

Automation and Income Inequality in Europe*

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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 of rapid adoption of industrial robots. Automation reduced relative hourly wages and employment of the most exposed demographic groups, similarly to results for the US. Using robot-driven wage and employment shocks as input to the EUROMOD microsimulation model, we find however that automation had minor effects on income inequality. Household labor income diversification, and tax and welfare policies, especially transfers, largely absorbed labor income shocks caused by automation.

JEL codes: J24, O33, J23

Keywords: robots, automation, tasks, income inequality, wage inequality, microsimulation

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The rapid automation of job tasks raises concerns about its effects on worker welfare. Does Europe, with its strong labor market institutions and high levels of redistribution, shield workers from potential adverse effects of automation? Evidence from country-specific studies remains inconclusive and is limited to the effects on wages and employment. Automation and other technologies that replace routine tasks often disadvantage low-wage workers while benefiting high-wage workers who perform non-routine tasks. This dynamic tends to widen wage inequality. In the U.S., for instance, the job and wage losses driven by robots were particularly pronounced for lower-paid workers (Acemoglu & Restrepo, 2022). European labor markets, however, may behave differently, as stronger employment protection laws, more generous safety nets, and higher unionization may limit the likelihood of automation-driven layoffs or wage cuts. This paper goes beyond assessing the labor market effects of automation by evaluating its impact on household incomes and inequality in 14 European countries. It also investigates the role of diversification of household incomes and tax-benefit systems in cushioning the impact of automation-driven labor demand shocks on income inequality.

To explore how automation, particularly the rise of industrial robots, affects household income inequality, we combine econometric and microsimulation methods. We measure automation as the growth of robots per worker, relative to economic output. First, we estimate automation's impact on wages and employment, two critical factors shaping income distribution. To this aim, we use large, linked employer-employee and household survey data from 14 European countries from 2006 to 2018—a period when the use of robots surged by over 80%. Following Acemoglu and Restrepo (2022), we distinguish 30 demographic groups (based on age, gender, and education) in each country, and estimate the effect of robot exposure on wages, employment rates, and household incomes across these groups. To obtain causal estimates, we employ an instrumental variable approach that leverages plausibly exogenous trends in robot adoption from five European countries outside our sample.

Second, we use the econometric results to calculate counterfactual scenarios which we then use in microsimulation models. Specifically, we calculate employment rate and wage levels that would have been recorded in 2018 if robot exposure remained at the 2006 level. These serve as inputs to the EUROMOD tax-benefit model. To assess how automation has shaped income inequality, we simulate household incomes in 2018 conditional on erasing the wage and employment changes driven by automation since 2006, and accounting for adjustments of taxes and transfers. By comparing the actual and counterfactual income distributions, we quantify the impact of automation on inequality. We also disentangle the role of wage and employment channels and isolate the role of diversification of household income sources, taxes, and benefits in alleviating automation-driven income losses.

1 Literature and contribution

The increase in income inequality in recent decades was driven primarily by the surging inequality in labor income (Acemoglu & Robinson, 2015). Acemoglu and Restrepo (2022) show that approximately two-thirds of changes in the U.S. wage inequality is due to adverse effects of task-displacing automation. However, in other highly developed countries, such as Germany or Japan, the employment effects of robots have been neutral or positive (Adachi et al., 2024; Dauth et al., 2021). Across high-income countries, automation increased productivity, while reducing employment shares of low-skilled workers and routine occupations (Chung & Lee, 2023; Graetz & Michaels, 2018; de Vries et al., 2020). It benefited younger workers and prime-aged women at the expense of older workers and prime-aged men (Albinowski & Lewandowski, 2024). Beyond potential aggregate effects, automation thus creates winners and losers. A flourishing literature has studied its employment and wage effects, but its impact on household incomes and distributional consequences remain under-researched.

This paper makes two contributions. First, we provide causal evidence of the medium-term effects of automation with industrial robots 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 labor 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 labor market effects of robot adoption in Germany are tiny, unlike in the U.S. Gregory et al. (2021) found worker displacement effects of routine-replacing technologies more generally, but also argued that product demand effect of these technologies counterbalanced them, leading to small net employment gains in Europe. 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, these studies also showed that robots reduce blue-collar workers' wages in adopting firms, and employment in non-adopting competitors. 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 and higher-skilled workers reap the benefits from automation.¹

Using plausibly exogenous variation in robot penetration, we show that, in Europe, the demographic groups more exposed to robots experienced relative wage and employment declines.² These effects are quantitatively moderate but they are robust to controlling for a wide

¹For instance, Aksoy et al. (2021) found that robot adoption widens the gender pay gap within sectors and occupations in Europe, as higher-skilled men benefit the most from robot-driven productivity improvements.

²Studies focusing on the within-sector effects showed that robots reduce the employment shares of lower-skilled (Graetz & Michaels, 2018) and of male routine (Albinowski & Lewandowski, 2024) workers, suggesting disequalising impacts of automation. However, such within-sector or within-occupation effects can be partly driven by changes in worker sorting over time (Böhm et al., 2024). Our approach of utilising variation in robot

range of potential confounders and cross-country differences in key labor market institutions, such as minimum wage policies.

Our second contribution is quantifying how these automation-driven labor market shocks have impacted national household income inequality levels. Our analysis isolates the overall distributive effect of automation across European countries – distinguishing between the contributions of automation-driven wage and employment channels.³ We assess the role of diversification of labor income sources within households and of the tax-benefit systems in mitigating the transmission of automation-driven shocks into disposable income inequality. There is little direct evidence on this issue to date although Bessen et al. (2025) found that benefits cushion the incomes of workers who lose jobs in the aftermath of robot adoption in the Netherlands. We show that the contribution of tax and benefits systems to mitigating automation-driven shocks differs across countries. As such, we contribute to the literature on the role of tax and benefit systems in cushioning economic shocks. Blundell et al. (2018) argued that the U.S. tax and benefit system had much less success than the British one in counteracting changes in the labor (and marriage) markets in 1980–2015. Dolls et al. (2012) already showed that automatic stabilisation through the tax and benefit system is stronger in Europe than in the U.S. We confirm that benefits played a vital role in cushioning the disqualifying impact of automation in most European countries.

2 Data and Measurement

Our analysis covers fourteen countries: Belgium, France, Germany, Netherlands, Sweden (Western European countries), Bulgaria, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, and Slovakia (Eastern European countries). This sample includes seven of the ten countries with the highest increase in robot exposure in Europe (see Figure B.1).⁴

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

penetration across demographic groups is more immune to this problem as it captures the impacts resulting from automation-driven changes in employment composition within demographic groups.

³The related literature on drivers of cross-national differences in income inequality examines broad drivers such as tax-benefit systems (Černiauskas et al., 2022; Paulus and Tasseva, 2020), employment and wage changes (Li et al., 2021; Doorley et al., 2021), or demographic change (Dolls et al., 2019).

⁴We do not include Southern European countries as they recorded a severe recession during the studied period. The omission of other EU countries reflects the unavailability of some data.

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 2006–2018 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 main unit of analysis is a demographic group. For each country, we define 30 demographic groups defined by gender (men and women), education (low – levels 0-2 of the International Standard Classification of Education, ISCED; middle – levels 3-4 of ISCED; and high – level 5 of ISCED), and age (10-year age groups: 20–29, 30–39, 40–49, 50–59, 60+). 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).⁵

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. Household market income refers to all household members' total amount of labor 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 (see Appendix C for more detail on EUROMOD).⁶ Household disposable incomes are expressed in single-adult equivalents to account for economies

⁵Lewandowski et al. (2022) showed that O*NET data approximate well the routine task intensity of occupations in European Union countries.

⁶We use version 14.0 of EUROMOD with input datasets based primarily on the EU-SILC 2006 and 2018 waves.

of scale in consumption across households of different sizes using the scale recommended by Eurostat.⁷

2.2 Measuring robot penetration and automation-induced task displacement

We use data on industrial robots from the International Federation of Robotics (IFR, 2021), which provides annual information covering the stock and the deliveries of industrial robots across countries, by industry and by application.⁸

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

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

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 use the initial (2006) employment levels as denominators. The second term adjusts for the overall change in industry i output, specifically to account for the secular decline or growth 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 2018.⁹

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

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

which comprises three terms:

- group's g exposure to different industries, $\omega_{g,c}^i$, 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), $\omega_{g,i,c}^R / \omega_{i,c}^R$;

⁷Total 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).

⁸According to the International Organization for Standardization (ISO 8373:201), an industrial robot is an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications."

⁹This adjustment is critical in our cross-country sample that includes Western European countries with moderate growth rates and Central Eastern European countries which were growing faster and converging with Western Europe thanks to rising total factor productivity and capital accumulation (Žuk & Savelin, 2018).

- 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.¹⁰

2.3 Descriptive statistics

Table 1 presents the sample 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% of total employment. On average, workers 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.

¹⁰We add a small constant because some groups experienced a slight decrease in the exposure to robots.

3 Empirical Strategy

Our analysis proceeds in three steps. First, we estimate the impact of automation on wages, employment rates and household incomes 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 and industry. Third, we evaluate the impacts on household income inequality and identify the role of tax and benefit systems in cushioning them, 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:

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

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, β , may be interpreted as a change in wages due to a 1% 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. Industry shifters absorb labor demand changes coming from the expansion of industries in which a demographic group specializes, and 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 equals one.

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

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 isolate

the component of robot penetration driven by changes in technology:

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

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), our instrument instead comprises three countries with the highest penetration of robots: Slovenia, Austria, Denmark, as well as Finland and the UK.¹¹ Our approach also follows Dauth et al. (2021) who instrumented robot adoption in Germany with the average across eight European countries.¹² 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. In robustness tests, we also present the results using the instrument comprising countries used by Acemoglu and Restrepo (2020), and using the robot adoption in the US as in Albinowski and Lewandowski (2024).

In addition to employment and wages, there is evidence that automation affects returns to capital (Moll et al., 2022), with implications for household receipt of investment income. However, we abstract from the potential impact of automation on household investment income for three reasons. First, these incomes tend to be poorly measured in survey data (Bartels & Waldenström, 2020). In particular, top-income households, who have higher investment income, are under-reported. Therefore, any investigation of the effect of automation on capital income in our framework would miss a substantial proportion of the income in question. Second, we cannot measure the exposure of households' assets to automation because the available survey data do not include information about the structure of these assets. Third, capital income forms a very small proportion of the disposable income of households, on average.¹³ Labor income is a much more significant proportion of household disposable income and is our focus in this study.

3.2 Microsimulation of effects on disposable income inequality

The second stage evaluates the contribution of automation to disposable household income inequality. We do so by first calculating the wage and employment impacts 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, $\hat{\beta}^e$) – and ‘injecting’ them into the household income

¹¹These countries are not included in our analysis because the SES data is unavailable for them.

¹²Other studies that instrument robot adoption in European countries with adoption in peer countries include Anelli et al. (2021), Bachmann et al. (2024), Damiani et al. (2023), Matysiak et al. (2023), and Nikolova et al. (2024).

¹³The 2018 EU-SILC data underlying EUROMOD shows that capital income represents less than 10% of disposable income in all fourteen countries in our sample and less than 5% of disposable income in ten of them.

data. We then use a tax-benefit microsimulation model to assess how much these changes may have impacted disposable household incomes and income inequality.¹⁴

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 labor incomes for all household members, adding non-labor incomes and imputing social transfers, taxes and social security contributions calculated from the 2018 tax-benefit calculator EUROMOD (see Appendix C for more detail on 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.

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

¹⁴See Appendix C for an extended description of the simulations conducted.

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 labor income source diversification) in its transmission.

As shown below, the distributive impacts of robot penetration on household incomes vary across countries. These differences may arise from differences across countries in the size of the robot penetration shock, or differences in how the shock was absorbed by household income pooling, other income sources, and taxes and benefits. To quantify these mechanisms, 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 $TDA_{g,DE}$ (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. They are statistically significant and negative (Table 2), but, as discussed in Section 3, OLS estimates may be biased because of other shocks affecting both investments in robots and labor 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.¹⁵

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).

¹⁵For instance, relatively declining exports and international competitiveness could incentivise investment in robots and slow down wage growth and a sector level. A similar pattern of IV estimates being larger in absolute terms than OLS estimates was found for European countries by Aksoy et al. (2021) and Albinowski and Lewandowski (2024).

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

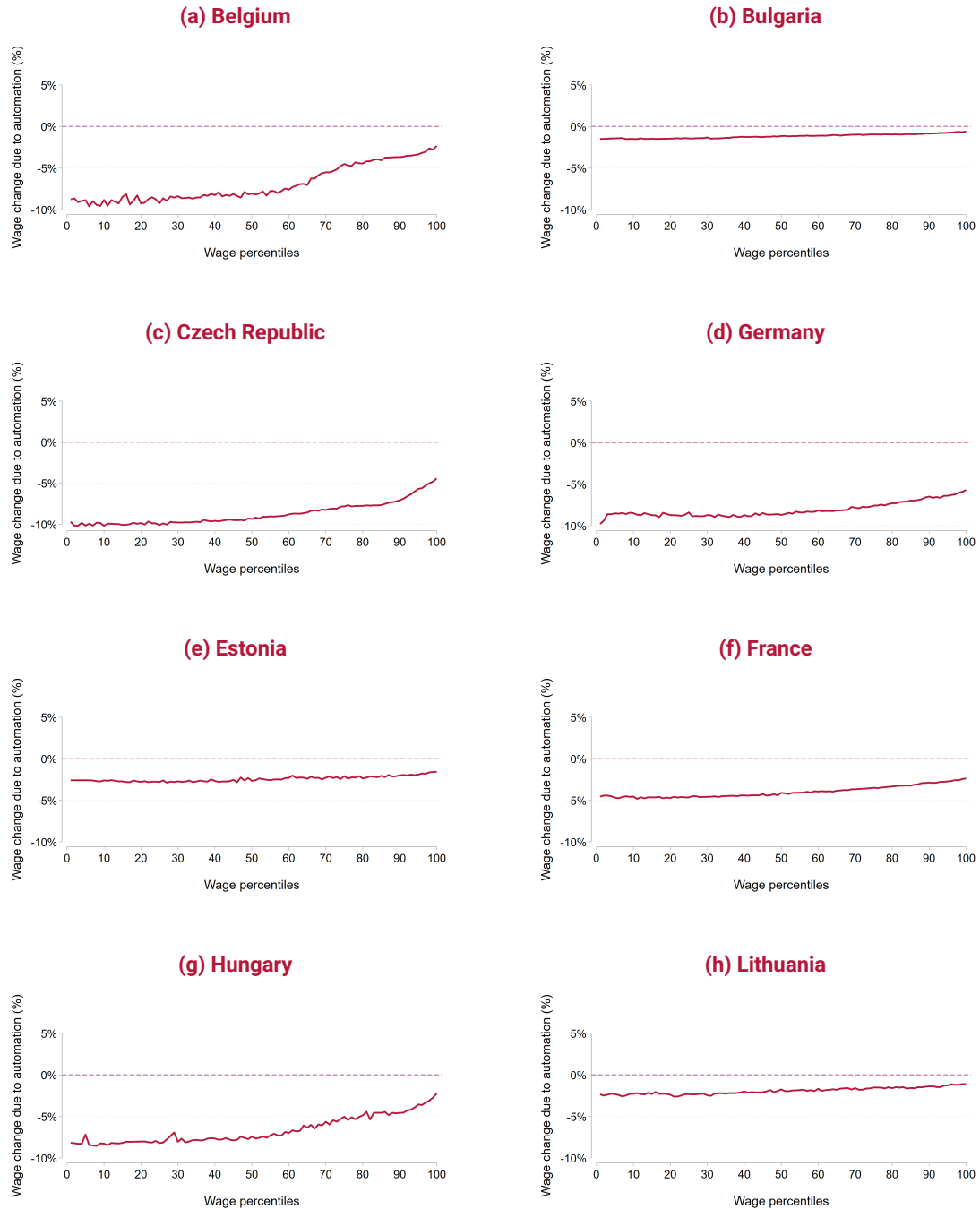
	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Automation: penetration of robots	-0.055*** (0.017)	-0.055*** (0.017)	-0.035** (0.016)	-0.041*** (0.015)
	2SLS	2SLS	2SLS	2SLS
Automation: penetration of robots	-0.093*** (0.023)	-0.091*** (0.022)	-0.057*** (0.022)	-0.064*** (0.021)
Country FE	yes	yes	yes	yes
Manufacturing 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: The upper panel shows the OLS estimates, and the bottom panel shows the IV estimates. The dependent variable is the change in log wages across 30 demographic groups in 14 European countries from 2006 to 2018. The instrument is the average robot penetration in five 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. The first stage F statistic is the statistic from the Kleibergen-Paap test. Table B.1 shows the first-stage results. Data: EU-SES. * p<.10; ** p<.05; *** p<.01

Results remain essentially unchanged if we additionally control for groups' specialisation 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 any particular country (Figure B.2). In further robustness checks, we 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 1-2 show wage changes attributed to automation by percentiles of the wage distribution in particular countries, and Figure B.3 pools these effects across all countries.

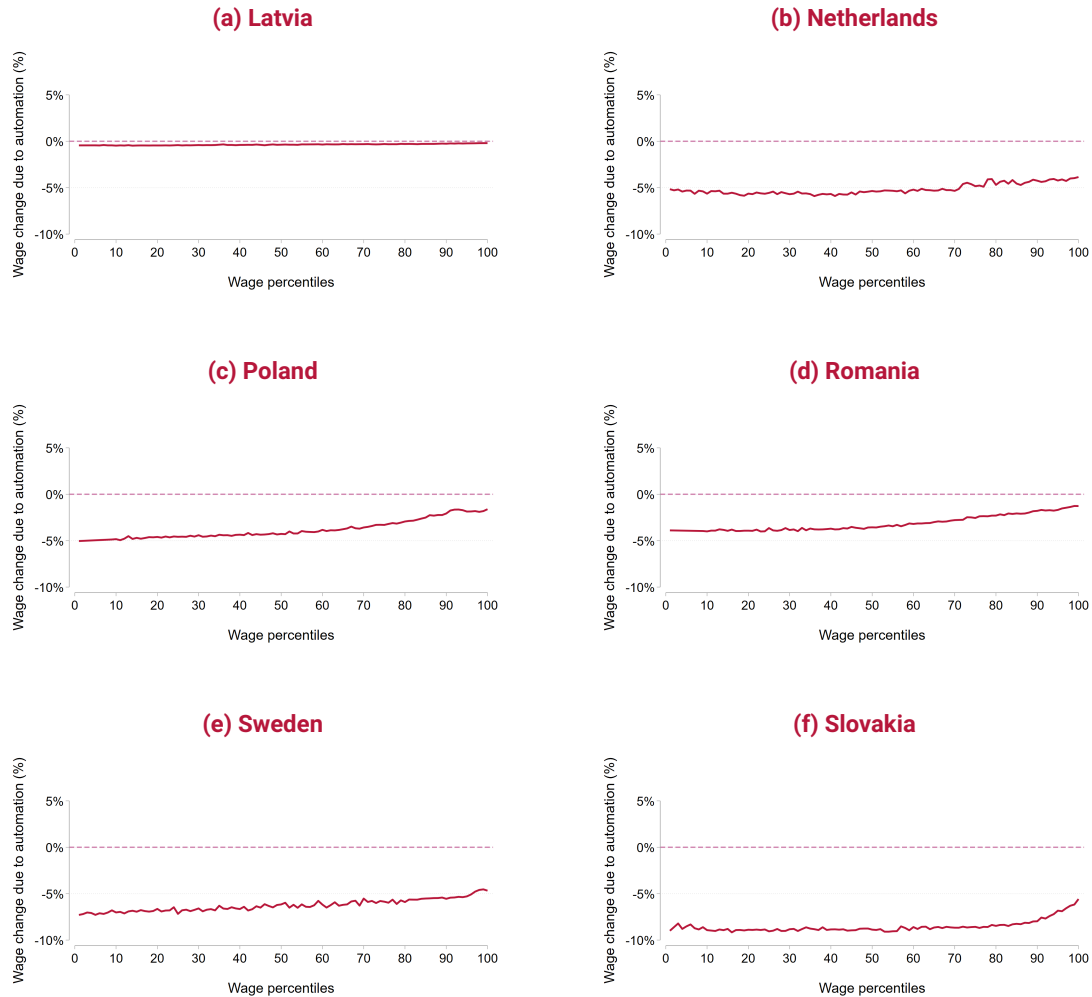
Figure 1. Wage changes due to automation, by percentiles of country-specific initial (2006) wage distributions (i.)



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 2. 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.

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 1–2). 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.¹⁶ Automation's impact on wages clearly varied across economies.

The negative labor demand shock due to automation not only reduced wages, but also had implications for employment. We find a significant, negative effect on employment rates of exposed groups (Table 3). It is, however, relatively small – according to our IV estimates, 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 labor market outcomes of more exposed groups.¹⁷

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

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Automation: penetration of robots	-0.011 (0.012)	-0.009 (0.013)	-0.023 (0.019)	-0.017 (0.014)
	2SLS	2SLS	2SLS	2SLS
Automation: penetration of robots	0.000 (0.016)	0.004 (0.018)	-0.033 (0.021)	-0.034* (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: The dependent variable is the change in employment rates across 30 demographic groups in 14 European countries from 2006 to 2018. The instrument is the average robot penetration in five European countries not included in the sample. Robust standard errors are reported. The first stage F statistic is the statistic from the Kleibergen-Paap test.

Data: EU-SES. * p<.10; ** p<.05; *** p<.01

Next, we assess whether robots' adverse impacts on labor market outcomes translated into effects on households' incomes, distinguishing between market and total (monthly) income measures from the EU-SILC data.¹⁸ While the estimates are less precise than those for employment and wages, we find a large reduction in individual monthly market income (column 1 of Table 4).¹⁹ At the same time, we find evidence of significant increases in the market

¹⁶In 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.

¹⁷Our finding of statistically significant, negative effect of robot penetration on the change in hourly wage dispersion within demographic groups (Appendix Table B.6) suggests that the adverse employment effect does not drive the negative wage effect through compositional changes. This facilitates combining wage and employment effects in quantifying the distributional impacts of automation.

¹⁸Unfortunately, due to low data quality, we had to exclude Bulgaria, Estonia, and Romania from this analysis.

¹⁹Market income is a sum of income from dependent and self-employment.

income of other household members (column 2 of Table 4), consistent with added worker effect (Lundberg, 1985). However, we do not see significant adjustments in household size (column 5 of Table 4). Thus, the diversification of household market income and the positive response of other household members' income appear sufficient to offset the reduction in labor income affecting workers exposed to automation. Consequently, we find no effects on equivalized households' market and disposable (after taxes and transfers) income. In Appendix B, we further decompose income responses of other household members. The results suggest these compensating responses are driven both by an increase in the number of working-age household members and by a higher market income per working-age household member (Table B.7).

Table 4. Automation and monthly income

	Market income			Disposable income	
	Individual (own)	Other members	Household equivalized	Household equivalized	Household size
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Automation: penetration of robots	-0.092* (0.048)	0.062 (0.042)	-0.004 (0.031)	0.027 (0.019)	0.015 (0.011)
	2SLS	2SLS	2SLS	2SLS	2SLS
Automation: penetration of robots	-0.120* (0.071)	0.099* (0.060)	0.023 (0.046)	0.009 (0.022)	-0.003 (0.013)
Country FE	yes	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes	yes
Gender	yes	yes	yes	yes	yes
Education	yes	yes	yes	yes	yes
Industry shifters	yes	yes	yes	yes	yes
F-statistic first stage	173.84	173.41	171.55	200.82	191.59
Mean of outcome	0.24	0.18	0.24	0.21	-0.03
Observations	330	330	330	330	330

Notes: The dependent variables represent changes in log individual monthly market income, total monthly market income of other household members, equivalized household market income, equivalized disposable income (after taxes and transfers), and household size for 30 demographic groups in 11 European countries from 2006 to 2018. Bulgaria, Estonia, and Romania were excluded from the analysis due to data quality issues. The instrument is the average robot penetration in five European countries not included in the sample. In all regressions, we control for the initial level of the dependent variable, country fixed effects, manufacturing share of employment, gender, education level, and industry shifters. Robust standard errors are reported. Data: EU-SILC (EUROMOD).

* p<.10; ** p<.05; *** p<.01

4.2 The contribution of automation to household income inequality

Our regression results suggests that, on average across European countries, automation-driven adverse labor market shocks tend to be cushioned by the diversification of incomes within households. In the next step, we assess the contribution of automation to household income inequality and examine the role of specific channels that either amplify or mitigate individual-level effects. We conduct this analysis at the country level, which enables us to account for the cross-country differences in intra-household adjustments and national tax and benefit systems.

To this end, we obtained the hypothetical values of wages and employment rates in 2018, assuming that robot exposure remained at the 2006 level. For each demographic group, we multiplied its robot penetration by the coefficients of automation's wage (column 4 of Table 2) and employment effects (column 4 of Table 3). 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.

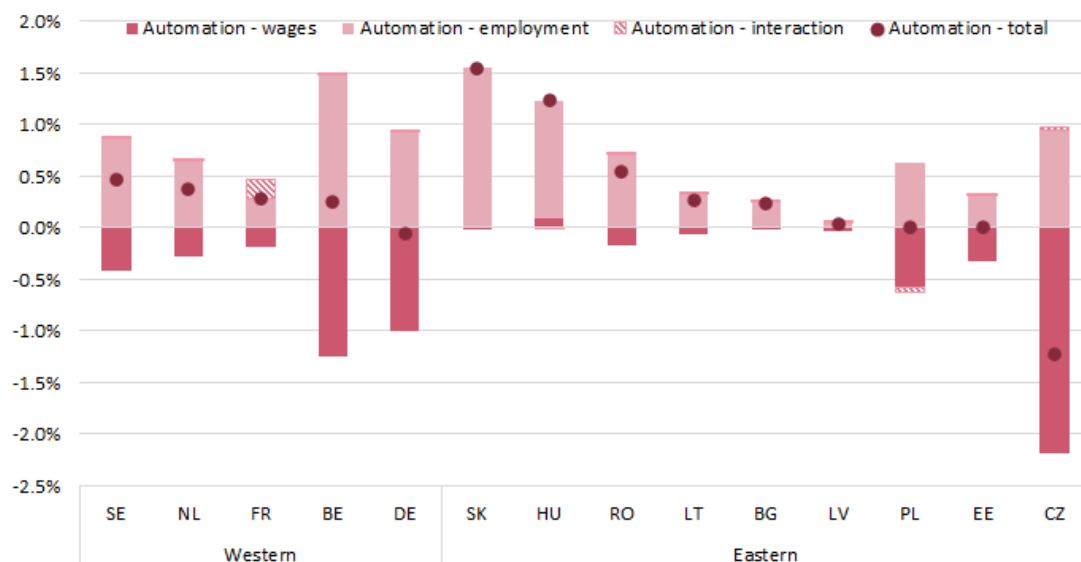
We start by presenting and discussing automation's contribution to income inequality by country (Figure 3). We distinguish between the contributions of (i) automation-induced wage changes (ii) automation-induced employment changes across demographic groups, and (iii) the combination of these two using the methods described in Appendix C. In Figure 3 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 (not directly affected by automation). This compressed the income distribution, reducing income inequality, even though automation widened between-group wage inequality (Figures 1–2). 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 3).

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 3), 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 con-

tribution 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 3).

Figure 3. 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 of automation. This effect can be interpreted as an indicator of how correlated the employment and wage effects are. For example, if employment losses are concentrated among the demographic groups who also experience wage losses, the inequality-reducing effect of wage changes would be cushioned by the interaction effect (as some of those who we simulate to receive a reduced wage would actually lose their job instead). Only in France is the interaction effect noticeable and positive. In other countries, it is negligible (Figure 3).

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 3).

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' labor income diversification and tax-benefit systems

We have found so far a tiny contribution of automation to household disposable income inequality in most European countries, despite its disequalising impact on wages (Figures 1 and 2) and its negative employment effects (Table 3). These labor 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' labor 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 4 presents the results. Comparing (i) to (ii) illustrates the role of pooling labor incomes within households in the transmission of the automation shock while comparing (ii) to (iii) shows the cushioning effect of taxes and benefits.

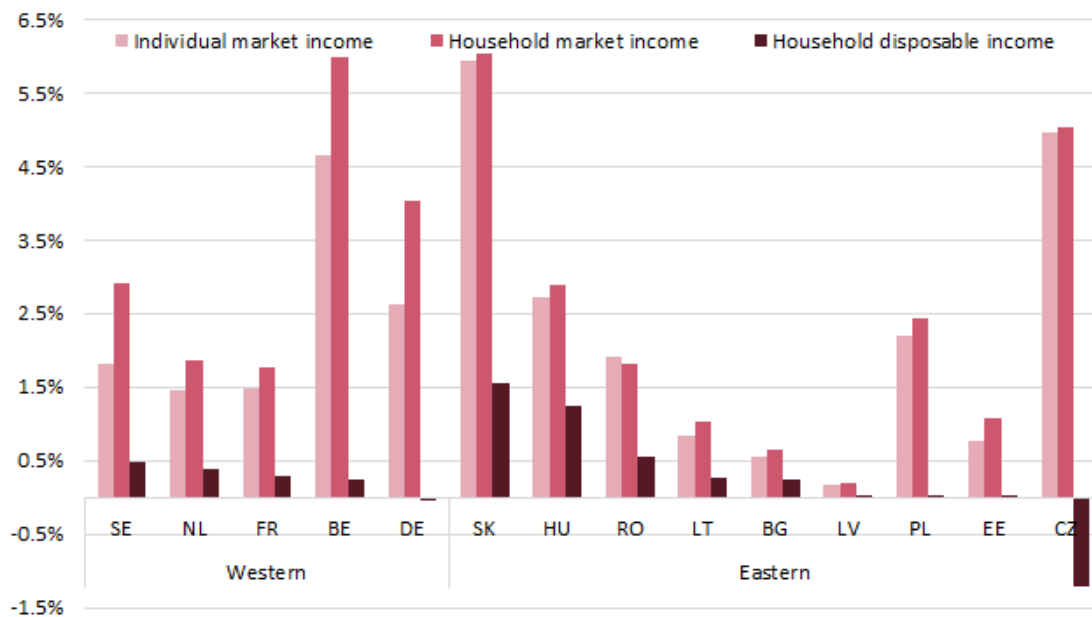
In all countries, automation widened inequality of individual-level market income, in line with the disequalising impact of robots on wages (Figures 1-2). The impact on individual market income inequality is largest (up to 6% of the 2018 Gini index) in countries with the strongest negative effect on 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 labor 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 labor income diversification within households over this period (Figure B.10).

Finally, we find evidence tax and benefit systems play a vital role in cushioning the effects of automation on household disposable income. The contribution of automation to disposable household income inequality is much smaller than to either measure of market income (Figure 4) – as discussed earlier, it is below 1% in most countries.

Figure 4. The effect of automation on income inequality using various income concepts



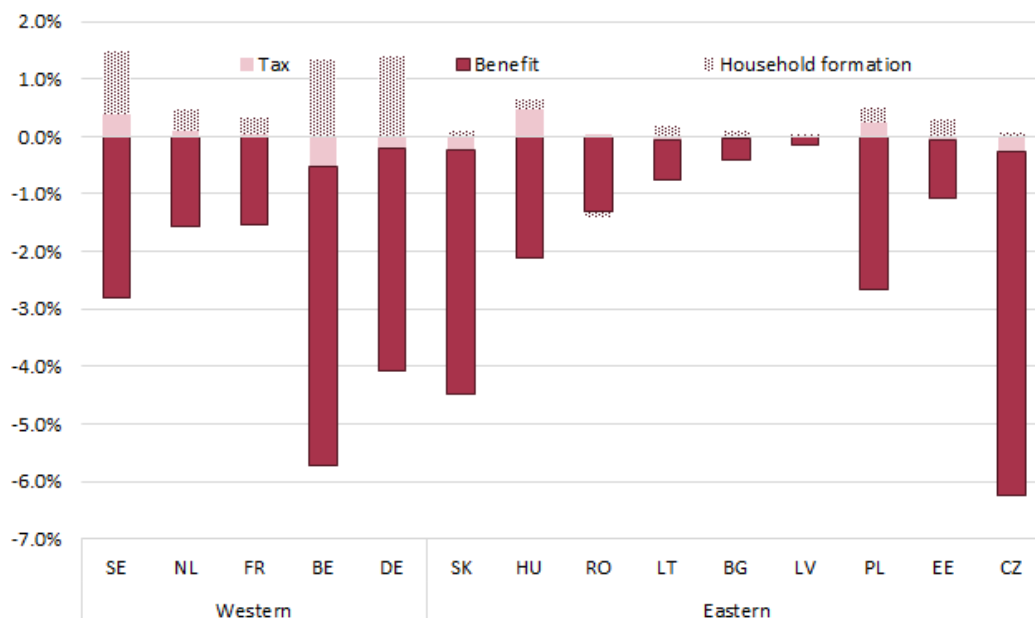
Notes: The figure shows the change in Gini Index due to automation where income is defined as (i) market income at the individual level (ii) equivalised market income at the household level and (iii) equivalised disposable income at the household level. In Eastern and Western Europe, countries are ordered 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 5). Taking the example of Germany, automation increased the 2018 Gini of individual-level market income by 2.5%. Accounting for household labor 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 5). Consequently, automation was essentially neutral for disposable household income inequality in Germany, reducing the 2018 Gini index by –0.1% (Figure 3).

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 5. 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 Figure B.10 in Appendix B. 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. This suggests that European tax and benefit systems have not evolved in any systematic direction in terms of their ability to cushion automation shocks. This alleviates potential concerns that the 2018 systems, which we use in our

baseline results, might have resulted from changes implemented in response to automation shocks.

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 6). 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 6). 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 5). The wage channel explains a larger share of these differences than the employment channel, and benefits again emerge as the key cushioning mechanism (Table 5).

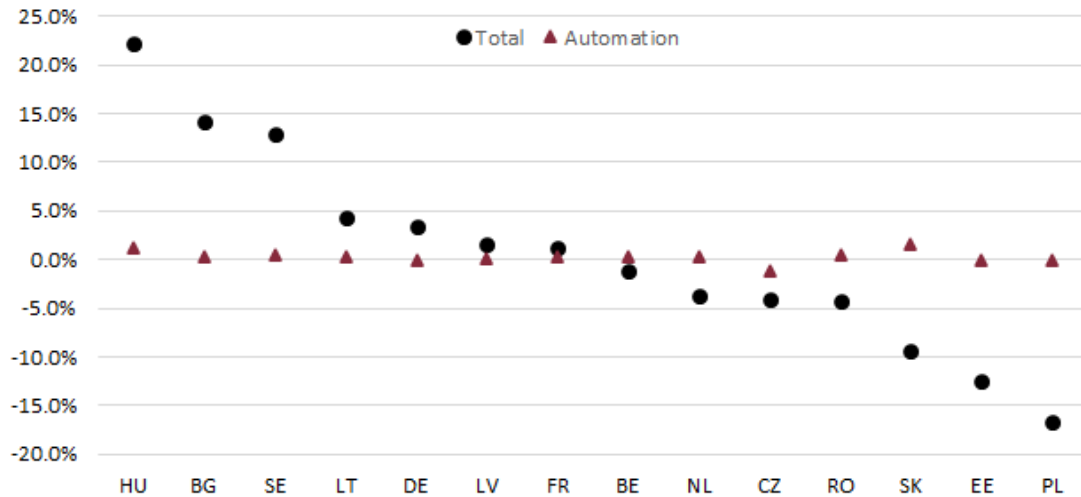
Other changes in market income and the tax-benefit systems played a much larger role than robot adoption in the evolution of income inequality in European countries between 2006 and 2018—a period which covered the Great Recession and a sovereign debt crisis in several EU countries.

Table 5. 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 6. 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.

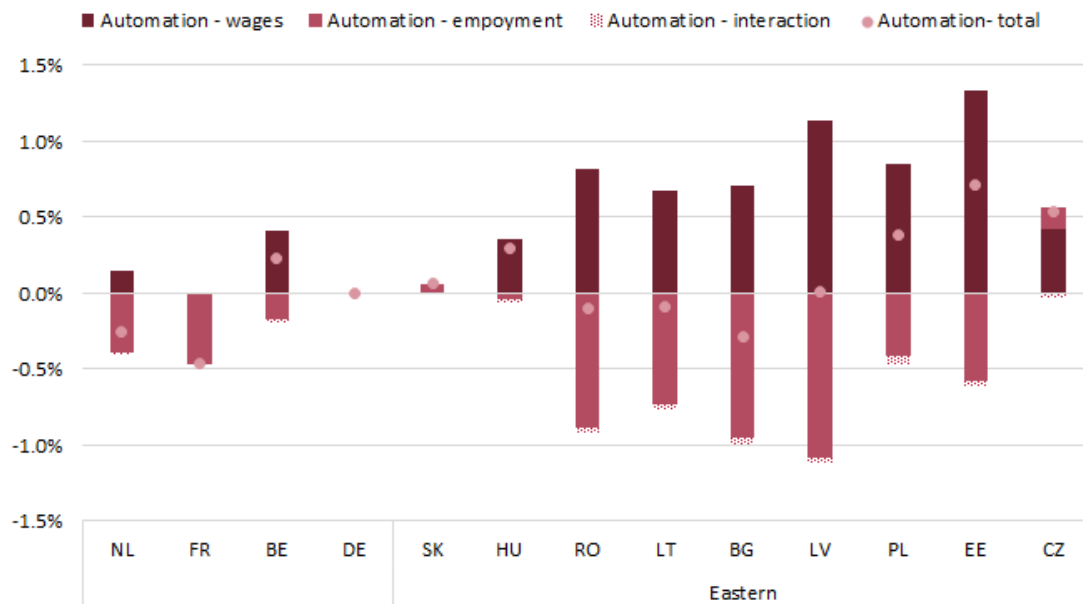
4.5 Isolating the role of differences in absorption of automation shocks: the effect of a “German” automation shock

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 finally 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 7 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 labor 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 more widespread adoption of robots in 2006–2018. Admittedly, we do not know how this would have affected the evolution of their income inequality before 2006.

Figure 7. 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 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.²⁰

²⁰In 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 fourteen European countries between 2006 and 2018. We have combined estimating the effects of robot penetration on labor 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 labor 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 has significantly reduced relative real hourly wages, employment rates and total market incomes of the directly affected groups in Europe, in line with the effects observed for the U.S. However, we have also shown that, for most countries, automation had little effect on household-level disposable income inequality. Automation-driven employment changes, which increased the number of adults without 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 labor incomes, related to occupational assortative mating and added worker effect, has, on average, cushioned the adverse automation-driven shocks in Europe. However, in some Western European countries, it exacerbated the small increases in income inequality.

We conclude that, while robot penetration measurably affected wages and employment in European countries, its contribution to income inequality was small. It was greatly outweighed by other market income and policy changes over that period – which 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-labor 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.²¹ We also focus on distributive impacts through labor 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 (Bartels & Waldenström, 2020; Ravallion, 2022) and therefore cannot be included reliably in our empirical analysis. Reassuringly, however, Carranza et al. (2023) showed that *trends* in income inequality over time, which are the focus of our paper, 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.

²¹The evidence on robots’ impact on fertility is limited. Anelli et al. (2024) 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 household size	difference in the household size calculated using OECD equivalence scales (2006-2018)	EU-LFS
Change in individual (own) market income	difference in log individual market income (2006-2018)	EU-SILC
Change in other members market income	difference in log total market income of other household members (excluding the individual, 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*** (0.020)	0.376*** (0.020)	0.425*** (0.027)	0.424*** (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*** (0.021)	-0.079*** (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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Automation: penetration of robots	-0.064*** (0.021)	-0.067*** (0.024)	-0.057*** (0.020)	-0.083*** (0.021)	-0.054*** (0.021)	-0.065*** (0.021)	-0.076*** (0.020)	-0.078*** (0.021)	-0.076*** (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)	(2)	(3)	(4)
	Hourly wage	Hourly wage	Employment	Employment
Automation: penetration of robots	-0.132*** (0.033)	-0.078*** (0.030)	0.012 (0.021)	-0.029 (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*** (0.023)	-0.034 (0.021)	-0.006 (0.016)	-0.043** (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*** (0.025)	-0.146*** (0.023)	-0.118*** (0.024)	-0.120*** (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

Table B.7. Automation and other members market income

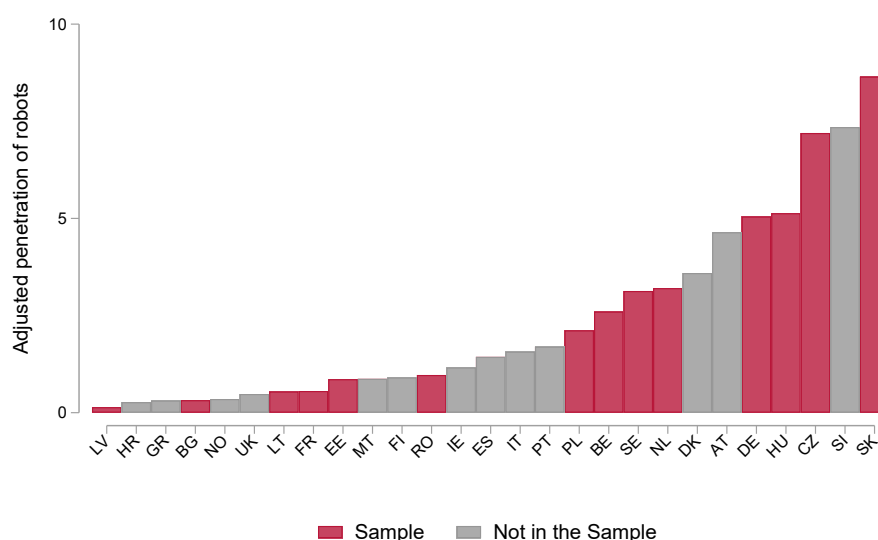
	Other members income (1) OLS	Working-age members (2) OLS	Income per working-age member (3) OLS
Automation: penetration of robots	0.062 (0.042)	0.054*** (0.014)	0.027 (0.034)
	2SLS	2SLS	2SLS
Automation: penetration of robots	0.099* (0.060)	0.043* (0.023)	0.058 (0.046)
Country FE	yes	yes	yes
Manufacturing share	yes	yes	yes
Gender	yes	yes	yes
Education	yes	yes	yes
Industry shifters	yes	yes	yes
F-statistic first stage	173.41	191.97	168.51
Mean of outcome	0.18	-0.04	0.22
Observations	330	330	330

Notes: The dependent variables represent changes in log total monthly market income of other household members, the number of household members in working age, and per-working-age-member monthly market income of other household members for 30 demographic groups in 11 European countries from 2006 to 2018. Bulgaria, Estonia, and Romania were excluded from the analysis due to data quality issues. The instrument is the average robot penetration in five European countries not included in the sample. In all regressions, we control for the initial level of the dependent variable, country fixed effects, manufacturing share of employment, gender, education level, and industry shifters. Robust standard errors are reported.

Data: EU-SILC (EUROMOD).

* p<.10; ** p<.05; *** p<.01

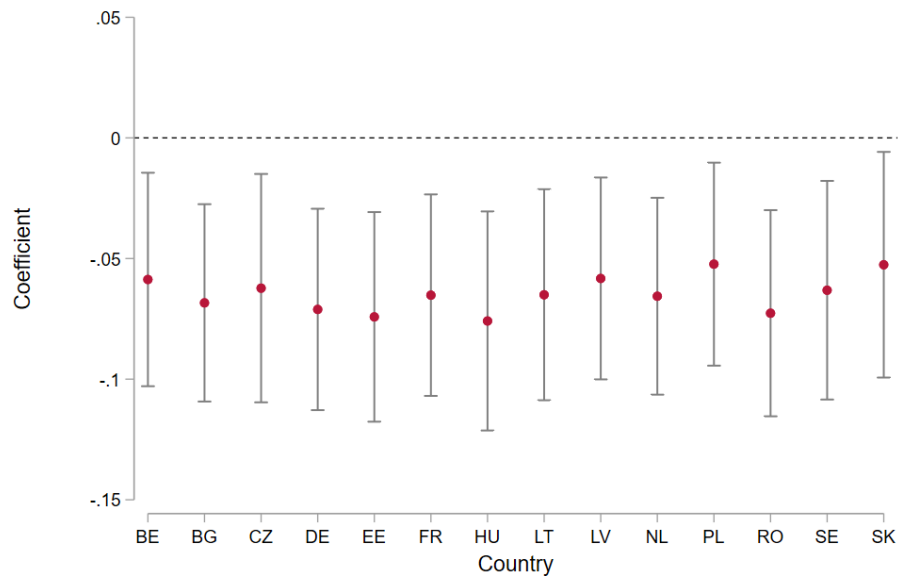
Figure B.1. Adjusted penetration of robots in Europe (2006-2018)



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.

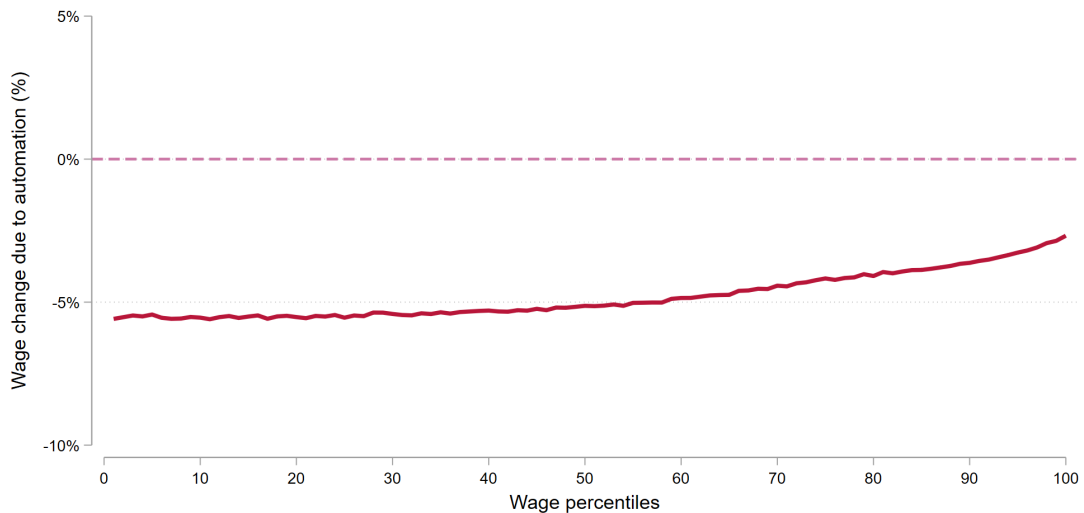
Data: IFR & Eurostat.

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).

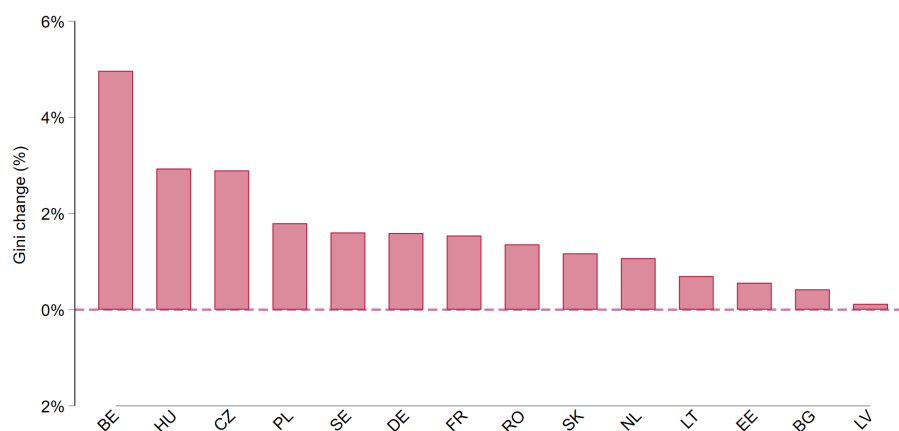
Figure B.3. Wage changes due to automation, by percentiles of the initial (2006) pooled wage distribution



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 1-2.

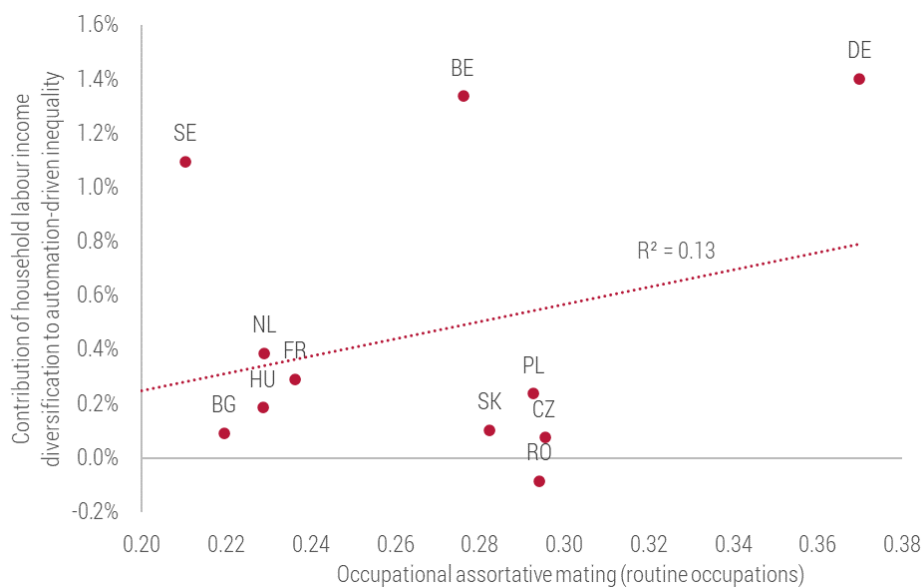
Data: EU-SES.

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



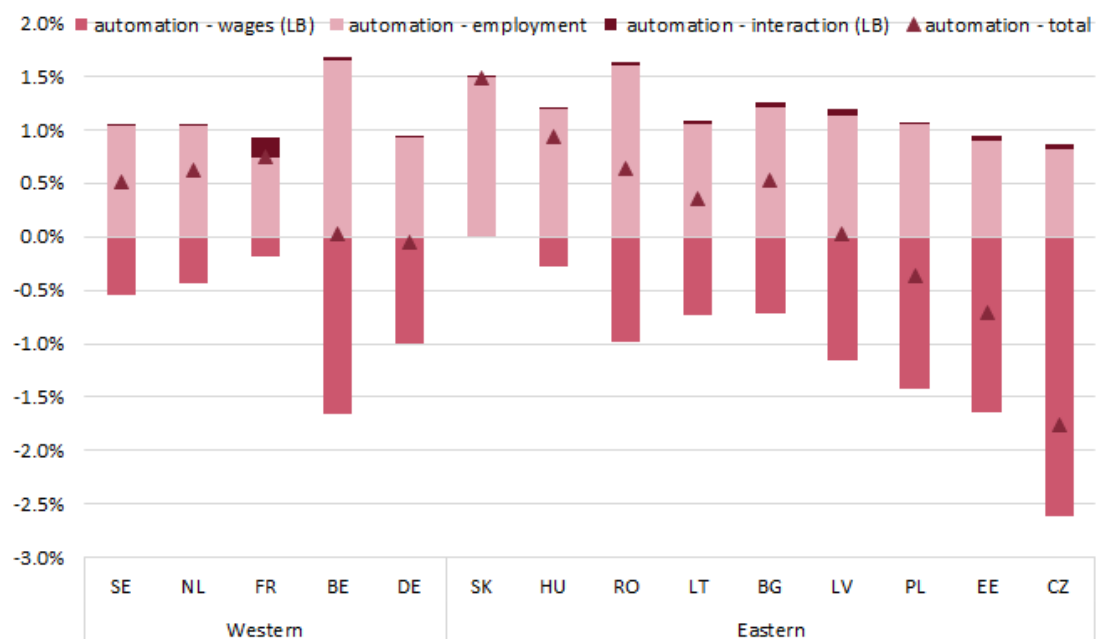
Notes: Figure shows the difference between the Gini index of hourly wages in 2018, and in a counterfactual scenario with no changes in automation between 2006-2018.
Data: EU-SES.

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



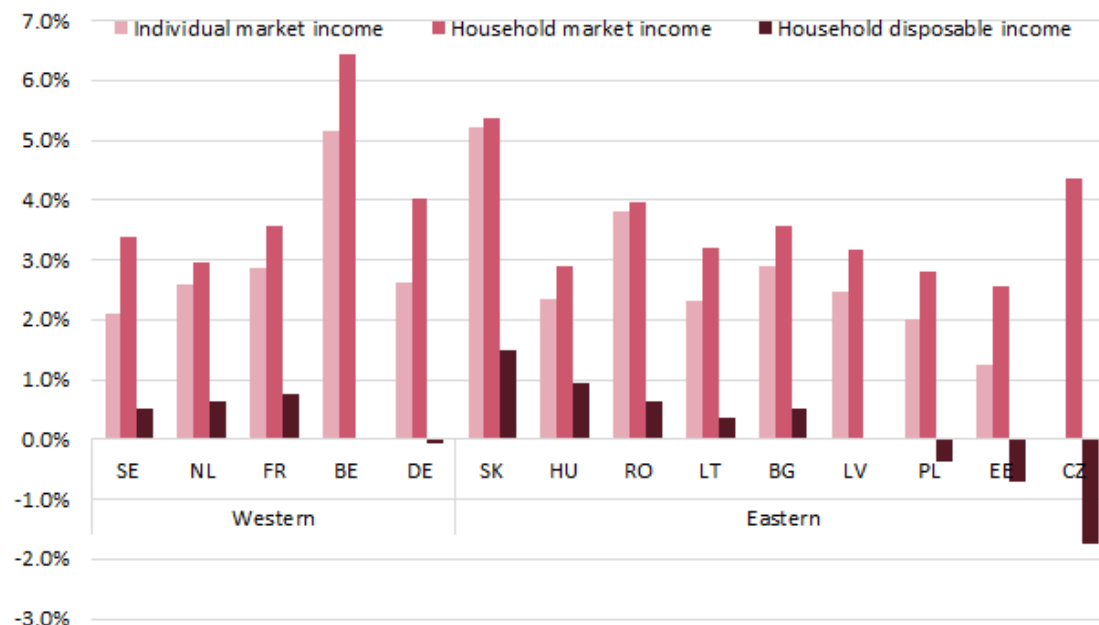
Notes: The incidence of assortative mating defined as a share of workers in routine occupations who form a household with a person who also works in a routine occupation, in all households that include at least one person working in a routine occupation.
Data: EUROMOD, EU-SILC.

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



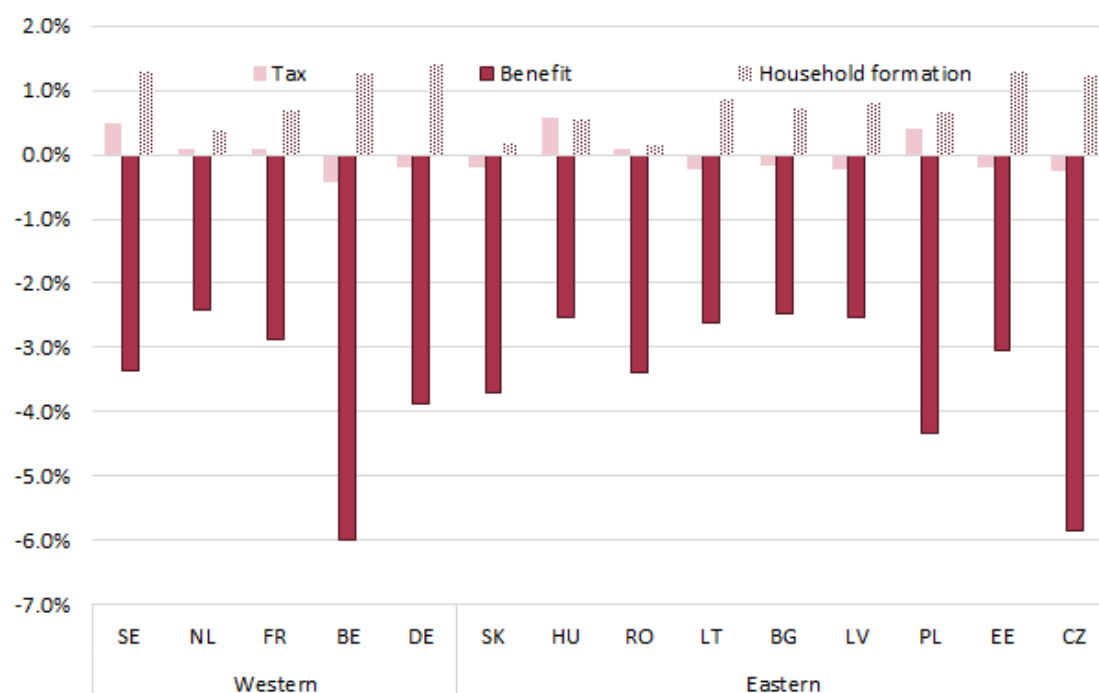
Notes: The figure shows the effect of a hypothetical German automation shock to the Gini Index in each country, decomposed into the contribution of wage, employment and interaction effects.). Data: EUROMOD, EU-SILC.

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

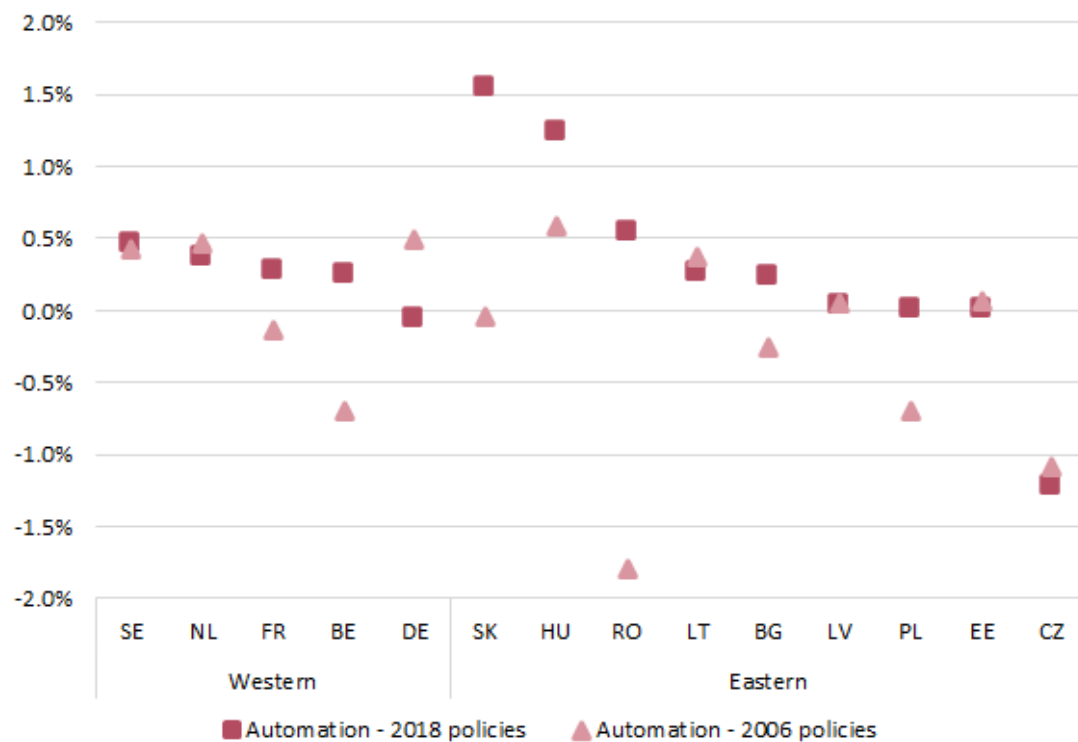
To investigate how the tax-benefit system interacts with automation-driven market income changes, we compare the automation effect shown in Figure 3 to a hypothetical scenario in which an indexed version of the 2006 tax-benefit system was in place in each country.²² In essence, this shows how discretionary changes to tax and welfare payments between 2006 and 2018 affected the transmission of automation-induced labor 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

²²This 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.

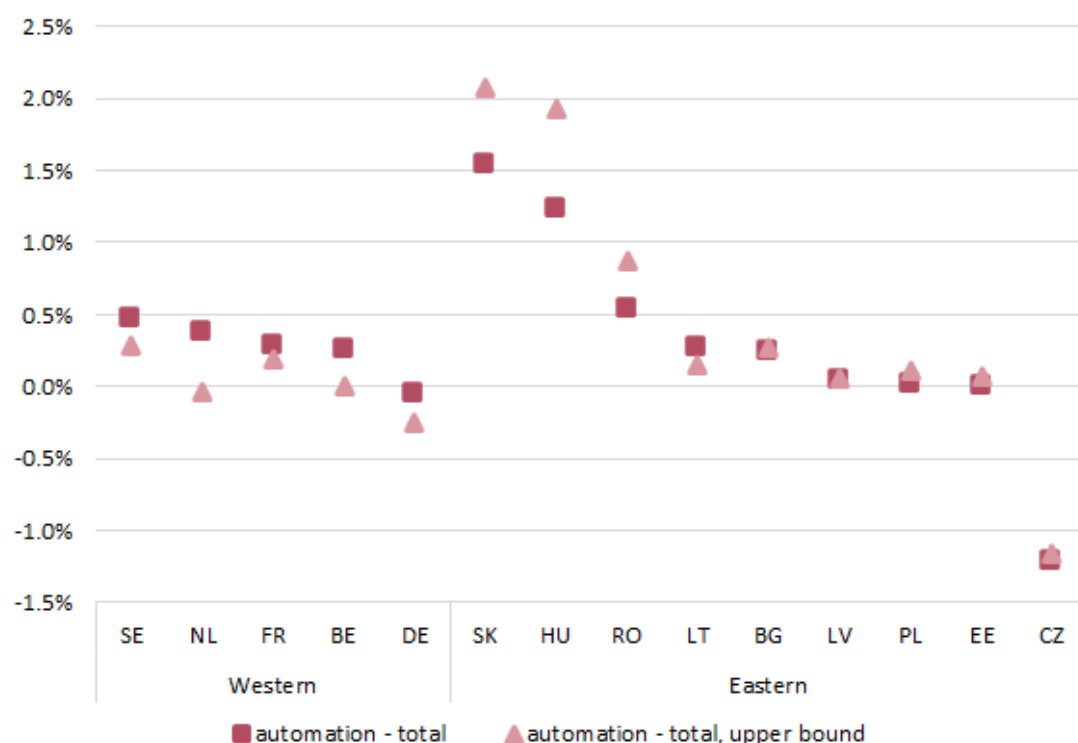
The cushioning effect of household formation: 2006 vs 2018

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 in-

equality 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 5. 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 5) 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 $I[y^d]$ 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 labour 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. EUROMOD is maintained, developed and managed by the Joint Research Centre (JRC) of the European Commission, in collaboration with Eurostat and national teams from the EU countries. It is documented and validated on an annual basis by this consortium.

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

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

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

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

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

$$\Delta^{AW}I = I[d_1((X_1, Y_1^L, Z_1), p_1)] - I[d_1((X_1, \tilde{Y}^{L1}, Z_1), p_1)]$$

where \tilde{Y}^{L1} 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

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

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:

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

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

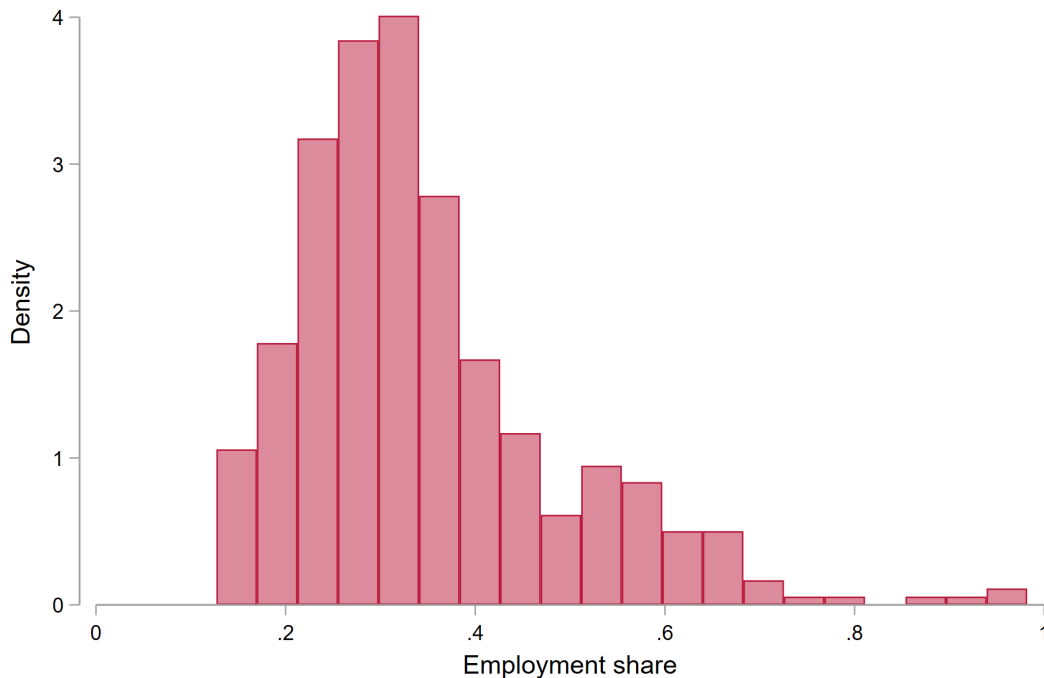
$$E_i \frac{p_{g,c}}{(1 + \hat{\beta}^e \cdot TDA_{g,c}) - p_{g,c}} + (1 - E_i) \frac{(1 + \hat{\beta}^e \cdot TDA_{g,c}) - p_{g,c}}{p_{g,c}}$$

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.

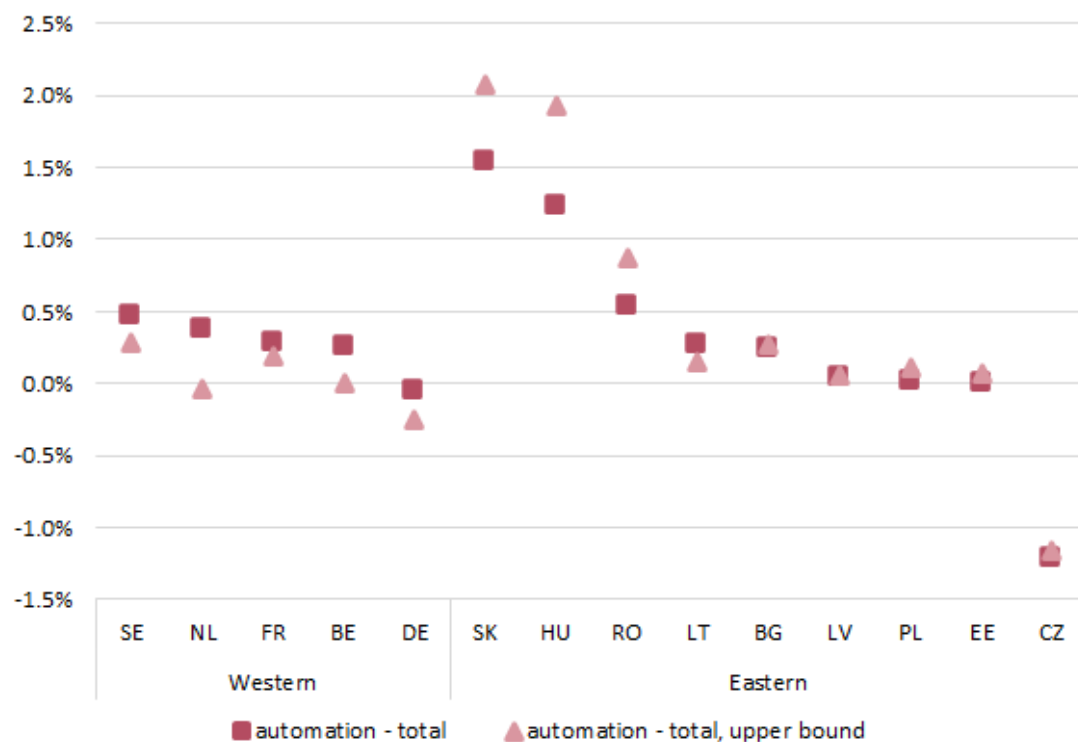
As automation technologies such as robots are generally used in larger firms, workers in the EU-SES sample are likely more exposed to robots than workers in smaller firms. As a consequence, automation's impact on workers in firms with at least 10 workers may be larger than the effects on all workers. 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.