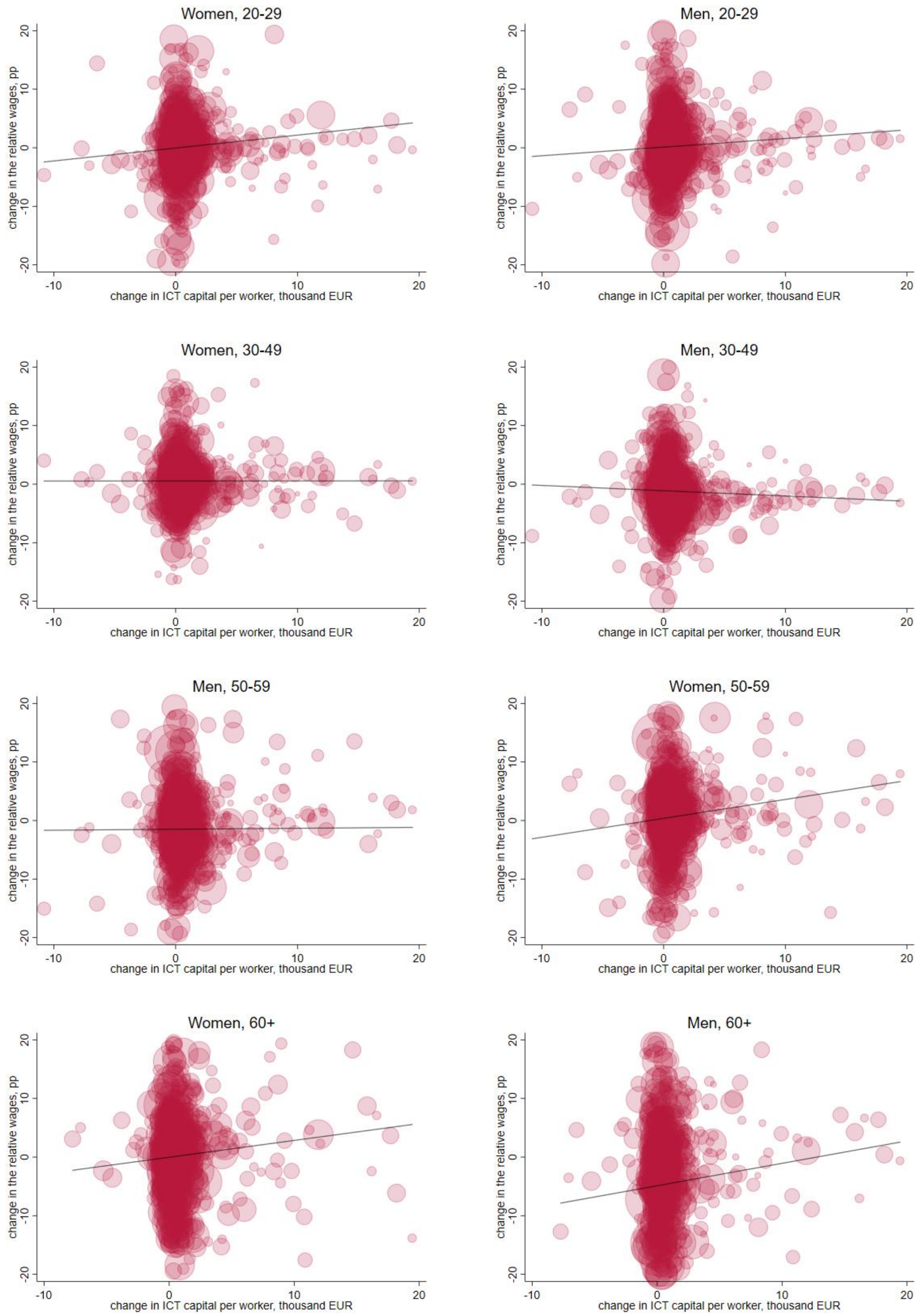
Source: Own elaboration based on EU-SES and Eurostat.

Figure B2. Growth in robot exposure and changes in the employment shares



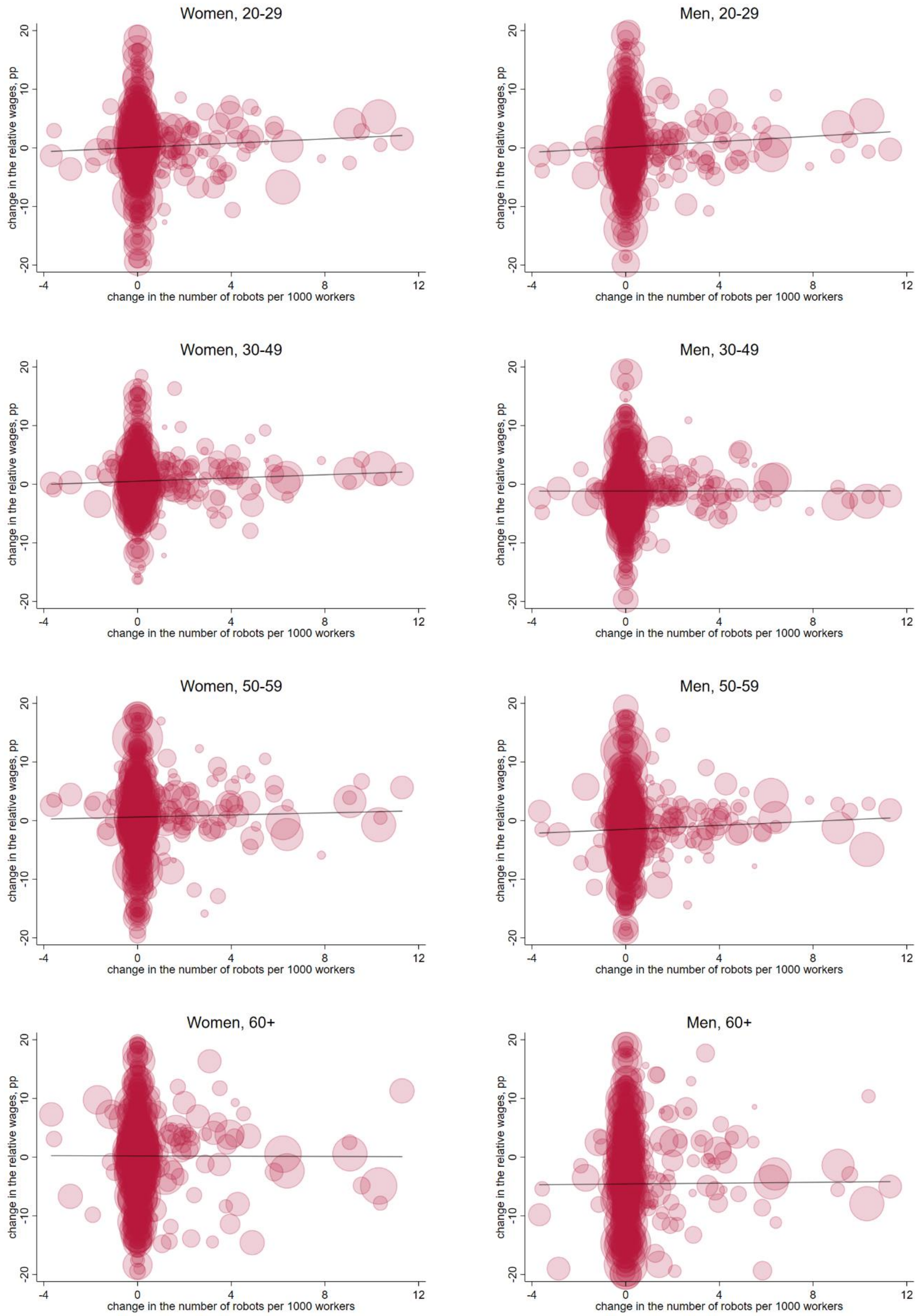
Source: Own elaboration based on EU-SES and Eurostat.

Figure B3. ICT capital growth and changes in the relative wages



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

Figure B4. Growth in robot exposure and changes in the relative wages



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

Appendix C. Estimation Results for Hours Worked

Variation in average hours worked may contribute to changes in the demographic groups' shares in the total wage bill, which is one of our outcome variables. In Table C1, we report the effects of technology on relative hours; that is, the group's average hours worked expressed as a % of the sector's average working hours. The only significant coefficients are found for prime-aged men, and their economic significance is rather limited. For example, an additional robot per one thousand workers increased the average hours by 0.29% of the sector's average; that is, by 27 minutes per month.

Table C1. The effects of technological change on hours worked by demographic groups

	Women, OLS	Women, 2SLS	Men, OLS	Men, 2SLS
A: Age 20-29				
Δ ICT capital	-0.004 (0.036)	-0.026 (0.106)	-0.044 (0.032)	0.054 (0.088)
Δ Robots	0.059 (0.066)	-0.008 (0.152)	-0.075 (0.048)	-0.046 (0.105)
Kleibergen-Paap rk Wald F statistic		11.4		10.7
No. of Observations	584	584	608	608
B: Age 30-49				
Δ ICT capital	0.030 (0.018)	0.004 (0.055)	0.023 (0.020)	0.168** (0.066)
Δ Robots	-0.057 (0.040)	-0.079 (0.066)	0.084** (0.039)	0.285*** (0.100)
Kleibergen-Paap rk Wald F statistic		12.0		12.1
No. of Observations	616	616	622	622
C: Age 50-59				
Δ ICT capital	0.003 (0.030)	-0.037 (0.083)	-0.006 (0.027)	0.047 (0.092)
Δ Robots	0.000 (0.055)	0.040 (0.092)	0.077* (0.045)	0.071 (0.092)
Kleibergen-Paap rk Wald F statistic		11.3		11.4
No. of Observations	606	606	618	618
D: Age 60+				
Δ ICT capital	-0.016 (0.077)	0.250 (0.233)	-0.004 (0.063)	-0.059 (0.178)
Δ Robots	0.066 (0.233)	-0.006 (0.238)	0.085 (0.094)	0.158 (0.199)
Kleibergen-Paap rk Wald F statistic		9.5		11.2
No. of Observations	520	520	586	586

*Note: The table presents the estimated coefficients of the OLS and 2SLS regressions. Standard errors (in brackets) are clustered at the country-sector level. The dependent variable is a four-year change in the demographic group's average working hours as a % of the sector's average. Δ ICT capital is the four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is the four-year change in the number of industrial robots per 1000 workers, where employment is fixed in 2010. Country-year fixed effects 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. For 2SLS, Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in other European countries. 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.*

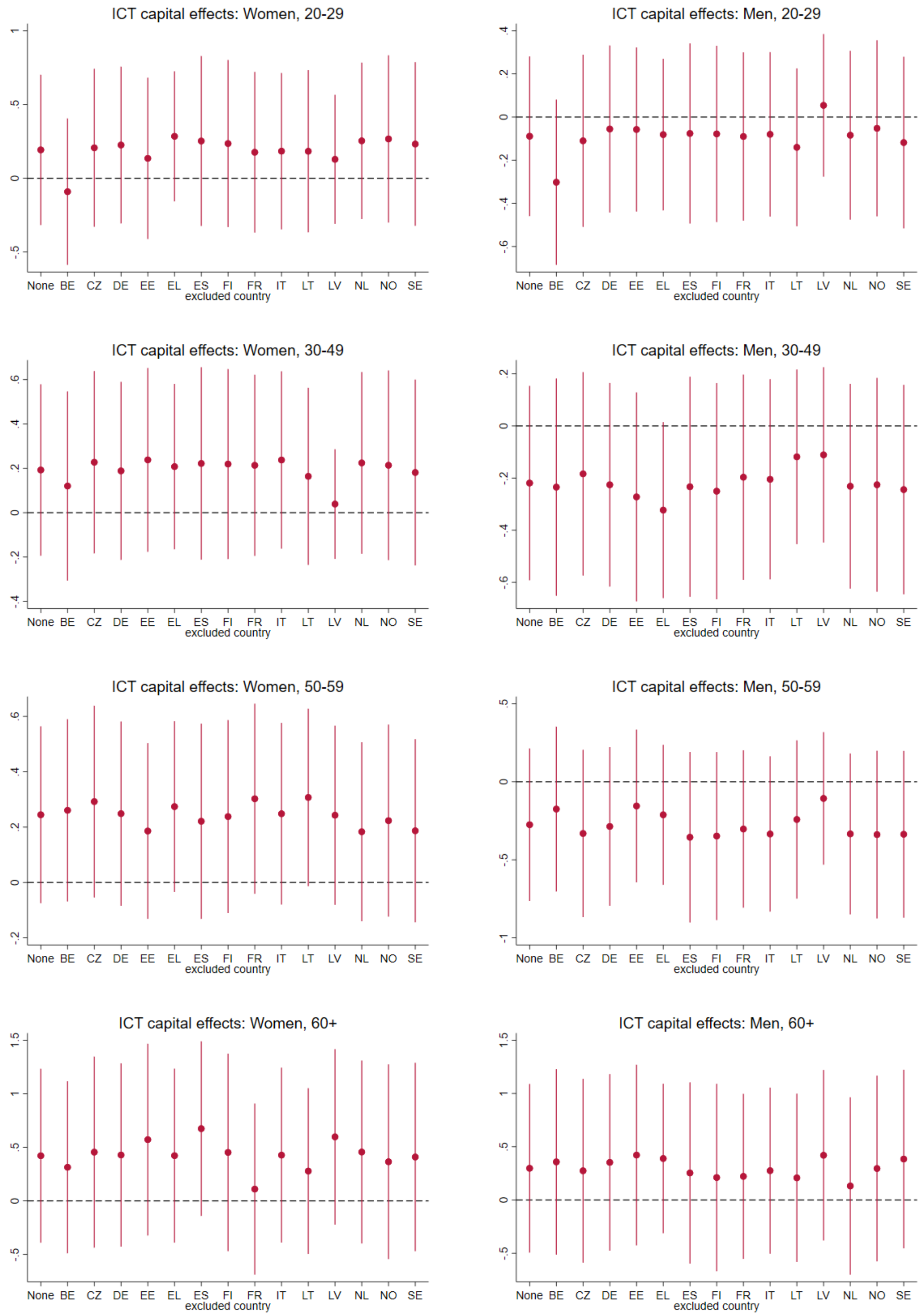
Appendix D. Robustness checks for relative wages and shares in the wage bill

Table D1. Robustness analysis of the estimated wage effects

	Women			Men		
	Baseline	No controls	8-year diff.	Baseline	No controls	8-year diff.
A: Age 20-29						
Δ ICT capital	0.192	0.200	-0.086	-0.089	-0.174	-0.226
	(0.260)	(0.252)	(0.199)	(0.189)	(0.182)	(0.165)
Δ Robots	0.117	0.075	-0.538	0.022	0.256	-0.210
	(0.231)	(0.166)	(0.383)	(0.221)	(0.211)	(0.289)
K-P F statistic	11.4	11.7	10.9	10.7	11.8	10.9
Observations	584	584	292	608	608	304
B: Age 30-49						
Δ ICT capital	0.192	0.209	0.126	-0.219	-0.244	-0.270
	(0.197)	(0.194)	(0.173)	(0.190)	(0.190)	(0.183)
Δ Robots	0.047	0.157	-0.050	0.355*	0.288*	0.133
	(0.190)	(0.157)	(0.263)	(0.190)	(0.154)	(0.168)
K-P F statistic	12.0	12.3	11.3	12.1	12.3	11.3
Observations	616	616	308	622	622	311
C: Age 50-59						
Δ ICT capital	0.245	0.310*	0.218	-0.275	-0.109	0.216
	(0.163)	(0.163)	(0.196)	(0.249)	(0.239)	(0.243)
Δ Robots	-0.067	0.024	0.180	-0.229	0.133	0.519
	(0.199)	(0.186)	(0.232)	(0.259)	(0.227)	(0.324)
K-P F statistic	11.3	11.8	10.8	11.4	11.8	11.0
Observations	606	606	303	618	618	309
D: Age 60+						
Δ ICT capital	0.422	0.274	0.106	0.298	0.845**	0.228
	(0.414)	(0.385)	(0.535)	(0.404)	(0.423)	(0.415)
Δ Robots	0.286	-0.021	0.762	0.388	0.213	0.754
	(0.508)	(0.405)	(0.658)	(0.517)	(0.442)	(0.699)
K-P F statistic	9.5	10.2	8.5	11.2	12.1	10.3
Observations	520	520	260	586	586	293

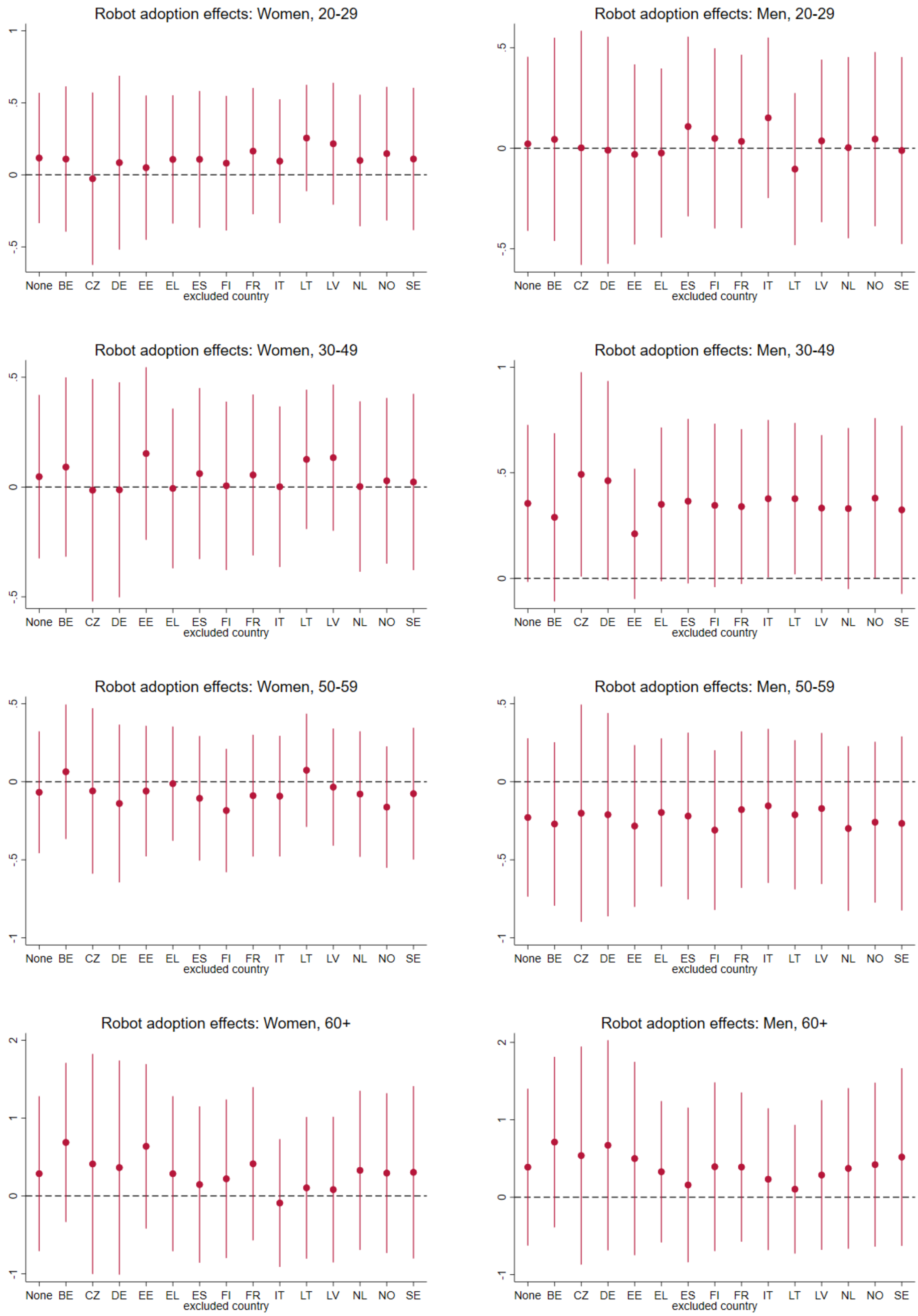
*Note: The table presents the robustness analysis of the baseline 2SLS wage regressions reported in Table 4. For each demographic group, we provide the baseline results in the first column. In the second column, we report the results of regressions that do not control for the change in the GVC participation and for the lagged share of tertiary-educated workers. The results of the regression using 8-year differences are presented in the third column. Standard errors (in brackets) are clustered at the country-sector 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.*

Figure D1. Robustness of the estimated wage effects of ICT capital



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

Figure D2. Robustness of the estimated wage effects of robot adoption



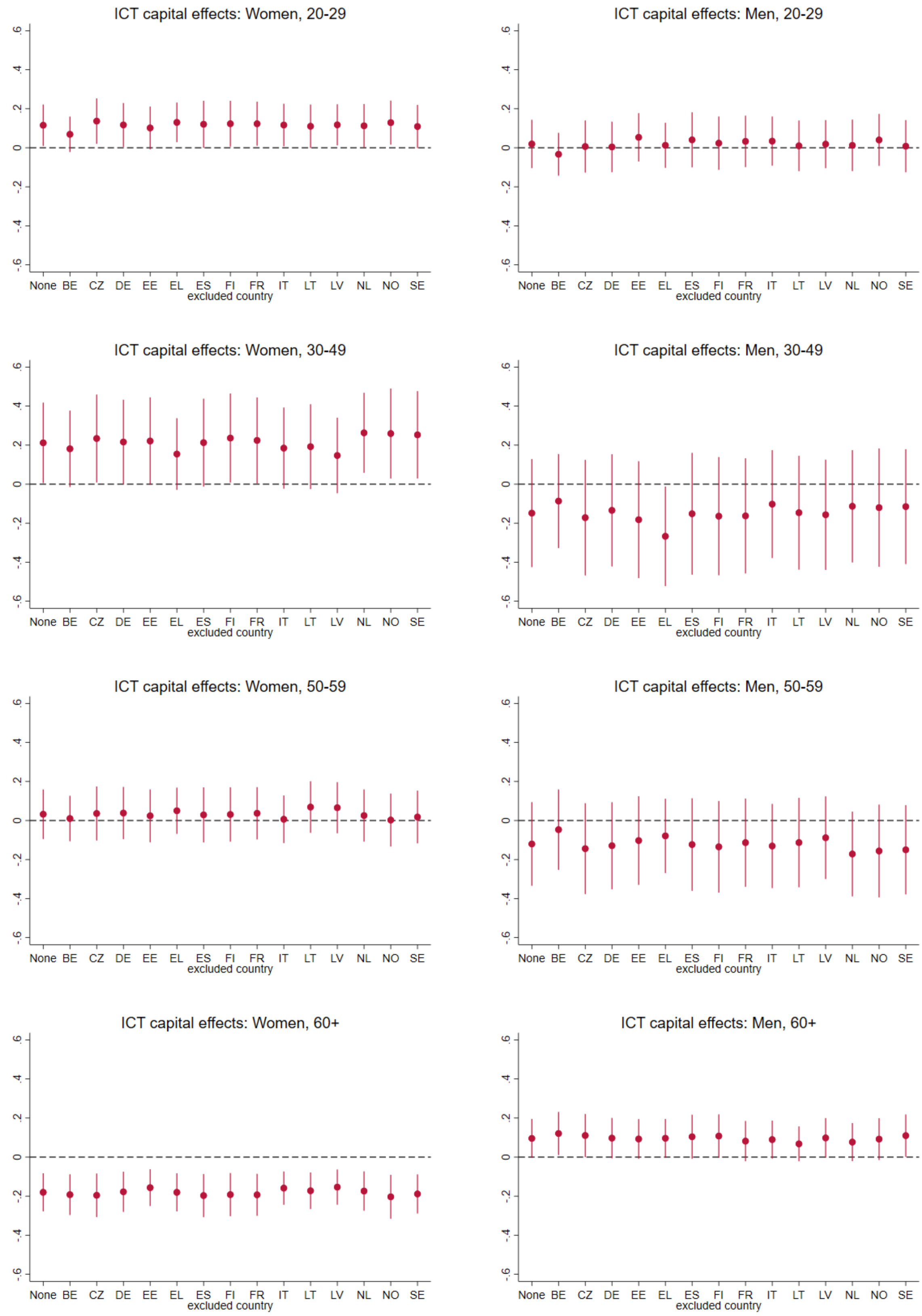
Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

Table D2. Robustness analysis of the estimated effects on the wage bill shares

	Women			Men		
	Baseline	No controls	8-year diff.	Baseline	No controls	8-year diff.
A: Age 20-29						
Δ ICT capital	0.115**	0.104*	0.039	0.020	0.060	-0.055
	(0.054)	(0.055)	(0.049)	(0.063)	(0.061)	(0.053)
Δ Robots	0.166***	0.236***	0.105*	-0.120	-0.061	0.028
	(0.060)	(0.069)	(0.057)	(0.076)	(0.061)	(0.080)
K-P F statistic	11.4	11.7	10.9	10.7	11.8	10.9
Observations	584	584	292	608	608	304
B: Age 30-49						
Δ ICT capital	0.212**	0.190*	0.299***	-0.148	-0.153	-0.161
	(0.105)	(0.103)	(0.110)	(0.141)	(0.139)	(0.123)
Δ Robots	0.097	0.090	0.030	-0.224	-0.283*	-0.328*
	(0.088)	(0.092)	(0.104)	(0.165)	(0.150)	(0.186)
K-P F statistic	12.0	12.3	11.3	12.1	12.3	11.3
Observations	616	616	308	622	622	311
C: Age 50-59						
Δ ICT capital	0.032	0.026	0.021	-0.120	-0.087	-0.104
	(0.065)	(0.064)	(0.054)	(0.109)	(0.104)	(0.103)
Δ Robots	-0.046	-0.093	-0.064	0.117	0.177*	0.162
	(0.057)	(0.058)	(0.068)	(0.098)	(0.093)	(0.129)
K-P F statistic	11.3	11.8	10.8	11.4	11.8	11.0
Observations	606	606	303	618	618	309
D: Age 60+						
Δ ICT capital	-0.180***	-0.165***	-0.176***	0.096*	0.120**	0.109**
	(0.050)	(0.045)	(0.054)	(0.051)	(0.050)	(0.050)
Δ Robots	-0.154**	-0.149**	-0.149*	0.053	0.058	0.119*
	(0.071)	(0.066)	(0.085)	(0.048)	(0.047)	(0.063)
K-P F statistic	9.5	10.2	8.5	11.2	12.1	10.3
Observations	520	520	260	586	586	293

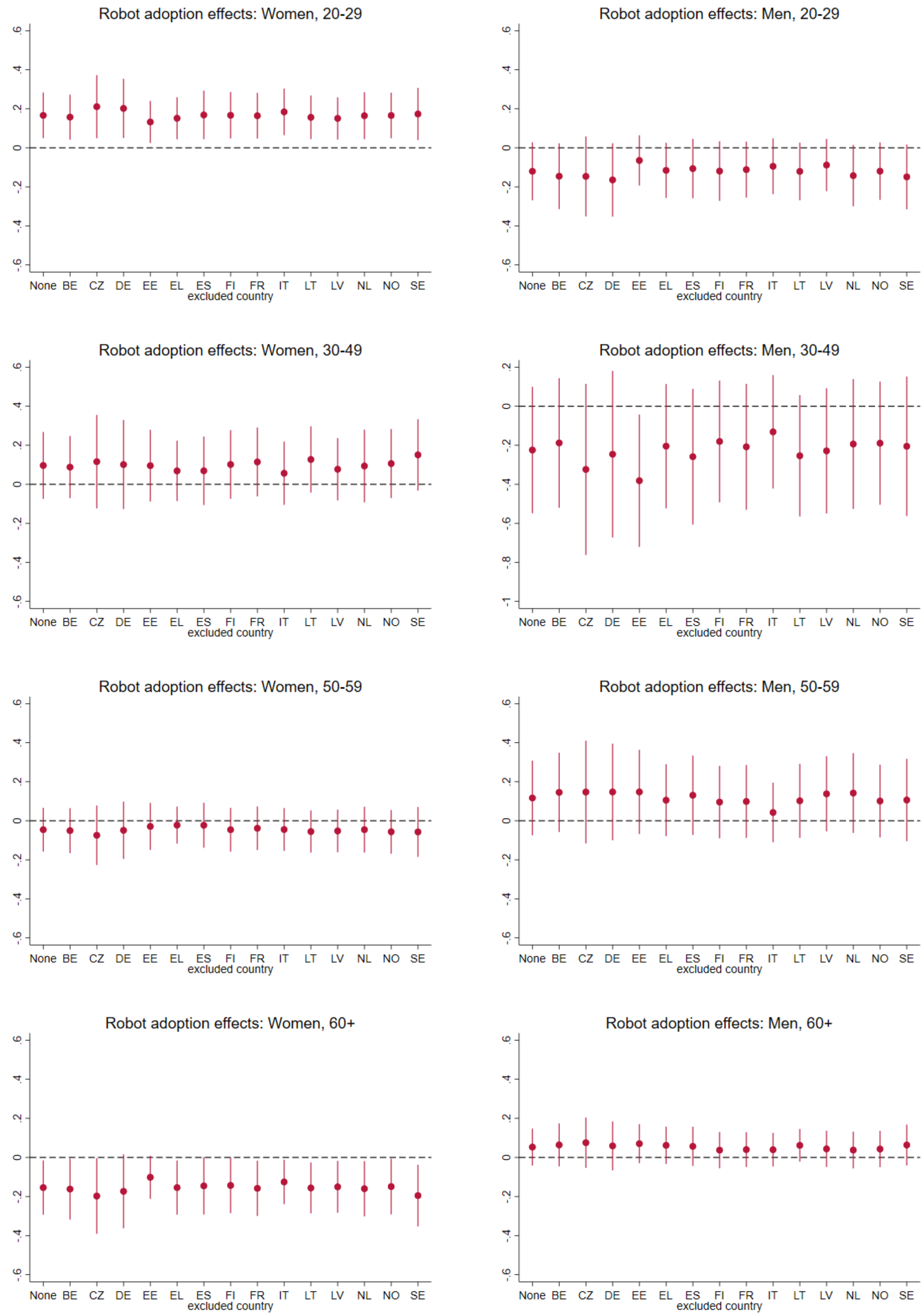
*Note: The table presents the robustness analysis of the baseline 2SLS wage bill share regressions reported in Table 5. For each demographic group, we provide the baseline results in the first column. In the second column, we report the results of regressions that do not control for the change in the GVC participation and for the lagged share of tertiary-educated workers. The results of the regression using 8-year differences are presented in the third column. Standard errors (in brackets) are clustered at the country-sector 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.*

Figure D3. Robustness of the estimated ICT capital effects on the wage bill shares



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

Figure D4. Robustness of the estimated robot adoption effects on the wage bill shares



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

Appendix E. Estimation Results for Occupation Groups

Here, we report the effects of technology adoption on the labour market outcomes of occupation groups. Consistent with our intuition, we find a statistically significant negative effect of robotisation on the employment share of routine manual workers, and – less precisely estimated – a negative effect on this group's share in total wages. Adoption of ICT technology had significantly negative effects on the relative wages of non-routine manual workers. While the overall effects of ICT capital seemed to be positive for non-routine cognitive employees, they were not statistically significant.

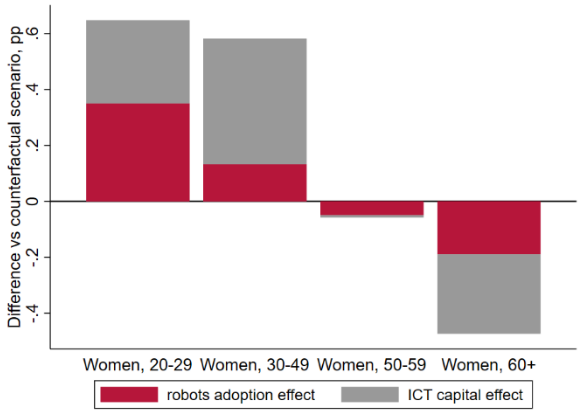
Table E1. The effect of technological change on the labour market outcomes of occupation groups

	Non-routine cognitive workers	Routine cognitive workers	Routine manual workers	Non-routine manual workers
A: Employment shares				
Δ ICT capital	0.551	-0.261	-0.153	-0.160
	(0.367)	(0.359)	(0.168)	(0.138)
Δ Robots	0.308	0.125	-0.481**	0.094
	(0.244)	(0.123)	(0.212)	(0.133)
Kleibergen-Paap rk Wald F statistic	11.8	11.8	12.9	11.5
No. of Observations	620	616	538	614
B: Relative wages				
Δ ICT capital	-0.257	-0.122	-0.320	-0.754**
	(0.297)	(0.149)	(0.273)	(0.336)
Δ Robots	-0.233	0.065	0.131	0.030
	(0.265)	(0.194)	(0.263)	(0.240)
Kleibergen-Paap rk Wald F statistic	11.8	11.8	12.9	11.5
No. of Observations	620	616	538	614
C: Shares in the wage bill				
Δ ICT capital	0.567	-0.245	-0.097	-0.229
	(0.355)	(0.329)	(0.150)	(0.155)
Δ Robots	0.237	0.078	-0.385*	0.109
	(0.252)	(0.113)	(0.207)	(0.129)
Kleibergen-Paap rk Wald F statistic	11.8	11.8	12.9	11.5
No. of Observations	620	616	538	614

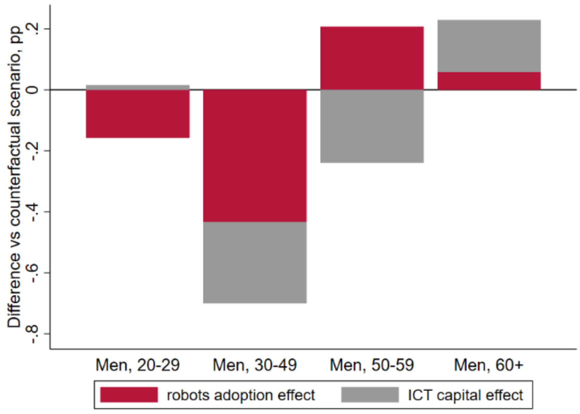
*Note: The table presents the estimated coefficients of the 2SLS regressions. Standard errors (in brackets) are clustered at the country-sector level. The dependent variable varies by panels. It is a four-year change in the occupation group's: share (in %) in total sector employment (panel A), average wage as a % of the sector's average (panel B), or share (in %) in total sector wages (panel C). Δ ICT capital is the four-year change in the ICT and software capital stock (in thousand EUR, constant prices) divided by employment as of 2010. Δ Robots is the 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 occupation group relative to the sector's average. Δ Robots and Δ ICT capital are instrumented using the growth of these types of capital in other European countries. 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.*

Appendix F. The employment effects of technology adoption by country, pp

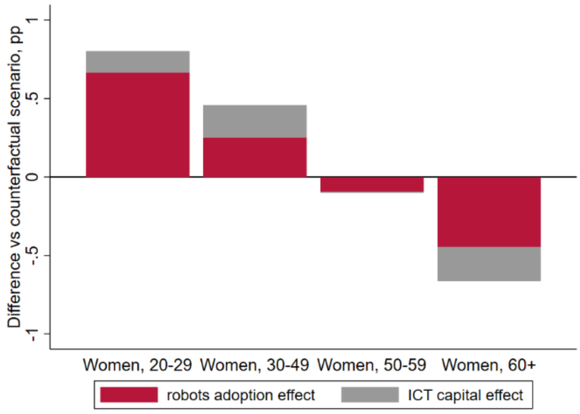
Belgium, women



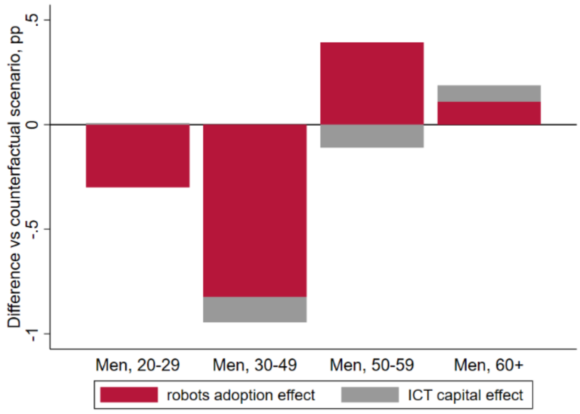
Belgium, men



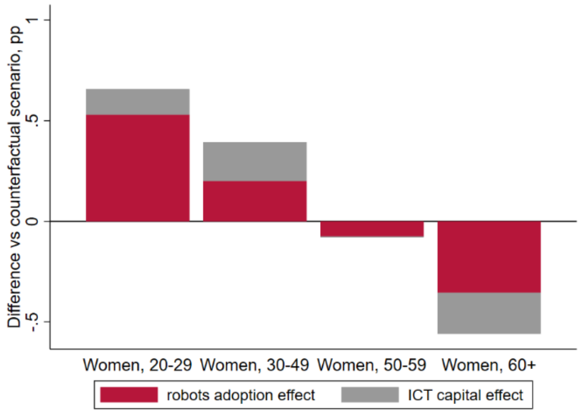
Czechia, women



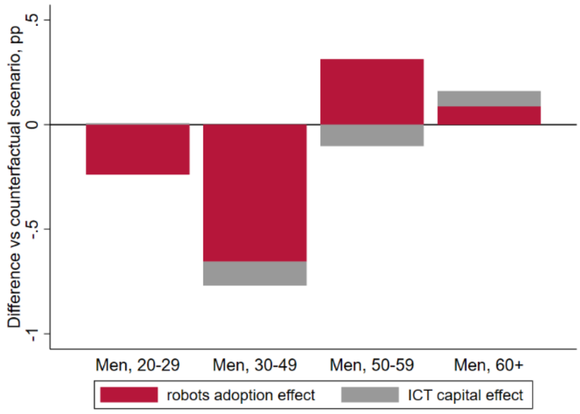
Czechia, men

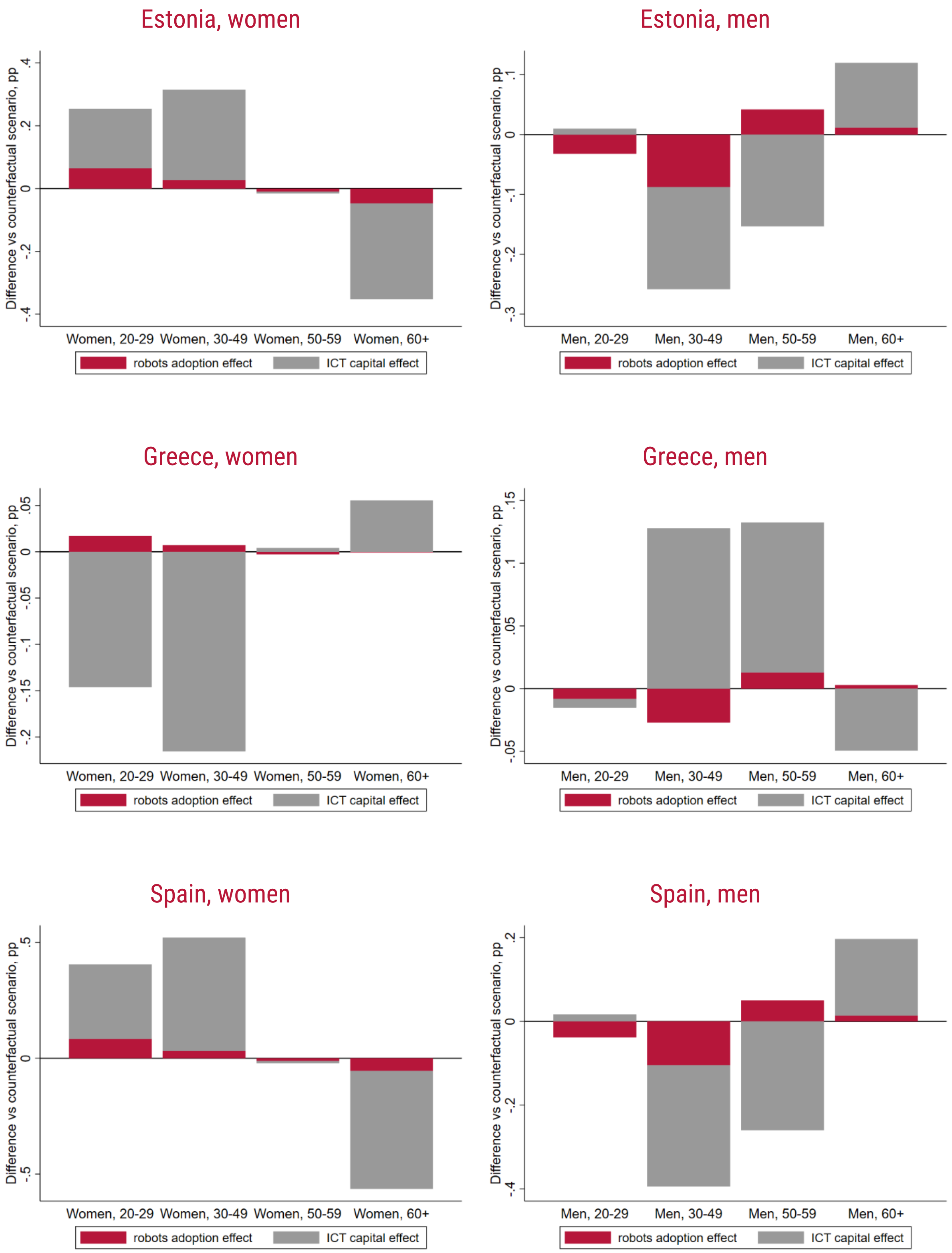


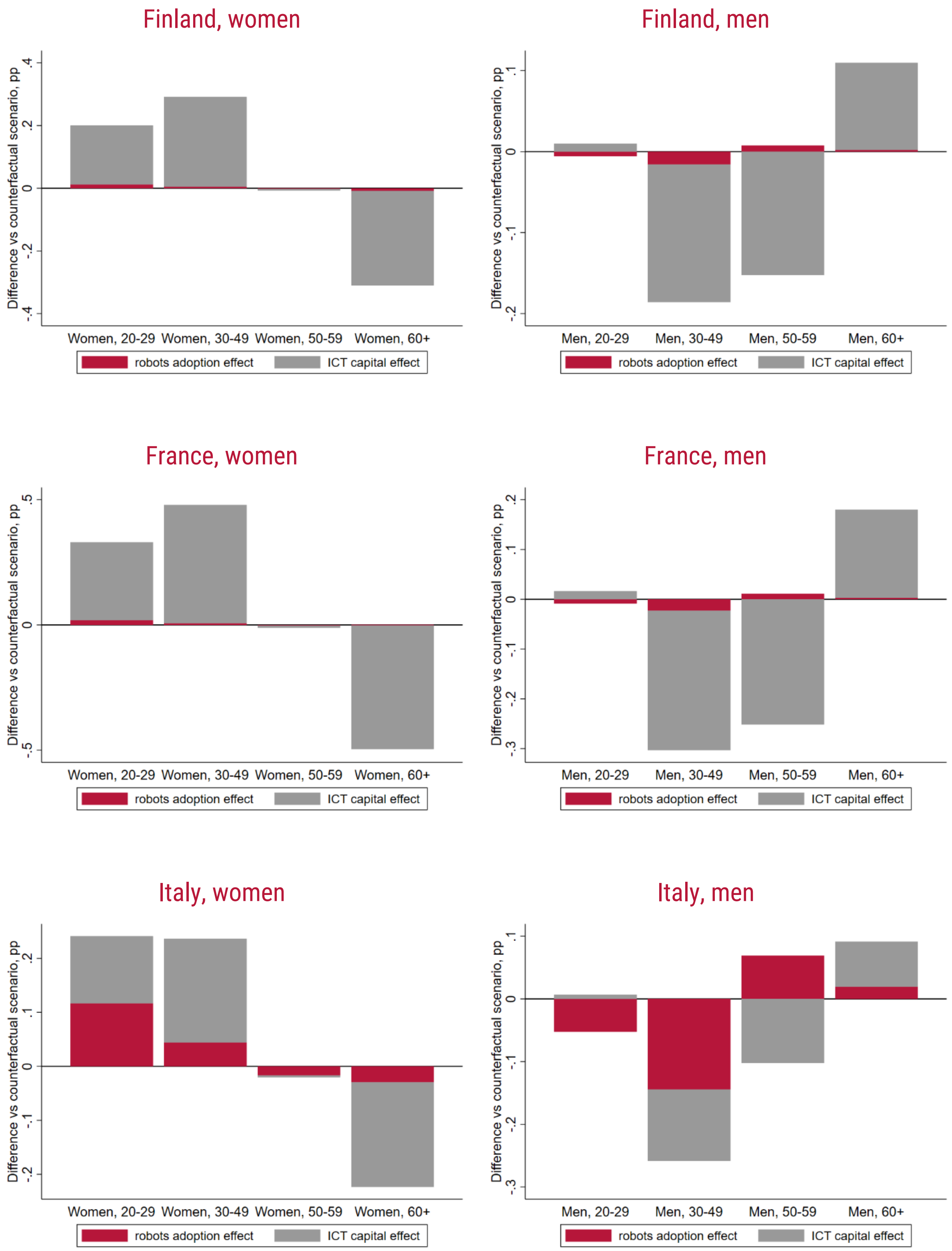
Germany, women

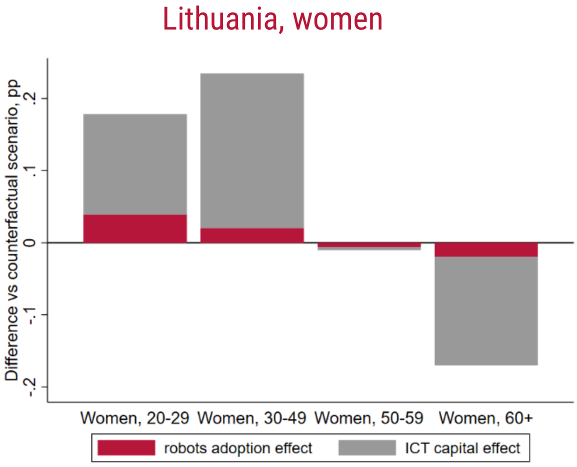


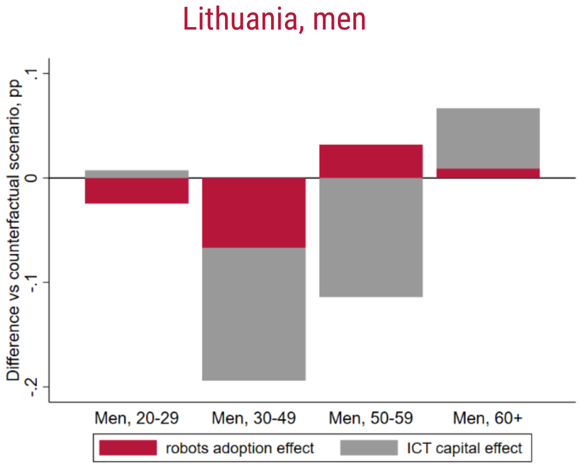
Germany, men

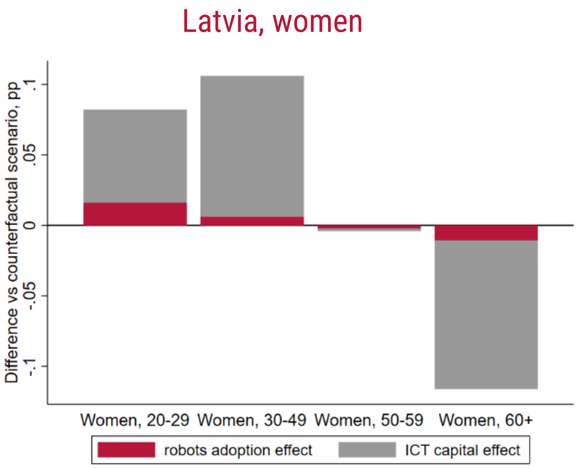


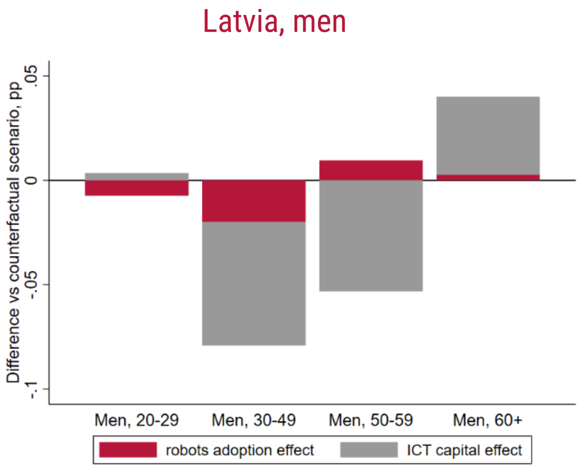

Estonia, women
Estonia, men
Greece, women
Greece, men
Spain, women
Spain, men
Difference vs counterfactual scenario, pp
Women, 20-29
Women, 30-49
Women, 50-59
Women, 60+
Men, 20-29
Men, 30-49
Men, 50-59
Men, 60+
robots adoption effect
ICT capital effect

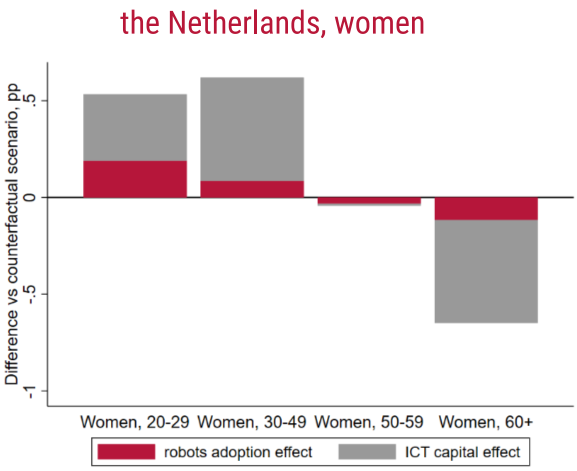

Finland, women
Difference vs counterfactual scenario, pp
-.4 -.2 0 .2 .4
Women, 20-29 Women, 30-49 Women, 50-59 Women, 60+
robots adoption effect
ICT capital effect
Finland, men
Difference vs counterfactual scenario, pp
-.2 -.1 0 .1
Men, 20-29 Men, 30-49 Men, 50-59 Men, 60+
robots adoption effect
ICT capital effect
France, women
Difference vs counterfactual scenario, pp
-.5 0 .5
Women, 20-29 Women, 30-49 Women, 50-59 Women, 60+
robots adoption effect
ICT capital effect
France, men
Difference vs counterfactual scenario, pp
-.3 -.2 -.1 0 .1 .2
Men, 20-29 Men, 30-49 Men, 50-59 Men, 60+
robots adoption effect
ICT capital effect
Italy, women
Difference vs counterfactual scenario, pp
-.2 -.1 0 .1 .2
Women, 20-29 Women, 30-49 Women, 50-59 Women, 60+
robots adoption effect
ICT capital effect
Italy, men
Difference vs counterfactual scenario, pp
-.3 -.2 -.1 0 .1
Men, 20-29 Men, 30-49 Men, 50-59 Men, 60+
robots adoption effect
ICT capital effect

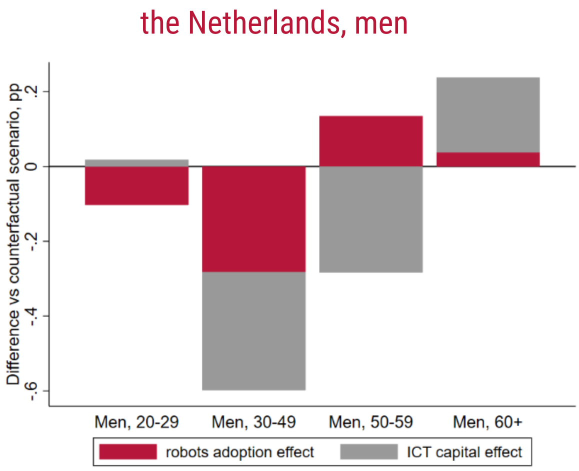

Lithuania, women
Difference vs counterfactual scenario, pp
.2
.1
0
-.1
-.2
Women, 20-29
Women, 30-49
Women, 50-59
Women, 60+
robots adoption effect
ICT capital effect

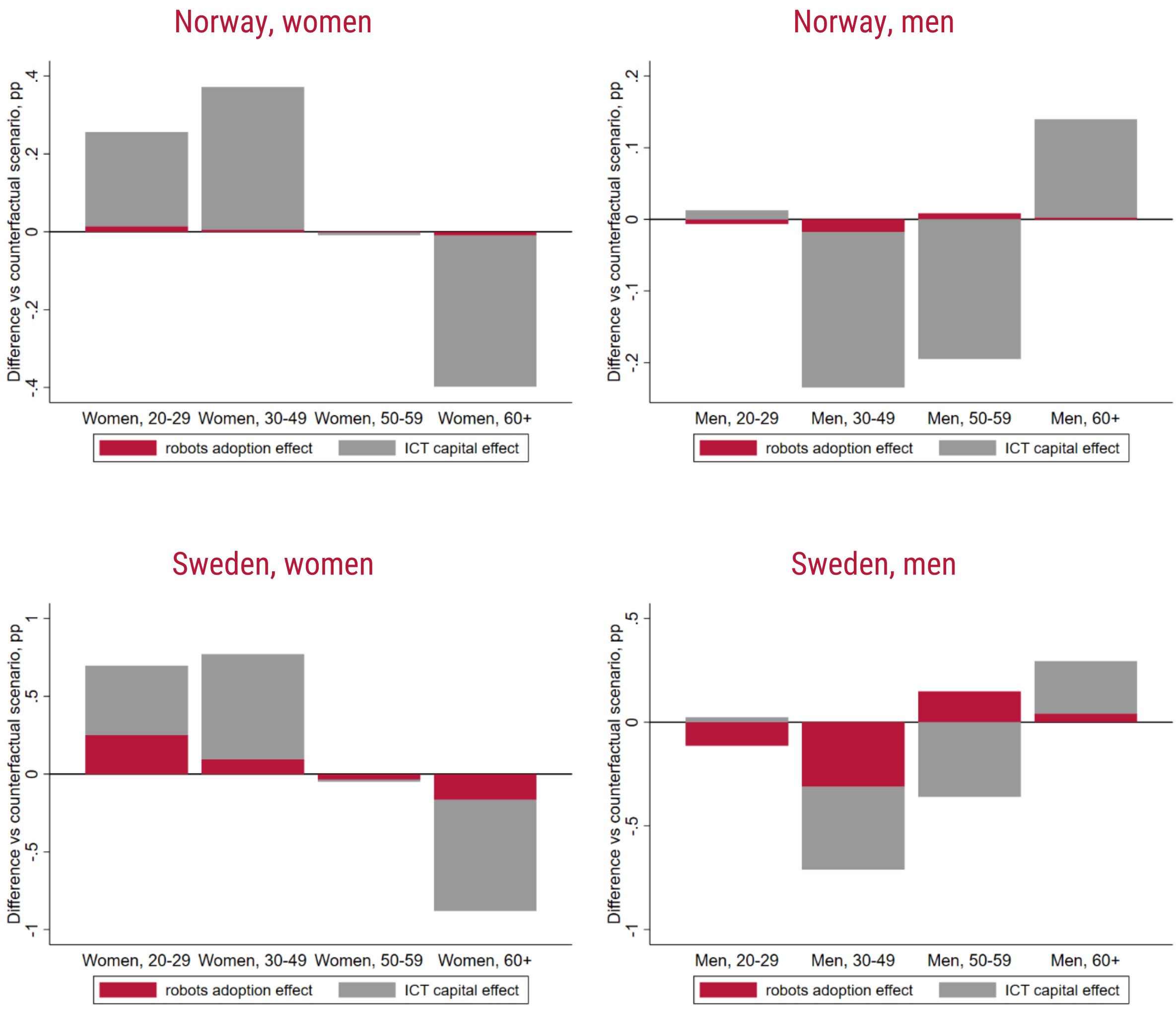

Lithuania, men
Difference vs counterfactual scenario, pp
.1
0
-.1
-.2
Men, 20-29
Men, 30-49
Men, 50-59
Men, 60+
robots adoption effect
ICT capital effect


Latvia, women
Difference vs counterfactual scenario, pp
.1
.05
0
-.05
-.1
Women, 20-29
Women, 30-49
Women, 50-59
Women, 60+
robots adoption effect
ICT capital effect


Latvia, men
Difference vs counterfactual scenario, pp
.05
0
-.05
-.1
Men, 20-29
Men, 30-49
Men, 50-59
Men, 60+
robots adoption effect
ICT capital effect


the Netherlands, women
Difference vs counterfactual scenario, pp
.5
0
-.5
-1
Women, 20-29
Women, 30-49
Women, 50-59
Women, 60+
robots adoption effect
ICT capital effect

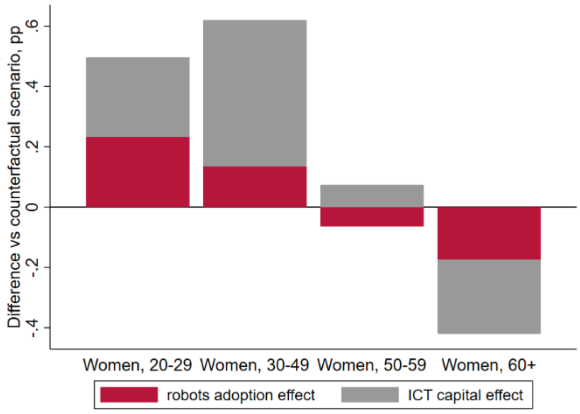

the Netherlands, men
Difference vs counterfactual scenario, pp
.2
0
-.2
-.4
-.6
Men, 20-29
Men, 30-49
Men, 50-59
Men, 60+
robots adoption effect
ICT capital effect



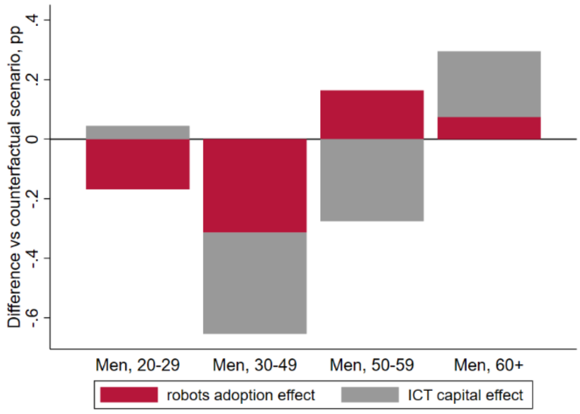
Note: The differences in the employment shares of demographic groups in the historical scenario and in the counterfactual scenario of no increase in ICT and robot exposure in the 2010–2018 period. Source: Authors' calculations based on the EU-SES, Eurostat, IFR, OECD TiVA, and EU-KLEMS data.

Appendix G. The effects of technology adoption on shares in wage bill by country, pp

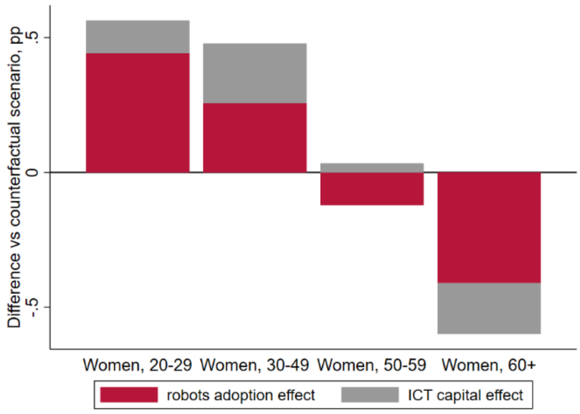
Belgium, women



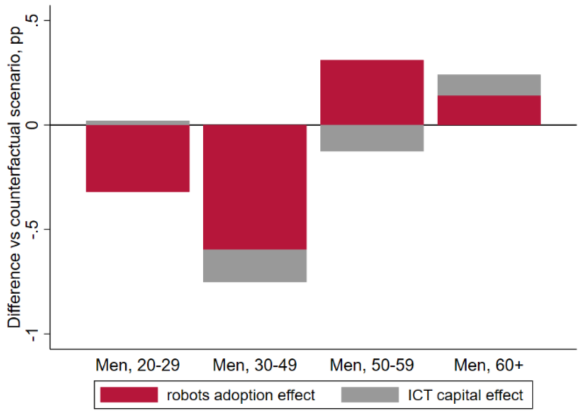
Belgium, men



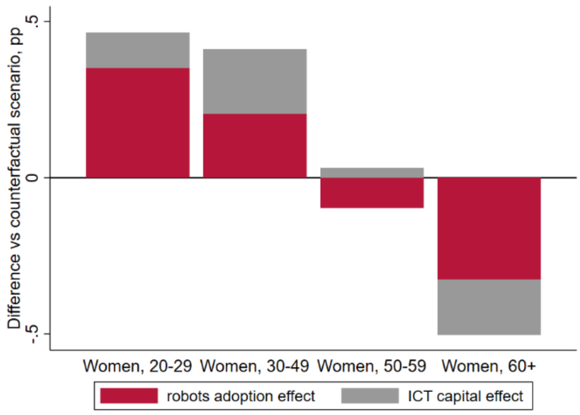
Czechia, women



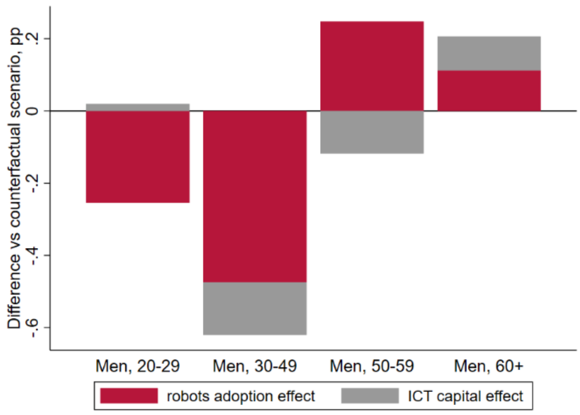
Czechia, men



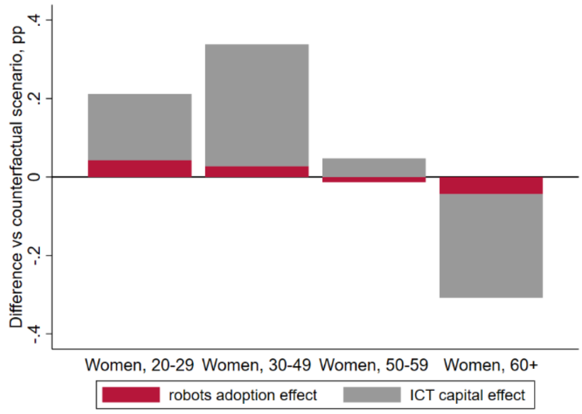
Germany, women



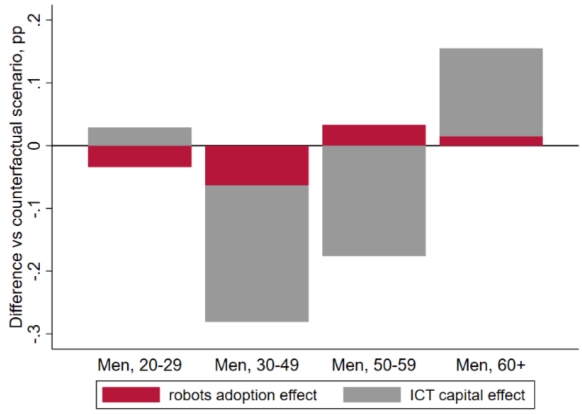
Germany, men



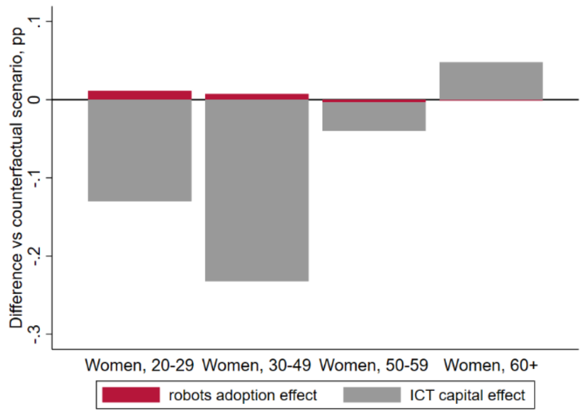
Estonia, women



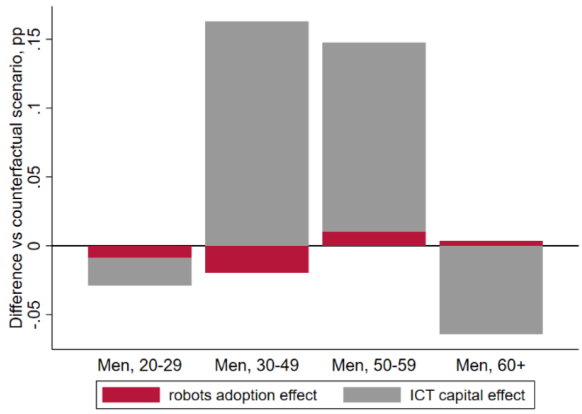
Estonia, men



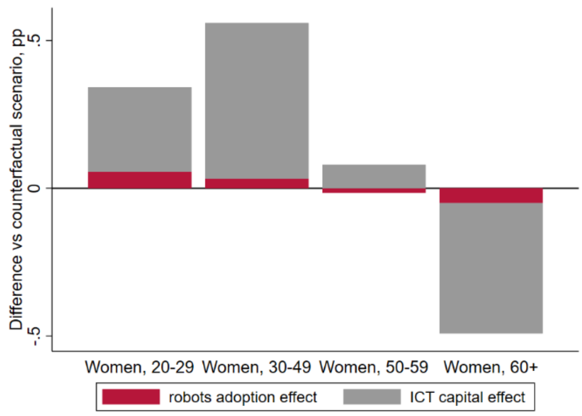
Greece, women



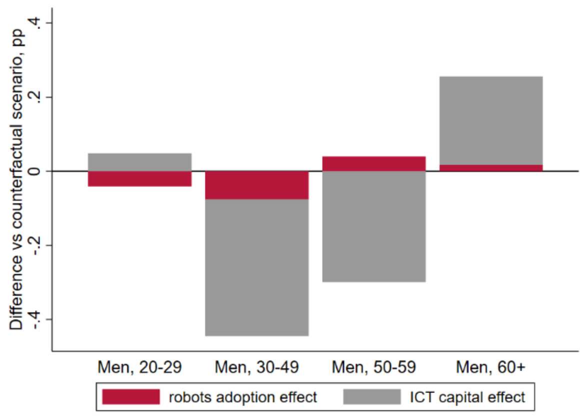
Greece, men



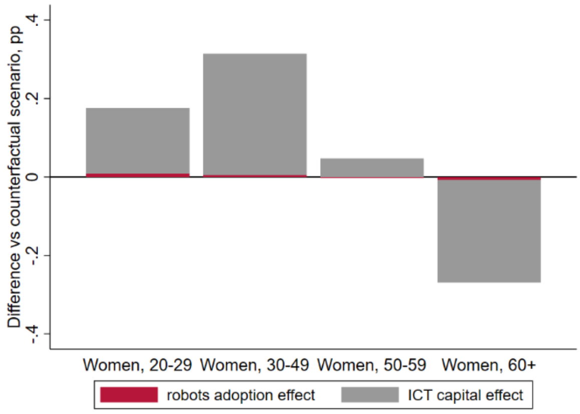
Spain, women



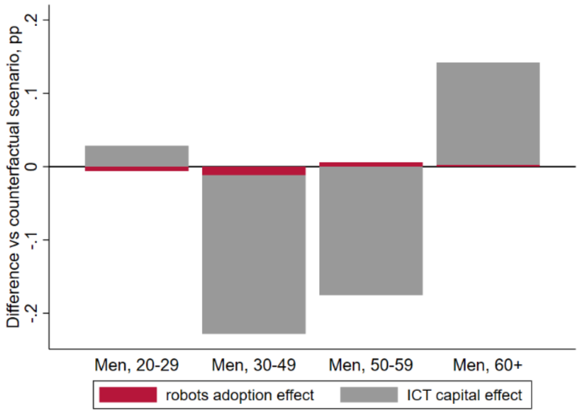
Spain, men



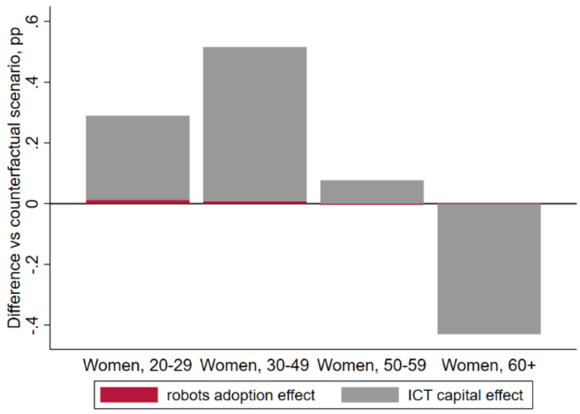
Finland, women



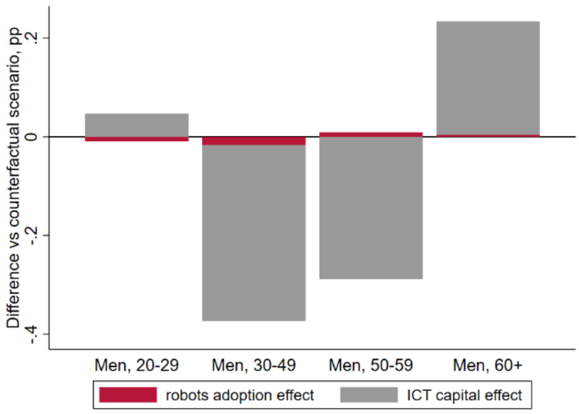
Finland, men



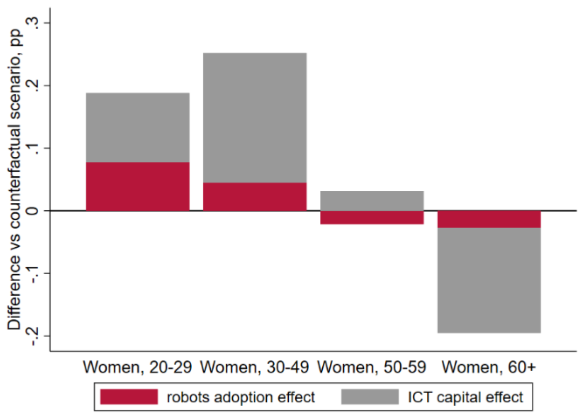
France, women



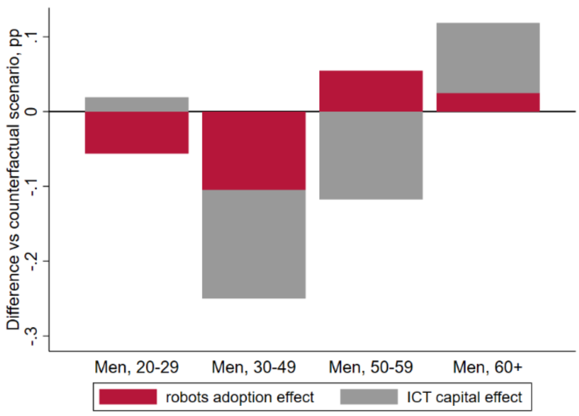
France, men



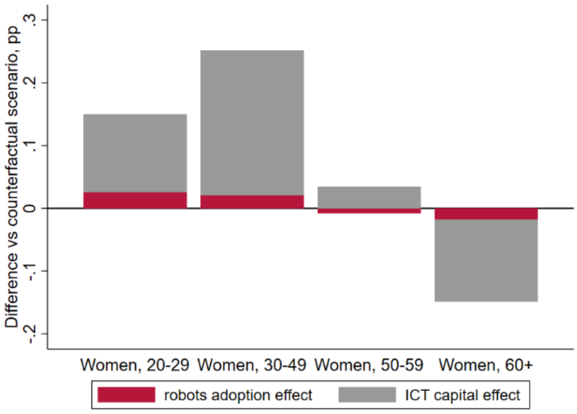
Italy, women



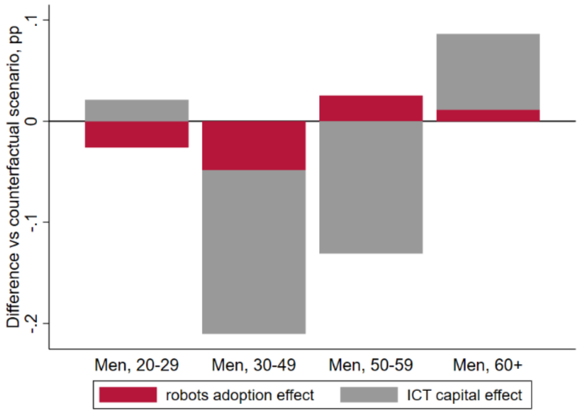
Italy, men



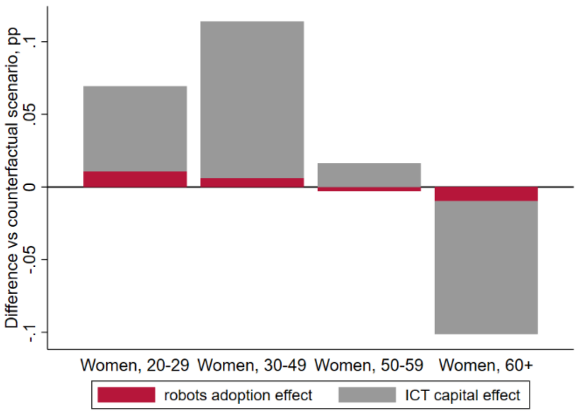
Lithuania, women



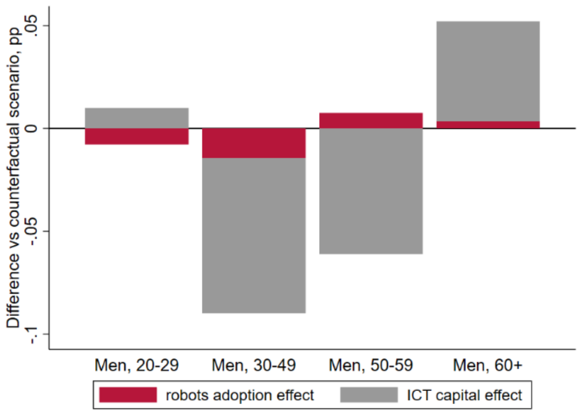
Lithuania, men



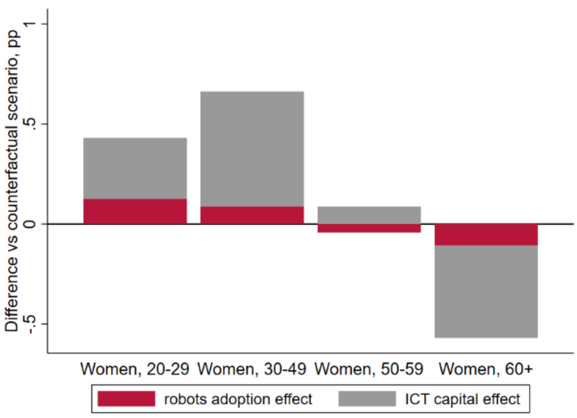
Latvia, women



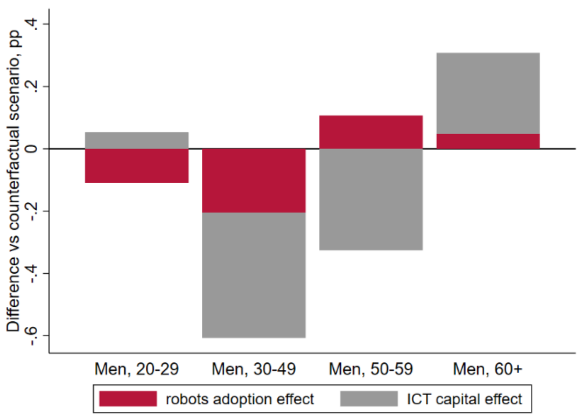
Latvia, men

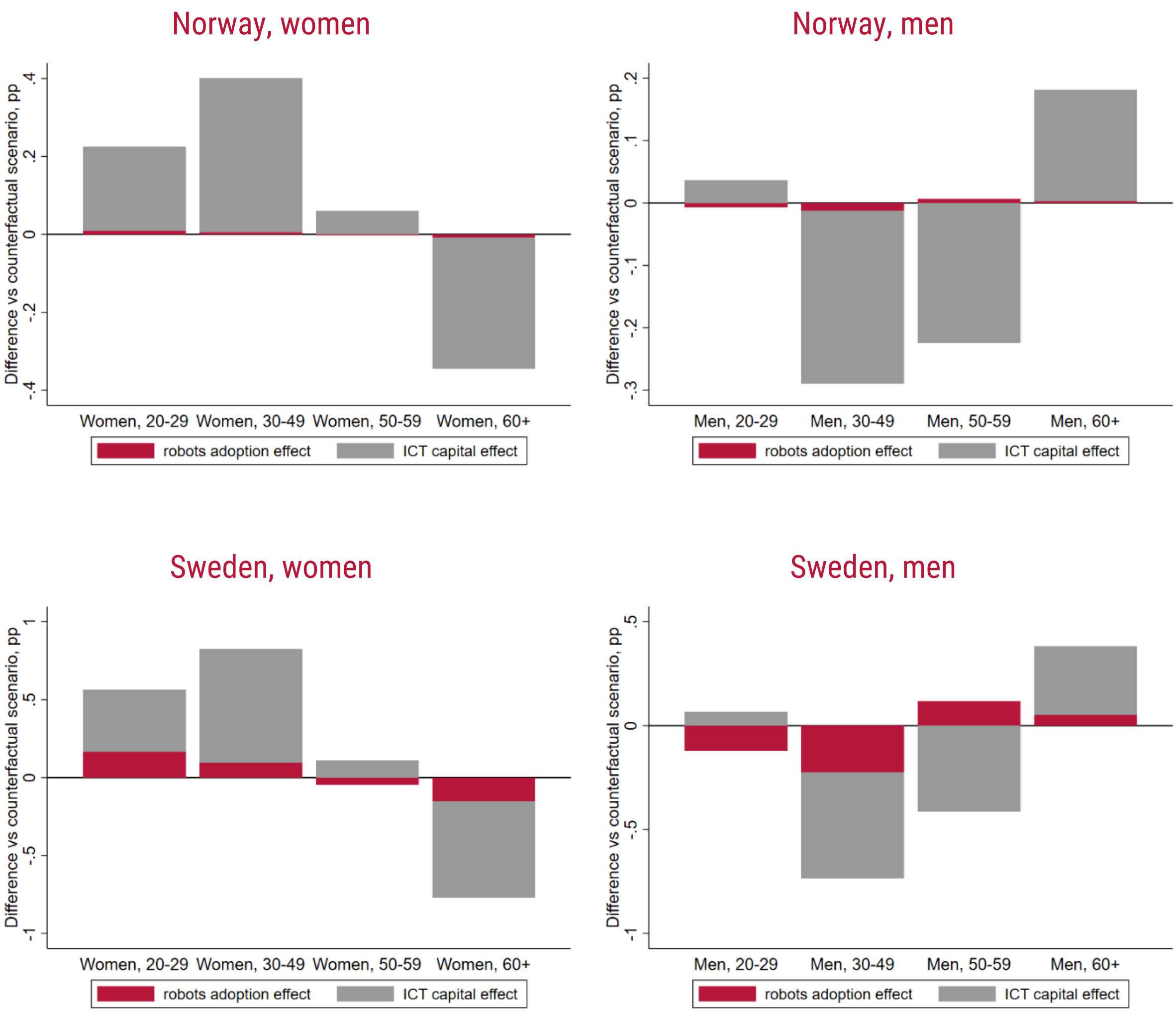


the Netherlands, women



the Netherlands, men





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