Automation and Income Inequality in Europe

Preliminary - please do not cite

Karina Doorley (ESRI, Trinity College Dublin, IZA)
Jan Gromadzki (IBS, SGH, IZA)
Piotr Lewandowski (IBS, IZA, RWI)
Dora Tuda (ESRI, Trinity College Dublin)
Philippe Van Kerm (LISER, University of Luxembourg)

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- This paper uses Eurostat data. Eurostat has no responsibility for the results or the conclusions, which are those of the authors.

Motivation

- Automation explains a large share of changes in wage inequality in the US (Acemoglu and Restrepo, 2022)
- Effects in Europe unclear: predistribution (minimum wages, unions, collective bargaining, Blanchet et al., 2022)
- No evidence on how automation affects household income inequality:
  - employment and wages effects → effects on individual earnings
  - assortative mating / risk-sharing in households → effects on household earnings
  - taxes and transfers → effects on household disposable income

Contribution and main findings

We evaluate the impact of automation (robots) on household income inequality in European countries, finding:

- Negative wage and employment effects despite high levels of predistribution
- Adverse and disequalising effects on individual earnings
- No effects on disposable incomes: risk-sharing and welfare systems mitigate the negative effects of automation (unlike in the U.S.)

Conceptual framework

- Output is produced by tasks that can be performed by capital or various types of labour
- Real wages are linked to task shares
- Automation increases the productivity of capital at tasks previously assigned to labour $\rightarrow$ decreases labour's task shares
- Thus, automation affects wages in two ways:
  - Positive effects: the increased productivity raises the wages of all workers (SBTC, market size effects, e.g. Katz and Murphy, 1992)
  - Negative effects: the decreased labour task shares reduce the wages of some workers (routine occupations)

We assess the effects of automation on household income inequality in Europe between 2006-2018

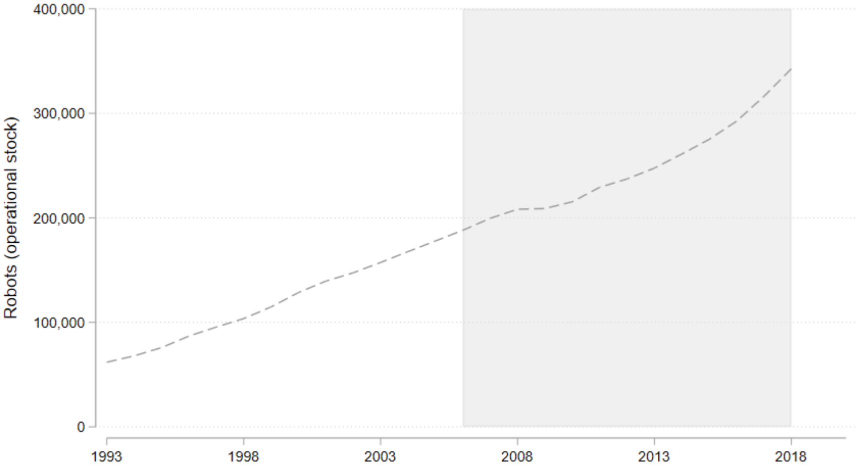
Estimate the effects of automation on changes in wages and employment rates in 2006-2018

Distinguish 30 socio-demographic groups in 14 European countries

Obtain counterfactual 2018 wages and employment rates – what would be the wage level and employment rate of a demographic group if the automation level would have remained at the 2006 levels)

Use EUROMOD microsimulations to investigate the impact of automation on household income inequality

Between 2006 and 2018, the stock of robots in Europe increased by 80%



Data

- Unit of observation - 30 demographic groups per country: gender x age x education groups x country
- Sample of 14 countries: Belgium, Bulgaria, Czechia, Estonia, France, Germany, Hungary, Latvia, Lithuania, Netherlands, Poland, Romania, Slovakia, Sweden
- Wages, specialization in industries and tasks: EU Structure of Earnings Survey (EU-SES)
- Employment rates: EU Labour Force Survey (EU-LFS)
- Annual earnings and disposable incomes: EU Statistics on Income and Living Conditions (EU-SILC)

Measuring exposure to automation (i.)

- Adjusted penetration of robots as in Acemoglu and Restrepo (2020).

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

- $M_{i,c,t}$: the number of robots in industry i in country c in year t (IFR data)
- $L_{i,c,2006}$: the baseline employment level in industry i and country c
- $Y_{i,c,t}$: real output of sector i in country c in year t
- We focus on industrial robots: technology that is well-measured and clearly task-replacing

Measuring exposure to automation (ii.)

- Direct measure of task displacement due to automation in group g (Acemoglu and Restrepo, 2022):

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

- $APR_{i,c}$: 2006-2018 change in the industry i's exposure to robots
- $\omega^{i}_{g,c}$: share of workers of group g in industry i in country c
- $\omega^{R}_{g,i,c} / \omega^{R}_{i,c}$: relative specialization of group g in industry i's routine jobs
- routine jobs defined at the 2-digit ISCO level with O*NET data (Lewandowski et al., 2020)

Wage and employment effects: OLS

- We estimate:

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

- We control for country-fixed effects, gender and education fixed effects, exposure to manufacturing, and industry shifters.
- OLS estimates may be biased: unobserved factors affect robot adoption and labour demand simultaneously.

Wage and employment effects: IV approach

- Average penetration in industry i in five European countries not in our sample: Austria, Denmark, Finland, Slovenia, and the UK

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

- Identifies the component of robot penetration driven by changes in technology
- Robustness: average for the same countries as in Acemoglu and Restrepo (2022): Denmark, Finland, France, Italy, and Sweden

Robust negative wage effects

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Automation: penetration of robots	-0.009*	-0.009*	-0.007	-0.008**
	(0.005)	(0.005)	(0.004)	(0.004)
	2SLS	2SLS	2SLS	2SLS
Automation: penetration of robots	-0.019***	-0.019***	-0.016***	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)
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	342.04	339.53	329.71	325.43
Mean of outcome	0.26	0.26	0.26	0.26
Mean of automation	1.76	1.76	1.76	1.76
Observations	420	420	420	420

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

Additional results

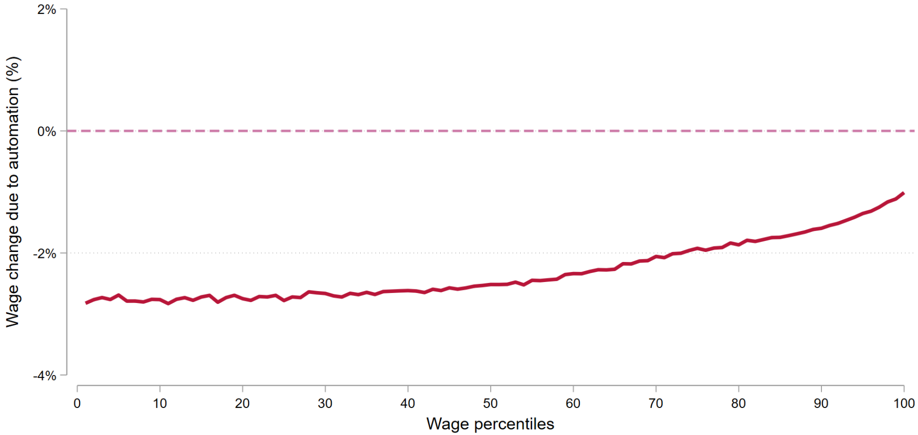
- Results robust to controlling for groups' specialization in routine jobs, and exposure to industry labour share decline, offshoring, Chinese imports penetration, and population changes. The exposure to minimum wage changes moderates the effects.
- effects are virtually identical in Western and Eastern Europe

Negative effects on employment rates

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Automation: penetration of robots	-0.005	-0.004	-0.006*	-0.006*
	(0.003)	(0.004)	(0.003)	(0.003)
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	387.22	341.40	274.89	272.48
Mean of outcome	0.04	0.04	0.04	0.04
Mean of automation	1.76	1.76	1.76	1.76
Observations	420	420	420	420

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

The resulting wage effects of robots are disequalising



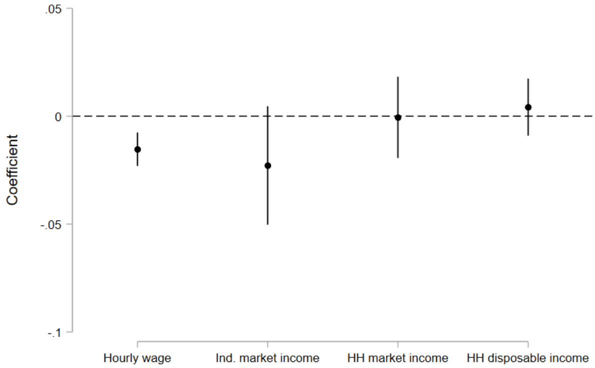
The wage changes due to automation in the U.S. (1980-2016) are stronger and even more disequalising

Let's look at household income inequality

Transmission of labour market shocks to household incomes is mediated by:

- Household composition: assortative mating vs. risk sharing within households
- Redistribution via tax-benefit systems

Negative earnings effects mitigated by household composition (risk sharing) and redistribution



U.S.

We use the EUROMOD tax-benefit microsimulation models to evaluate the effects on household disposable incomes

Using the 2006 and 2018 EU Survey of Income and Living Conditions (EU-SILC) data, for each country we:

1. Rescale the 2018 wages/employment data by demographic groups, using the (log-)wage/employment change attributed to automation

We use the EUROMOD tax-benefit microsimulation models to evaluate the effects on household disposable incomes

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1. Rescale the 2018 wages/employment data by demographic groups, using the (log-)wage/employment change attributed to automation
2. Keep household formation and all other market incomes unchanged

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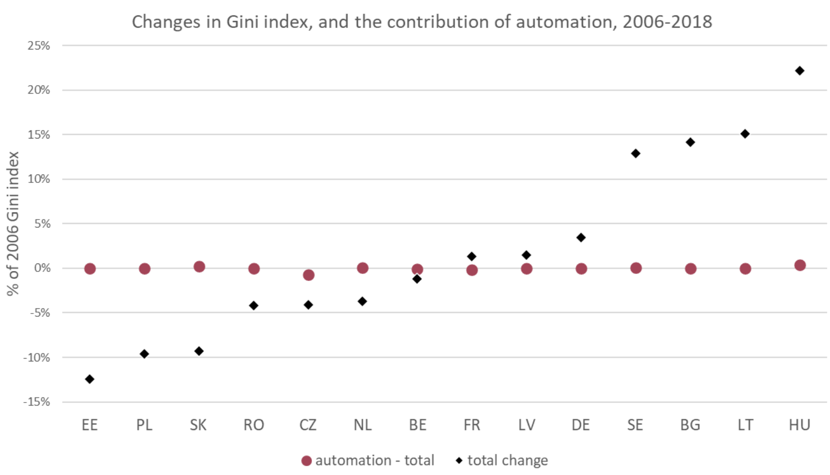
1. Rescale the 2018 wages/employment data by demographic groups, using the (log-)wage/employment change attributed to automation
2. Keep household formation and all other market incomes unchanged
3. Derive corresponding disposable, equivalised household incomes using EUROMOD with 2018 policy tax-benefit parameters

We use the EUROMOD tax-benefit microsimulation models to evaluate the effects on household disposable incomes

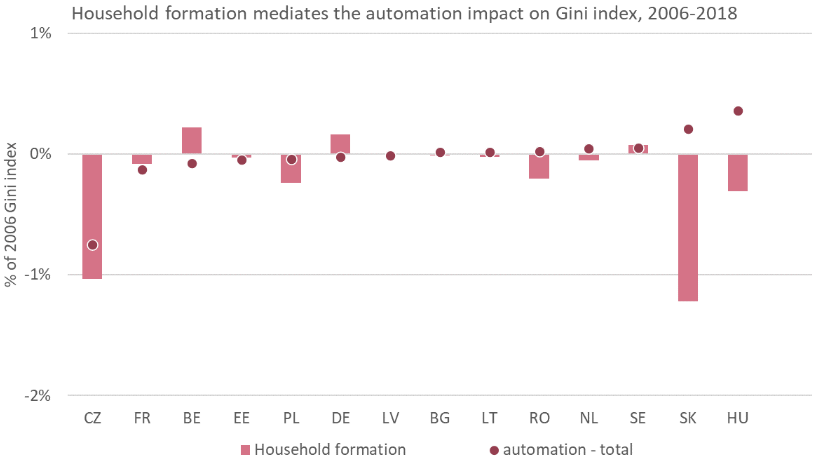
Using the 2006 and 2018 EU Survey of Income and Living Conditions (EU-SILC) data, for each country we:

1. Rescale the 2018 wages/employment data by demographic groups, using the (log-)wage/employment change attributed to automation
2. Keep household formation and all other market incomes unchanged
3. Derive corresponding disposable, equivalised household incomes using EUROMOD with 2018 policy tax-benefit parameters
4. Calculate inequality indices in data and in the counterfactual scenario

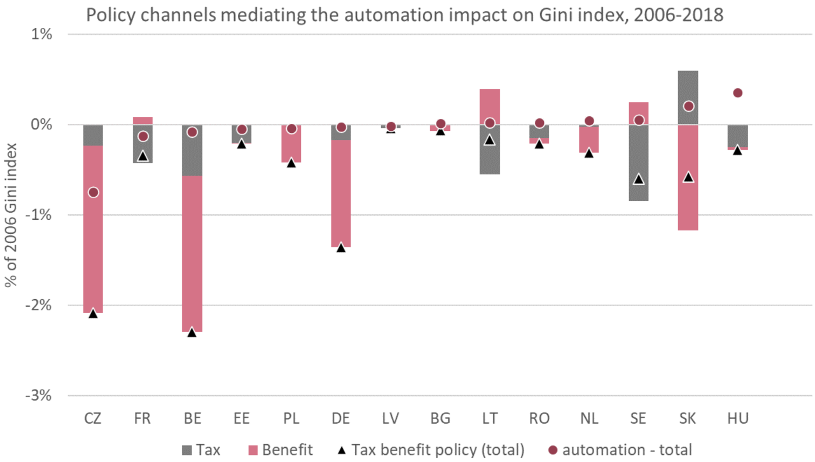
Automation contributed a small share of changes in household income inequality in 2006-2018



In most countries, household formation limited the impact of automation on inequality



Benefits played a larger role than taxes in cushioning the effects of automation



Robots increase inequality mainly through wages; household formation and benefits counterbalance these effects

Table: Decomposition of channels behind and mechanisms cushioning the effect of robots on income inequality, in % of cross-country variance of that effect

Wages	Employment	Interaction	Household formation	Tax	Benefit
102	3	-5	45	25	82

The contribution of a variable x, to the variance of outcome variable y calculated as Morduch and Sicular, 2002

$$\sigma_x = cov(x,y)/var(y)$$

Conclusion

- Between 2006 and 2018, the adoption of robots significantly reduced wages and employment in Europe.
- Automation widened wage inequality...
- ...but had minimal impact on household income inequality.
- Risk sharing in households and redistribution cushion the effect of automation (unlike in the U.S.).

THANKS FOR LISTENING!

Piotr Lewandowski

piotr.lewandowski@ibs.org.pl

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First-stage results

	(1) Automation: penetration of robots	(2) Automation: penetration of robots	(3) Automation: penetration of robots	(4) Automation: penetration of robots
Automation: penetration of robots (IV)	1.002***	1.038***	1.088***	1.091***
	(0.051)	(0.056)	(0.063)	(0.063)
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	387.78	341.78	302.38	298.30
Observations	420	420	420	420

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

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Automation and changes in real hourly wages, IV using the same countries as Acemoglu and Restrepo, 2022

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Automation: penetration of robots	-0.029***	-0.030***	-0.021***	-0.019***
	(0.006)	(0.006)	(0.006)	(0.005)
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	182.02	182.45	185.24	190.04
Mean of outcome	0.26	0.26	0.26	0.26
Mean of automation	1.76	1.76	1.76	1.76
Observations	420	420	420	420

Note: IV using the average for Denmark, Finland, France, Italy, and Sweden. Data: EU-SES.
* $p < .10$; ** $p < .05$; *** $p < .01$

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Automation and changes in real hourly wages - additional controls

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS
Automation: penetration of robots	-0.015***	-0.015***	-0.018***	-0.017***	-0.010**	-0.016***	-0.012**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Country FE	yes	yes	yes	yes	yes	yes	yes
Manufacturing share	yes	yes	yes	yes	yes	yes	yes
Gender	yes	yes	yes	yes	yes	yes	yes
Education	yes	yes	yes	yes	yes	yes	yes
Industry shifters	yes	yes	yes	yes	yes	yes	yes
Routine tasks	no	yes	no	no	no	no	yes
Offshoring	no	no	yes	no	no	no	no
Chinese imports penetration	no	no	no	yes	no	no	yes
Minimum wage bite	no	no	no	no	yes	no	yes
Population change	no	no	no	no	no	yes	yes
F-statistic first stage	325.43	252.88	488.96	318.40	305.80	341.80	181.68
Observations	420	420	420	420	420	420	420

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

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Automation and changes in monthly market income

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Automation: penetration of robots	-0.005	0.000	0.001	-0.001
	(0.009)	(0.009)	(0.009)	(0.010)
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	184.77	148.12	126.56	126.92
Mean of outcome	0.76	0.76	0.76	0.76
Mean of automation	1.76	1.76	1.76	1.76
Observations	330	330	330	330

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

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Automation and changes in monthly household income after taxes and transfers

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Automation: penetration of robots	0.001	0.006	0.005	0.004
	(0.006)	(0.007)	(0.007)	(0.007)
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	176.35	148.90	133.66	135.09
Mean of outcome	0.69	0.69	0.69	0.69
Mean of automation	1.76	1.76	1.76	1.76
Observations	330	330	330	330

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

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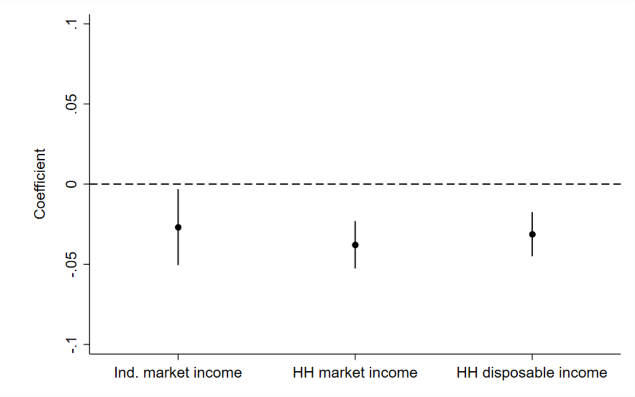
Negative earnings effects translate into negative income effects in the U.S.



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