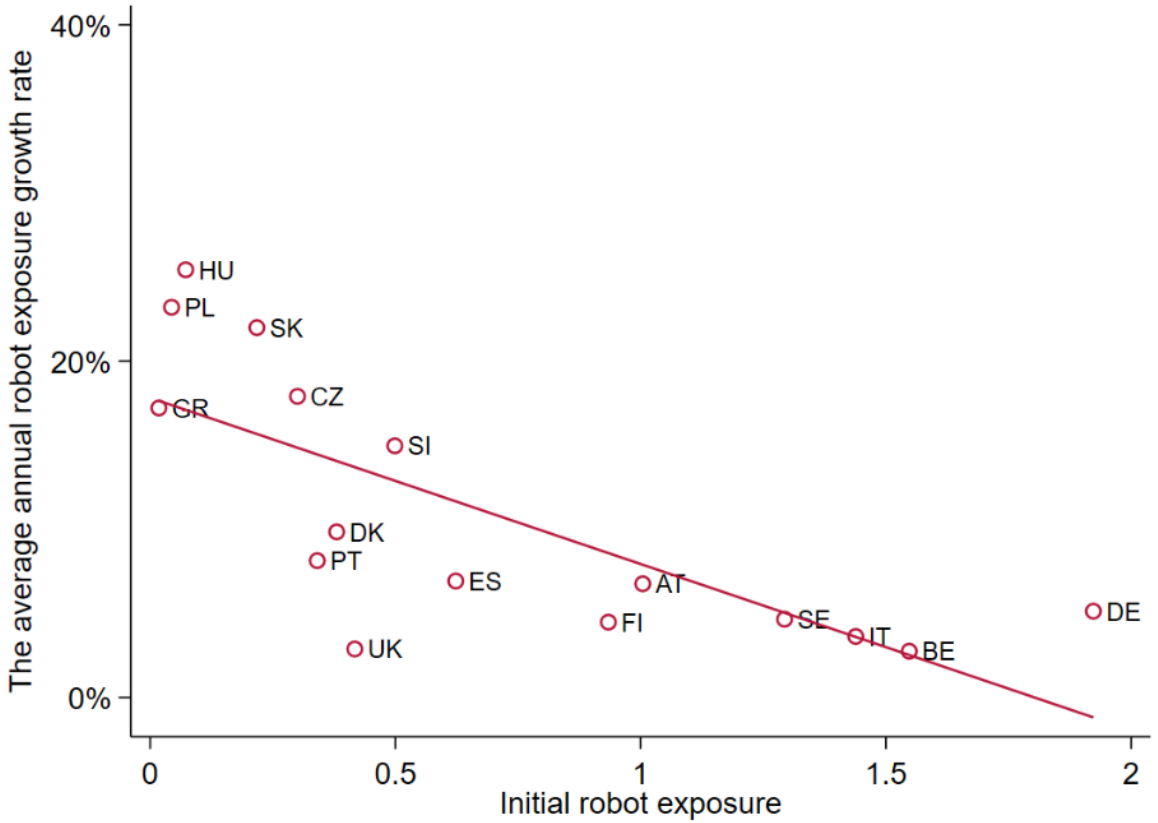
The Impact of Robots on Labour Market Transitions in Europe

Ronald Bachmann (RWI, DICE, IZA)
Myrielle Gonschor (RWI, DICE)
Piotr Lewandowski (IBS, IZA)
Karol Madoń (IBS)

STRONG GROWTH OF ROBOT EXPOSURE ACROSS INDUSTRIALISED COUNTRIES



- Fear of negative employment consequences

Growth rate in robot exposure from late 1990s/early 2000s to 2017

Source: IFR data.

INTERNATIONAL EVIDENCE ON THE EMPLOYMENT EFFECTS OF ROBOT IS MIXED

- Negative employment and wage effects in the US (Acemoglu/Restrepo 2019)
- No effects on total employment in Germany **(**Dauth et al. 2021)
- Negative effect on routine manual employment in high-income countries, but not in emerging/transition countries (de Vries et al. 2020)

WHAT CAN EXPLAIN THE MIXED EVIDENCE?

- **Labour-saving effect:** Robots take over tasks previously performed by workers
- **Product-demand effect:** Automation induces additional employment by increasing product demand
- **Demand-spillover effect:** Increased product demand raises income and leads to increased local spending that increases local labour demand

  - Ex-ante effect of automation on employment ambiguous
  - Evidence that positive effects have been dominant in Europe over the time period 1999-2010 (Gregory et al. 2021)

OUR CONTRIBUTION

- Focus on cross-country differences
- Focus on worker transitions as:
  - Reveal underlying mechanisms
  - Very important for individual welfare

- Research questions:
  1. What was the effect of robot exposure on job separation and job finding rates in Europe, what role did labour costs play?
  2. How did the effect differ between worker groups?
  3. What are the implications for employment and unemployment rates?

DATA

- European Labour Force Survey (EU-LFS)
  - Repeated cross-section
  - Labour market status in the current and previous year
  - 16 European countries
  - Time period: 1998-2017
  - Final sample: EU flow 11.8 M; UE flow 1.3 M
- Data from the International Federation of Robotics (IFR):
  - Country-industry level
- O*NET Database
- Industry Data: EU KLEMS, RIGVC, Comtrade

EMPIRICAL STRATEGY: ESTIMATION EQUATION

1) $Prob(flow = 1|X) = (\boldsymbol{R_{o,j,c,t-1}}, L_c, L_c^2, M_{oct-1}, B_{r,t-1}, X_i, p_s, \delta_t)$

2) $Prob(flow = 1|X)$

$$= (\boldsymbol{R_{ojct}}, \boldsymbol{R_{ojct}} \times \boldsymbol{L_c}, \boldsymbol{R_{ojct}} \times \boldsymbol{L_c^2}, L_c, L_c^2, M_{oct-1}, B_{r,t-1}, X_i, p_s, \delta_t)$$

R_{ojct} Robot Exposure (robot stock/employment 1995)

L_c Labour Costs in 2004

M_{ojct} Controls for macroeconomic conditions

$B_{r,t-1}$ Controls for change in labour demand at regional level

X_i Controls for individual characteristics

i = individual, o = occupation, j = industry, c = country, t = time, r = region

DEALING WITH ENDOGENEITY

- Robots might be endogenous to economic conditions in a sector/country
- Use control function approach (similar to IV approach)

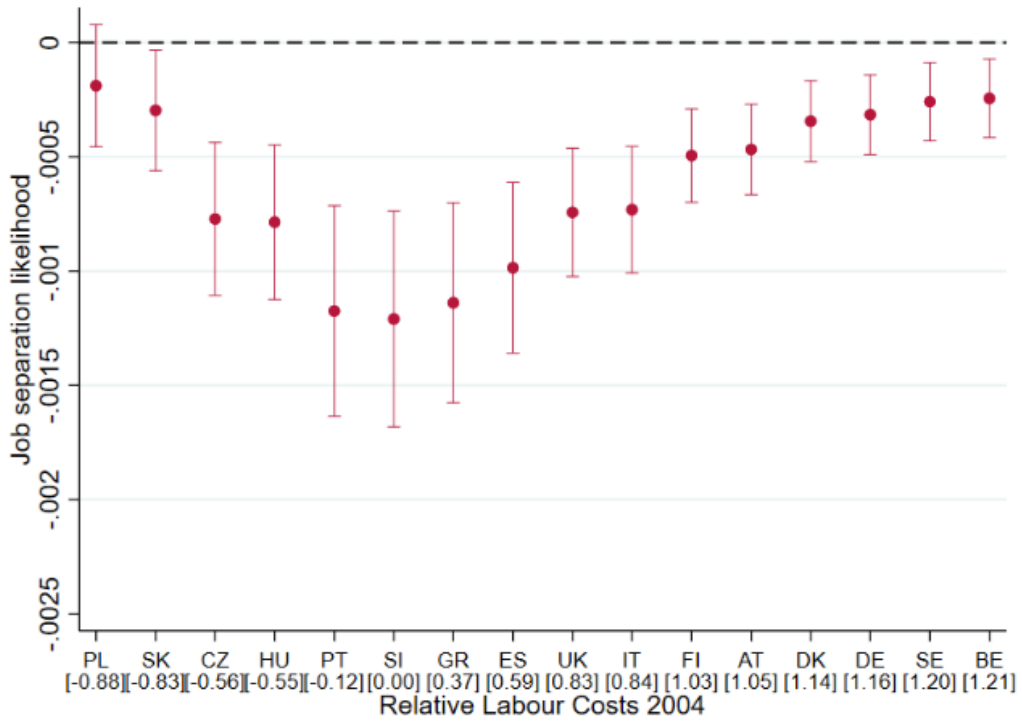
- Technology frontier instrument: average robot exposure in the same industries in the Western European countries in the sample (except for the country the instrument is applied to)

BASELINE RESULTS: JOB SEPARATIONS

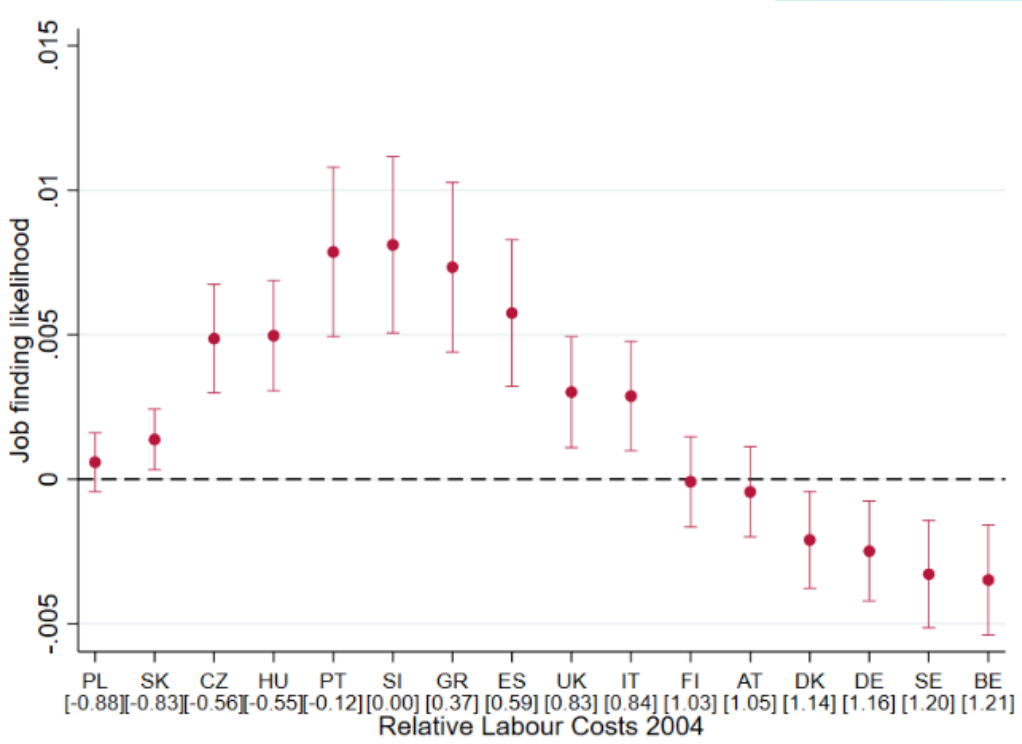
	(1) Probit	(2) CF	(3) Probit	(4) CF
Robot Exposure	-0.003***	-0.007***	-0.005***	-0.016***
	(0.001)	(0.002)	(0.002)	(0.003)
Robot Exposure x Labour Costs			-0.002*	-0.005***
			(0.001)	(0.001)
Robot Exposure x (Labour Costs)^2			0.003	0.012***
			(0.002)	(0.003)
Labour Costs	-0.105***	-0.103***	-0.102***	-0.096***
	(0.009)	(0.009)	(0.009)	(0.010)
(Labour Costs)^2	-0.032***	-0.029**	-0.034***	-0.044***
	(0.011)	(0.011)	(0.012)	(0.013)
No. of Observations	11.8 M	11.8 M	11.8 M	11.8 M
F-statistic for weak identification		351 870.7		17 735.7

MARGINAL EFFECTS OF ROBOT EXPOSURE FOR LIKELIHOOD OF JOB SEPARATION AND JOB FINDING

- **Job separations**



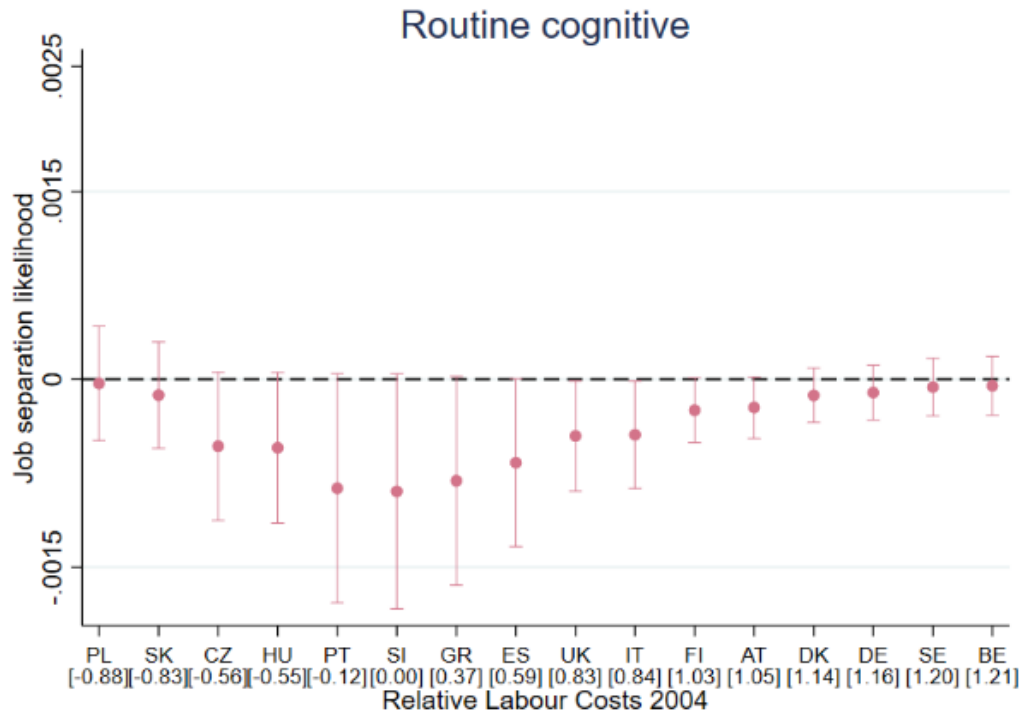
- **Job findings**



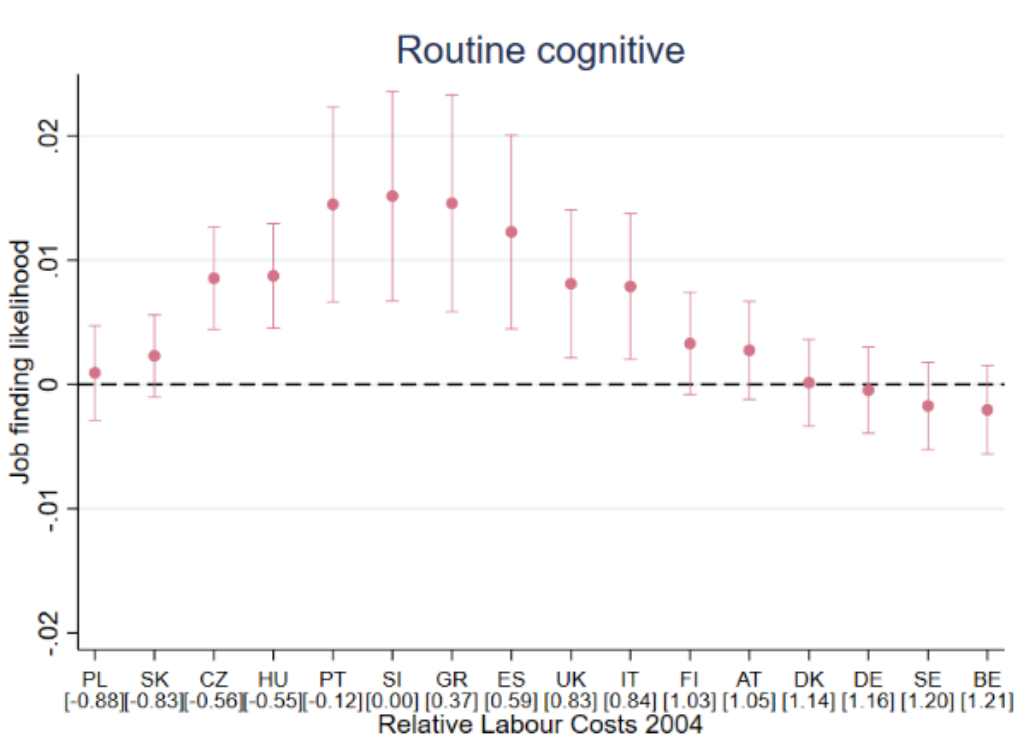
MARGINAL EFFECTS OF ROBOT EXPOSURE BY TASK GROUP

ROUTINE COGNITIVE TASK GROUP

- **Job separations**



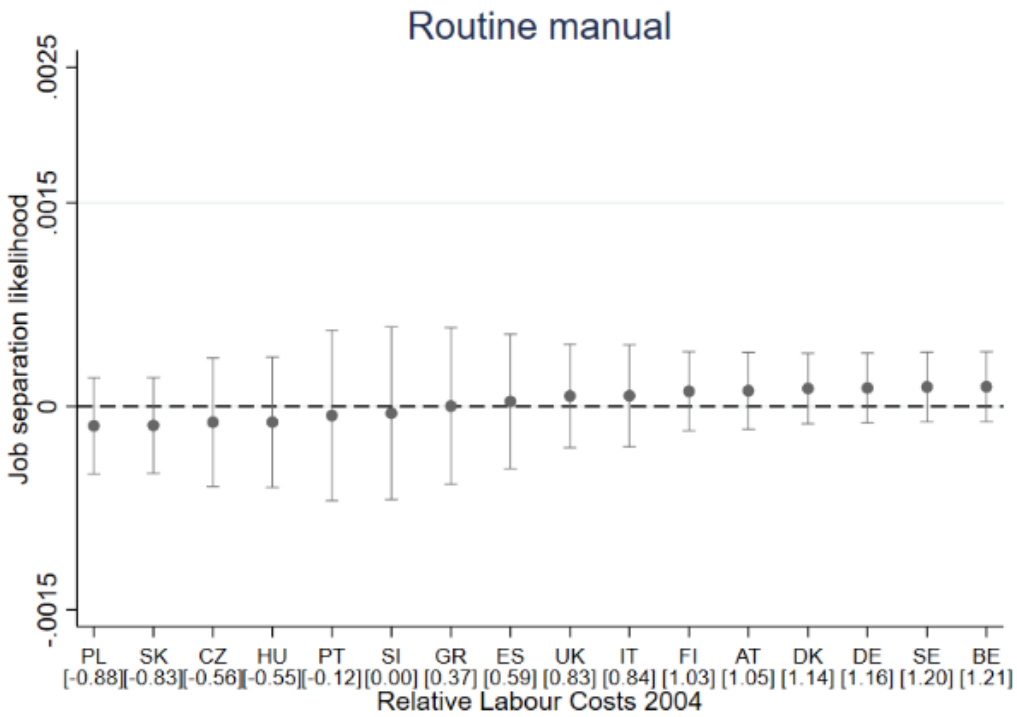
- **Job findings**



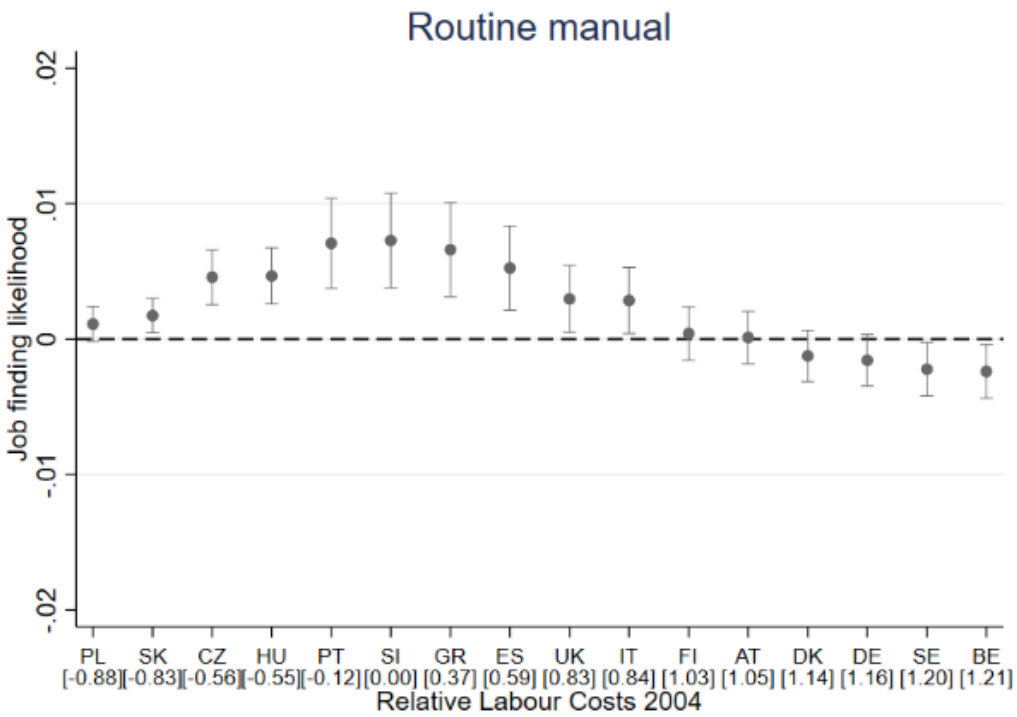
MARGINAL EFFECTS OF ROBOT EXPOSURE BY TASK GROUP

ROUTINE MANUAL TASK GROUP

- **Job separation**



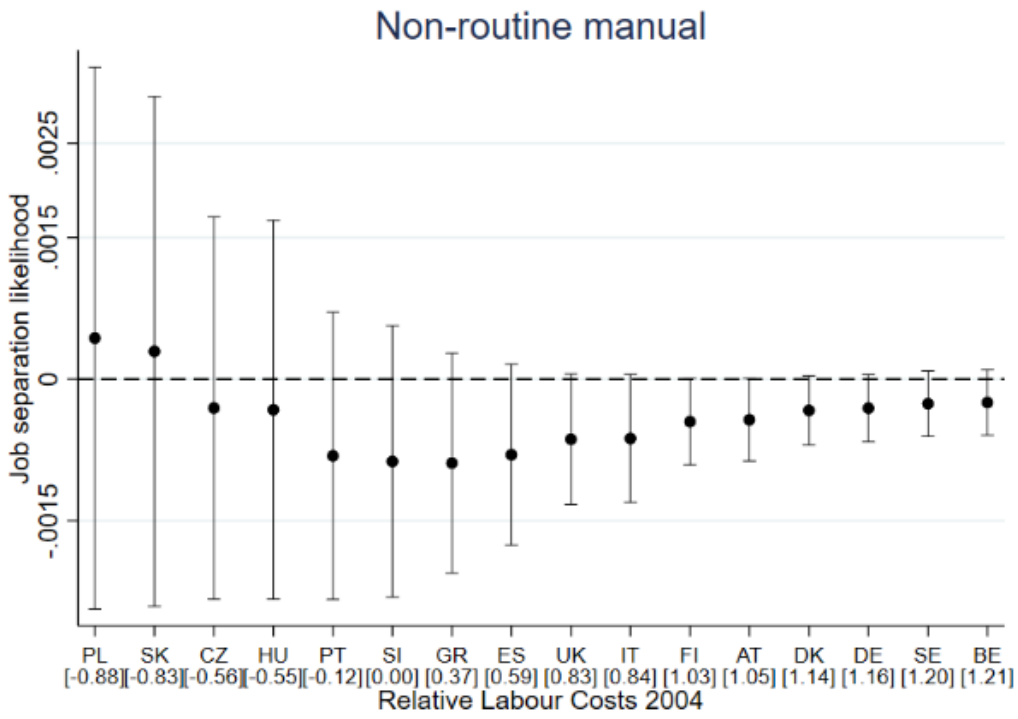
- **Job finding**



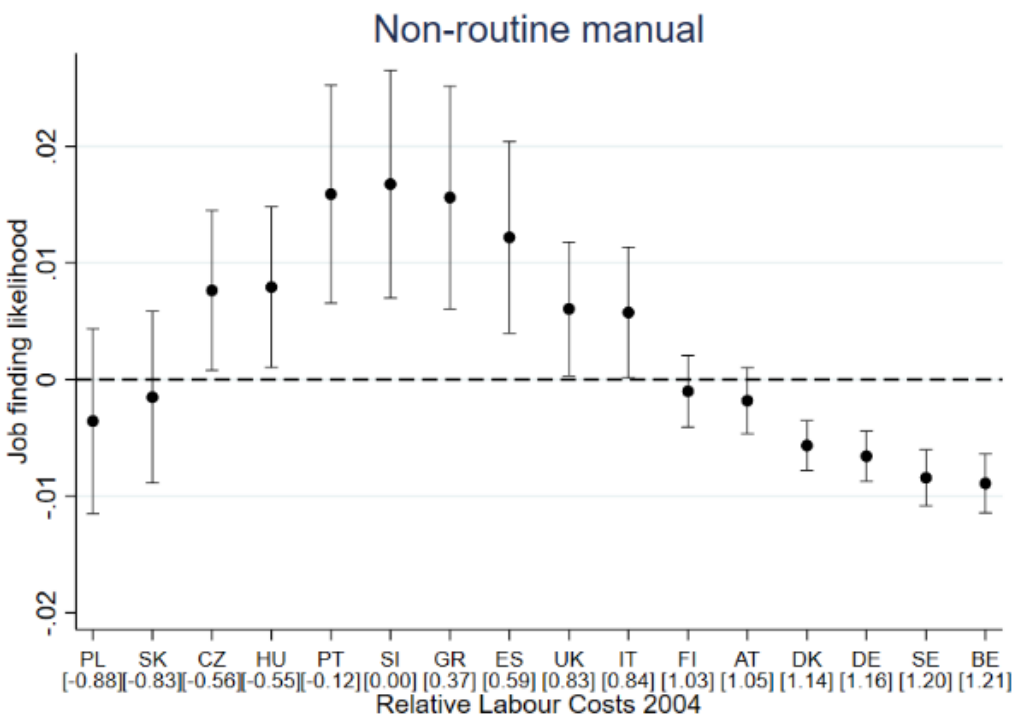
MARGINAL EFFECTS OF ROBOT EXPOSURE BY TASK GROUP

NON-ROUTINE MANUAL TASK GROUP

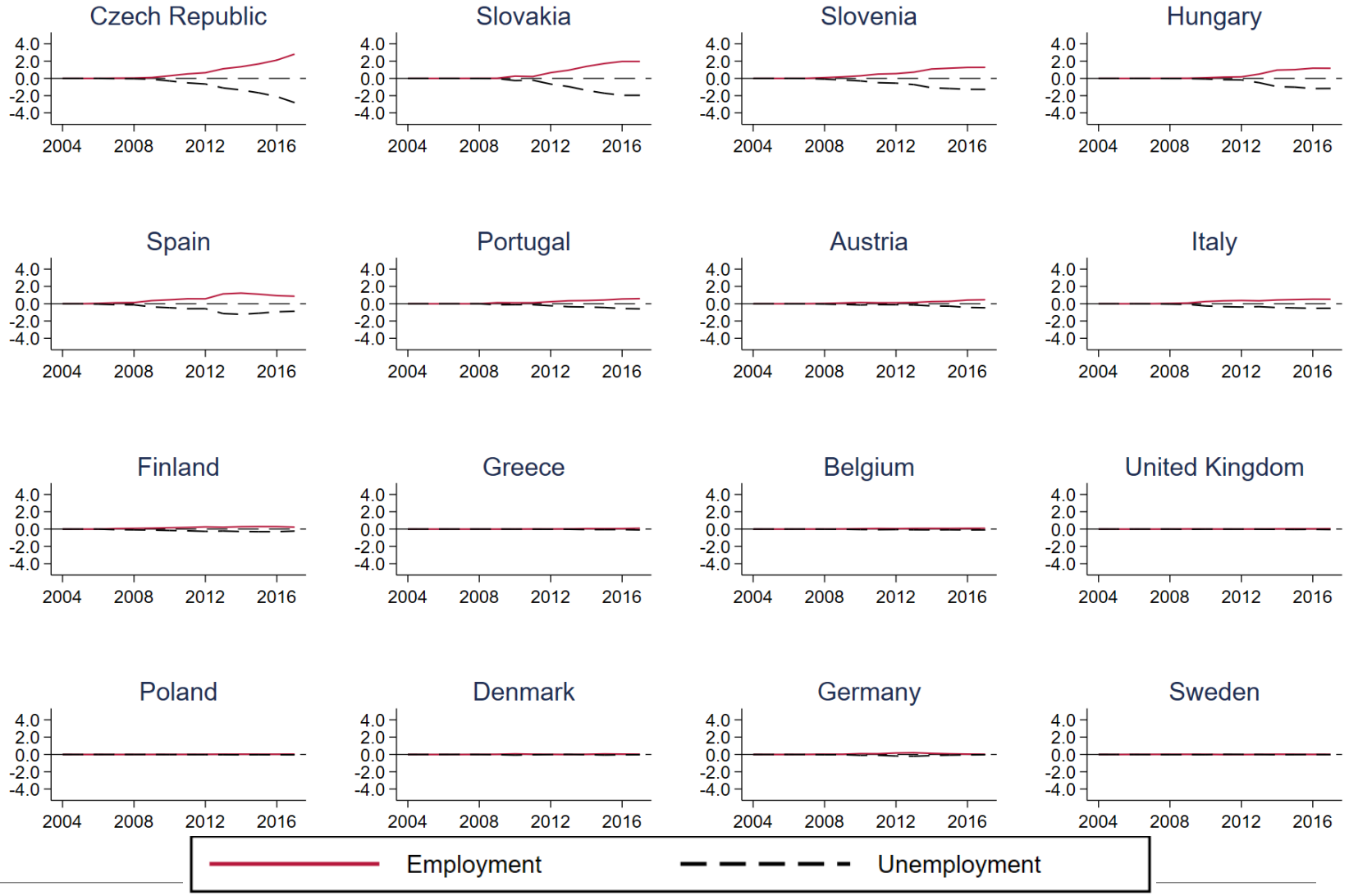
- **Job separation**



- **Job finding**



EFFECTS OF ROBOTS ON EMPLOYMENT RATES



SUMMARY

- In Europe as a whole, robots have a small negative effect on job separations and a small positive effect on job findings
- Labour costs play an important role for cross-country differences in the labour market effects of robot adoption
  - Effects are stronger in countries with average labour costs
- The likelihood of finding a job is increased especially for routine (!) workers, but also NRM
- Small positive effects of robot adoption on employment rates, particularly in countries with average labour costs

IMPLICATIONS

- Large cross-country differences in the effects of robot adoption

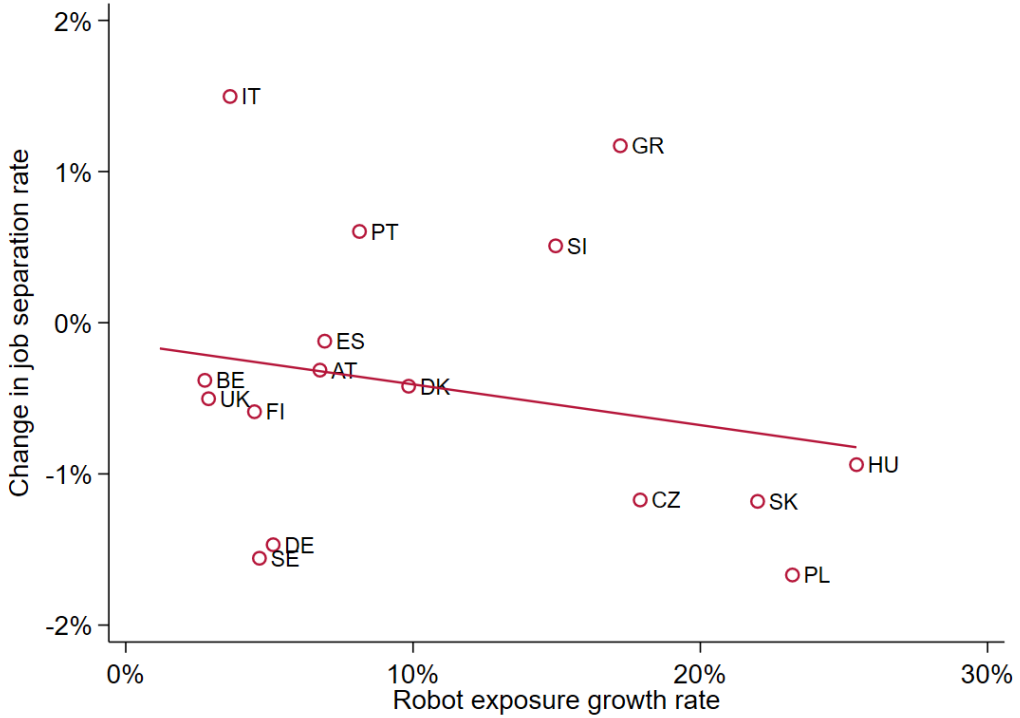
➢ Policy and re-training measures need to be country-specific

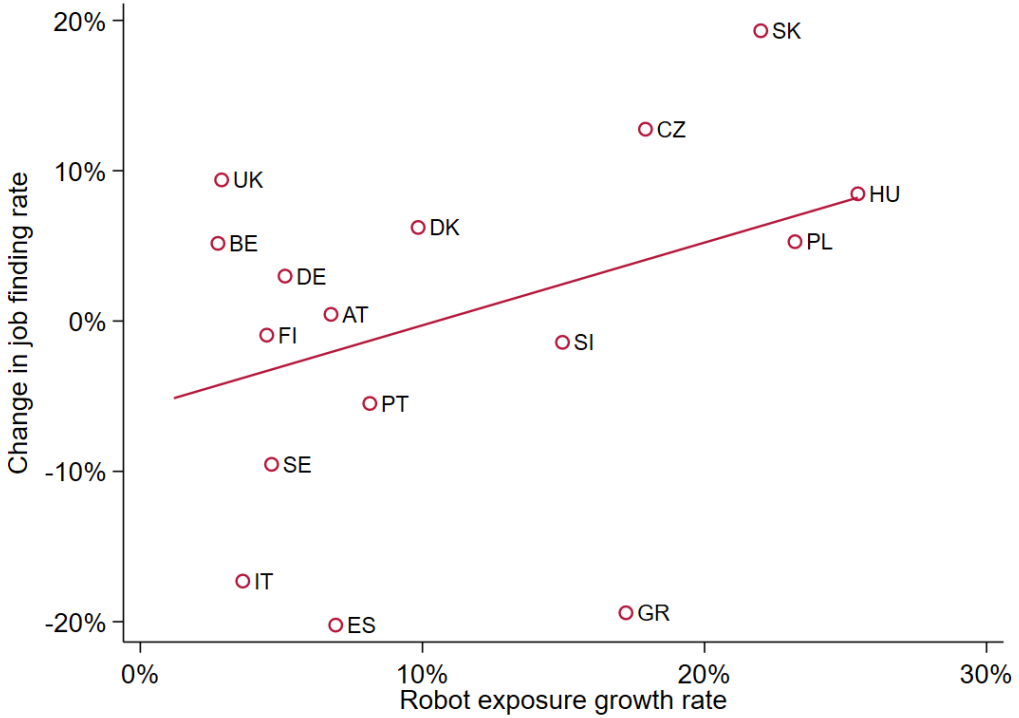
- Routine workers do not seem to be as negatively affected as the polarization literature suggests

➢ Focus of policy and re-training measures should not exclusively be on routine workers

Thank you for your attention!

CORRELATION BETWEEN ROBOT GROWTH AND CHANGE IN FLOW RATES

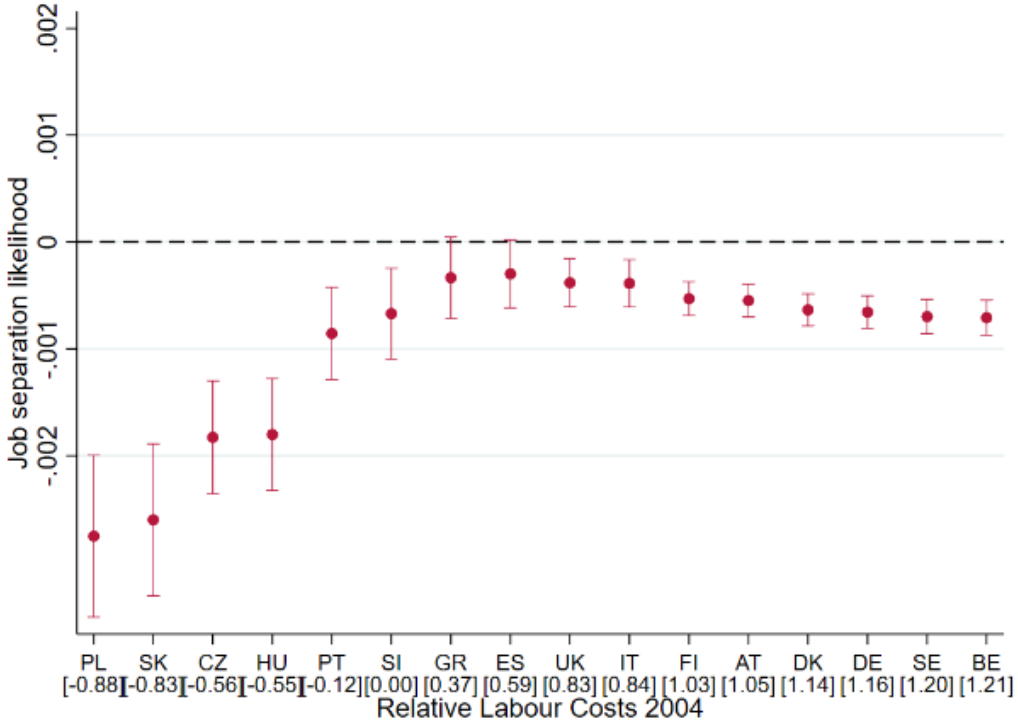




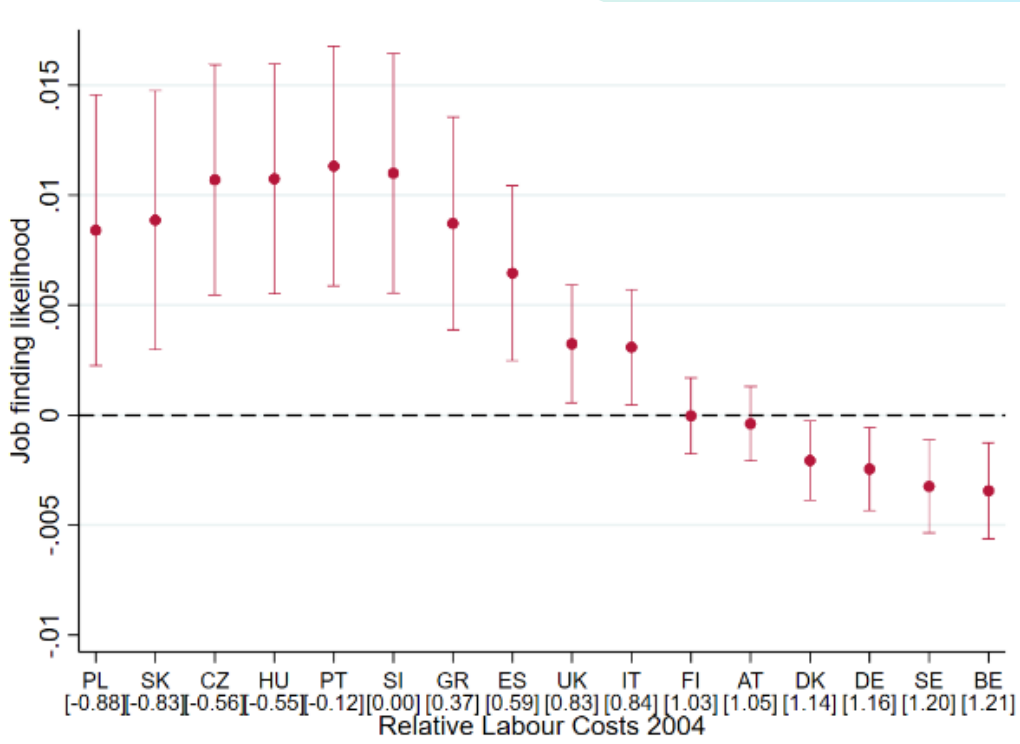
Change in labour market flow rates vs average robot exposure growth rate in European countries, 1998-2018.

MARGINAL EFFECTS OF ROBOT EXPOSURE BY AGE GROUP

- **Job separation: Age 55-70**



- **Job finding: Age 15-24**



Older workers are less likely to lose a job, while young workers are more likely to find a job.

BASELINE RESULTS: JOB FINDING

	(1) Probit	(2) CF	(3) Probit	(4) CF
Robot Exposure	0.002***	0.005***	0.024***	0.026***
	(0.001)	(0.001)	(0.003)	(0.004)
Robot Exposure X Labour Costs			0.005***	0.005**
			(0.001)	(0.002)
Robot Exposure X (Labour Costs)^2			-0.026***	-0.027***
			(0.003)	(0.004)
Labour Costs	0.058***	0.057***	0.051***	0.052***
	(0.018)	(0.018)	(0.019)	(0.019)
(Labour Costs)^2	0.079***	0.077***	0.107***	0.109***
	(0.023)	(0.023)	(0.023)	(0.024)
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
F-statistic for weak identification		23 035.3		3 993.5