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Automation and income inequality in Europe

Karina **DOORLEY**[1,2,3]
Jan **GROMADZKI**[3,4,5]
Piotr **LEWANDOWSKI**[3,5,6]
Dora **TUDA**[1,2]
Philippe **VAN KERM**[7,8]

[1] ESRI Dublin, Ireland
[2] Trinity College, Ireland
[3] IZA, Germany
[4] Vienna University of Economics and Business, Austria
[5] Institute for Structural Research (IBS), Poland
[6] RWI Essen, Germany
[7] Luxembourg Institute of Socio-Economic Research, Luxembourg
[8] University Luxembourg, Luxembourg

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Automation and Income Inequality in Europe[*]

Karina Doorley[†] Jan Gromadzki[‡] Piotr Lewandowski[§]
Dora Tuda[¶] Philippe Van Kerm[‖]

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Abstract

We study the effects of robot penetration on household income inequality in 14 European countries between 2006–2018, a period marked by the rapid adoption of industrial robots. Automation reduced relative hourly wages and employment of more exposed demographic groups, similarly to the results for the United States. Using robot-driven wage and employment shocks as input to the EUROMOD microsimulation model, we find that automation had minor effects on income inequality. Household labour income diversification and tax and welfare policies largely absorbed labour market shocks caused by automation. Transfers played a key role in cushioning the transmission of these shocks to household incomes.

JEL codes: J24, O33, J23
Keywords: robots, automation, tasks, income inequality, wage inequality, microsimulation

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[†]ESRI Dublin; Trinity College Dublin; IZA. E-mail: karina.doorley@esri.ie.

[‡]Department of Economics, Vienna University of Economics and Business; Institute for Structural Research (IBS); IZA. E-mail: jan.gromadzki@wu.ac.at.

[§]Institute for Structural Research (IBS); IZA; RWI. E-mail: piotr.lewandowski@ibs.org.pl.

[¶]ESRI Dublin; Trinity College Dublin. E-mail: dora.tuda@esri.ie.

[‖]Luxembourg Institute of Socio-Economic Research; University of Luxembourg. E-mail: philippe.vankerm@liser.lu.

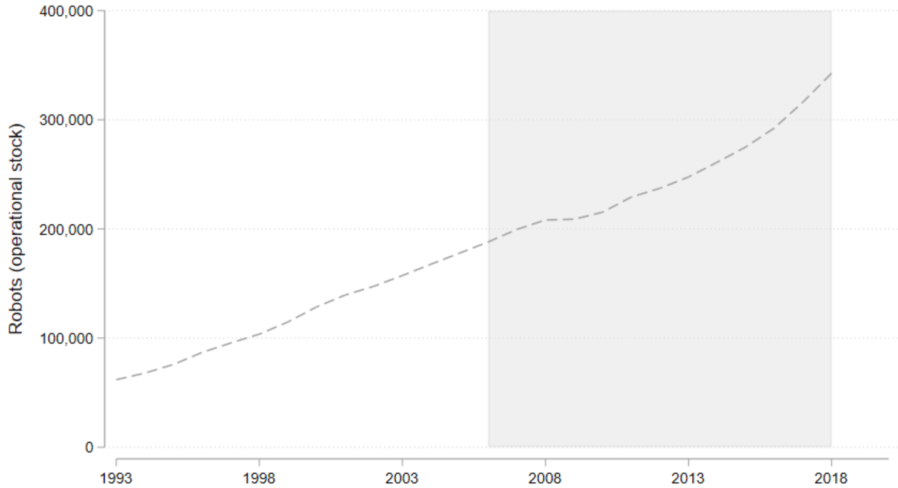
1 Introduction

The rapid automation of tasks performed by workers raises concerns about the effects of automation on workers' welfare. In the U.S., task displacement due to automation substantially reduced wages and employment, especially at the bottom of the wage distribution (Acemoglu & Restrepo, 2022). However, in other highly developed countries, such as Germany or Japan, the employment effects have been neutral or positive (Adachi et al., 2022; Dauth et al., 2021). Across the OECD countries, robots increased productivity and average wages (Graetz & Michaels, 2018), while reducing employment shares of routine occupations (de Vries et al., 2020), thus creating winners and losers.

Does Europe, with its high levels of redistribution, shield workers from the adverse effects of automation? We answer this question by assessing the effect of industrial robots on income inequality in 14 European countries between 2006 and 2018. We quantify automation with the industry-specific adjusted penetration of robots – an increase in the number of robots per worker relative to output growth, as proposed by Acemoglu and Restrepo (2020). We focus on robots as the measure of automation for several reasons. First, robots are usually implemented to improve efficiency in performing existing tasks and have a clear task displacement component (Acemoglu & Restrepo, 2020). This distinguishes them from general information and communication technologies (ICT), which enable communication, data storage, etc., and more often augment human labour and have benign employment effects (Castellacci & Tveito, 2018; Mann & Püttmann, 2023). Second, it was robots and specialised machinery that predominantly drove changes in the wage structure in the U.S. (Acemoglu & Restrepo, 2022). It is important to evaluate if European countries, often ahead of the U.S. in robot adoption, follow a similar or a different pattern. Third, robot use has been rapidly increasing: according to the International Federation of Robotics data (IFR, 2021), between 2006 and 2018, the operational stock of robots in Europe increased by more than 80% (Figure 1). Finally, data quality on other task-replacing technologies, such as ICT capital and software, is low in most European countries.

To assess the effect of robot penetration on household income inequality, we first evaluate their impact on key labour market channels: wages and employment. The labour market impacts of automation tend to be heterogeneous: robots and other routine-replacing technologies tend to substitute for workers who perform routine tasks but complement workers who perform non-routine tasks (Acemoglu & Autor, 2011). Thus, rising robot exposure has likely led to wage and employment *gains* and *losses* for different types of workers. The net effect on the pretax (market) labour income distribution is ambiguous, especially across countries differing in industrial and occupational structures. It depends on the direction and strength of wage and employment effects, as well as the relative position of affected workers in the earnings distribution.

Figure 1. The evolution of industrial robot stock in Europe, 1993-2018



Notes: The operational stock of robots in 14 European countries (Belgium, Bulgaria, Czechia, Estonia, France, Germany, Hungary, Latvia, Lithuania, Netherlands, Poland, Romania, Slovakia and Sweden). The shaded area covers the period of our analysis (2006-2018).
Source: International Federation of Robotics.

We estimate the labour market effects of automation using the approach proposed by Acemoglu and Restrepo (2022). Using large, harmonised linked employer-employee data from the EU Structure of Earnings Survey and the EU Labour Force Survey data, we regress labour market outcomes of demographic groups against changes in their exposure to automation-driven task displacement which takes into account demographic groups' sectoral and occupational employment structures. We define 30 demographic groups in each country based on workers' age, gender, and education. Since adopting robots may be endogenous to labour demand and may be affected by other shocks that also shape labour market outcomes, we use an instrumental variable approach. We exploit plausibly exogenous variation in the penetration of robots based on trends in robot adoption in five European countries outside our sample. We interact these trends with the initial employment structures of demographic groups. In other words, our instrument measures the exposure to robots of demographic groups if industries in which they specialise would follow international trends in robot adoption. We show that, in Europe, robot penetration reduced relative wages and employment rates of more exposed workers between 2006 and 2018. The impacts on wages were more significant and relatively stronger than those on employment. These adverse effects align with findings for the U.S. (Acemoglu & Restrepo, 2022). By studying the impact across demographic groups, we avoid the problem of worker selection that affects estimates across occupations (Böhm et al., 2022).

In the second part of the paper, we investigate how these automation-induced labour market shocks contributed to the evolution of household income inequality observed between 2006 and 2018. Changes in inequality have been heterogeneous across EU countries in that period. About half of the countries we study experienced increases in disposable income inequality – e.g., the Gini coefficient increased by almost 20% in Hungary – but the other half witnessed declining inequality. To do so, we use the EUROMOD tax-benefit microsimulation model to simulate a counterfactual distribution of disposable household incomes for 2018 after 'undoing' the change in employment and wages that we attribute to increased robot penetration since 2006. Specifically, we map the estimated, demographic group-level changes in wages and employment onto individual-level micro-data to simulate changes in pretax earnings. We then use EUROMOD to calculate changes in taxes and benefits for all households, obtaining counterfactual market and disposable household incomes. We isolate the effect of automation on income inequality by comparing the Gini coefficients of incomes in the data and in this counterfactual scenario.[1]

We find that despite a significant, adverse effect on labour market outcomes, automation hardly affected total household disposable incomes in European countries. We show that welfare state systems were key in mitigating workers' wage and employment losses due to rising robot exposure. Benefits cushioned most of these losses, while taxes played a minor role. In most countries, household composition slightly amplified the automation shocks, but the size of this effect was tiny, especially compared to the role of benefits. Consequently, the rising penetration of industrial robots barely contributed to changes in income inequality in European countries. In most countries, its contribution is below 1.0% of the baseline level of income inequality in 2018, as measured with the Gini index of equivalised household income.

The paper, therefore, makes two key contributions. First, we provide the first causal evidence of the medium-term effects of robot penetration on wages and employment in a European cross-country setting. These effects may differ from those estimated for the U.S. (Acemoglu & Restrepo, 2022) due to substantial differences in labour market institutions, including more binding minimum wages, higher collective bargaining coverage, stronger unions, and higher employment protection in Europe (Bhuller et al., 2022). Dauth et al. (2021) showed that the local labour market effects of robot adoption in Germany are tiny, unlike in the U.S. Firm-level studies found positive employment and wage impacts of robot adoption in Denmark, the Netherlands, and Spain (Acemoglu et al., 2023; Bessen et al., 2020; Humlum, 2023; Koch et al., 2021). However, firm-level studies show that blue-collar workers in adopting firms experience earnings losses, and non-adopting competitors significantly reduce employment. In addition, firms more likely to adopt robots tend to be more productive even before doing it. Hence, the aggregate impacts are ambiguous, and wage inequality may widen if high-productivity firms reap the benefits from automation. As automation creates winners and losers in labour markets, its redistributive effects are key for understanding the welfare con-

[1] We follow a decomposition framework formalised by Bargain and Callan (2010). Similar methods have been used to evaluate the contributions of tax-benefit policy (Černiauskas et al., 2022; Paulus and Tasseva, 2020), of employment and wage changes (Li et al., 2021; Doorley et al., 2021) and of demographic change (Dolls et al., 2019) to changes in income inequality in Europe.

sequences.[2] Using the exogenous variation in robot penetration, we show that, in Europe, the demographic groups more exposed to robots experienced relative wage and employment declines. However, the effects are quantitatively moderate. Importantly, they are robust to controlling for a wide range of potential confounders and cross-country differences in key labour market institutions, such as minimum wage policies.

Our second contribution is quantifying how these automation-driven labour market shocks have contributed to household income inequality in several European countries. The literature on drivers of income inequality has focused on tax-benefit systems (Černiauskas et al., 2022; Paulus and Tasseva, 2020), employment and wage changes (Li et al., 2021; Doorley et al., 2021), and demographic change (Dolls et al., 2019). To our knowledge, ours is the first evaluation that isolates the effect of automation alone. We distinguish between the contributions of automation-driven wage and employment shocks. We also assess the role of diversification of sources of labour income within households and of the tax-benefit systems in mitigating the transmission of these shocks into disposable income inequality. Bessen et al. (2023) found that benefits cushion the incomes of workers who lose jobs in the aftermath of robot adoption in the Netherlands. We confirm that benefits played a vital role in cushioning the impacts of automation in most European countries in our sample.

The paper is organised as follows. In section 2, we present our data and measurements. In section 3, we outline our empirical strategy. In section 4, we present and discuss our results, and in section 5, we summarise and conclude.

2 Data and Measurement

2.1 Data sources

Our sources of worker-level data are the European Union Structure of Earnings Survey (EU-SES), the EU Labour Force Survey (EU-LFS), and the EU Statistics on Income and Living Conditions (EU-SILC). The EU-SES is the most comprehensive, cross-country survey of earnings in the EU. It provides representative and harmonised information on employees in firms with at least 10 workers. It also includes detailed, two-digit sector information. We use it to calculate wage outcomes and to assign robot data to workers, based on sector of employment. The EU-LFS is the main cross-country survey in the EU that provides data on employment outcomes, covering all workers. We use it to calculate employment outcomes. Finally, the EU-SILC is the main cross-country survey in the EU that measures incomes, both market and non-market, before and after taxation, at individual and household level. We study the 2006–

[2] For instance, Aksoy et al. (2021) found that robot adoption increases wages for the gender pay gap within sectors and occupations in Europe, as higher skilled men benefit the most from robot-driven productivity improvements.

2018 period. The EU-SES has been conducted every four years since 2002, but the 2002 data for Estonia, Latvia, and Hungary are incomplete. The EU-SILC was established in 2004, but covers most EU countries from 2005 on.

Our analysis covers the following fourteen countries: Belgium, France, Germany, Netherlands, Sweden (Western European countries), Bulgaria, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, and Slovakia (Eastern European countries).[3] Our sample includes seven of the top ten countries with the highest increase in robot exposure in Europe (see Figure B.1).

Our main unit of analysis is a demographic group. For each country, we define 30 demographic groups defined by gender (men and women), education (basic, secondary, tertiary), and age (10-year age groups). We use the linked employer-employee EU-SES data to calculate average real hourly wages by demographic group and country in 2006 and 2018. We calculate gross hourly wages by dividing gross monthly earnings for the reference month by the number of hours paid during the reference month. Gross monthly earnings include earnings related to overtime, special payments for shift work, compulsory social contributions, and taxes. They do not include irregular, *ad hoc* and exceptional bonuses and other payments that do not feature every pay period.

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

Finally, we use the EU-SILC to assess the impacts on disposable incomes. We associate respondents in EU-SILC with their demographic group and country of residence in 2006 and 2018. Our measure of household disposable income includes both market and non-market incomes of all household members, net of taxes and social contributions and after the receipt of all types of cash benefits. Household market income refers to all household members' total amount of labour income (excluding employer social insurance contributions), capital income, private pensions and private transfers, i.e., income before taxes and benefits. Disposable income is obtained by adding public pensions and social transfers, and deducting taxes and social security contributions. Household-level social transfers, taxes and social security contributions are simulated by the tax-benefit microsimulation model EUROMOD (Sutherland & Figari, 2013), according to national tax-benefit rules applied to respondents' household market incomes and composition observed in EU-SILC.[4] Household disposable incomes are expressed in single-adult equivalents to account for economies of scale in consumption across households of different sizes using the scale recommended by Eurostat.[5]

[3] We do not include Southern European countries as they recorded a severe recession during the studied period.

[4] We use version I4.0 of EUROMOD with input datasets based primarily on the EU-SILC 2006 and 2018 waves.

[5] Total household disposable income is divided by the number of consumption units calculated as $1-0.5(a-1)+0.3c$ (with a and c the number of individuals aged, respectively above and below, 15 in the household).

2.2 Measuring robot penetration and automation-induced task displacement

Data on industrial robots come from the International Federation of Robotics (IFR, 2021), which provides annual information covering the current stock and the deliveries of industrial robots across countries, by industry and by application.

We use the adjusted robot penetration to measure automation, following Acemoglu and Restrepo (2020), and distinguishing fourteen industries in each country:

$$APR_{i,c} = \frac{M_{i,c,2018} - M_{i,c,2006}}{L_{i,c,2006}} - \frac{Y_{i,c,2018} - Y_{i,c,2006}}{Y_{i,c,2006}} \cdot \frac{M_{i,c,2006}}{L_{i,c,2006}} \tag{1}$$

where $M_{i,c,t}$ represents the number of robots in industry i in country c in year t (current stock), $L_{i,c,2006}$ represents the baseline employment level in industry i and country c, and $Y_{i,c,t}$ represents real output of sector i in country c in year t.

The first term captures the increase in robots used per worker in the industry i. Since employment in 2018 is endogenous to robot adoption, we divide the change in the stock of robots by the initial (2006) employment levels. The second term adjusts for the overall change in industry i output, specifically to account for the secular decline of some industries. Hence, the adjusted penetration of robots, $APR_{i,c}$, reflects the increase in robots installed per worker above the output change in industry i and country c between 2006 and 2018.

Finally, following Acemoglu and Restrepo (2022), for each demographic group g and country c, we construct the measure of task displacement due to automation (robot penetration) as

$$TDA_{g,c} = \sum_{i \in I} \omega^{i}_{g,c} \cdot (\omega^{R}_{g,i,c}/\omega^{R}_{i,c}) \cdot APR_{i,c} \tag{2}$$

which comprises three terms:

- group's g exposure to different industries, $\omega^{i}_{g,c}$, given by the share of industry i in total earnings of workers in group g in country c;
- the relative specialization of group g in the industry i routine occupations (where displacement is assumed to take place), $\omega^{R}_{g,i,c}/\omega^{R}_{i,c}$;
- the adjusted penetration of robots in industry i in country c, $APR_{i,c}$.

The task displacement measure, $TDA_{g,c}$, is a weighted exposure to adjusted robot penetration – the sector structure of the group's g total earnings serve as the first weight, and the group's g shares in routine jobs in particular sectors serve as the second weight. Similarly, we construct industry shifters as weighted averages of changes in sectoral value added using the shares of various sectors in a demographic group's employment structure as weights. We take logs of one plus $TDA_{g,c}$ to account for a skewed distribution of task displacement.[6]

[6] We add a small constant because some groups experienced a slight decrease in the exposure to robots.

2.3 Descriptive statistics

Table 1 presents the averages of variables used to assign workers into socio-demographic groups, and of those used in regressions. Most of the workers in our sample are secondary educated, and most are prime-aged. Manufacturing accounted for 27 percent of total employment in our sample. On average, workers in European countries in our sample experienced wage growth of 26 log points between 2006 and 2018, while the employment rates increased slightly (by 4 pp). They were exposed to a 21 log points increase in real value added (average industry shifter), and a large increase in robot penetration.

Table 1. Descriptive statistics

	Mean	Standard Deviation	Observations
Dependent Variables			
Log wage growth	0.26	0.30	420
Employment rate change	0.04	0.07	420
Task Displacement			
Automation: penetration of robots	0.83	0.59	420
Control Variables			
Gender: woman	0.48	0.50	420
Gender: man	0.52	0.50	420
Basic education	0.15	0.36	420
Secondary education	0.56	0.50	420
Tertiary education	0.29	0.45	420
Age: 20-29	0.19	0.39	420
Age: 30-39	0.27	0.44	420
Age: 40-49	0.28	0.45	420
Age: 50-59	0.22	0.41	420
Age: 60+	0.05	0.21	420
Initial wages	1.59	0.98	420
Industry shifters	0.21	0.15	420
Manufacturing share	0.27	0.13	420
Not elsewhere classified manufacturing share	0.04	0.02	420

Notes: This table presents weighted means, standard deviation and the number of observations for selected variables. We weigh observations by their within-country employment shares. The sources and description of the variables can be found in Table A.1. Detailed descriptive statistics for all variables for the whole sample are presented in Table A.2.

3 Empirical Strategy

Our analysis proceeds in three steps. First, we estimate the impact of automation on wages and employment rates of demographic groups, following the method of Acemoglu and Restrepo (2022). Second, we use the estimated coefficients to calculate counterfactual wages and employment rates that would have been recorded in 2018 if robot penetration remained at the 2006 level in each country. Third, we evaluate the effects on household incomes, using these counterfactual effects as inputs in the EUROMOD microsimulation model.

3.1 Effects of automation on wages and employment rates

We estimate the following equation to investigate the impact of automation on wages:

$$\begin{aligned}\Delta \ln w_{g,c} &= \rho \cdot \ln w_{g,c}^{2006} + \beta \cdot TDA_{g,c} + \kappa \cdot X_{g,c} \\ &\quad + \alpha_{edu(g,c)} + \gamma_{gender(g,c)} + \eta_{country(g,c)} + \nu_{g,c}\end{aligned} \tag{3}$$

where $\Delta \ln w_{g,c}$ denotes the log change in real hourly wages for workers in a demographic group g in the country c between 2006 and 2018. The coefficient of interest is β, which may be interpreted as a change in wages due to a one percent increase in exposure to automation. We control for initial wage levels, country fixed effects, $\eta_{country(g,c)}$, gender and education fixed effects ($\gamma_{gender(g,c)}$ and $\alpha_{edu(g,c)}$), and additional control variables ($X_{g,c}$): exposure to manufacturing, and industry shifters. While industry shifters absorb labour demand changes coming from the expansion of industries in which a demographic group specializes, the group-specific shifters account for demand factors related to changing wage premia associated with gender, education, and working in manufacturing. Regressions are weighted by the share of each group in each country's employment so that the sum of weights in each country is equal to one.

We use the same approach for employment rates, the only difference is that we use differences in employment rates rather than log differences as in the case of wages.

OLS estimation of equation (3) may lead to biased estimates because robot adoption in industry i in country c may be determined by changes in unobservable factors that simultaneously affect labor demand in this industry. Hence, we use the approach of Acemoglu and Restrepo (2020) and instrument the penetration of robots in industry i by an average penetration in this industry among five European countries not included in our analysis, e to identify the component of robot penetration driven by changes in technology:

$$APR_i^{IV} = \frac{1}{5}\sum_{e=1}^{5}\left[\frac{M_{i,e,2018} - M_{i,e,2006}}{L_{i,e,2006}} - \frac{Y_{i,e,2018} - Y_{i,e,2006}}{Y_{i,e,2006}} \cdot \frac{M_{i,e,2006}}{L_{i,e,2006}}\right] \tag{4}$$

The original instrument in Acemoglu and Restrepo (2020) comprised Denmark, Finland, France, Italy, and Sweden. Since two of these countries are included in our sample (France, and Sweden), we must modify the original instrument. Our instrument comprises three countries with the highest penetration of robots: Slovenia, Austria, Denmark, as well as Finland and the UK.[7] In robustness tests, we also present the results using the instrument comprising countries selected originally by Acemoglu and Restrepo (2020). The instrument at the demographic group level is then constructed using equation (2). Similarly to the task displacement variable, we take logs of the instrument.

3.2 Microsimulation of effects on disposable income inequality

The second analysis stage draws implications of automation for disposable household income inequality. We do so by 'injecting' our estimates of wage and employment effects of automation – measured by $\hat{\beta} \cdot TDA_{g,c}$ for each demographic group g and country c (estimated for wage growth, $\hat{\beta}^w$, and employment change, $\hat{\beta}^e$) – into the household income data and use a tax-benefit microsimulation model to assess how much these changes may have impacted disposable household incomes and income inequality.[8]

To quantify the impact of wage growth, we first divide the hourly wages of all employed workers in the 2018 EU-SILC by $(1+\hat{\beta}^w \cdot TDA_{g,c})$ according to their demographic group g and country c. Such deflated wages reflect counterfactual wages in 2018 the absence of increased robot penetration since 2006. Moreover, for each demographic cell, we multiply these counterfactuals by the share of workers in firms with at least 10 workers (based on the EU-LFS data, see Figure D.1 in Appendix D.). The EU-SES data cover only workers in firms with at least 10 workers, and smaller firms are unlikely to implement robots. Unfortunately, the EU-SILC data used for microsimulation do not provide information on firm size. The re-weighting of counterfactuals explained above allows operationalising the assumption that workers in firms with fewer than 10 workers are not directly affected by robots. As a robustness check, we also simulate the upper-bound results assuming that all workers are affected as workers in firms with at least 10 workers - see Appendix D.

We then recalculate household incomes by aggregating deflated wages into annual labour incomes for all household members, adding non-labour incomes and imputing social transfers, taxes and social security contributions calculated from the 2018 tax-benefit calculator EUROMOD. Differences in inequality measures calculated on the original 2018 household incomes versus those obtained from the simulated series give us measures of the distributive impact of robot penetration.

[7] These countries are not included in our analysis because the SES data is unavailable for these countries.

[8] See Appendix Appendix C for an extended description of the simulations conducted.

To inject changes in employment into 2018 EU-SILC, we 'reweight' each respondent by a factor

$$E_i \frac{p_{g,c}}{(1+\hat{\beta}^e \cdot TDA_{g,c}) - p_{g,c}} + (1-E_i)\frac{(1+\hat{\beta}^e \cdot TDA_{g,c}) - p_{g,c}}{p_{g,c}}$$

where $E_i = 1$ if respondent i is employed and 0 otherwise, $p_{g,c}$ is the 2018 employment rate of individuals in group g and country c, and $\hat{\beta}^e \cdot TDA_{g,c}$ is the estimated employment effect of robot penetration. The reweighted 2018 EU-SILC samples have employment rates by group and country that reflect what would have been observed without employment effects from robot penetration. Differences in inequality measures calculated on the original 2018 incomes and sampling weights versus those obtained from the 2018 incomes and reweighted sampling weights give us measures of the distributive impact of robot penetration. Both simulations are combined to generate counterfactual data and inequality estimates reflecting the combined effect of robot penetration on wage growth and employment.

To further probe into the role of tax-benefit systems in cushioning automation-induced earnings changes, we calculate Gini coefficients for both disposable and market incomes. The double differences between pre-tax and post-tax distributions, with and without neutralising automation-induced changes, reflect how much taxes and benefits absorbed the impacts on disposable incomes. We also calculate Gini coefficients for individual-level market incomes (for those aged 20-65). Comparing these to the Gini coefficients of household-level market income, with and without the automation shock, quantifies the role of income pooling within the household (and therefore labour income source diversification) in its transmission.

As shown below, the distributive impacts of robot penetration on household incomes vary across countries. To sort out whether these differences arise mainly from differences across countries in the size of the robot penetration shock versus differences in how the shock was absorbed by household income pooling, other income sources and taxes and benefits, we finally report a separate set of estimates obtained by injecting in all countries the automation-induced wage and employment changes observed in Germany – that is, by using $TDA_{g,\mathrm{DE}}$ (for Germany) instead of $TDA_{g,c}$ in the simulations.

4 Results

4.1 The wage and employment effects of robot exposure

We start by discussing the OLS estimates of the effects of robot exposure on relative wage growth in Europe. These effects are statistically significant and negative (Table 2). As described in subsection 3, OLS estimates may be biased because other shocks may have affected both investments in robots and labour market outcomes. However, we obtain very similar results with the instrumental variable approach (Table 2). The IV estimates are larger in absolute terms than the OLS ones. This could mean that some omitted variable is negatively correlated with changes in exposure to task displacement technologies, leading to a downward bias of the OLS estimates.[9] The estimated effects are robust to changes in specification and to the addition of more controls. Our preferred specification is in Column 4 of Table 2. It includes controls for group-specific shifters (gender and education fixed effects, as well as demographic groups' exposures to manufacturing) and industry shifters (groups' exposures to changes in value added of sectors they specialise in). The coefficient has no direct interpretation, but we can relate it to a standard deviation of the task displacement. Quantitatively, the IV estimates imply that one standard deviation increase in robot penetration across demographic groups (equal to 0.59, see Table A.2) translated into a relative wage decrease of about 4%. Notably, the direction and the magnitude of the effects are virtually identical in Western and Eastern Europe (see Table B.2).

Results remain essentially unchanged if we additionally control for groups' specialization in routine jobs and exposure to offshoring, Chinese imports penetration, minimum wage, collective bargaining coverage, and population changes (Table B.3 in Appendix B). In a leave-one-out test, we show that the results are not driven by a particular country (Figure B.2). In further robustness checks, we also use two alternative instruments for automation. First, we use an instrument based on countries selected by Acemoglu and Restrepo (2022) and we find strong negative wage effects (Table B.4). Second, we use the adjusted penetration of robots in the US and we obtain estimates that are similar to the baseline estimates but less precise (Table B.5). Moreover, we find statistically significant, negative effects of robot penetration on the change in wage dispersion within demographic groups (Table B.6). This pattern confirms that directing attention towards the impacts of task displacement between demographic groups captures the crucial disequalising channel of automation.

Next, we use the estimated coefficients to calculate wage changes due to automation for all demographic groups in 14 countries in our sample. We combine this information with the initial demographic structure of percentiles of within-country wage distribution to visualise the impact of automation on wage inequality. Figures 2-3 show wage changes attributed

[9] For instance, relatively declining exports and international competitiveness could incentivise investment in robots and slow down wage growth and a sector level.

Table 2. Automation and changes in real hourly wages, 2006–2018

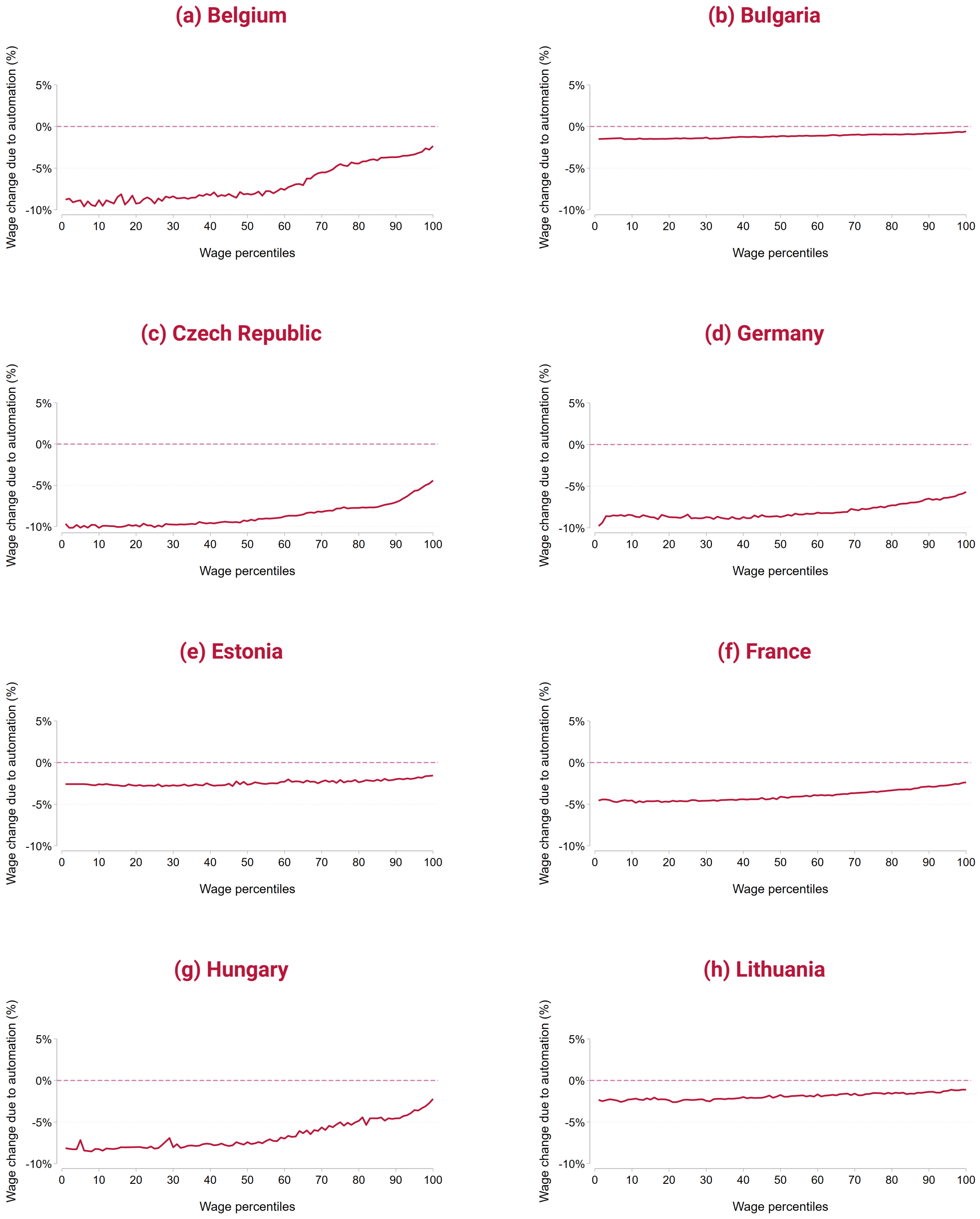
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Automation: penetration of robots	-0.055***	-0.055***	-0.035**	-0.041***
	(0.017)	(0.017)	(0.016)	(0.015)
	2SLS	2SLS	2SLS	2SLS
Automation: penetration of robots	-0.093***	-0.091***	-0.057***	-0.064***
	(0.023)	(0.022)	(0.022)	(0.021)
Country FE	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes
Gender	no	yes	yes	yes
Education	no	no	yes	yes
Industry shifters	no	no	no	yes
F-statistic first stage	314.55	308.72	261.09	260.93
Mean of outcome	0.26	0.26	0.26	0.26
Mean of automation	0.83	0.83	0.83	0.83
Observations	420	420	420	420

Notes: Table shows estimates of the relationship between task displacement due to automation and the change in log wages across 30 demographic groups in 14 European countries. The upper panel shows the OLS estimates, and the bottom panel shows the IV estimates. The dependent variable is the change in log wages for each group from 2006 to 2018. The instrument is the average robot penetration in 5 European countries not included in the sample. All regressions are weighted by the group's share of the country's employment. Column 4 shows our baseline estimates. Robust standard errors are reported. Table B.1 shows the first-stage results.
Data: EU-SES. * p<.10; ** p<.05; *** p<.01

to automation by percentiles of the wage distribution in particular countries, and Figure B.3 pools these effects across all countries. In most countries, the wage decline attributed to automation was concentrated in the bottom half of the wage distribution. This disequalising pattern is most pronounced in Belgium, Czech Republic, Hungary, Germany, and Poland – in all these countries, the wage reductions for groups at the bottom exceeded 5%, roughly double the size of those recorded on the top of the wage distribution (Figures 2-3). These countries recorded a large growth in robot penetration between 2006–2018 (Figure B.1), and relatively high exposure to robot penetration among groups earning below-median wages. At the same time, in the Baltic countries or the Netherlands, the effects attributed to automation were more evenly spread across the wage distribution.[10]

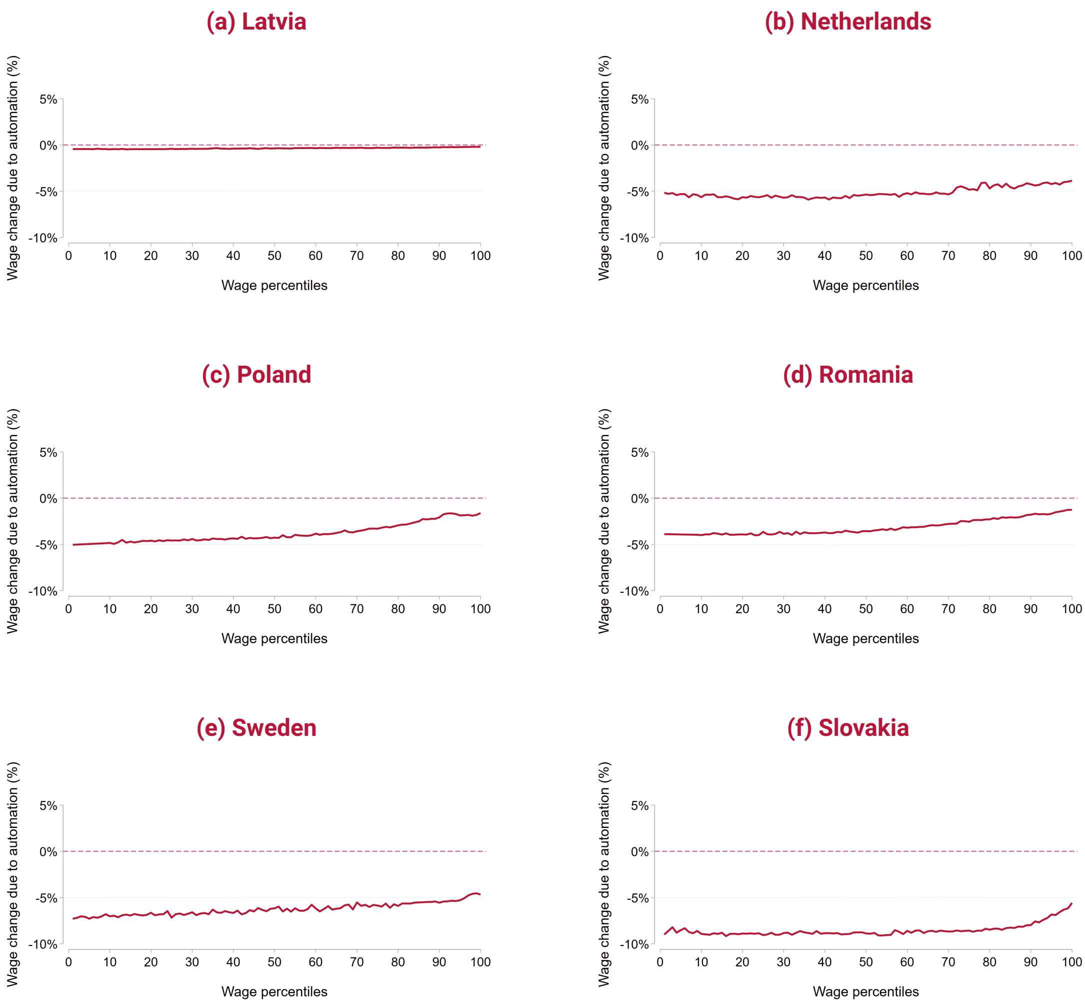
[10] In the pooled sample, wage changes due to automation for the bottom decile were twice as large as changes due to automation for the top decile (Figure B.3). However, this partly reflects the fact that Eastern countries had lower wages and recorded rather large increases in robot penetration.

Figure 2. Wage changes due to automation, by percentiles of country-specific initial (2006) wage distributions (i.)



Notes: Figures show the average wage changes due to automation for percentiles of the wage distribution. Wage changes due to automation are calculated by multiplying the group's increase in exposure to automation by the wage effects of automation from the equation 3.
Data: EU-SES.

Figure 3. Wage changes due to automation, by percentiles of country-specific initial (2006) wage distributions (ii.)



Notes: Figures show the average wage changes due to automation for percentiles of the wage distribution. Wage changes due to automation are calculated by multiplying the group's increase in exposure to automation by the wage effects of automation from the equation 3.
Data: EU-SES.

Finally, we discuss the impact of automation on employment rates. Again, we find a significant, negative effect (Table 3). It is, however, relatively small – one standard deviation higher robot penetration led to a 2 percentage point decrease in employment rates. Combined with negative wage effects (Table 2), our estimates suggest a negative impact of automation on labour market outcomes of more exposed groups in European countries.

Table 3. Automation and changes in employment rates, 2006–2018

	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
Automation: penetration of robots	0.000	0.004	-0.033	-0.034*
	(0.016)	(0.018)	(0.021)	(0.021)
Country FE	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes
Gender	no	yes	yes	yes
Education	no	no	yes	yes
Industry shifters	no	no	no	yes
F-statistic first stage	353.80	339.95	233.69	233.61
Mean of outcome	0.04	0.04	0.04	0.04
Mean of automation	0.83	0.83	0.83	0.83
Observations	420	420	420	420

Notes: Table shows estimates of the relationship between task displacement due to automation and the change in employment rates across 30 demographic groups in 14 European countries. The dependent variable is the change in employment rates for each group from 2006 to 2018. The instrument is the average robot penetration in 5 European countries not included in the sample. Robust standard errors are reported.
Data: EU-SES. * p<.10; ** p<.05; *** p<.01

4.2 The contribution of automation to household income inequality

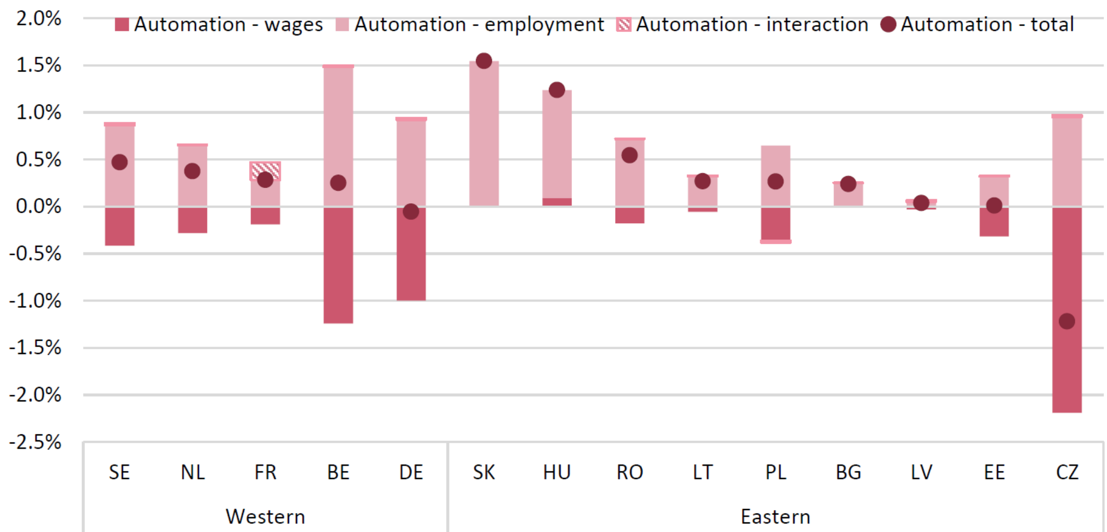
Next, we evaluate the consequences of automation for household income inequality. For each demographic group, we obtained the hypothetical values of wages and employment rates in 2018, assuming that robot exposure remained at the 2006 level. For each group, we multiplied its robot penetration by the coefficients of automation's wage and employment effects. Then, we inject these values into the microsimulation model EUROMOD, and calculate counterfactual simulations of income distribution; see section 3 and Appendix C for details.

We start by presenting and discussing automation's contribution to income inequality by country (Figure 4). We distinguish between the contributions of (i) automation-induced wage changes (ii) automation-induced employment changes across demographic groups, and (iii) the combination of these two using the methods described in Appendix C. In Figure 4 and what follows, we separate countries by Western or Eastern European status as the tax and welfare systems tend to differ systematically in these regions. Within the Eastern and Western European categories, we order countries by the effect of automation on income inequality.

Automation-induced wage changes – which we estimated to be negative for all demographic groups (Table 2) – have had small, negative contributions to disposable household income inequality in most countries studied. Automation generally reduced wage levels, mechanically reducing the income of those in employment compared to those out of work or on fixed incomes, such as pensions (unaffected by automation). This compressed the income distribution, reducing income inequality, even though automation widened between-group wage inequality (Figures 2-3). This reduction in income inequality is most pronounced in Western European countries and Czechia, but minor in other Eastern European countries. Still, its magnitude is very small in all countries, around 1–2% of the 2018 value of the Gini index in Czechia, Belgium, and Germany, and below 0.5% in other countries (Figure 4).

Automation-driven employment changes – which we also estimated to be negative (Table 3) – have modestly widened inequality in most countries. The employment reduction triggered by automation increased the mass of individuals at the bottom of the market income distribution (with zero market income) thereby widening income inequality. The employment contribution operates oppositely to the wage contribution in most countries (Figure 4), partly or wholly counteracting the wage contribution in most of them. Small economies with large robot penetration, such as Belgium, Slovakia, and Hungary, stand out with the largest contribution of the employment channel to income inequality (1.2–1.5% of the country-specific Gini index in 2018). In other countries, the contribution of automation-driven employment changes is below 1% of the 2018 Gini index (Figure 4).

Figure 4. Contribution of automation to disposable household income inequality



Notes: The figure shows the terms of the decomposition of the change in household income inequality (automation-induced wage effect, automation-induced employment effect, their interaction and the total automation effect). In Eastern and Western Europe, countries are ordered in decreasing order of the total change in the Gini Index due to automation. Data: EUROMOD, EU-SILC.

We also quantify the contribution of the interaction between the wage and employment effects – measured as the additional effect of combining both wage and employment impacts automation. Only in France is the interaction effect noticeable and positive. In other countries, it is negligible (Figure 4).

The overall impact of automation on household income inequality is the sum of the wage, employment, and interaction contributions. In most countries, automation widened income inequality, but only slightly – its contribution is below 1.5% of the 2018 Gini index. Only in Czechia, the total contribution is negative, mainly because of the wage channel (Figure 4).

As a robustness check, we also simulated inequality assuming that in each demographic group, all workers were affected by robots in the same way as workers in firms with at least 10 workers, who are more likely to be exposed to robots. For most countries, the baseline and upper-bound results are very similar (Figure D.2 in Appendix D). The upper-bound results are noticeably larger (in absolute terms) than the baseline results only in Eastern European countries with the largest contribution of automation to income inequality, such as Slovakia and Hungary. Still, the upper-bound contribution in these countries is around 2% of the 2018 Gini coefficient.

4.3 Factors shaping the distributional impact of automation: households' labour income diversification and tax-benefit systems

We have found a tiny contribution of automation to household disposable income inequality in most European countries, despite its disequalising impact on wages (Figures 2 and 3) and its negative employment effects (Table 3). These labour market effects should, however, widen inequality in market income. Here, we quantify the contribution of automation to market income inequality and assess the role of key factors that could have mitigated its transmission into household income inequality: the diversification of households' labour income sources (among co-residents) and tax and benefit systems.

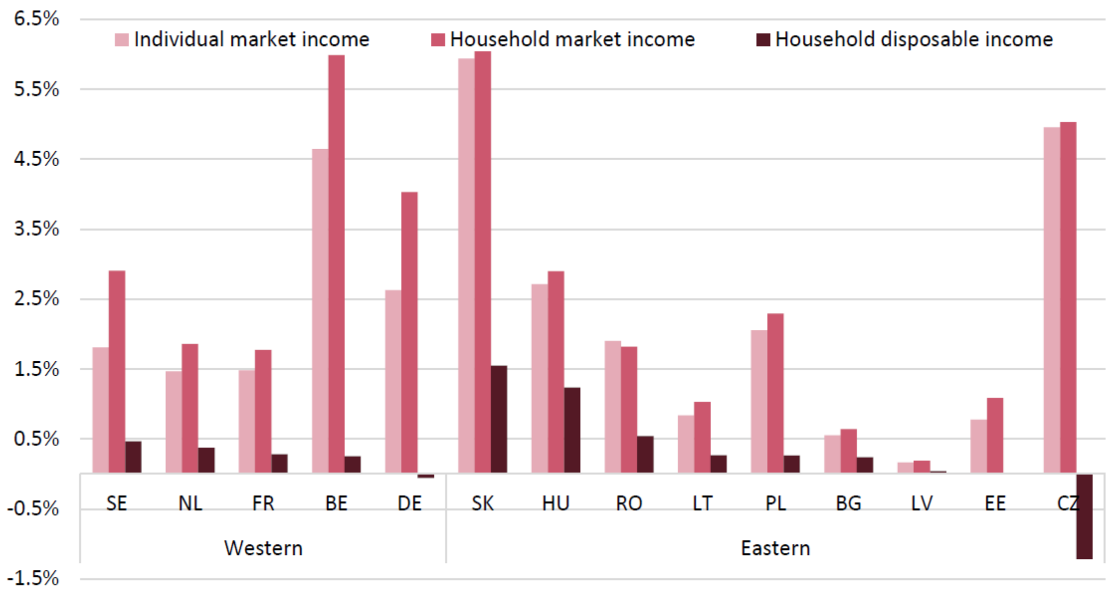
To tease this out, we calculate the automation-induced change in the Gini index for different income concepts: (i) individual-level market income of those aged 20-65 (earnings, plus investment income and private pensions, before taxes and transfers), (ii) equivalised household market income and (iii) equivalised household disposable income (after taxes and transfers). Figure 5 presents the results. Comparing (i) to (ii) illustrates the role of pooling labour incomes within households in the transmission of the automation shock while comparing (ii) to (iii) shows the cushioning effect of taxes and benefits.

In all countries in our sample, automation widened inequality of individual-level market income, in line with the disequalising impact of robots on wages (Figures 2-3). The impact on individual market income inequality is largest (up to 6% of the 2018 Gini index) in countries with the strongest negative effect on wages at the bottom of the country-specific wage distribution, such as Belgium, Slovakia, Czechia, and Germany. In these countries, automation widened wage inequality to the largest extent (Figure B.4). It is the weakest (close to zero) in countries with the smallest effect on low earnings, such as Bulgaria, Latvia, and Estonia, where automation barely affected wage inequality (Figure B.4).

For Western European countries, automation's contribution to household market income inequality is visibly larger than its contribution to individual market income inequality. This indicates that household formation exacerbates the transmission of the automation shock. In most Eastern European countries, that difference is much smaller, indicating a stronger diversification of market incomes within households. Moreover, we find suggestive evidence that the contribution of household labour income diversification to automation-driven inequality is positively related to countries' incidence of assortative mating in routine occupations (Figure B.5). A sensitivity analysis, described in Appendix B, shows that, in most countries, household formation in 2018 amplified the automation effect by less than household formation in 2006 would have, indicating an increase in labour income diversification within households over this period (Figure B.10).

Finally, the contribution of automation to disposable household income inequality is much smaller than to either measure of market income (Figure 5) – as discussed earlier, it is below 1% in most countries. This suggests that the tax and benefit systems play a vital role in cushioning the effects of automation on household disposable income.

Figure 5. The effect of automation on income inequality using various income concepts

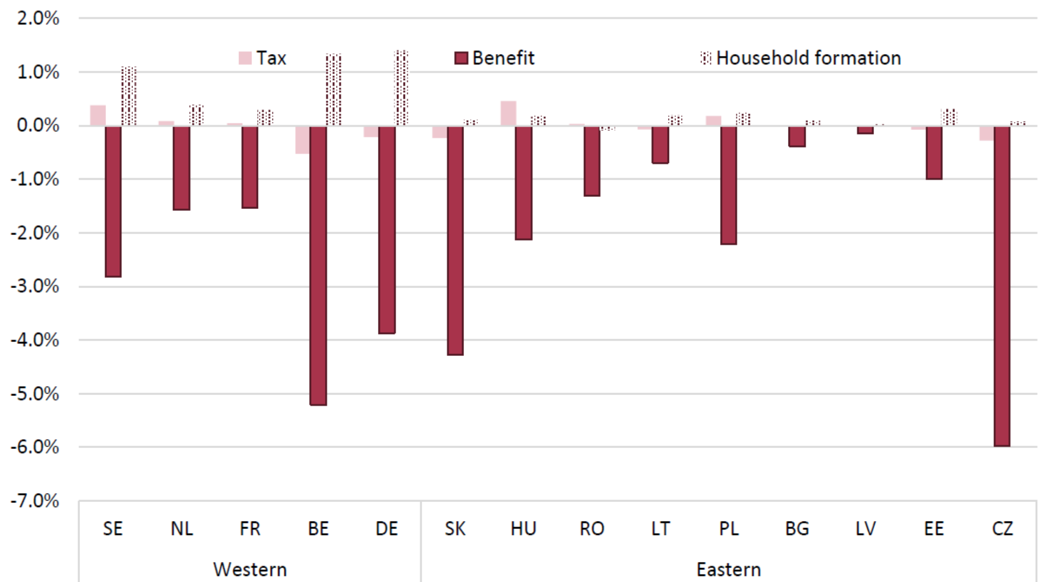


Notes: The figure shows the change in Gini Index due to automation where income is defined as (i) market income at the individual level (ii) equivalised market income at the household level and (iii) equivalised disposable income at the household level. In Eastern and Western Europe, countries are ordered in decreasing order of the total change in the Gini Index due to automation. Data: EUROMOD, EU-SILC.

Next, we isolate the role of taxes from benefits in cushioning the automation shock. We do this by simulating the Gini index of household market income, of gross income (market income plus benefits) and of net income (market income minus income tax). We find that benefits do much of the heavy lifting while taxes play a minor role (Figure 6). Taking the example of Germany, automation increased the 2018 Gini of individual-level market income by 2.5%. Accounting for household labour income pooling, the corresponding increase in the Gini index of household market income extends to 3.7%. The tax system had a negligible impact – it reduced inequality by only 0.2% of the Gini index. However, the benefits almost completely cushioned the automation-driven increase of household market inequality, reducing the Gini index by 3.9% (Figure 6). Consequently, automation was essentially neutral for disposable household income inequality in Germany, reducing the 2018 Gini index by −0.1% (Figure 4). In other Western European countries, the contribution of benefits to cushioning automation-driven shocks was also substantial.

In Eastern European countries, the contribution of the tax and welfare systems was more muted than in Western Europe, except for Czechia and Slovakia, where benefits reduced the 2018 Gini index by 6.0% and 4.0%, respectively. This aligns with the wider literature on the stabilising effects of European tax-benefit systems. For example, Dolls et al., 2022 reported that income stabilisation coefficients (the stabilising effect of the tax and welfare system for a stylised 5% shock to household market income) range from 20% to 30% in some Eastern and Southern European countries to around 60% in Belgium, Germany, and Denmark.

Figure 6. The cushioning effect of the tax-benefit system and household formation on automation-induced inequality changes



Notes: The figure shows the effect of taxes, benefits and household risk-sharing on the change in the Gini Index due to automation. In Eastern and Western Europe, countries are ordered in decreasing order of the total change in the Gini Index due to automation. Data: EUROMOD, EU-SILC.

Findings on the role of tax and benefit systems are similar if we apply the 2006 systems instead of the 2018 systems. Results are presented in Appendix B, specifically Figure B.10. In Romania, Slovakia, and Belgium, the 2006 tax and benefit systems would have cushioned the automation shock noticeably more than the 2018 systems. Only in Germany did the tax and benefit system shift in the opposite direction - the 2018 system mitigated the automation shock to a larger extent than the 2006 system would have. In the remaining countries, the outcomes are virtually the same under both systems.

4.4 Comparing automation's contribution to inequality to the total change in income inequality 2006–2018

Having quantified the overall contribution of automation to household income inequality and its components, we now compare it to the changes in inequality recorded in 2006–2018 in particular countries. This allows us to assess the economic significance of automation-driven inequality shifts.

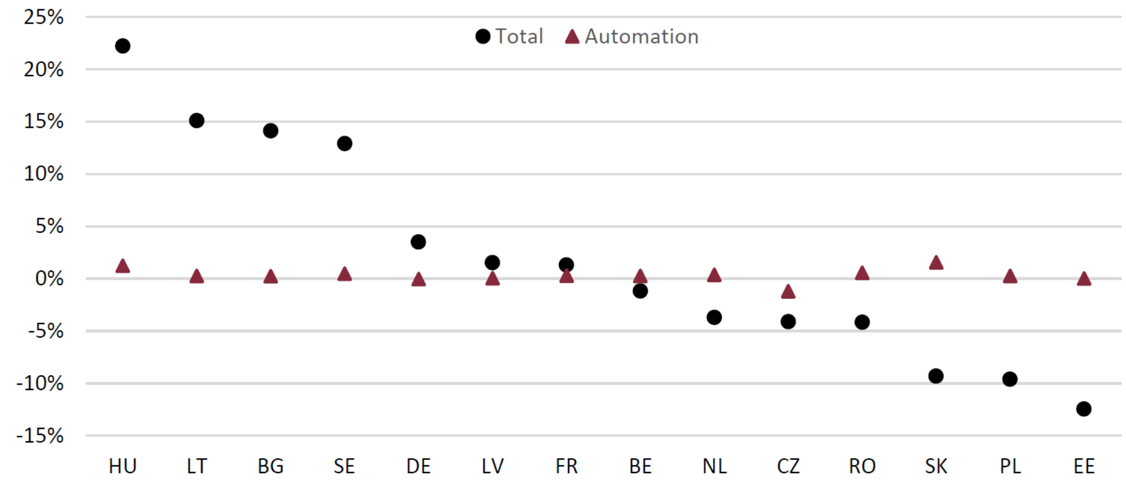
The change in income inequality between 2006 and 2018, as measured by the Gini index, varies widely across European countries in our sample (Figure 7). In some countries (Hungary, Bulgaria, Lithuania, and Sweden), income inequality widened substantially, with the Gini index increasing by more than 10%. In others (Slovakia, Poland, and Estonia), income inequality declined. Compared to these overall recorded changes, the contribution of automation is very small, as it ranges from –1.2% of the 2018 Gini in Czechia to 1.5% of the 2018 Gini in Slovakia (Figure 7). Across countries in our sample, the contributions of automation to inequality explain only 1.2% of the variance of changes in the Gini indices between 2006–2018 (Table 4). The wage channel explains a larger share of these differences than the employment channel, and benefits again emerge as the key cushioning mechanism (Table 4). Other changes in market income and the tax-benefit systems played a much larger role than robot adoption in the evolution of income inequality in European countries between 2006 and 2018—a period which covered the Great Recession and a sovereign debt crisis in several EU countries.

Table 4. Decomposition of channels behind and mechanisms cushioning the effect of automation on income inequality, in % of cross-country variance in the change in household income Gini index between 2006–2018

Automation (total)	Wage channel	Employment channel	Interaction	Household formation	Taxes	Benefits
1.2	1.6	-0.4	0.0	0.5	1.1	4.3

Notes: The contribution of a variable x (variables of interest in the table), to the variance of outcome variable y (the change in household income Gini index between 2006–2018) calculated as in Morduch and Sicular (2002): $\sigma_x = cov(x, y)/var(y)$. Data: EUROMOD, EU-SILC.

Figure 7. The change in household income Gini index between 2006–2018, and the contribution of automation



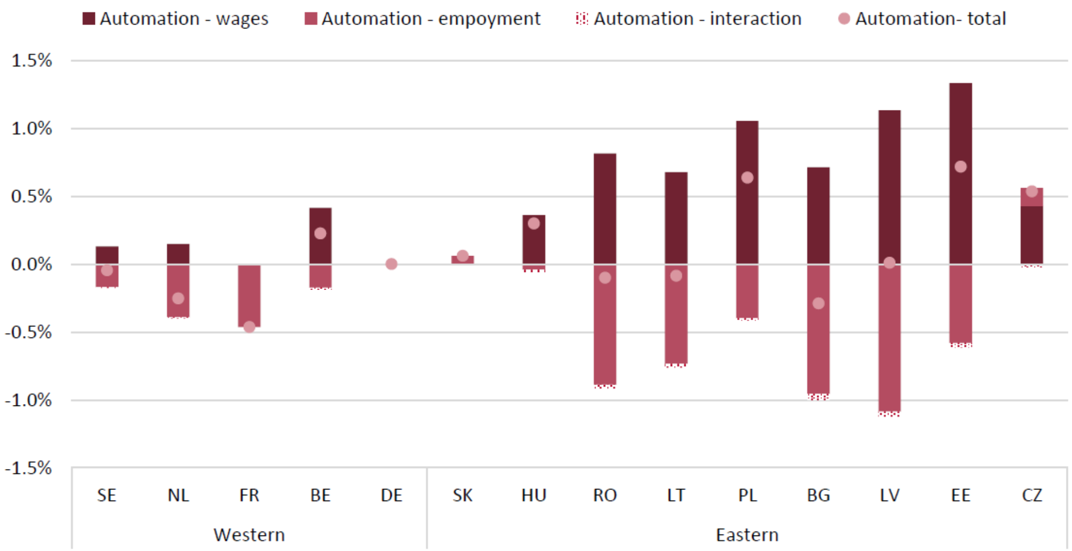
Notes: The figure shows the total change in the Gini Index between 2006 and 2018 as well as the automation-driven change in the Gini Index over the same period. Countries are ordered in decreasing order of the total change in the Gini Index. Data: EUROMOD, EU-SILC.

4.5 Isolating the role of differences in absorption of automation shocks: the effect of a "German" automation shock

Cross-country differences in automation-driven inequality shifts can result from differences in the size of the automation shock – the pace and scale of robot adoption – or from differences in the shock absorption. To differentiate between these, we construct another counterfactual scenario, using the same, hypothetical automation shock for each country. Specifically, we assess how income inequality would have changed if each country had experienced the German automation shock (Germany leads Europe in robot adoption) rather than a country-specific shock. This allows a degree of comparison across countries using a common, technological shock. Figure 8 shows how the country-specific automation shock impacts the 2018 Gini index, above and beyond what we expect from the German shock.

Generally, country-specific labour income shocks due to automation increased inequality more than the German automation shock would have. The effect of country-specific automation-induced employment changes drives this trend. In most countries, they compress inequality compared to German employment changes, as most countries lagged behind Germany in robot penetration (Figure B.1). In some countries, country-specific wage changes counteract this, as they widen inequality compared to German wage changes. Our results suggest that in most countries, rising robot penetration widened inequality less than if they had experienced the German path of automation of more widespread adoption of robots in 2006–2018. Admittedly, we do not know how this would have changed the path of their income inequality changes before 2006.

Figure 8. The difference between country-specific and German automation-driven changes in the Gini Index



Notes: The figure shows the difference between the country-specific and the German change in the Gini Index due to automation, decomposed into the difference between the country-specific and German wage effect, employment effect and interaction effect. Data: EUROMOD, EU-SILC.

We present further results on the German automation shock in Figures Appendix B. The composition of the German automation shock is illustrated in Figure B.6 while the cushioning of the German automation shock by country-specific household market income diversification and tax-benefit systems is illustrated in Figures B.7 and B.8. The former effect is reasonably similar for both the country-specific and German automation shocks. However, the country-specific tax-benefit systems in Eastern European countries cushion the German automation shock to a greater extent than they cushion the country-specific shocks. Owing to the inequality-increasing nature of the German employment shock, the main driver of this cushioning is the benefits system in each country. Taxation plays a more muted role.[11]

[11] In Appendix B, we also present evidence of how the transmission of the automation shock would be different under an alternative set of tax-benefit policies, namely those in effect in each country in 2006.

5 Conclusion

In this paper, we have studied the effects of robot exposure on household income inequality in 14 European countries between 2006 and 2018. We have combined estimating the effects of robot penetration on labour market outcomes (wages and employment rates) with microsimulation models that use these effects as input. This allows us to assess the relative role of automation and its interaction with household labour income diversification and tax-benefit systems in changes in household income inequality. Our unit of analysis has been a demographic group – we have defined 30 groups per country, based on gender, education, and age, and used an IV approach to obtain causal estimates. The impact we capture is, therefore, the contribution of 'between-group' differentials in wage growth and employment.

We have found that robot penetration had a significant negative impact on changes relative real hourly wages, employment rates, and individual market incomes of the directly affected groups in Europe, in line with the effects observed for the U.S. However, we have found that, for most countries, automation had little effect on household-level disposable income inequality. Automation-driven employment changes, which increased the number of adults with no market income, widened inequality. Automation-driven wage changes, which resulted in wage falls, decreased inequality in disposable income. The ability of the welfare system to 'passively' stabilise the income distribution – as described by Doorley et al. (2021) – resulted in some convergence between the incomes of those in and out of work and a corresponding fall in income inequality. As a result, inequality-increasing employment changes were partly or wholly counteracted by inequality-decreasing wage changes.

Delving into the mechanics of how automation-driven market income shocks translate into disposable income inequality, we found that tax-benefit systems provided much cushioning, especially in Western European countries. In general, the benefit systems played a dominant role, owing to the inequality-increasing nature of the automation employment shock. Taxation played a much more muted role, perhaps because wage effects already reduced inequality. The diversification of household labour incomes, related to occupational assortative mating, exacerbated the small increases in income inequality, mainly in Western European countries.

We conclude that, while robot penetration measurably affected wages and employment in European countries, its contribution to income inequality is small. It is greatly outweighed by other market income and policy changes over that time period – which, one must remember, also covered the Great Recession, the sovereign debt crisis, and resulting austerity measures in several countries. Consequently, automation explains only a minor share of changes in household income inequality in European countries between 2006 and 2018.

To be clear, our results on the distributive impacts of robot penetration should be interpreted as first-order estimates. The simulations do not consider behavioural responses to the increase in robot penetration as part of the "automation impacts". Changes in non-labour market incomes, fertility, or household structures between 2006 and 2018 that may have resulted from rising exposure to automation are *not* included in our calculation.[12] We also focus on distributive impacts through labour incomes: any potential increase in (the concentration of) capital income due to automation is not captured in the automation effect. Evidence from the U.S. suggests that automation raises capital incomes at the very top of the income distribution, thus widening inequality (Moll et al., 2022). In spite of recent moves by many statistical agencies to link survey data to administrative income information, capital incomes and top income earners remain both notoriously underestimated and underrepresented in survey data such as EU-SILC (see, e.g. Ravallion, 2022) and are therefore difficult to include reliably in our empirical analysis. Reassuringly, however, Carranza et al. (2023) show that *trends* in income inequality over time are not overly influenced by whether or not top income households are accurately represented.

Similarly, changes in tax-benefit parameters that may have been implemented in direct response to automation are not attributed to automation. However, we are not aware of any such policies being implemented in the countries we study. Finally, operating at the level of a demographic group by country, we follow Acemoglu and Restrepo (2022) and implicitly assume that robot penetration affects all individuals in a given demographic group and country equally. Our setting does not allow us to directly capture any potential increase in within-group wage dispersion due to automation, nor employment impacts that disproportionately affect specific sub-groups of workers within the demographic groups. However, we observe a negative relationship between automation and changes in within-demographic-group wage dispersion (Table B.6). Higher robot penetration reduced wages and employment of more exposed groups, but it tended to compress the within-group wage dispersion. Our (small) inequality-increasing impacts that neglect this within-group wage compression can therefore be interpreted as upper bounds.

[12]The evidence on robots' impact on fertility is limited. Anelli et al. (2021) showed that robots had no impact on fertility in the U.S. Matysiak et al. (2023) showed mixed effects in six European countries – negative for some groups, and positive for others.

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Appendix A Data Appendix

Table A.1. Variable descriptions

Variable	Description	Source
Socio-demographic characteristics		
Gender	a binary variable describing worker's sex (woman / man)	EU-SES
Education	a categorical variable describing worker's highest level of education completed, three categories: basic education (ISCED 0-2), secondary education (ISCED 3-4), and tertiary education (ISCED 5-8)	EU-SES
Age group	a categorical variable describing worker's age, five categories: 20-29, 30-39, 40-49, 50-59, 60 or more	EU-SES
Dependent Variables		
Change in real hourly wages	difference in log hourly wages (2006-2018)	EU-SES
Change in employment rate	difference in employment rate (2006-2018)	EU-LFS
Change in individual market income	difference in log individual market income (2006-2018)	EU-SILC
Change in household market income	difference in log equivalised household market income (2006-2018)	EU-SILC
Change in household disposable income	difference in log equivalised household disposable income (2006-2018)	EU-SILC
Group's industry-level exposure		
Automation	difference in the group's exposure to robots (robots per 1,000 workers, 2006-2018)	International Federation of Robotics
Industry shifters	group's exposure to change in log value added (2006-2018)	Eurostat
Routine tasks	relative specialization of a group g in industry i's routine jobs in 2006	EU-SES
Offshoring	difference in the group's exposure to offshoring measured as foreign value added in gross output (2006-2018)	OECD TiVA Indicators
Chinese imports penetration	difference in the group's exposure to the Chinese import penetration following Acemoglu et al. (2016): change in import from China (2006-2018) divided by initial absorption (industry outputs plus industry imports minus industry exports)	OECD TiVA Indicators
Collective bargaining coverage	exposure to collective bargaining coverage levels in 2006 (national- or industry-level agreements)	EU-SES
State ownership	exposure to firms controlled by the state in 2006 (over 50% of shares owned by the public authorities or de-facto control)	EU-SES
Other variables		
Manufacturing share	group's wage share in manufacturing in 2006	EU-SES
N.e.c. manufacturing share	group's wage share in manufacturing nowhere else classified (residual category) in 2006	EU-SES
Minimum wage bite	the number of workers with wages in 2006 below the 2018 minimum wage level divided by the number of all workers	EU-SES
Population change	change in log population of a group (2006-2018)	Eurostat
Employment rate change	change in employment rate of a group (2006-2018)	Eurostat

Notes: Description of variables used in the analysis.

Table A.2. Descriptive statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Gender: woman	420	0.48	0.50	0.00	1.00
Gender: man	420	0.52	0.50	0.00	1.00
Basic education	420	0.15	0.36	0.00	1.00
Secondary education	420	0.56	0.50	0.00	1.00
Tertiary education	420	0.29	0.45	0.00	1.00
Age: 20-29	420	0.19	0.39	0.00	1.00
Age: 30-39	420	0.27	0.44	0.00	1.00
Age: 40-49	420	0.28	0.45	0.00	1.00
Age: 50-59	420	0.22	0.41	0.00	1.00
Age: 60+	420	0.05	0.21	0.00	1.00
Log wage growth	420	0.26	0.30	-0.45	1.01
Employment rate change	420	0.04	0.07	-0.21	0.26
Automation: penetration of robots	420	0.83	0.59	0.01	2.40
Initial wages	420	1.59	0.98	-0.48	3.67
Industry shifters	420	0.21	0.15	-0.12	0.72
Offshoring	420	-0.00	0.01	-0.03	0.02
Chinese imports penetration	420	0.02	0.02	-0.00	0.23
Manufacturing share	420	0.27	0.13	0.02	0.72
N.e.c. manufacturing share	420	0.04	0.02	0.00	0.21
Routine tasks	420	1.00	0.40	0.11	3.22
Log income growth	390	0.70	0.59	-0.14	2.30
Employment rate change	420	0.04	0.07	-0.21	0.26
Minimum wage bite	420	0.40	0.31	0.00	1.00
Collective bargaining coverage	420	0.26	0.32	0.00	1.00
State ownership	420	0.25	0.16	0.01	0.77
Population change	420	-0.06	0.38	-2.10	1.14

Notes: This table presents the following statistics for each variable: Number of Observations, Average Value, Standard Deviation, Maximum and Minimum Value. The sources and description of the variables can be found in Table A.1.

Appendix B Additional Results

Table B.1. Automation and changes in real hourly wages - IV first stage results

	(1) Automation: penetration of robots	(2) Automation: penetration of robots	(3) Automation: penetration of robots	(4) Automation: penetration of robots
Automation: penetration of robots (IV)	0.377***	0.376***	0.425***	0.424***
	(0.020)	(0.020)	(0.027)	(0.027)
Country FE	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes
Gender	no	yes	yes	yes
Education	no	no	yes	yes
Industry shifters	no	no	no	yes
F-statistic first stage	351.39	340.74	253.84	255.54
Observations	420	420	420	420

Notes: Table reports the first stage for our baseline IV estimation. The dependent variable is the change in log wages for each group from 2006 to 2018. In all regressions, we control for initial wage levels, manufacturing share of employment, manufacturing n.e.c. share of employment, gender, education, industry shifters and country fixed effects. All regressions are weighted by the share of the country's employment. Robust standard errors are reported.
Data: EU-SES. * p<.10; ** p<.05; *** p<.01

Table B.2. Automation and changes in real hourly wages - heterogeneity by region

	2SLS	2SLS
Automation: penetration of robots	-0.064***	-0.079***
	(0.021)	(0.027)
Automation*Western Europe		0.025
		(0.058)
Manufacturing share	yes	yes
Gender	yes	yes
Education	yes	yes
Industry shifters	yes	yes
F-statistic first stage	260.93	74.95
Mean of outcome	0.26	0.26
Mean of automation	0.83	0.83
Observations	420	420

Notes: Table shows the effects of penetration of robots on change in log wages. Column 1 shows the baseline results. In column 2, we add the interaction of the penetration variable with a dummy variable for Western Europe. The coefficient on the interaction shows the difference in the effects between Western and Eastern Europe. In column 1, we control for initial wage levels, manufacturing share of employment, manufacturing n.e.c. share of employment, gender, education, industry shifters and country fixed effects. In column 2, we additionally control for the interactions of all control variables with the region dummy. All regressions are weighted by the share of the country's employment. Robust standard errors are reported.
Data: EU-SES. * p<.10; ** p<.05; *** p<.01

Table B.3. Automation and changes in real hourly wages - additional controls

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) 2SLS	(9) 2SLS
Automation: penetration of robots	-0.064***	-0.067***	-0.057***	-0.083***	-0.054***	-0.065***	-0.076***	-0.078***	-0.076***
	(0.021)	(0.024)	(0.020)	(0.021)	(0.021)	(0.021)	(0.020)	(0.021)	(0.026)
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes	yes	yes	yes	yes	yes
Gender	yes	yes	yes	yes	yes	yes	yes	yes	yes
Education	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry shifters	yes	yes	yes	yes	yes	yes	yes	yes	yes
Routine tasks	no	yes	no	no	no	no	no	no	yes
Offshoring	no	no	yes	no	no	no	no	no	no
Chinese imports penetration	no	no	no	yes	no	no	no	no	yes
Minimum wage bite	no	no	no	no	yes	no	no	no	yes
Collective bargaining coverage	no	no	no	no	no	yes	no	no	yes
State ownership	no	no	no	no	no	no	yes	no	yes
Population change	no	no	no	no	no	no	no	yes	yes
F-statistic first stage	260.93	165.41	269.57	247.26	254.06	265.02	273.17	257.70	167.01
Observations	420	420	420	420	420	420	420	420	420

Notes: Table shows estimates of the relationship between task displacement due to automation and the change in log wages across 30 demographic groups in 18 European countries. The dependent variable is the change in log wages for each group from 2006 to 2018. In all regressions, we control for initial wage levels, manufacturing share of employment, manufacturing n.e.c. share of employment, gender, education, industry shifters and country fixed effects. All regressions are weighted by the share of the country's employment. Column 1 shows our baseline estimates. In column 2, we additionally control for the relative specialization in routine tasks. In column 3, we additionally control for the increase in the exposure to offshoring. In column 4, we additionally control for the Chinese imports penetration. In column 5, we additionally control for minimum wage bite. In column 6, we additionally control for initial collective bargaining coverage. In column 7, we additionally control the initial employment share in state-controlled firms. In column 8, we additionally control for population change. In column 9, we control for all additional variables. The sources and description of the variables can be found in Table A.1. Robust standard errors are reported.
Data: EU-SES. * p<.10; ** p<.05; *** p<.01

Table B.4. Effects of automation on changes in real hourly wages and employment rates - original Acemoglu & Restrepo instrument

	(1) Hourly wage	(2) Hourly wage	(3) Employment	(4) Employment
Automation: penetration of robots	-0.132***	-0.078***	0.012	-0.029
	(0.033)	(0.030)	(0.021)	(0.028)
Country FE	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes
Gender	no	yes	no	yes
Education	no	yes	no	yes
Industry shifters	no	yes	no	yes
F-statistic first stage	169.38	139.05	186.19	96.32
Mean of outcome	0.26	0.26	0.04	0.04
Mean of automation	0.83	0.83	0.83	0.83
Observations	420	420	420	420

Notes: Table shows estimates of the effects of the penetration of robots on changes in log wages and employment rates between 2006 and 2018. The alternative instrument is based on five countries selected by Acemoglu and Restrepo (2022): Denmark, Finland, France, Italy, and Sweden. All regressions are weighted by the group's share of the country's employment. Robust standard errors are reported.
Data: EU-SES. * p<.10; ** p<.05; *** p<.01

Table B.5. Effects of automation on changes in real hourly wages and employment rates - US instrument

	Hourly wage	Hourly wage	Employment	Employment
Automation: penetration of robots	-0.060***	-0.034	-0.006	-0.043**
	(0.023)	(0.021)	(0.016)	(0.020)
Country FE	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes
Gender	no	yes	no	yes
Education	no	yes	no	yes
Industry shifters	no	yes	no	yes
F-statistic first stage	319.95	286.18	345.62	244.01
Mean of outcome	0.26	0.26	0.04	0.04
Mean of automation	0.83	0.83	0.83	0.83
Observations	420	420	420	420

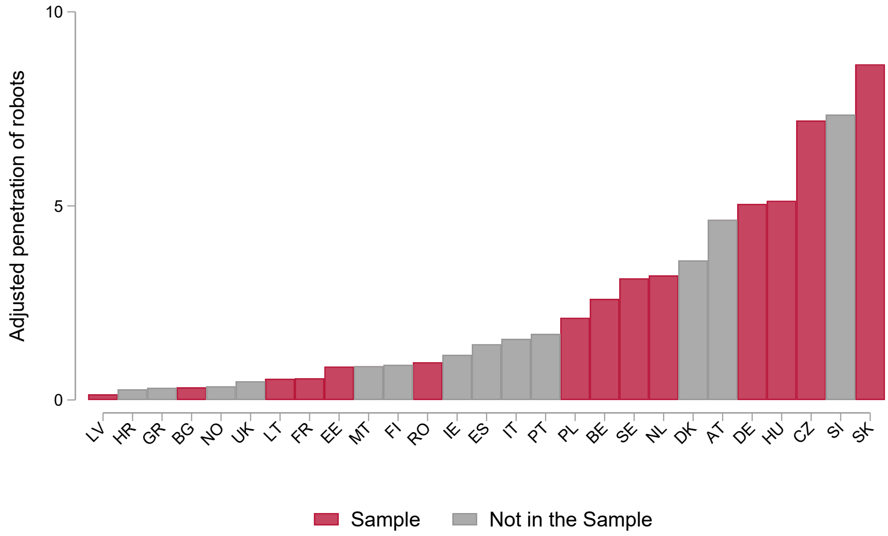
Notes: Table shows estimates of the effects of the penetration of robots on changes in log wages and employment rates between 2006 and 2018. We instrument the industry-level adjusted penetration of robots by the adjusted penetration of robots in the United States. All regressions are weighted by the group's share of the country's employment. Robust standard errors are reported.
Data: EU-SES. * p<.10; ** p<.05; *** p<.01

Table B.6. Automation and changes in wage dispersion within demographic groups, 2006-2018

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Automation: penetration of robots	-0.171***	-0.146***	-0.118***	-0.120***
	(0.025)	(0.023)	(0.024)	(0.024)
Country FE	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes
Gender	no	yes	yes	yes
Education	no	no	yes	yes
Industry shifters	no	no	no	yes
F-statistic first stage	346.14	337.11	250.05	250.93
Mean of outcome	0.04	0.04	0.04	0.04
Mean of automation	0.83	0.83	0.83	0.83
Observations	420	420	420	420

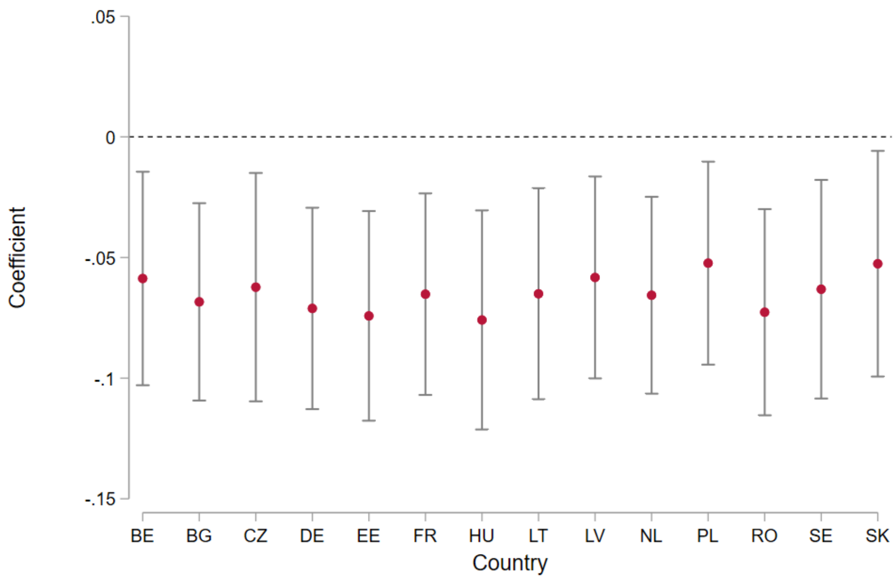
Notes: Table shows estimates of the effects of the penetration of robots on changes in within-demographic-group wage dispersion between 2006 and 2018. The dependent variable is the change in the coefficient of variation of wages from 2006 to 2018. All regressions are weighted by the group's share of the country's employment. Robust standard errors are reported.
Data: EU-SES. * p<.10; ** p<.05; *** p<.01

Figure B.1. Adjusted penetration of robots in Europe (2006-2018)



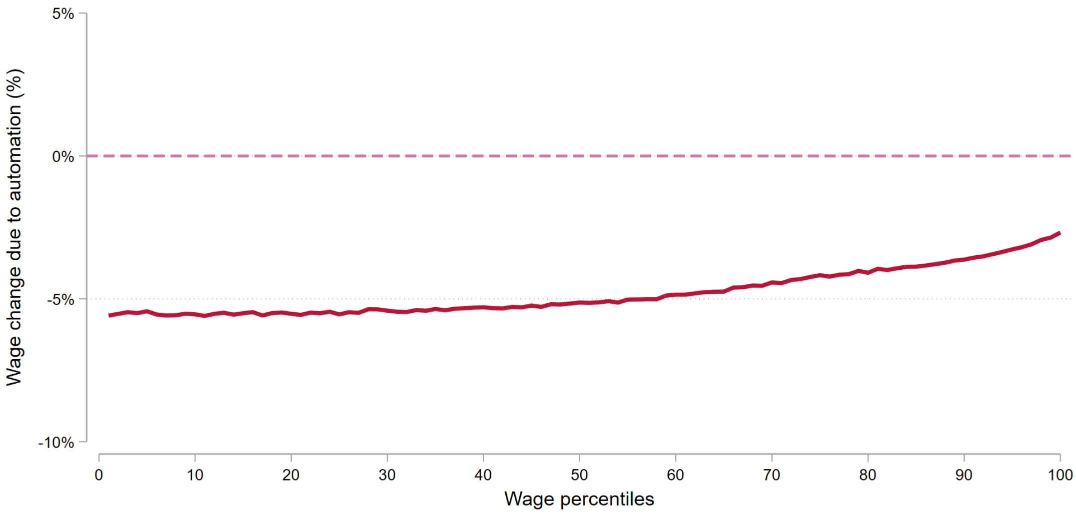
Notes: Figure shows the adjusted penetration of robots in European countries (the 2006-2018 increase in the robots per worker adjusted for the industry-level growth of output). The red bars denote the countries included in our study.
Data: IFR & Eurostat.

Figure B.2. Automation and changes in real hourly wages, leave-one-out test



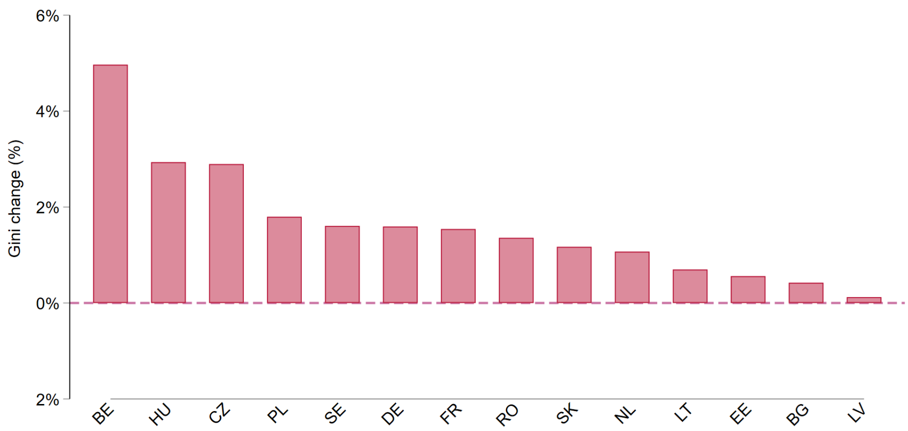
Notes: Figure shows the point estimates and 95% confidence intervals of the effects of the penetration of robots on changes in log wages between 2006 and 2018. In each regression, we remove one country (displayed on the x-axis).

Figure B.3. Wage changes due to automation, by percentiles of the initial (2006) pooled wage distribution



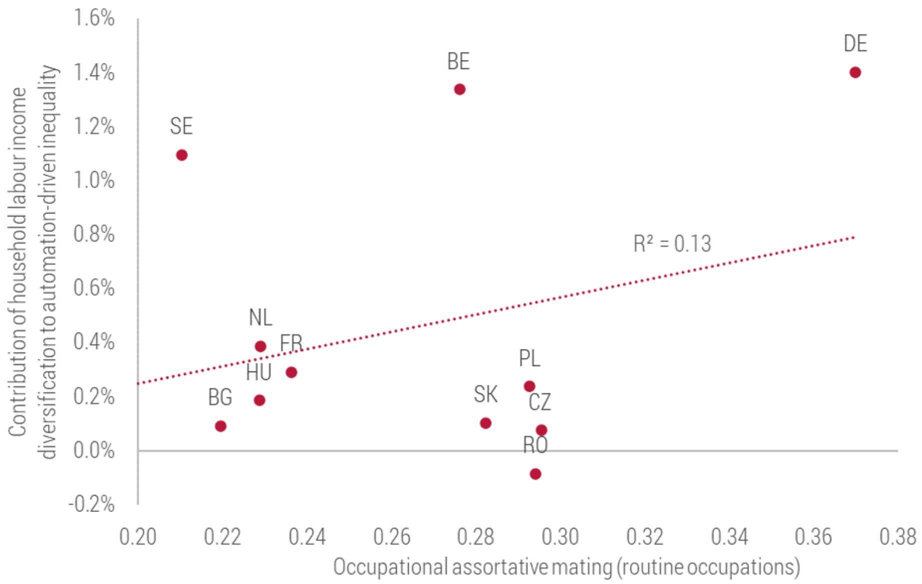
Notes: Figures show the average wage changes due to automation for percentiles of the within-country wage distribution. Wage changes due to automation are computed by multiplying the group's increase in exposure to automation by the wage effects of automation from the equation 3. We compute the wage changes due to automation for each percentile of the 2006 wage distribution within each country and then calculate average wage changes across 14 countries in the sample. Results by country are shown in Figures 2-3.
Data: EU-SES.

Figure B.4. The contribution of automation to wage inequality (Gini index of hourly earnings)



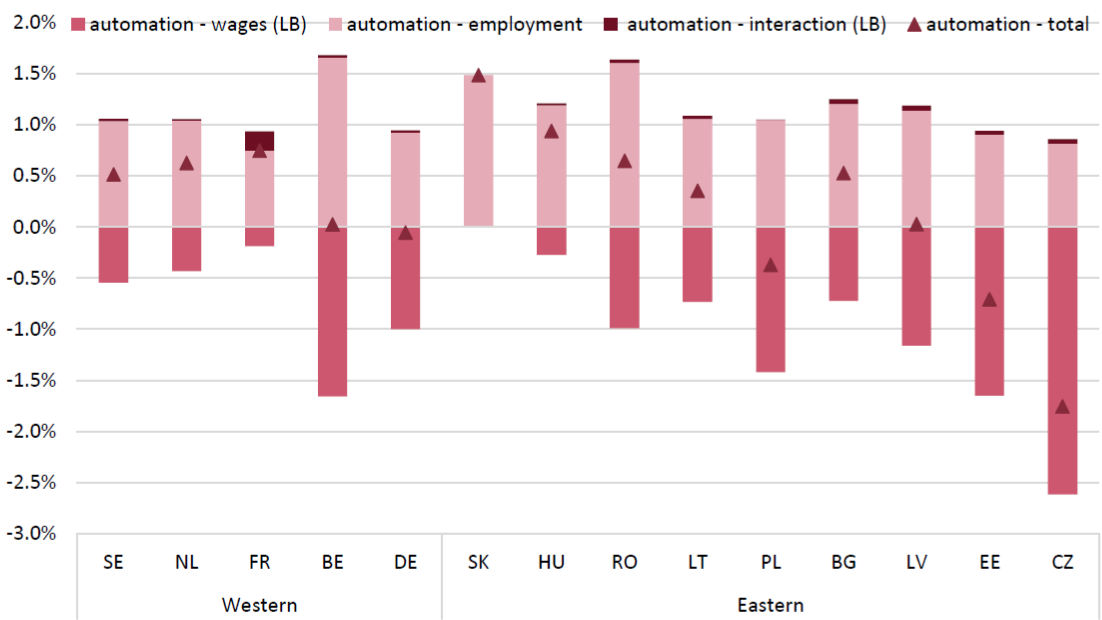
Notes: Figure shows the difference between the Gini index of hourly wages in 2018, and in a counterfactual scenario with no changes in automation between 2006-2018.
Data: EU-SES.

Figure B.5. The contribution of household income diversification to automation-driven inequality vs. the incidence of occupational assortative mating among workers in routine occupations



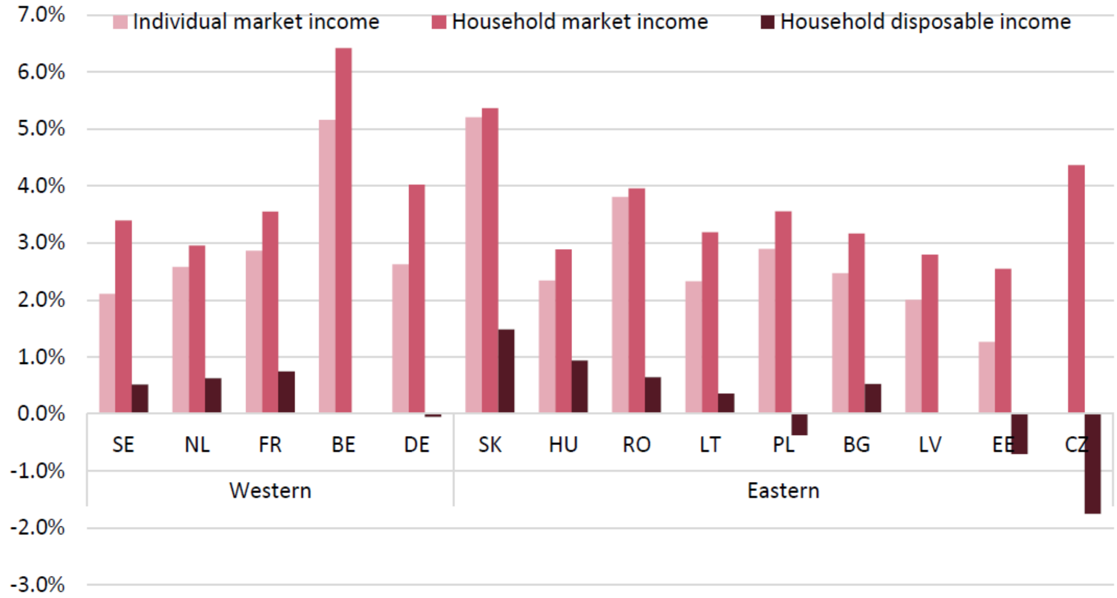
Notes: The incidence of assortative mating defined as a share of workers in routine occupations who form a household with a person who also works in a routine occupation, in all households that include at least one person working in a routine occupation.
Data: EUROMOD, EU-SILC.

Figure B.6. The effect of German automation shock on inequality in disposable household income



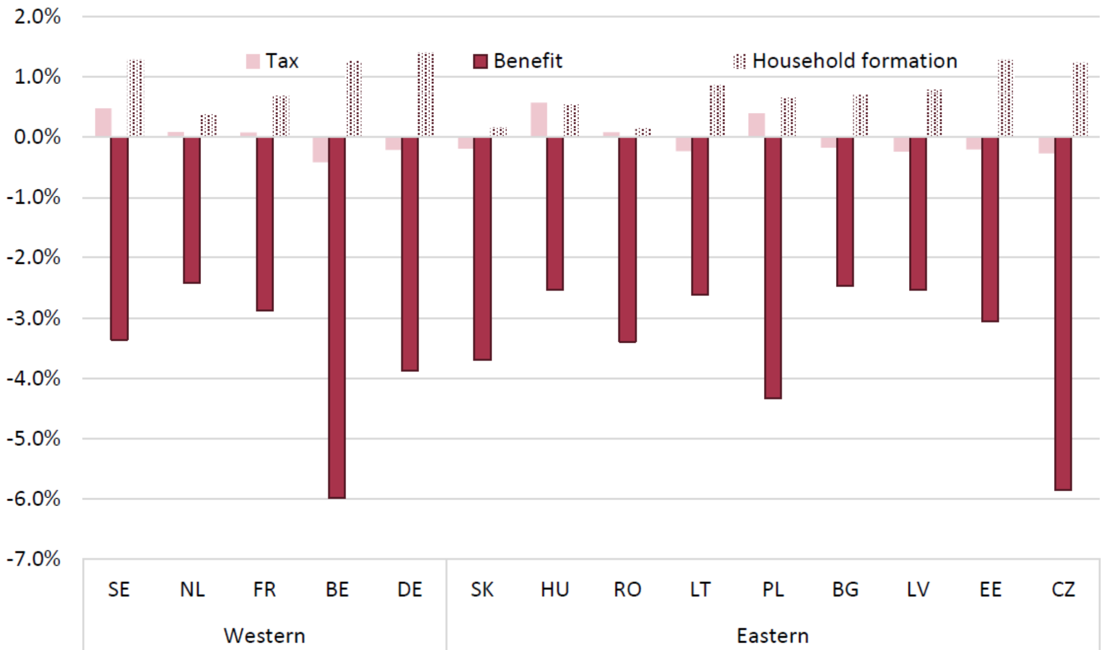
Notes: The figure shows the effect of a hypothetical German automation shock to the Gini Index in each country, decomposed into the contribution of wage, employment and interaction effects.). Data: EUROMOD, EU-SILC.

Figure B.7. The contribution of automation to income inequality using various income concepts - German automation shock



The figure shows the change in income inequality due to a hypothetical German automation shock where income is defined as (i) market income at the individual level (ii) equivalised market income at the household level and (iii) equivalised disposable income at the household level. Countries are ordered, within Eastern and Western Europe, in decreasing order of the total change in the Gini Index due to automation. Data: EUROMOD, EU-SILC.

Figure B.8. The cushioning effect of the tax-benefit system and household formation on automation-induced inequality changes - German automation shock



Notes: The figure shows the effect of taxes, benefits and household risk-sharing on the change in the Gini Index due to the German automation shock. Countries are ordered, within Eastern and Western Europe, in decreasing order of the total change in the Gini Index due to automation. Data: EUROMOD, EU-SILC.

The cushioning effect of the tax-benefit system: 2006 vs 2018

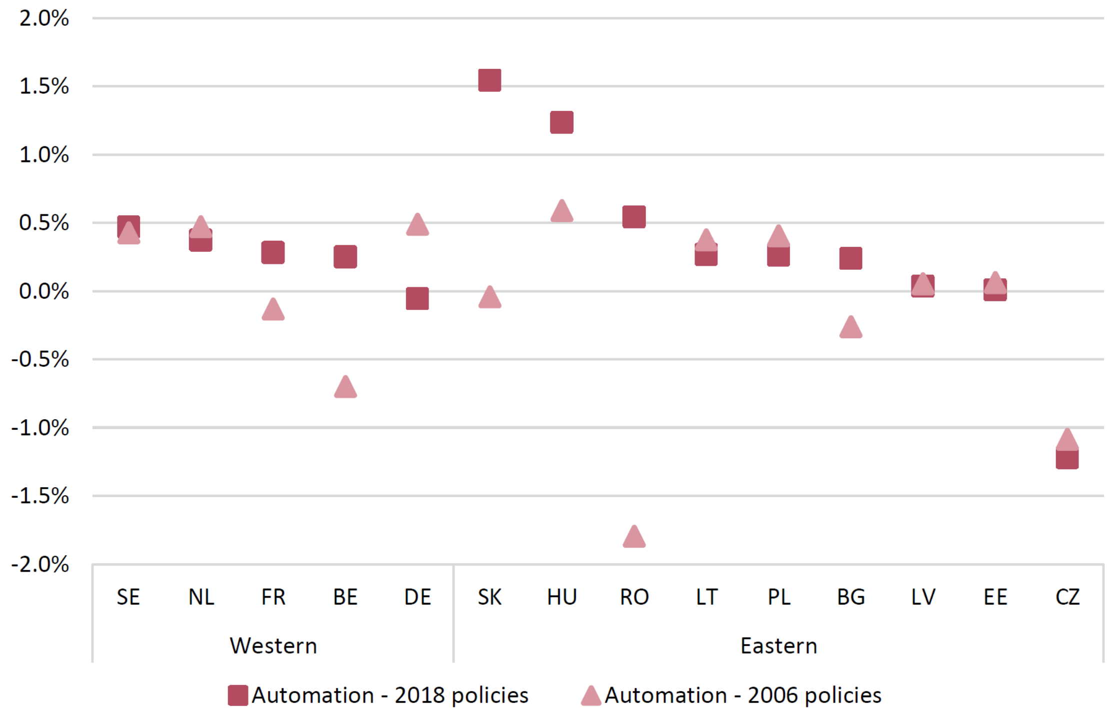
To investigate how the tax-benefit system interacts with automation-driven market income changes, we compare the automation effect shown in Figure 4 to a hypothetical scenario in which an indexed version of the 2006 tax-benefit system was in place in each country.[13] In essence, this shows how discretionary changes to tax and welfare payments between 2006 and 2018 affected the transmission of automation-induced labour income changes into disposable income inequality. The hypothetical effect of automation on income inequality if an indexed 2006 tax-benefit system was in place in 2018 is shown in Figure B.9.

In most countries, the transmission of the automation-induced market income changes is very similar under the set of 2006 policies. So, for most countries in the sample, the 2018 tax-benefit system does not interact with automation changes differently to a price-indexed

[13] This is accomplished by applying the 2006 tax-benefit system to the 2018 population where incomes are deflated by HICP.

2006 system. Two exceptions to this are Romania and Slovakia. In both countries, the 2006 tax-benefit system would have cushioned the automation driven inequality changes by substantially more than the 2018 system.

Figure B.9. Effect of automation on inequality in disposable household income: 2006 vs 2018 tax and benefit policies



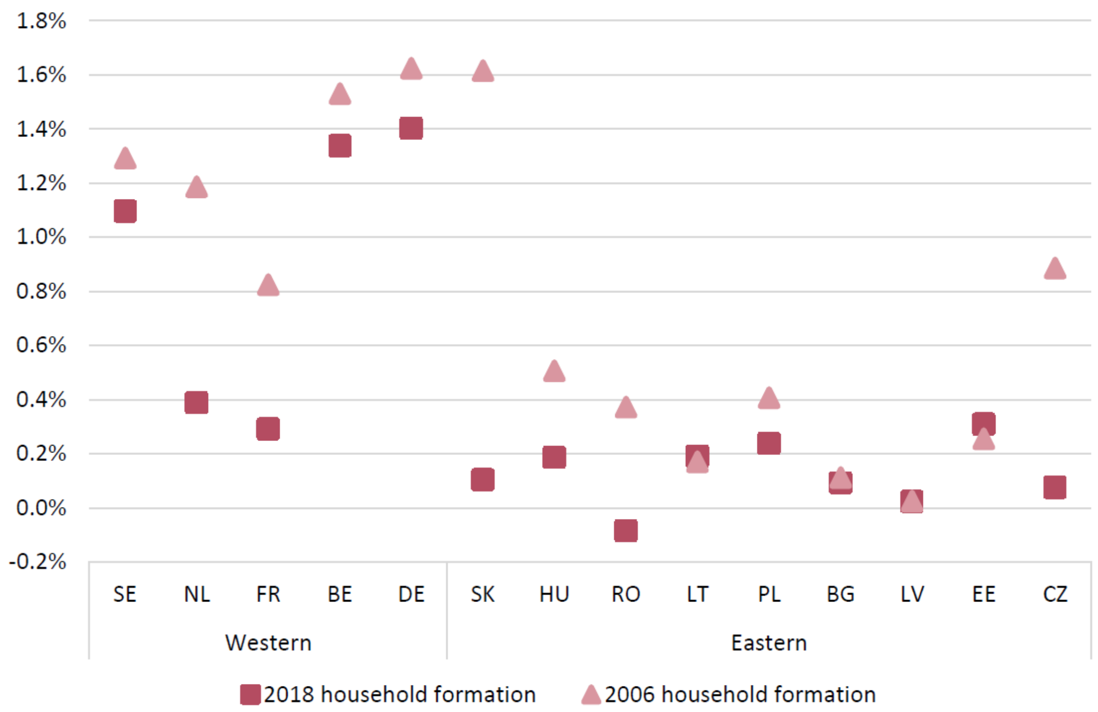
Notes: The figure shows the simulated effect of automation on income inequality under (i) the 2018 tax-benefit system and (ii) if an indexed 2006 tax-benefit system was in place in 2018. Countries are ordered, within Eastern and Western Europe, in decreasing order of the total change in the Gini Index due to automation. Data: EUROMOD, EU-SILC.

The cushioning effect of household formation: 2006 vs 2018

Household formation changes over time. Notable trends in Europe over the last few decades include delayed marriage and childbirth (Eurostat, 2021), and the elderly living longer (Eurostat, 2022). In this sensitivity analysis, we compare the cushioning effect of household formation on the automation shock to its counterfactual value if household formation in 2018 followed the 2006 structure. In practical terms, this involves injecting the automation shock into the 2006 simulation of income inequality, calculating the difference between how individual level market income inequality changes and how household level market income inequality changes, and comparing this double difference to the same calculation performed on the 2018 simulation of income inequality, with and without the automation shock.

Figure B.10 shows how household formation affects the transmission of the automation shock using the 2006 population structure and the 2018 population structure. The latter effect replicates that already shown in Figure 6. For most countries, the cushioning effect of household formation on the automation shock is similar for the two population structures. Some exceptions in Western Europe include the Netherlands, Germany and France. In all cases, household formation in 2006 would have amplified the effect of automation on income inequality, compared to household formation in 2018. This indicates more household risk sharing in these countries in 2018 compared to 2006. In Eastern Europe, only Slovakia and Czechia display different cushioning effects in the two scenarios. Similar to the patterns for Western Europe, in both cases, household formation in 2018 performs more cushioning for the automation shock than household formation in 2006.

Figure B.10. The cushioning effect of household formation: 2006 vs 2018



Notes: The figure shows the cushioning effect of household formation on the automation shock in 2018 (similar to Figure 6) and a counterfactual cushioning effect if household formation followed the 2006 structure.

Appendix C Details on the microsimulation of wage and employment shocks

To assess the impact of wage and employment changes on the evolution of income inequality between 2006 and 2018, we build on the framework outlined by Bargain and Callan (2010).

First, denote $\mathbf{Y} := (X, Y^L, Z)$ a $N \times k$ matrix with, for each of N households, $k-2$ socio-demographic characteristics (X, including gender, education and age of all household members), labour income (Y^L), and other market incomes (Z). Let $d(\cdot, p)$ denote a 'tax-benefit function' which calculates household disposable income on the basis of household characteristics, pre-tax incomes, and a set of tax-benefit policy rules and parameters. p denotes nominal values of monetary tax-benefit parameters (e.g., tax brackets, benefit amounts, eligibility thresholds, etc.). So, $y^d = d(\mathbf{Y}, p)$ is a $N \times 1$ vector of final disposable incomes implied by the tax-benefit system for a population with market incomes and characteristics given by $\mathbf{Y}$. Income inequality in disposable income is denoted $I\left[y^d\right]$ where $I : R^N \mapsto [0, 1]$ is a summary inequality index such as the Gini coefficient.

Here, the function d is the EUROMOD tax-benefit calculator. EUROMOD is a static tax-benefit calculator for the EU countries, which allows for a comparative analysis of tax-benefit systems through a common framework (Sutherland and Figari, 2013). With information about socio-demographic and labor market characteristics as well as market incomes (earnings, but also capital income) of all household members, EUROMOD simulates disposable income for households by applying (existing or counterfactual) tax-benefit rules. Input data from EUROMOD is obtained from EU-SILC and the vector of N household observations is therefore representative of the populations of all European Union countries.

Introducing subscripts for time, we write inequality in year t as $I\left[d_t((X_t, Y_t^L, Z_t), p_t)\right]$. The total change in a given distributional index between two time periods, $t = 0$ (2006) and $t = 1$ (2018), can then be written as

$$\Delta I = I\left[d_1((X_1, Y_1^L, Z_1), p_1)\right] - I\left[d_0((X_0, Y_0^L, Z_0), p_0)\right] \qquad (5)$$

We use this formulation to assess the (marginal) change in the Gini coefficient induced by automation-induced employment changes and automation-induced wage changes. The automation-induced employment change effect is obtained by constructing

$$\Delta^{AE}I = I\left[d_1((X_1, Y_1^L, Z_1), p_1)\right] - I\left[d_1((\tilde{X}_1, Y_1^L, Z_1), p_1)\right]$$

where $\tilde{X}_1$ is the period 1 data reweighted such that employment probabilities by socio-demographic groups (by education, gender and age cells) map the employment probabilities that would have been expected in 2018 in the absence of automation effects. The automation-induced wage effect is obtained as

$$\Delta^{AW}I = I\left[d_1((X_1, Y_1^L, Z_1), p_1)\right] - I\left[d_1((X_1, \tilde{Y}^{L_1}, Z_1), p_1)\right]$$

where $\tilde{Y}^{L_1}$ is period 1 wages of employed individuals scaled down by the automation-induced predicted wage growth by socio-demographic group between period 0 and 1

$$\tilde{Y}_1^L = diag(dw(X_0))Y_1^L \tag{6}$$

where $dw(X_0)$ is the vector automation-induced relative change in wage for the year 0 population (X_0 includes gender, education, age characteristics). The contribution of the combination between wage and employment is obtained by combining counterfactuals:

$$\Delta^{AWE}I = I\left[d_1((\tilde{X}_1, \tilde{Y}_1^L, Z_1), p_1)\right] - I\left[d_1((X_1, Y_1^L, Z_1), p_1)\right].$$

The three terms Δ^{AE}, Δ^{AW} and Δ^{AWE} capture the effect of automation that we are primarily interested in (holding everything else constant in the base year 1—other incomes, individual characteristics, and tax-benefit policies). The estimates of the terms can be interpreted as the marginal change in the Gini coefficient that we would observe relative to 2018 if we apply a 'time-machine' that undoes the effect of automation-induced employment and/or wage change since 2006.

As explained in the main text, to adjust wages, we first divide the hourly wages of all employed workers in the 2018 EU-SILC by $(1 + \hat{\beta}^w \cdot TDA_{g,c})$ according to their demographic group g and country c. Such deflated wages reflect counterfactual wages in 2018 the absence of increased robot penetration since 2006. We then recalculate household incomes by aggregating deflated wages into annual labour incomes for all household members, adding non-labour incomes and imputing social transfers, taxes and social security contributions calculated from the 2018 tax-benefit calculator EUROMOD.

To inject changes in employment into 2018 EU-SILC, we 'reweight' each respondent by a factor

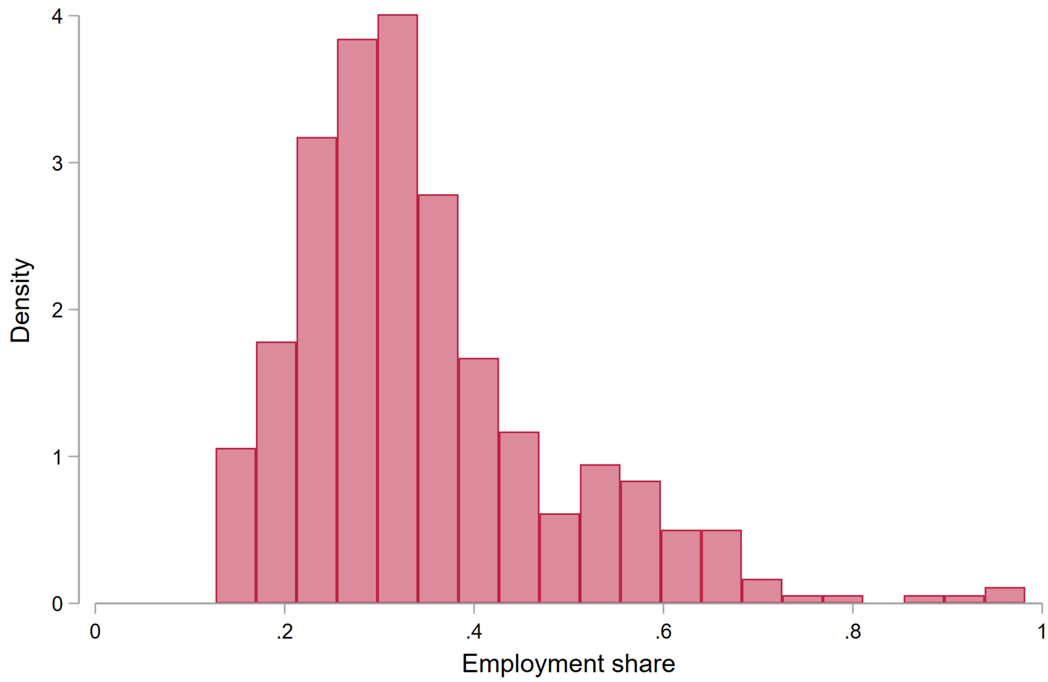
$$E_i \frac{p_{g,c}}{(1+\hat{\beta}^e \cdot TDA_{g,c}) - p_{g,c}} + (1-E_i)\frac{(1+\hat{\beta}^e \cdot TDA_{g,c}) - p_{g,c}}{p_{g,c}}$$

where $E_i = 1$ if respondent i is employed and 0 otherwise, $p_{g,c}$ is the 2018 employment rate of individuals in group g and country c, and $\hat{\beta}^e \cdot TDA_{g,c}$ is the estimated employment effect of robot penetration. Accordingly, the reweighted 2018 EU-SILC samples have employment rates by group and country that reflect what would have been observed in the absence of employment effects from robot penetration.

Appendix D Accounting for incomplete coverage of employment in small firms

The EU-SES data we use to estimate the effects of robot penetration cover only firms with at least 10 workers. The employment share of workers employed in firms with fewer than 10 workers or self-employed varies substantially across demographic groups in our sample. Still, it is substantial in some of them (see Figure D.1).

Figure D.1. The share of workers in firms with fewer than 10 workers, or self-employed, across demographic groups (% of groups' total employment)



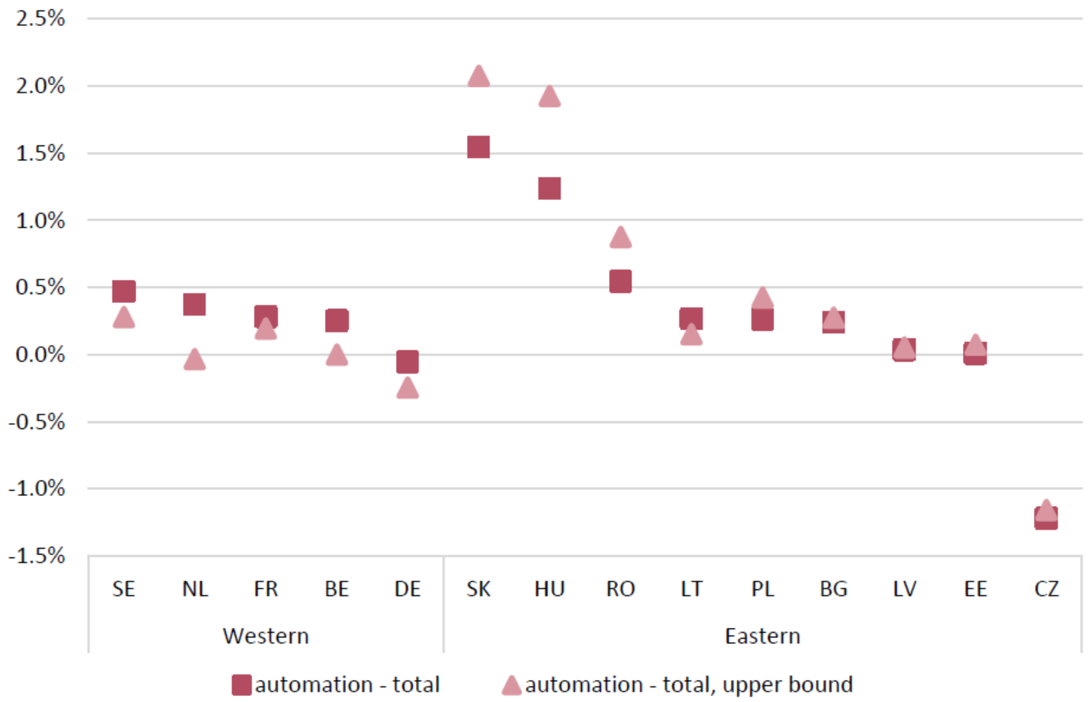
Data: EU-LFS.

As automation technologies such as robots are generally used in larger firms, workers in the EU-SES sample are likely more exposed to robots than workers in smaller firms. As a consequence, automation's impact on workers in firms with at least 10 workers may be larger than the effects on all workers. Hence, for each demographic cell, we multiplied the counterfactuals by the share of workers in firms with at least 10 workers.

As a robustness check, we also simulated household incomes assuming that in each demographic group, all workers were affected by robots in the same way as workers in the EU-SES sample. This provides an upper-bound calculation of automation's contribution to household inequality.

For most countries, the baseline and upper-bound results are very similar (Figure D.2). The upper-bound results are noticeably larger (in absolute terms) than the baseline results only in Eastern European countries with the largest contribution of automation to income inequality, such as Slovakia and Hungary. Still, the upper-bound contribution in these countries is around 2% of the 2018 Gini coefficient.

Figure D.2. The contribution of automation to income inequality – baseline results vs. upper-bound results



Notes: baseline results - for each demographic group, we weighted the counterfactual that isolates labour market effects of robot penetration in 2006-2018 by the employment share of firms with at least 10 workers. Upper-bound results - for each demographic group we assume that all workers are affected by robot penetration in the same way as those in firms with at least 10 workers.
Data: EU-LFS.

LUXEMBOURG INSTITUTE OF
SOCIO-ECONOMIC RESEARCH

11, Porte des Sciences
Campus Belval
L-4366 Esch-sur-Alzette

T +352 58 58 55-1
F +352 58 58 55-700

www.liser.lu