Automation and Income Inequality in Europe[•]

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Abstract

This paper examines the impact of industrial robot adoption on household income inequality in 14 European countries between 2006 and 2018. Automation reduced relative wages, employment, and market incomes of more exposed demographic groups. However, feeding these automation-induced wage and employment shocks into the EUROMOD microsimulation model shows that their effect on inequality in disposable household income was small. Tax-benefit systems, particularly transfers, largely absorbed the disequalizing labor income shocks caused by automation. Household labour income diversification cushioned the automation-induced labour income shocks, but played a limited role for inequality.

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The rapid automation of job tasks raises concerns about its consequences for worker welfare and income inequality. A large literature documents that technologies replacing routine tasks tend to disadvantage lower-wage workers while benefiting those in non-routine, high-skill jobs, thereby widening wage inequality. Evidence from the United States indicates that robot adoption led to sizable job and wage losses among lower-paid workers (Acemoglu and Restrepo, 2022). Whether similar dynamics operate in Europe remains an open question. European labour markets feature stronger employment protection, more extensive redistribution, and higher union coverage, which may alter both the magnitude of automation-driven labour market shocks and how these shocks translate into household living standards.

This paper assesses the distributional impact of automation by examining not only wages and employment, but also household incomes. Automation affects workers through changes in earnings and employment probabilities; however, household income inequality ultimately depends on how these shocks are transmitted through income pooling within households and redistribution via taxes and transfers. Household labour income diversification may mitigate individual losses, for example, through added-worker effects, or amplify them when exposure to a shock is positively correlated across household members. At the same time, progressive tax-benefit systems can cushion labour market shocks, particularly those operating through employment losses. The net impact of automation on household income inequality is therefore theoretically ambiguous and must be determined empirically.

We study the impact of industrial robot adoption on household income inequality in 14 European countries between 2006 and 2018. We combine econometric estimates of automation's effects on wages, employment and households' market incomes, with microsimulation methods to trace their transmission to household disposable incomes and inequality. Following Acemoglu and Restrepo (2022), we define 30 demographic groups per country by age, gender, and education, and estimate the causal effects of robot exposure using an instrumental-variable strategy based on robot adoption trends in technologically advanced European countries outside our sample. We then construct counterfactual wage and employment levels for 2018 under constant robot exposure and feed these into the EUROMOD tax-benefit model. Comparing observed and counterfactual income distributions enables us to quantify the contribution of automation to income inequality and to disentangle the roles of wage and employment channels, household income diversification, and tax-benefit systems in shaping distributional outcomes.

1 Literature and contribution

Automation-driven labor market shocks affect workers through changes in employment probabilities, wages, and task composition. A large literature documents these effects at the individual, occupational, sectoral, or regional level (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018). In the US, task-displacing automation reduced employment and contributed approximately two-thirds of changes in wage inequality (Acemoglu and Restrepo, 2022, 2020). 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). Beyond potential aggregate effects, automation creates winners and losers. Across high-income countries, it increased productivity and reduced employment shares of low-skilled workers in routine occupations (Chung and Lee, 2023; de Vries et al., 2020; Graetz and Michaels, 2018), benefiting younger workers and prime-aged women at the expense of older workers and prime-aged men (Albinowski and Lewandowski, 2024).

Yet, the impact of automation on household incomes and its distributional consequences remain under-researched. Filling this gap is important since the increase in income inequality has been driven primarily by the surge in labor income inequality (Acemoglu and Robinson, 2015). It is also essential from a policy perspective. Headline indicators of living standards, such as the at-risk-of-poverty rate and the Gini index, rely on household incomes, particularly on equivalised household disposable incomes adjusted for household size and composition, which account for income pooling and economies of scale within households. These measures form the basis for redistribution through the tax and transfer system, assessing households' ability to meet basic needs, and monitoring risks to social cohesion arising from polarisation in living standards.

Since inequality is ultimately experienced at the household level, it is shaped by income pooling and diversification of income sources of household members and by redistribution through tax-benefit systems. Labor market shocks do not map mechanically into household income inequality. Understanding the distributional consequences of automation requires (i) quantifying its impact on wages and employment, (ii) tracing how individual-level shocks propagate through households, and (iii) evaluating how public policy cushions their impact on disposable incomes and inequality.

Both wage and employment reductions hurt workers' welfare, but their distributional consequences usually differ. Wage declines tend to compress the income distribution since they generally reduce the income gap between the employed and non-employed subpopulations. Employment losses, however, increase the number of households with jobless individuals, widening inequality. Thus, the first step of our study is to estimate the wage and employment effects of automation, specifically industrial robots, in European countries.

Within households, three key mechanisms shape the impact of automation-driven shocks on disposable income. First, because household income is the sum of labor incomes from possibly multiple earners, how much labor shocks transfer to household income depends on the correlation in the exposure of household members to shocks. Negatively correlated income sources could in principle offset individual labor income shocks. In contrast, positive assortative mating by occupation and education tends to increase the correlation of labor market risks (Greenwood et al., 2014). European evidence shows strong assortative matching in terms of education, occupation, and earnings (Esteve et al., 2016). This increases the sensitivity of household incomes to sectoral or occupational shocks and limits the insurance role of household-level income pooling.

Second, households may respond to adverse labor market shocks by adjusting the labor supply of unaffected members. The added-worker effect predicts that secondary earners, often women, increase their labor supply when the primary earner experiences a job loss or an earnings decline (Bargain et al., 2014; Lundberg, 1985). Such adjustments can partially offset income losses and mitigate increases in household inequality, although their strength depends on labor market institutions and gender norms.

Third, household size and composition influence the transmission of individual shocks to equivalised incomes. The number of earners and the presence of children and other dependent individuals shape the scope for intra-household risk sharing (OECD, 2011; Shore, 2010). Automation-driven labor market shocks affecting prime-age earners in single-earner households are likely to have stronger distributional consequences than similar shocks in dual-earner households with diversified income sources.[1]

Tax-benefit systems constitute the final, critical layer of adjustment. Progressive taxation compresses post-tax wage and income distributions (Guvenen et al., 2014; OECD, 2011) and mitigates the disequalising effects of wage dispersion. At the same time, transfers, particularly unemployment benefits and social assistance, act as automatic stabilizers that cushion employment losses and prevent sharp declines in household incomes during labor market disruptions (Dolls et al., 2012; OECD, 2011).

The relative importance of taxes versus transfers depends on the nature of automation shocks and the design of safety nets. Adverse wage shocks are primarily offset by tax progressivity, whereas

[1] In the long-run, shocks may also influence the distribution of household structures (Anelli et al., 2024).

employment losses generate discrete income drops that rely more heavily on benefit systems for insurance. Since automation-driven labor market shocks can also increase non-participation (Di Giacomo and Lerch, 2026), it is essential to account for the entirety of safety nets. Cross-country variation in benefit generosity, eligibility, and replacement rates (Dolls et al., 2022; Doorley et al., 2021; OECD, 2011) may therefore translate into heterogeneous inequality responses to automation.

In sum, while automation can substantially affect employment and wages, its impact on household disposable income inequality depends on household income diversification and redistributive tax-benefit institutions that jointly attenuate the transmission of labor market shocks into household inequality. Differences in assortative mating, household structures, and welfare state design imply that the distributional impact of automation is inherently country-specific. This motivates our empirical strategy: integrating the econometric identification of the labor market effects with country-specific microsimulation models calibrated with countries' parameters of tax-benefit system, which shed light on the transmission of automation-induced labor market shocks to household incomes and the cushioning role of tax-benefit systems.

This paper makes two contributions. First, we provide causal evidence of the medium-term effects of automation with industrial robots on wages, employment, and household income in a European cross-country setting. These effects may differ from those estimated for the US (Acemoglu and 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). Indeed, the effects of robot adoption in Germany are substantially smaller than in the US (Dauth et al., 2021). Routine-replacing technologies more generally led to small net employment gains in Europe, thanks to product demand effects (Gregory et al., 2022). Using plausibly exogenous variation in robot penetration, we demonstrate that in Europe, demographic groups more exposed to robots experienced moderate declines in wages and employment.[2] These effects are robust to controlling for potential confounders and cross-country differences in key labor market institutions, such as minimum wage policies.

[2] Studies focusing on the within-sector effects showed that robots reduce the employment shares of lower-skilled (Graetz and Michaels, 2018) and of male routine (Albinowski and Lewandowski, 2024; de Vries et al., 2020) 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 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. Using this framework, Lewandowski and Szymczak (2025) found that robots contributed to the rise of atypical employment in Europe. We discuss the methodological aspects in more detail in Section 3.

Our second contribution is to quantify the contribution of automation-driven labor market shocks to national household income inequality. We assess the overall distributive effect of automation across European countries, distinguishing between the wage and employment channels.[3] We use country-specific microsimulation models to evaluate 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 role of benefits in mitigating automation-driven shocks is generally larger than that of taxes, although it varies 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 UK tax and benefit system counteracted labor and marriage market changes in 1980–2015 more effectively than the US system. Dolls et al. (2012) showed that such automatic stabilization is stronger in Europe than in the US.

2 Data and Measurement

Our analysis covers fourteen countries: Belgium, France, Germany, the Netherlands, Sweden (Western European countries), Bulgaria, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, and Slovakia (Eastern European countries). This sample includes seven of 10 countries with the highest increase in robot exposure in Europe (Appendix Figure B.1).[4]

2.1 Data sources

Our sources of worker-level data are the cross-country European Union Structure of Earnings Survey (EUSES), the EU Labour Force Survey (EU-LFS), and the EU Statistics on Income and Living Conditions (EU-SILC). The EU-SES is a linked employer-employee survey and the most comprehensive survey of earnings in the EU. It provides representative and harmonized information on employees in firms with at least 10 workers, and includes detailed, two-digit sector information (NACE Rev. 2.1). The EU-LFS is the primary EU survey on employment outcomes, covering all workers. The EU-SILC is the primary EU survey of incomes, including both market and non-market, before and after taxation, at the individual and household levels.

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

[4] We omit 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.

The demographic group is our main unit of analysis. For each country, we define 30 demographic groups 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 examine the period from 2006 to 2018.[5] We calculate all outcomes by demographic group and country in 2006 and 2018.

We use the EU-SES data to calculate average gross real hourly wages by dividing gross monthly earnings by the number of paid hours worked in the reference month. These earnings include overtime pay, special payments for shift work, compulsory social contributions, and taxes. However, they exclude irregular, *ad hoc* bonuses and other payments that do not occur on a regular basis. We use the EU-LFS to calculate employment rates.

Finally, we use the EU-SILC to calculate income measures. Household market income refers to all household members' total 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 using the tax-benefit microsimulation model EUROMOD (Sutherland and Figari, 2013), according to national tax-benefit rules applied to respondents' household market incomes and composition as observed in EU-SILC. Appendix C provides more details on EUROMOD.[6] Household disposable incomes are expressed in single-adult equivalents to account for economies of scale in consumption across households of different sizes using the scale recommended by Eurostat.[7]

2.2 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 on the stock and the deliveries of industrial robots by country and industry.[8]

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[5] 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 it covers most EU countries from 2005 onwards.

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

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

[8] According 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."

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

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

where $M_{i,c,t}$ represents the robot stock in industry *i* in country *c* in year *t*, $L_{i,c,2006}$ represents the initial 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 some industries' secular decline or growth. 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

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

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), $\omega_{g,i,c}^{R} / \omega_{i,c}^{R}$;
- 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 serves as the first weight, and the group's *g* shares in routine jobs in particular sectors are the second weight (calculated with the EU-SES data). We define routine occupations at the 2-digit level of the International Standard Classification of Occupations (ISCO) and apply the typology of Lewandowski et al. (2020) based on the Occupational Information Network (O*NET) data.

[9] This 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 (Żuk and Savelin, 2018).

The construction of the task displacement measure is motivated by task-based models proposed by Acemoglu and Autor (2011). Robots can perform routine tasks only. Hence, the demand for workers from a particular demographic group is directly affected by robot adoption in a given sector only to the extent that they specialize in routine tasks. Importantly, the between-group variation in $TDA_{g,c}$ derives not only from differences in average task displacement across each particular characteristic (country, age, education, and gender), but also from how these factors jointly influence the extent to which groups are exposed to automation.

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 to 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 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.

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

Table 1. Descriptive statistics

Dependent Variables	Mean	Standard Deviation	Observations
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: We weigh observations by their within-country employment shares. The sources and description of the variables can be found in Appendix Table A.1. Detailed descriptive statistics for all variables for the whole sample are presented in Appendix Table A.2.

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. Second, we use the estimated coefficients to construct counterfactual wages and employment rates for 2018, assuming that robot penetration had remained at its 2006 level in each country and industry. Third, we evaluate the impacts on household income inequality and the cushioning role of tax and benefit systems by feeding these counterfactuals into the EUROMOD microsimulation model.

3.1 Effects of automation on labour market outcomes

We estimate the impact of automation on wages using the following specification:

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

where $\Delta\ln w_{g,c}$ denotes the log change in real hourly wages for demographic group g in country c between 2006 and 2018. The coefficient of interest, β, captures the wage response to a 1% increase in automation, *TDA*. 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 controls ($X_{g,c}$) of exposure to manufacturing and industry shifters. Industry shifters absorb labor demand changes driven by sectoral expansion, while group-specific shifters capture changes in wage premia related to gender, education, and working in manufacturing. We weight regressions by groups' employment shares so that weights sum to one within each country.

We apply the same framework to employment rates, household incomes and size, using changes rather than log changes for employment rates and household size.

Since robot adoption may respond to unobserved shocks that also affect labour demand, we instrument robot penetration using the approach of Acemoglu and Restrepo (2020). Specifically, we instrument the robot penetration in a given industry with an average penetration in the same industry among technologically advanced European countries not included in our sample, *e*: [11]

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

Our baseline instrument draws on Slovenia, Austria, Denmark, Finland, and the United Kingdom, while robustness checks utilize alternative instruments based on Acemoglu and Restrepo (2020)[12] and robot adoption in the US, following Albinowski and Lewandowski (2024).

We adopt the demographic-group approach of Acemoglu and Restrepo (2022), which aggregates outcomes by gender, age, and education groups and estimates long-run differences. Unlike industry-level (Aksoy et al., 2021; Albinowski and Lewandowski, 2024; de Vries et al., 2020; Graetz and Michaels, 2018) or regional-level (Acemoglu and Restrepo, 2020; Dauth et al., 2021) approaches, this framework captures adjustment through cross-industry and cross-regional mobility of workers,

[11] Instrumenting robot adoption in European countries with adoption in peer countries is widely used (Bachmann et al., 2024; Damiani et al., 2023; Dauth et al., 2021; Matysiak et al., 2023; Nikolova et al., 2024).

[12] Denmark, Finland, France, Italy, and Sweden.

and is well suited to studying wage and income inequality, including household-level outcomes.[13] Importantly, the effects identified by comparing demographic groups are less likely to be driven by changes in worker sorting than those identified by comparing sectors (Böhm et al., 2024). Compared to the firm-level, event-study approach (Acemoglu et al., 2025; Barth et al., 2026; Bessen et al., 2025, 2020; Koch et al., 2021), the demographic-group framework is less precise in identifying direct exposure to automation, but allows capturing impacts on all workers in exposed jobs, since robots may reduce workers' power and affect wages outside the robot-adopting firms. In our context, it is an important advantage.

The main limitation of the demographic-group framework is that education is fixed by construction, thereby preventing analysis of automation-induced educational upgrading (Di Giacomo and Lerch, 2023). In our context, this limitation is unlikely to be important, as educational attainment changes little among working-age individuals over a 12-year horizon.

Finally, we focus on labor income and abstract from capital income channels for three reasons. First, the available survey data measure capital income poorly and underrepresent top-income households (Bartels and Waldenström, 2021). Second, the data do not provide sufficient information on household asset portfolios to link them to automation exposure. Third, capital income represents a small share of disposable income for most households,[14] while labour income remains the dominant channel through which automation affects living standards.

3.2 Microsimulation of disposable income inequality

In the second stage, we evaluate the contribution of automation to disposable household income inequality. We begin by calculating the estimated wage and employment impacts of automation for each demographic group g and country c – as $\hat{\beta}^{w} \cdot TDA_{g,c}$ for wage growth, and $\hat{\beta}^{e} \cdot TDA_{g,c}$ for employment change – and 'injecting' them into the 2018 EU-SILC microdata.

To simulate wage effects, we divide the 2018 hourly wages of demographic group g in country c by $(1+\hat{\beta}^{w} \cdot TDA_{g,c})$, generating counterfactual wages that would have prevailed absent post-2006 robot adoption. We then reweight these counterfactuals by the share of workers employed in firms with at least 10 employees (based on the EU-LFS data, see Appendix Figure D.1) to reflect that robot adoption primarily occurs in larger firms. As a robustness check, we also simulate an upper-bound scenario in which all workers are affected (Appendix D). We aggregate counterfactual wages into

[13] The regional-level approach is also unfeasible with the EU surveys because the regional information is highly aggregated.

[14] The 2018 EU-SILC data shows that capital income represents less than 10% of disposable income in all 14 countries in our sample and less than 5% of disposable income in 10 of them.

annual labour incomes at the household level and recompute taxes, social security contributions, and transfers using the 2018 EUROMOD tax-benefit rules. We leave non-labor incomes unchanged.[15] Differences between inequality measures (the Gini index) calculated on observed and simulated household incomes capture the distributive impact of automation through wages.

To simulate employment effects, we reweight each respondent in the 2018 EU-SILC with:

$$E_i \frac{er_{g,c}}{\left(1+\widehat{\beta^e}\cdot TDA_{g,c}\right)-er_{g,c}}+(1-E_i)\frac{\left(1+\widehat{\beta^e}\cdot TDA_{g,c}\right)-er_{g,c}}{er_{g,c}} \tag{5}$$

where E_i = 1 if respondent i is employed and 0 otherwise, $er_{g,c}$ 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. This provides counterfactual employment rates, assuming no change in robot penetration after 2006. Differences between inequality measures calculated using observed and simulated household incomes capture the distributive impact of automation through employment. We combine wage and employment simulations to obtain counterfactual income distributions reflecting the joint effect through wages and employment. Due to non-linearities, the joint effect can differ from the sum of wage and employment effects; we express this difference as an interaction effect.

To assess the role of income pooling within the household (and therefore labor income source diversification) for the transmission of automation-driven shocks, we compare observed and simulated distributions of individual-level and household-level market incomes (for those aged 20-65).

Finally, to assess the cushioning role of tax-benefit systems, we compute Gini indices for market and disposable incomes, additionally distinguishing between incomes after transfers and those after taxes and transfers. The double differences between pre- and post-tax distributions, observed and simulated, capture how much taxes and benefits cushioned the impacts on disposable incomes.

To be clear, this microsimulation analysis is a comparative-static exercise – it maps the automation-induced shocks into disposable household income while holding household structures and tax-benefit rules fixed. We evaluate the automation shock under both pre-shock (2006) and post-shock (2018) household structures and policy regimes, but differences between these scenarios reflect a combination of endogenous responses to automation and unrelated institutional and demographic changes. We therefore do not identify behavioural responses of households to automation, nor policy adjustments enacted in response to technological change.

[15] See Appendix C for more details on EUROMOD and the simulation methodology.

4 The effects of robot exposure on wages, employment, market income, and household structure

OLS estimates of the effect of robot exposure on relative wage growth in Europe are statistically significant and negative (Table 2): demographic cells exposed to higher robot penetration experienced lower wage growth. However, as discussed in Section 3, OLS estimates may be biased if unobserved shocks affect both robot adoption and labor market outcomes simultaneously. Instrumental variable estimates address this concern and provide very similar results, albeit larger in absolute terms (Table 2).[16] This could mean that OLS estimates may be biased towards zero, possibly because of omitted factors correlated negatively with changes in exposure to task-displacing technologies.[17]

Table 2. The effect of automation on changes in real hourly wages, 2006–2018

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

Notes: 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. Appendix Table B.1 shows the first-stage results. Data: EU-SES. * p<.10; ** p<.05; *** p<.01

[16] Appendix Table B.1 presents first-stage results.

[17] For instance, declining international competitiveness could incentivise robot investment and slow down wage growth. 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).

Results are robust across specifications. Our preferred specification, reported in Column 4 of Table 2, includes group-specific shifters (gender and education fixed effects, as well as exposure to manufacturing) and industry shifters capturing changes in sectoral value added. While the coefficient lacks a direct interpretation, scaling it by a standard deviation of robot penetration across demographic groups (0.59, Appendix Table A.2) implies that a one-standard-deviation increase in exposure reduced relative wage growth by about 4%. Notably, the direction and magnitude of the effect are virtually identical in Western and Eastern Europe (Appendix Table B.2).

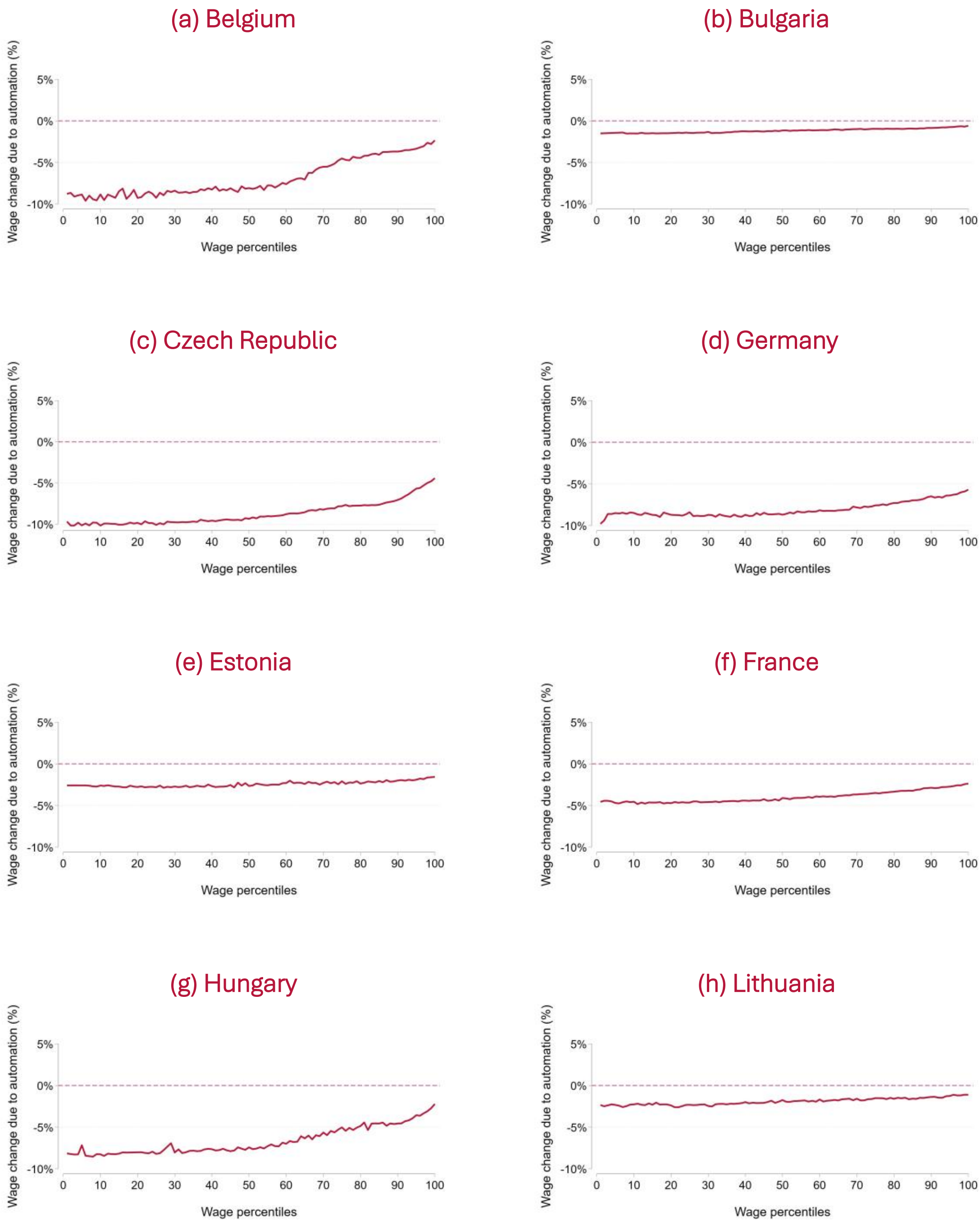
Results remain essentially unchanged when controlling for additional factors, such as specialization in routine jobs, exposure to offshoring, Chinese imports penetration, minimum wage, collective bargaining coverage, and population changes (Appendix Table B.3). Leave-one-out tests show that no single country drives the results (Appendix Figure B.2). We also obtain consistent findings using alternative instruments, using robot adoption (i) in the same set of countries as in Acemoglu and Restrepo (2022) and (ii) in the United States, although the latter estimates are less precise (Tables B.4 and B.5). In addition, robot penetration significantly compresses wage dispersion within demographic groups (Appendix Table B.6). This indicates that the disequalising, between-group effects constitute a key distributional channel of automation and validates our focus this channel.

In most countries, automation-induced wage declines tend to concentrate in the lower half of the wage distribution. To highlight this, we used the estimated coefficients to calculate automation-induced wage changes all demographic groups in 14 countries in our sample, and map them onto the initial within-country wage distribution. Figures 1-2 show these effects by percentiles of the wage distribution in particular countries, while Appendix Figure B.3 aggregates the results across countries.

Automation's impact on wages varied greatly across Europe. The disequalising pattern is most pronounced in Belgium, the Czech Republic, Hungary, Germany, and Poland, where wage reductions for groups at the bottom exceed 5%, roughly double the size of those recorded at the top (Figures 1–2). These countries experienced rapid robot adoption between 2006 and 2018 (Appendix Figure B.1), with high exposure among below-median earners. By contrast, in the Baltic countries or the Netherlands, wage effects appear more evenly distributed.[18]

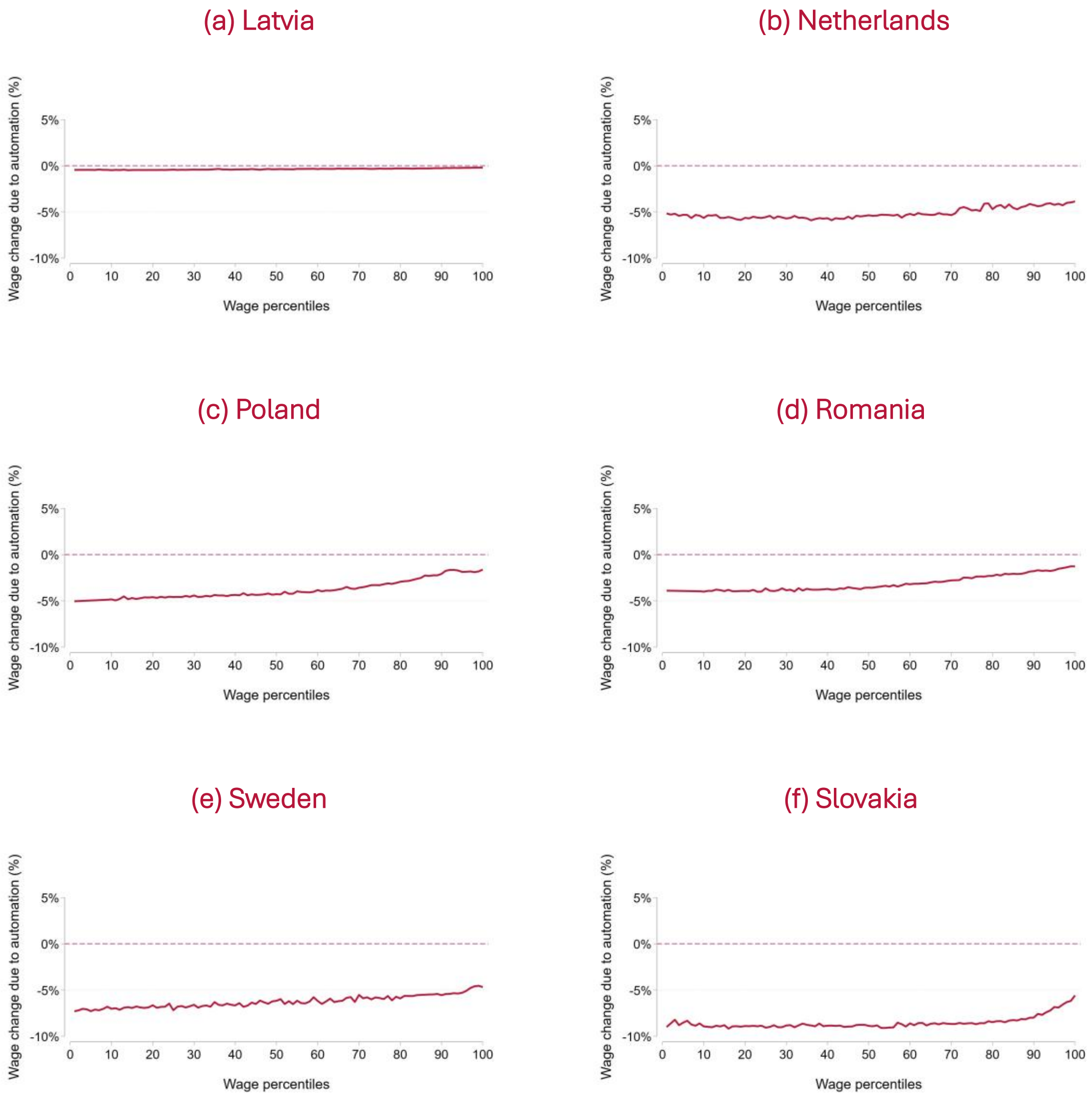
[18] In the pooled sample, wage changes due to automation for the bottom decile were twice as large as changes due to automation for the top decile (Appendix Figure B.3). However, this partly reflects the fact that Eastern countries had lower wages and recorded rather large increases in robot penetration.

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



Notes: 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: 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.

Automation also affected employment. We find a statistically significant decline in employment rates among more exposed groups (Table 3). It is, however, relatively small. According to IV estimates, a one-standard-deviation increase in robot penetration reduced employment rates by about two percentage points. Combined with adverse wage effects (Table 2), these findings suggest a negative impact of automation on labor market outcomes of more exposed groups.[19]

Table 3. The effect of automation on changes in employment rates, 2006–2018

	(1)	(2)	(3)	(4)
	OLS			
Automation: penetration of robots	-0.011	-0.009	-0.023	-0.017
	(0.012)	(0.013)	(0.019)	(0.014)
	2SLS			
Automation: penetration of robots	0.000	0.004	-0.033	-0.034*
	(0.016)	(0.018)	(0.021)	(0.021)
Country FE	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes
Gender	no	yes	yes	yes
Education	no	no	yes	yes
Industry shifters	no	no	no	yes
F-statistic first stage	353.80	339.95	233.69	233.61
Mean of outcome	0.04	0.04	0.04	0.04
Mean of automation	0.83	0.83	0.83	0.83
Observations	420	420	420	420

Notes: 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

As discussed above, adverse impacts on wage and employment do not necessarily imply negative shocks to household incomes. Table 4 shows reduced-form estimates of the impact of our cohort-level robot exposure measures on households' incomes, distinguishing between market (the sum of income from dependent and self-employment) and total (monthly) income measures, using EU-SILC data.[20] While the estimates are less precise than for wages and employment, we find a considerable reduction in *individual* monthly market income (column 1 of Table 4) that is consistent

[19] Our 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

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

with wage and employment impacts. At the same time, market income of other household members increased significantly (column 2 of Table 4), consistent with an added-worker response (Lundberg, 1985). Combining these effects, market income per working-age household member and the average equivalized market income remained unaffected by robot exposure, resulting in no impact on disposable income (columns 3-5 of Table 4). While we observe a small positive effect of robot exposure on the number of working-age household members, we see no evidence of adjustments in household size (columns 5-6 of Table 4). 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.

Table 4. The effect of automation on changes in monthly income and household structure, 2006-2018

	Market income				Disposable income	Household size	
	Individual (own) income	Other members' income	Income per working-age member	Household equivalized income	Household equivalized income	Working-age members	Household size
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				OLS			
Automation: penetration of robots	-0.092*	0.062	0.027	-0.004	0.027	0.054***	0.015
	(0.048)	(0.042)	(0.034)	(0.031)	(0.019)	(0.014)	(0.011)
				2SLS			
Automation: penetration of robots	-0.120*	0.099*	0.058	0.023	0.009	0.043*	-0.003
	(0.071)	(0.060)	(0.046)	(0.046)	(0.022)	(0.023)	(0.013)
Controls	yes	yes	yes	yes	yes	yes	yes
F-statistic first stage	173.84	173.41	168.51	171.55	200.82	191.97	191.59
Mean of outcome	0.24	0.18	0.22	0.24	0.21	-0.04	-0.03
Observations	330	330	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, market income per working-age member, equivalized household market income, equivalized household disposable income (after taxes and transfers), the number of working-age household members, and household size for 30 demographic groups in 11 European countries from 2006 to 2018. All regressions include controls for country, gender and education fixed effects, manufacturing share, and industry shifters. Due to data quality issues, Bulgaria, Estonia, and Romania were excluded from the analysis. The instrument is the average robot penetration in five European countries that were 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.

5 The income inequality effect of robot exposure

The transmission of automation-driven shocks to household income inequality reflects the interaction of three mechanisms: changes in wages and employment, income pooling within households, and redistribution through taxes and transfers. Section 4 provided evidence of automation's adverse impact on wages, employment and individual incomes of exposed workers in Europe. However, wage declines tend to compress the income distribution, while employment losses increase the share of households with little or no market income, thereby raising inequality. Household structures further shape these outcomes, as assortative mating can amplify income shocks when multiple earners face similar exposure, while labor supply adjustments by other household members may offset them. Finally, progressive tax-benefit systems mitigate both effects.

5.1 The contribution of automation to household income inequality

Our regression results indicated that, on average across Europe, adverse labor market effects of automation tended to be cushioned by income diversification within households. Here, we assess the contribution of automation to household income inequality and identify the channels that amplify or mitigate individual-level shocks. We conduct this analysis at the country level to account for the cross-country differences in intra-household adjustment mechanisms and tax-benefit systems.

We construct counterfactual wages and employment rates for 2018, assuming that robot exposure remained at the 2006 level. For each demographic group and country, we multiply robot penetration by the estimated wage and employment coefficients, as reported in columns 4 of Tables 2 and 3, respectively. We inject these values into the EUROMOD microsimulation model to generate counterfactual income distributions.

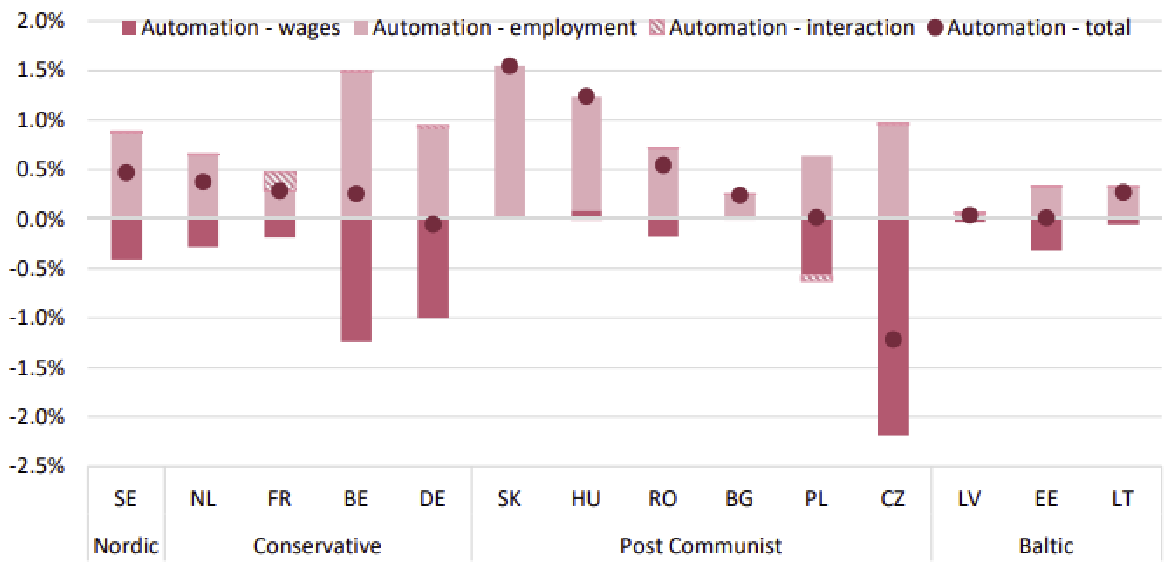
We start by examining automation's contribution to income inequality by country (Figure 3), distinguishing between the wage and employment channels and their interaction. To help relating impacts to tax-benefit systems, we group countries by welfare regime following Olivera (2018): Nordic (Sweden); Conservative (Belgium, France, Germany, and the Netherlands); Baltic (Estonia, Latvia, and Lithuania), and Post-Communist (Bulgaria, Czechia, Hungary, Poland, Slovakia, and Romania). Within each group, we order countries by the contribution of automation on income inequality.

Automation-induced wage changes, which are negative across all demographic groups (Table 2), slightly reduced disposable household income inequality in most countries. Although automation widened wage inequality (Figures 1-2), lower wages compress the income distribution by reducing the income gap between workers and those out of work or on fixed incomes, such as pensions. This equalizing mechanism is most pronounced in Nordic, Conservative, and some Post-Communist countries, but its magnitude remains small, around 1–2% of the 2018 Gini index in Czechia, Belgium, and Germany, and below 0.5% elsewhere (Figure 3).

Automation-driven employment losses operated in the opposite direction. They increase the mass of individuals at the bottom of the market income distribution (with zero market income), modestly widening inequality in most countries. This channel partly or wholly offsets the wage effect. Countries with large robot penetration, such as Belgium, Slovakia, and Hungary, exhibit the largest employment-induced contribution to income inequality, reaching 1.2-1.5% of the 2018 Gini index. In other countries, the employment channel contributes less than 1% of the 2018 Gini index (Figure 3). The interaction between wage and employment effects is negligible in all countries except France, suggesting that in France, employment losses disproportionately affect groups that also experience wage declines.

Summing all components, we find that automation increased household income inequality only slightly in most countries, by less than 1.5% of the 2018 Gini index. Only in Czechia, the wage effect dominates and slightly reduces inequality (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 each group, countries are ordered in decreasing order of the total change in the Gini Index due to automation. Data: EUROMOD, EU-SILC.

As a robustness check, we simulate an upper-bound scenario in which all workers face the same robot exposure as workers in firms with at least 10 employees. For most countries, the results closely match the baseline results (Appendix Figure D.2). The upper-bound results are noticeably larger (in absolute terms) only in some Post-Communist countries with high robot adoption, such as Slovakia and Hungary, but they remain around 2% of the 2018 Gini index.

5.2 The distributional impact of automation: households' labor income diversification and tax-benefit systems

Why has automation contributed so little to disposable income inequality in European countries? To assess the role of key mechanisms: the diversification of households' labor income sources, and tax and benefit systems, we compare automation-induced changes in inequality across three 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). 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. Figure 4 summarises the results.

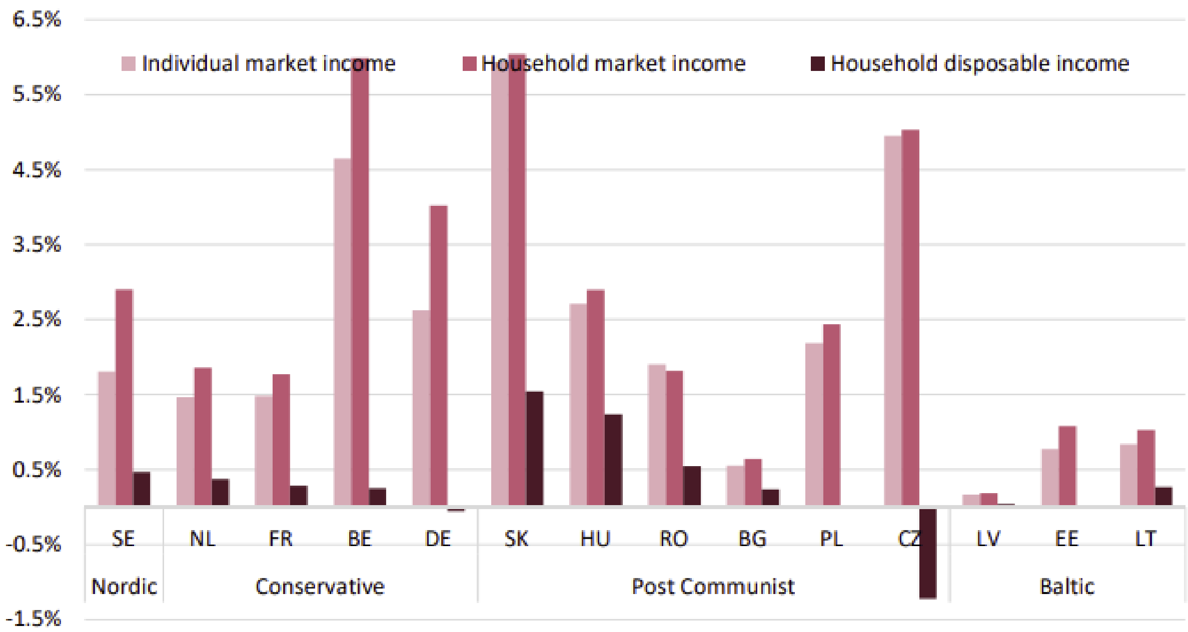
Automation consistently increases inequality in individual-level market income, reflecting wage dispersion and employment losses. The effect is largest in countries where automation disproportionately reduced wages at the bottom of the distribution, including Belgium, Slovakia, Czechia, and Germany, where individual-level Gini indices rise by up to 6%. In countries where automation barely affected low wages, such as Bulgaria, Latvia, and Estonia, the effect is close to zero.

In all countries, automation widened inequality of individual-level market income, reflecting the disequalizing impact of robots on wages (Figures 1-2) and the accompanying fall in employment, which further polarises the distribution of market income. The impact is the largest (up to 6% of the 2018 Gini index) in countries where automation disproportionately reduced wages at the bottom of the distribution, such as Belgium, Slovakia, Czechia, and Germany, widening wage inequality (Appendix Figure B.4). It is the weakest (close to zero) in countries where automation barely affected low wages and wage inequality, such as Bulgaria, Latvia, and Estonia.

However, moving from individual to household market income highlights the key role of household structures in mitigating the impact of automation. In Nordic and Conservative countries, automation's contribution to household market income inequality is visibly larger than its contribution to individual market income inequality, indicating that household income pooling exacerbates the transmission of the automation shock. In the Post-Communist and Baltic countries, the difference is much smaller or negative, indicating a stronger diversification of market incomes within households. Appendix Figure B.5 shows that the magnitude of household labor income diversification by country is positively correlated with countries' incidence of assortative mating in routine occupations. A sensitivity analysis (Appendix B) confirms that, in most countries, household formation in 2018 amplified the automation effect by less than household formation in 2006 would have (Appendix Figure B.6), in line with a decline in assortative mating in routine occupations that also happened in most countries. However, these changes in the contribution of household formation to automation are small, in absolute terms generally below 0.05% of the Gini coefficient (Appendix Figure B.6).

Finally, 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 its contribution to either measure of market income (Figure 4), remaining below 1% in most countries. However, in some Post-Communist countries (Slovakia and Hungary), the automatic stabilization by the tax-benefit system was unable to prevent a rise in household income inequality.

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

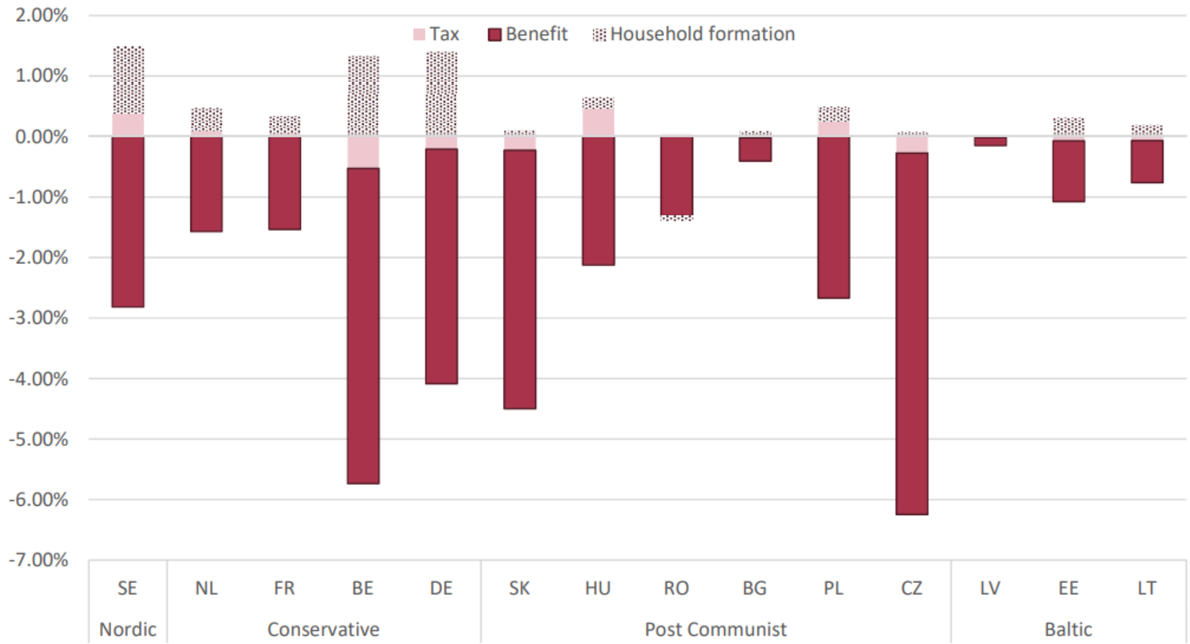


Notes: The Figure shows the change in Gini Index due to automation, where income is defined as (i) market income at the individual level, (ii) equivalised market income at the household level, and (iii) equivalised disposable income at the household level. In each group, countries are ordered in decreasing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

Most of the cushioning effect of tax-benefit systems is due to benefits. To isolate the role of taxes and benefits, we examine Gini indices of household market income, gross income (market income plus benefits), and net income (market income minus income tax) . Benefits do much of the heavy lifting, particularly in the Nordic, Conservative and Post-Communist regimes, while taxes play a minor role (Figure 5). Taking the example of Germany, automation increased the 2018 Gini index of individual-level market income by 2.5% and of household market income by 3.7%. Taxes reduced inequality only marginally, by 0.2% of the Gini index, while benefits offset nearly the entire automation-driven increase in inequality, reducing the Gini index by 3.9% (Figure 5). Consequently, disposable income inequality remained essentially unchanged (Figure 3). In the Baltic countries, neither taxes nor benefits play a strong role, likely reflecting the small size of the automation shock.

These findings align with the literature on the stabilizing effects of European tax-benefit systems. Dolls et al. (2022) reported that such effects for a stylized 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 each group, countries are ordered in decreasing order of the total change in the Gini Index due to automation. Data: EUROMOD, EU-SILC.

In most countries, the cushioning of the automation-induced shocks under the set of 2006 policies would have been very similar to that under the 2018 policies (see Appendix Figure B.7). In Romania, Slovakia, and Belgium, the 2006 systems would have cushioned the automation shock noticeably more than the 2018 systems, while the opposite pattern emerges only in Germany. In the remaining countries, the outcomes are virtually the same under both systems. This indicates that the stabilizing role of European tax-benefit systems has not been a direct policy response to automation but instead is a secular feature of European tax-benefit systems.

5.3 Automation and overall income inequality trends in 2006–2018

We conclude by comparing automation's contribution to inequality with observed changes in income inequality between 2006 and 2018. Inequality evolved very differently across countries during this period, increasing sharply (by more than 10% of the Gini index) in Hungary, Bulgaria, Lithuania, and Sweden, and declining in Slovakia, Poland, and Estonia (Figure 6). Against these changes, automation has played a minor role. Its contribution ranges from -1.2% of the 2018 Gini index in Czechia to 1.5% in Slovakia.

Across countries in our sample, automation explains only 1.2% of the cross-country variation in inequality changes (Table 5). The wage channel accounts for a larger share of automation's contribution than the employment channel, while benefits emerge as the key mitigating force (Table 5).

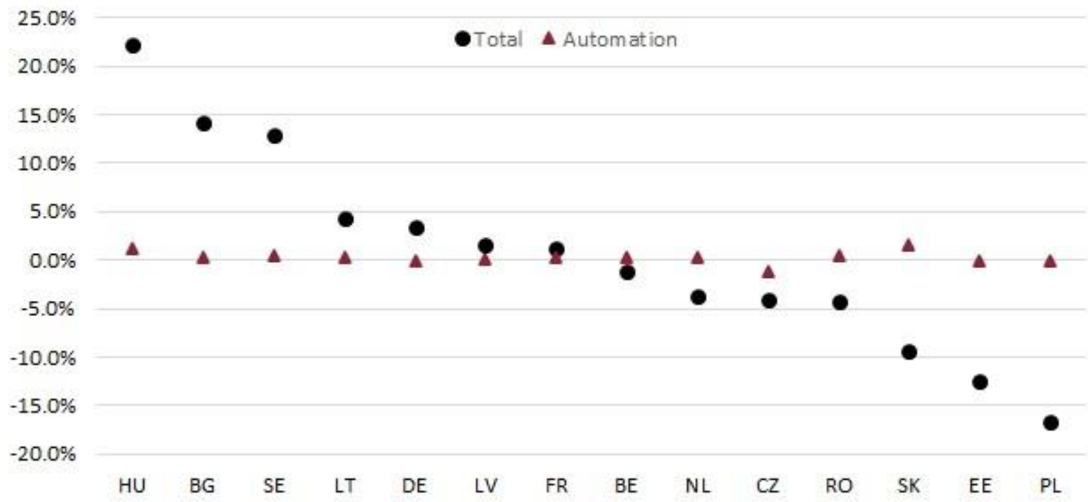
Other economic shocks and policy changes, including the Great Recession and the sovereign debt crisis, played a much larger role than robot adoption in shaping the evolution of income inequality in European countries over this period.

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 and 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.

6 Conclusion

This paper examines how automation, measured by industrial robot penetration, affected wages, employment, and household income inequality in 14 European countries between 2006 and 2018. We combine causal estimates of automation's impact on wages and employment at the demographic-group level with tax-benefit microsimulations to trace how labour market shocks translate into household disposable incomes. By focusing on demographic groups defined by gender, education, and age, and using an instrumental-variable strategy, we capture the contribution of automation-induced, between-group differences in wage growth and employment to inequality. We disentangle the role of adjustment mechanisms within households, related to household composition and income pooling, as well as the cushioning role of tax-benefit systems.

Consistent with evidence from the United States, we find that higher robot exposure significantly reduced relative real wages, employment rates, and market incomes of more exposed groups. However, automation-induced declines of individual market income of exposed workers were partly offset by rising market incomes among other household members, consistently with an added-worker effect (Lundberg, 1985). As a result, average market income per working-age household member, equivalised market income, and disposable income remained largely unaffected by robot exposure. Household size remained unchanged, although the number of working-age household members increased slightly, reinforcing income diversification within households.

The adverse labour market effects translated only weakly into household disposable income inequality. The key reason lies in the interaction of wage and employment shocks with household income pooling and redistribution. Automation-induced employment losses tended to increase inequality by expanding the mass of households with zero market income. In contrast, automation-induced wage declines compressed the income distribution by narrowing gaps between those in work and those on fixed incomes. The ability of the welfare system to passively stabilize income distribution (Doorley et al., 2021) reduced the gaps between the incomes of those in and out of work and a corresponding fall in income inequality. In most countries, these opposing forces largely cancel each other out.

Examining the transmission mechanisms in more detail, we observe that tax-benefit systems played a central role in cushioning automation-driven shocks, particularly in Nordic and Conservative welfare regimes. Benefits accounted for most of the stabilization, reflecting the employment-based nature of the automation shock, while taxation played a more limited role. Household labour income diversification did not, on average, mitigate automation's impact on inequality. In several Nordic and Conservative countries, it even slightly amplified inequality. Evidence suggests that the mitigating force of household labour income diversification was negatively related to assortative mating in routine occupations, which increases the correlation of automation exposure among household members. Added-worker responses offset individual income losses, but not sufficiently to meaningfully affect inequality.

Overall, while automation measurably affected wages and employment, its contribution to changes in household income inequality was relatively small compared to other forces shaping income distributions during this period, including the Great Recession, sovereign debt crises, austerity measures, and associated policy changes. Across countries, automation accounts for only a minor share of the observed changes in inequality between 2006 and 2018.

Our results should be interpreted as first-order distributional effects. The simulations abstract from behavioural responses, changes in household formation, fertility, [21] or non-labour incomes induced by automation. We also focus on labour income channels and do not capture potential automation-driven increases in capital income concentration, which remain poorly measured in household

[21] The evidence on robots' impact on fertility is limited. Anelli et al. (2024) found no impact in the U.S., Matysiak et al. (2023) showed mixed effects in six European countries.

surveys.[22] Despite recent efforts by statistical agencies to link survey data to administrative income information, capital incomes and top income earners remain underestimated and underrepresented in surveys such as EU-SILC (Bartels and Waldenström, 2021; Ravallion, 2022) and therefore cannot be included reliably in our 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 top-income households are accurately represented.

Finally, operating at the demographic-group level implies that we do not capture within-group heterogeneity. However, we find that automation reduces labour incomes of more exposed groups but also appears to compress within-group wage dispersion (Appendix Table B.6). Therefore, our estimates of inequality capture the key disequalising force – the between-group income changes.

From a policy perspective, our findings highlight that existing European tax-benefit systems have been effective at absorbing automation-driven labour market shocks, primarily through benefits rather than taxes. At the same time, household structures can amplify exposure when labour market risks are correlated within households. Future automation shocks may therefore place greater strain on redistribution mechanisms in countries with weaker automatic stabilizers or stronger assortative mating. Policies aimed at strengthening income stabilization during employment transitions, rather than broad labour market interventions, appear most relevant for limiting the distributional consequences of automation.

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[22] Evidence from the US suggests that automation raises capital incomes at the very top of the income distribution, thus widening inequality (Moll et al., 2022).

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Appendix A. Data Appendix

Table A.1. Variable descriptions

Variable	Description	Source
Socio-demographic characteristics		
Gender	a binary variable (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 (20062018)	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

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

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

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

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

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

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

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

Table B.3. Automation and changes in real hourly wages, with additional controls. 2SLS results

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

Notes: Table shows estimates of the relationship between task displacement due to automation and the change in log wages across 30 demographic groups in 18 European countries. The dependent variable is the change in log wages for each group from 2006 to 2018. In all regressions, we control for initial wage levels, manufacturing share of employment, manufacturing n.e.c. share of employment, gender, education, industry shifters and country fixed effects. All regressions are weighted by the share of the country's employment.

Column 1 shows our baseline estimates. In column 2, we additionally control for the relative specialization in routine tasks. In column 3, we additionally control for the increase in the exposure to offshoring. In column 4, we additionally control for the Chinese imports penetration. In column 5, we additionally control for minimum wage bite. In column 6, we additionally control for initial collective bargaining coverage. In column 7, we additionally control the initial employment share in state-controlled firms. In column 8, we additionally control for population change. In column 9, we control for all additional variables. The sources and description of the variables can be found in Table A.1. Robust standard errors are reported.

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

Table B.4. Effects of automation on changes in real hourly wages and employment rates - original Acemoglu & Restrepo instrument, 2SLS

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

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

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

Table B.5. Effects of automation on changes in real hourly wages and employment rates - US instrument, 2SLS

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

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

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

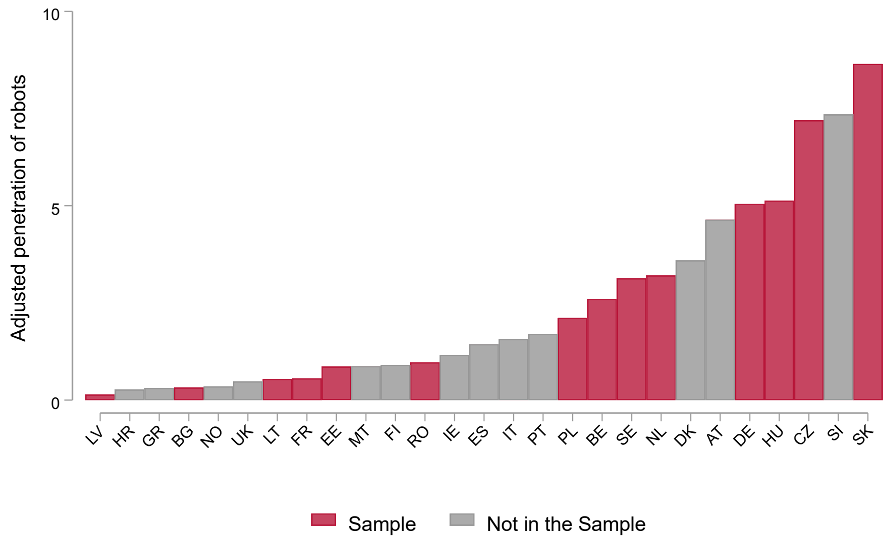
Table B.6. Automation and changes in wage dispersion within demographic groups, 2006-2018

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

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

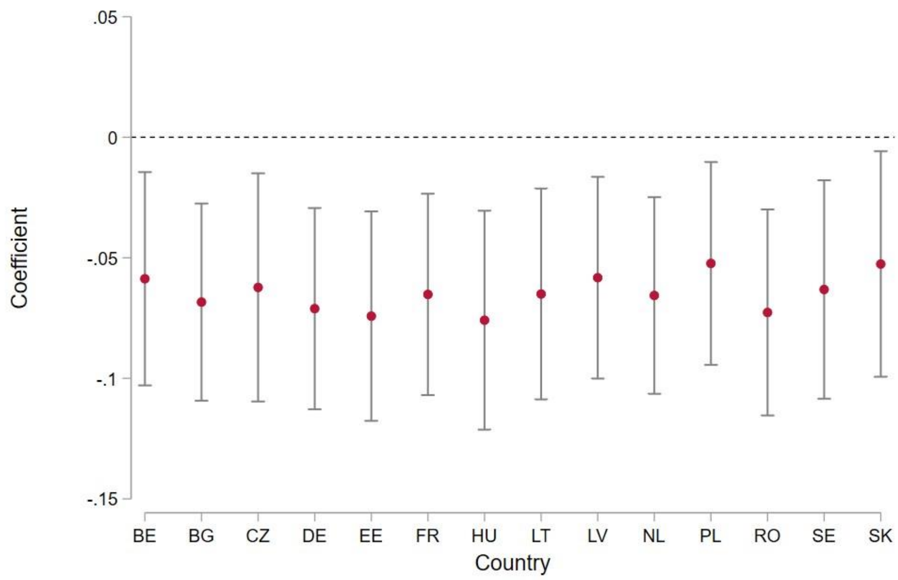
Data: EU-SES. * p<.10; ** p<.05; *** p<.01

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



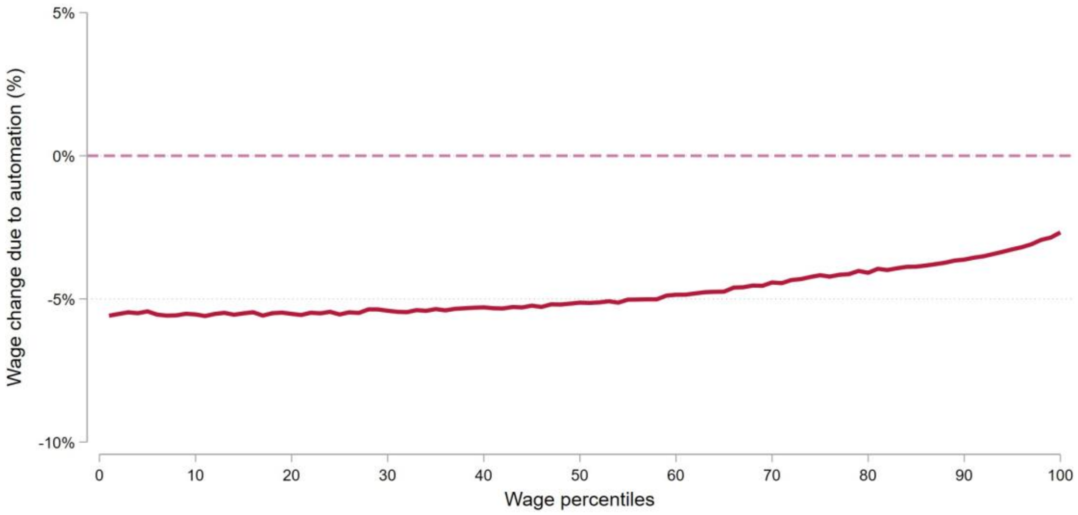
Notes: Figure shows the adjusted penetration of robots in European countries (the 2006-2018 increase in the robots per worker adjusted for the industry-level growth of output). The red bars denote the countries included in our study. Data: IFR & Eurostat.

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



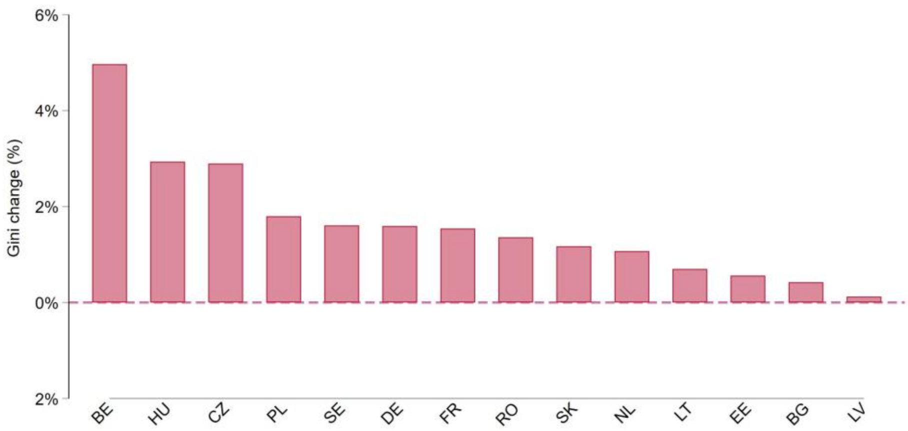
Notes: Figure shows the point estimates and 95% confidence intervals of the effects of the penetration of robots on changes in log wages between 2006 and 2018. In each regression, we remove one country (displayed on the x-axis).

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



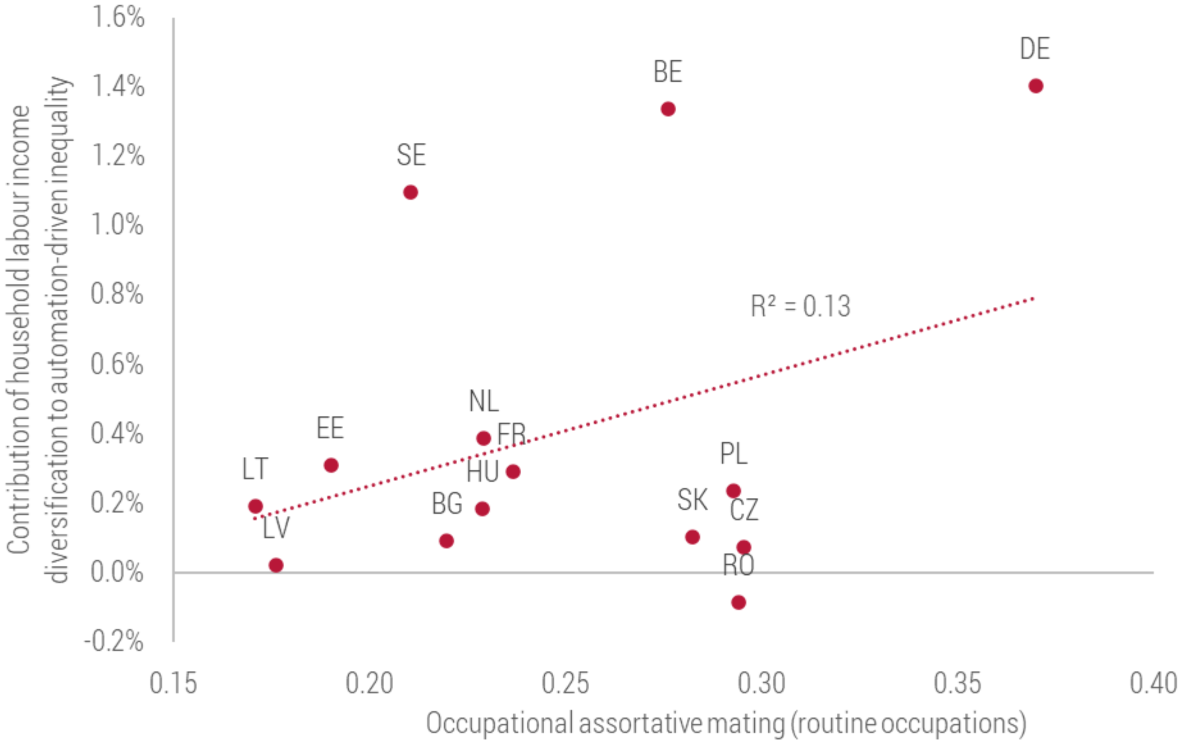
Notes: Figures show the average wage changes due to automation for percentiles of the within-country wage distribution. Wage changes due to automation are computed by multiplying the group's increase in exposure to automation by the wage effects of automation from the equation 3. We compute the wage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

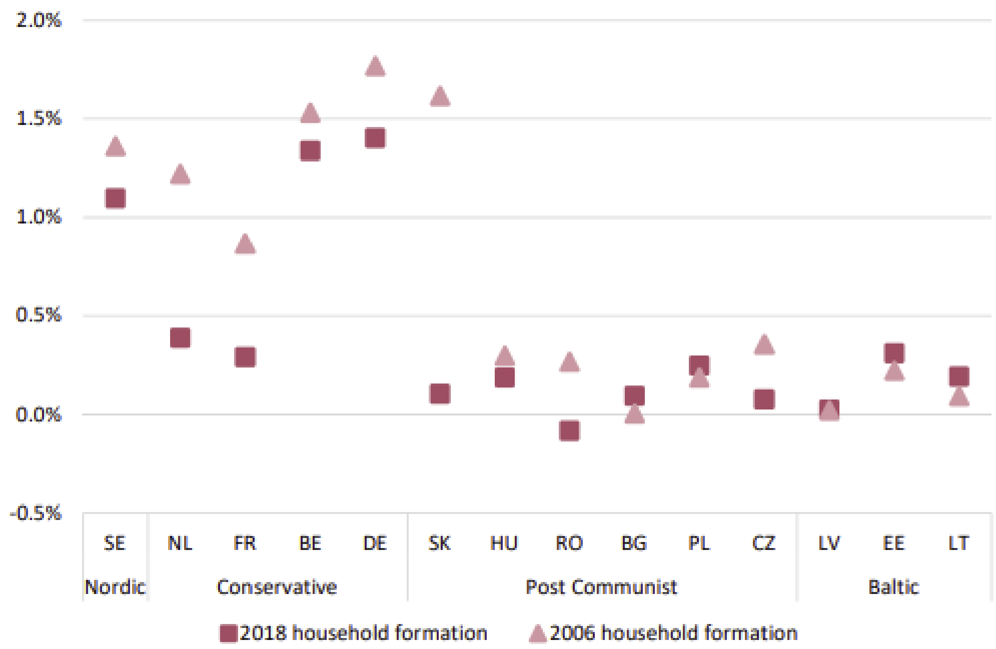
Data: EUROMOD, EU-SILC.

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, and the elderly living longer. In this sensitivity analysis, we compare the cushioning effect of household formation on the automation shock to its counterfactual value if household formation in 2018 followed the 2006 structure. In practical terms, this involves injecting the automation shock into the 2006 simulation of income inequality, calculating the difference between how individual level market income inequality changes and how household level market income inequality changes, and comparing this double difference to the same calculation performed on the 2018 simulation of income inequality, with and without the automation shock.

Figure B.6 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 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.6. The contribution of household formation to the automation-induced household inequality: 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.

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.[23]

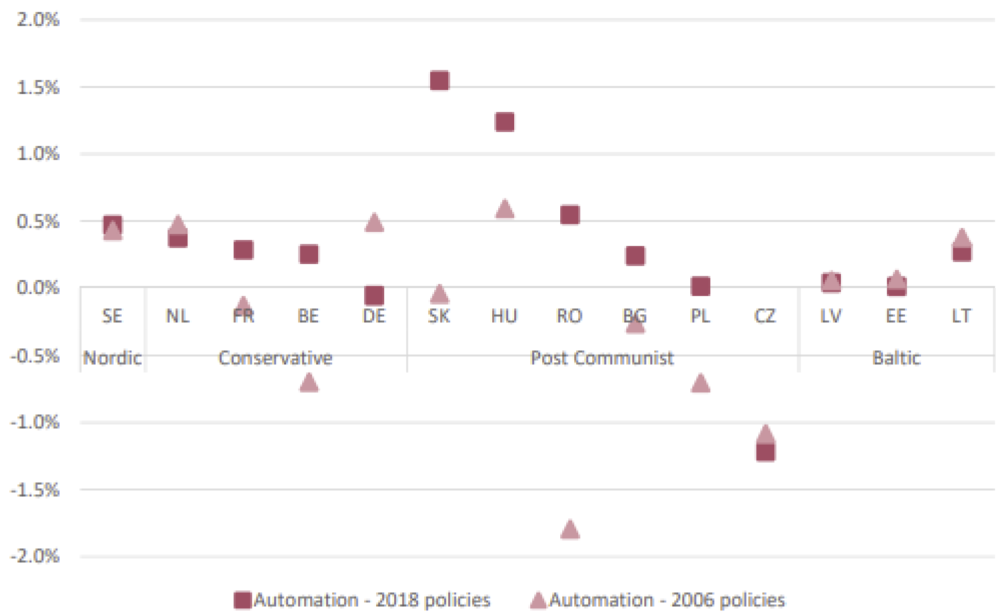
In essence, this shows how discretionary changes to tax and welfare payments between 2006 and 2018 affected the transmission of automation-induced labor income changes into disposable income inequality. The hypothetical effect of automation on income inequality if an indexed 2006 tax-benefit system was in place in 2018 is shown in Figure B.7.

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

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

system does not interact with automation changes differently to a price-indexed 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.7. 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.

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 Y := (X, Y^L, Z) a $N \times k$ matrix with, for each of N households, $k - 2$ sociodemographic 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, $y^d = d(\mathrm{Y},p)$ 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 Y. Income inequality in disposable income is denoted $I\,[y^d]$ where $I : R^N$ 7→ [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

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

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

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

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

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

where $\tilde{Y}^{L1}$ 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) $$\tilde{Y}_1^L = diag(dw(X_0))Y_1^L$$

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:

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

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

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

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

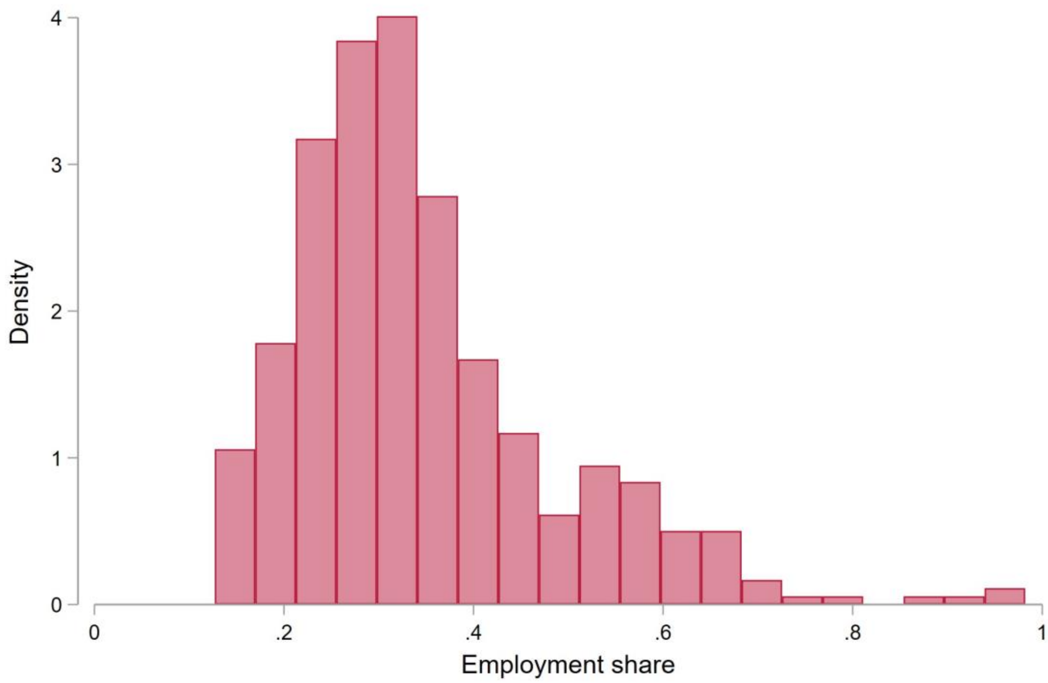
$$E_i \frac{p_{g,c}}{(1 + \hat{\beta}^e \cdot TDA_{g,c}) - p_{g,c}} + (1 - E_i)\frac{(1 + \hat{\beta}^e \cdot TDA_{g,c}) - p_{g,c}}{p_{g,c}}$$

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

Appendix D. Accounting for incomplete coverage of employment in small firms

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

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



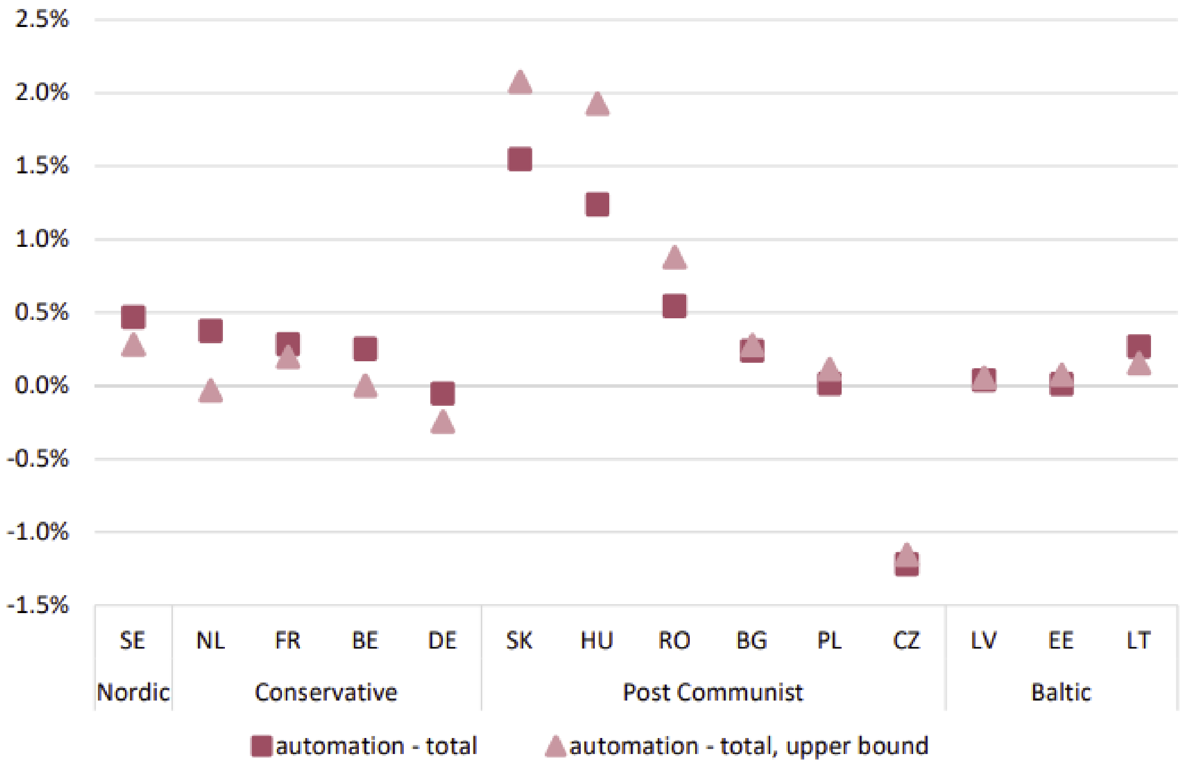
Data: EU-LFS.

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

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

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

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



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