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Regimes of robotization in Europe

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ABSTRACT

This work analyses the impact of robots on employment testing for the presence of different *robotization regimes*. Focusing on European manufacturing industries, we find that robot adoption positively affects total employment. Heterogeneous patterns are detected across both countries and occupational groups, however. The labour-friendly impact of robotization is detected only in core and service-oriented countries and for those at the top of the occupational structure (i.e. managers and technicians). In turn, peripheral countries and manual workers do not seem to benefit at all from robotization.

1. Introduction

The recent wave of robotization has brought the 'robot-workers race' back to the fore. As in the past, economists are divided between optimists and pessimists, the latter envisaging new risks of mass technological unemployment (Autor, 2022). The available evidence is inconclusive, though. This is due to the number of heterogeneity sources – level of analysis, country, sector, skills – affecting the relationship at stake. Here, we focus on Europe and test for the existence of different *robotization regimes*, bridging two strands of literature: contributions analysing the employment impact of robotization (Aghion et al., 2022) and those focusing on core–periphery divides in Europe (Celi et al., 2018). A 'labour-friendly' regime is expected to emerge in areas characterized by a technologically advanced manufacturing base, centrality in GVCs, competitiveness strategies based on innovation and more intense use of high-skilled labour (Petit et al., 2023; Pianta and Reljic, 2022). In turn, in structurally weaker areas, where cost-competitiveness strategies prevail, a 'labour-saving' robotization regime is expected to emerge. Relying on a panel of European manufacturing industries observed from 2011 to 2018, we find that robots have a positive impact on employment. However, only those at the top of the occupational structure (i.e. managers, professionals and technicians) benefit from such a 'robot-push', while those at the bottom (i.e. manual workers) are penalized. As for robotization regimes, we confirm the expectations regarding the core–periphery divide. The labour-friendly impact of industrial robots is circumscribed to the core and service-oriented countries while no effects emerge in the Southern and Eastern periphery.

2. Data and descriptive evidence

The analysis is carried out at the industry level, merging different data sources referring to 15 NACE Rev. 2 manufacturing industries in 21 European countries observed between 2011 and 2018. The International Federation of Robotics (IFR) data on robots are matched with labour market variables from the European Labour Force Survey (EU-LFS). The OECD's Input–Output tables are used to calculate offshoring indicators while sectoral value added stems from the OECD-STAN database. The Routine Task Index (RTI) and the Digital Task (DT) indicator are built by combining qualitative information from the INAPP-ISTAT Survey on Italian Occupations[1] and employment weights from the EU-LFS (Cirillo et al., 2021).

A steep increase in robot diffusion is shown in Fig. 1, highlighting the unfolding of a 'robotization wave' in Europe (Fernandez-Macias et al., 2021).

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[1] A unique O*NET-type data source for Europe.

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Table 1
Robotization and employment growth rate.

	(1) OLS 1	(2) OLS 2	(3) FE	(4) IV 1	(5) IV 2	(6) IV 3	(7) HW, IV
Robot density	0.0455***	0.0302***	0.113**	0.0444*	0.0547**	0.0413**	0.0611**
	(0.0133)	(0.0112)	(0.0564)	(0.0238)	(0.0251)	(0.0201)	(0.0297)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year	No	Yes	No	No	Yes	No	No
Country × Pavitt	No	Yes	No	No	No	Yes	No
Kleibergen–Paap F statistic				16.366	15.588	22.849	13.650
Constant	−0.285	4.734*	0.0374	3.484	3.173	5.123**	1.047
	(0.503)	(2.685)	(4.243)	(2.505)	(2.496)	(2.378)	(3.108)
Observations	2166	1971	1971	1971	1971	1971	1805
R-squared	0.138	0.369	0.118	0.203	0.333	0.238	0.130

Notes: Robust standard errors clustered at country-industry level in parentheses. All specifications include time, country and broad industry fixed effects. Controls are broad offshoring, digital tasks, RTI, annual demand growth, and labour market characteristics (share of female, low-skilled, med-skilled, temporary workers, age group 55+, age group 15–24). ***p < 0.01, **p < 0.05, *p < 0.1.

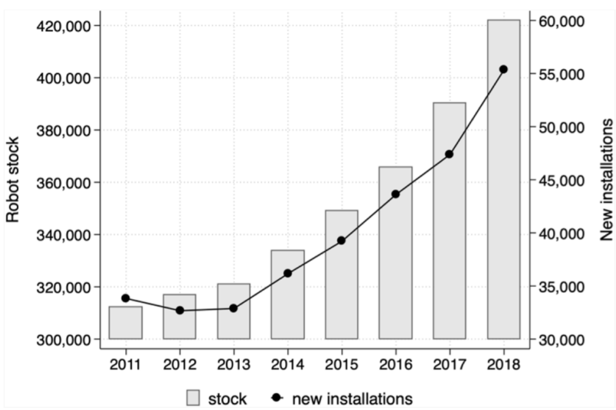

Fig. 1. Robot stock and new installations.
Source: Authors' elaboration based on the IFR data.

A significant country- and sectoral-level heterogeneity is observable, however. Unsurprisingly, industrial robots are predominantly concentrated in Germany, Europe's manufacturing powerhouse, followed by Italy, France, Spain and the UK. From a sectoral point of view, automotive has the lion's share, with smaller but non-negligible shares also detected in rubber & plastic, food, metal and machinery (see Fig. 2).

To test for the presence of robotization regimes, we cluster European countries according to key structural dimensions.[2] The cluster analysis reflects the well-documented core–periphery divide in Europe (Fig. 3) – *core* (Austria, Germany, Denmark, Finland, France, Netherlands, Sweden), *southern periphery* (Italy, Spain, Greece, Portugal) *with Baltics* (Lithuania and Latvia), *eastern periphery* (Czechia, Hungary, Poland, Slovakia) and *service-oriented countries* (Belgium, Estonia, Ireland, United Kingdom, Slovenia) – displaying systematic heterogeneity concerning our theory-driven clustering variables.

3. Empirical strategy and results

We first estimate the effect of robotization on total employment, controlling for a number of factors likely to affect employment dynamics. Second, we split the sample by cluster to inspect which robotization regime prevails in *core*, *southern periphery with Baltics*, *eastern periphery* and *service-oriented* countries. Third, we explore the impact of robotization across occupational groups: managers, clerks, craft and manual workers.

The following specification is estimated:

$$\Delta \ln Y_{ijt} = \alpha_0 + \beta_1 Robot_{ijt-1} + \beta_2 ICT_{ijt-1} + \beta_3 Trade_{ijt-1} + X'_{ijt-1}\gamma + \mu_i + \chi_j + \tau_t + \varepsilon_{ijt} \quad (1)$$

where the annual change in log employment in the industry (i)-country(j) pair is expressed as a function of our key explanatory variable *robot density* – defined as robot stock per 1000 workers – and a set of industry-level controls referring to t–1. In line with the literature (Aghion et al., 2022), we control for *ICT* – proxied by the share of occupations performing digital tasks within each industry – and *trade* — proxied by broad offshoring (defined as a share of imported intermediate inputs in total intermediate inputs). The X vector includes further controls: *RTI index*, *annual changes in demand (proxied by the annual growth of sectoral value added)* and *labour market characteristics* (gender, age, education, contract type); μ stands for industry fixed effects, proxied by broad industry Pavitt dummies (Pavitt, 1984)[3]; χ and τ are country and time fixed effects, while ε is the error term.[4]

Eq. (1) is estimated using OLS, FE and, to address endogeneity concerns, IV, following the procedure proposed by Acemoglu and Restrepo (2020). Robot density is instrumented using industry-level robot stock per 1000 workers in Japan.[5] The assumption is that technological progress and robot demand in Japan are correlated with robotization in Europe without directly affecting its employment dynamics.

Table 1 displays a positive effect of robotization on total employment. This is supported by a series of robustness checks: different estimation strategies; including more stringent country-year and industry-year fixed effects in Columns 5–6; using an alternative proxy of employment (i.e. hours worked) in Column 7.

[2] We run a two-step cluster analysis to group European countries according to 14 variables potentially affecting the nexus between employment and robotization: knowledge and technological patterns (public R&D, number of researchers, patent applications, public procurement, broadband and investment in intangibles), production capabilities and GVCs positioning (average firm size, share of manufactured high-tech value-added, degree of foreign control, domestic value added in gross exports and functional specialization in fabrication, R&D, marketing and management). We employ a hierarchical Ward's linkage method to determine the number of clusters in the data referring to 2011.

[3] The Pavitt taxonomy groups industries according to their innovation patterns into Science Based, Specialized Suppliers, Scale Intensive and Supplier Dominated.

[4] All regressions are weighted using employment at the initial year (2011).

[5] Alternatively, we use robot density in the US yielding qualitatively similar results.

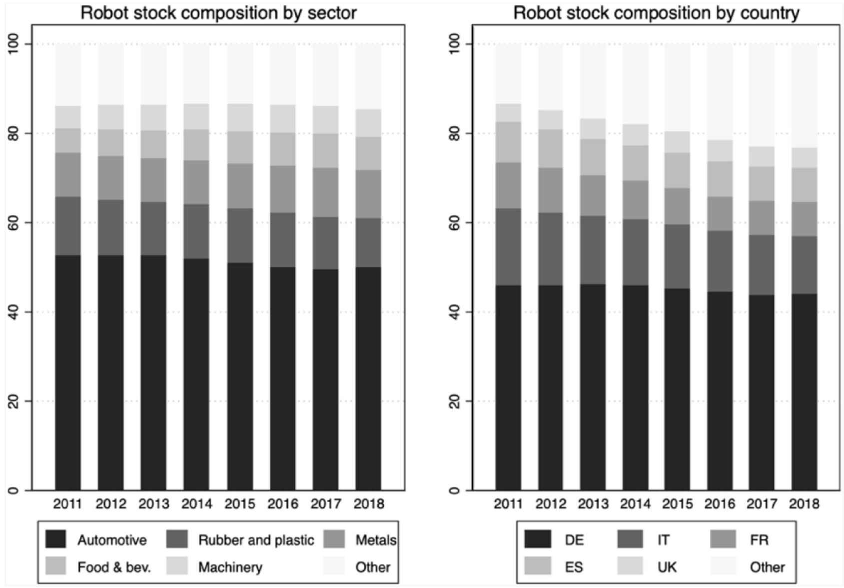

Fig. 2. Decomposition of robot stock by sector and country.
Source: Authors' elaboration based on the IFR data.

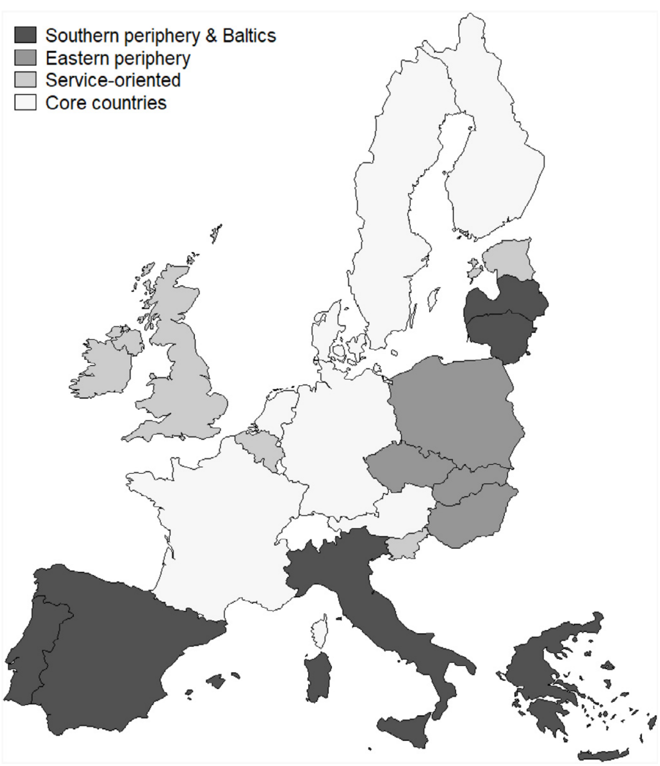

Fig. 3. Country clusters.
Source: Authors' elaboration.

Next, we provide evidence on distinct robotization regimes (Table 2) by splitting the sample into the abovementioned clusters. Confirming our hypothesis, employment growth is positively affected by robot adoption in core and service-oriented countries, pointing to a 'labour-friendly' regime. Strong technological capabilities and 'high-end' competitiveness strategies based on innovation and skills are likely to reward in terms of market shares and, thus, employment dynamics (Petit et al., 2023). As expected, in turn, such a labour-creating effect vanishes when it comes to the periphery. This does not necessarily mean that robots have no efficiency or labour-saving effects: the latter are likely to be more than counterbalanced by demand-pull factors in core and service-oriented countries while barely materializing in the periphery.

Finally, Table 3 highlights that an increase in robot adoption is associated with higher demand for managers, the only professional group directly involved in governing and managing new technologies in the workplace. On the other hand, the coefficients associated to the other occupational categories are negative, albeit statistically significant only for manual workers, suggesting that employment gains from robotization are asymmetrically distributed not only between country-clusters countries but also across occupations.

4. Conclusions

The employment implications of technological change should not disregard the heterogeneities related to the hierarchical positioning of industries and countries. This holds also in the case of robotization.

The robot-employment nexus is explored by clustering countries according to their structural and technological characteristics. While a 'labour-friendly' effect is detected in core and service-oriented countries, no effects materialize in the peripheral regions. This may justify, at least partly, the inconclusive evidence in the empirical literature.

Overall, our findings are in line with those contributions highlighting that robots are 'not so disruptive yet' (Fernandez-Macias et al., 2021). However, only stronger economies (i.e. core and service-oriented) and occupational groups are reaping the benefits from the robotization process in Europe.

Data availability

The authors do not have permission to share data.

Table 2
Robotization and employment growth by cluster.

	(1) Core	(2) Southern periphery & Baltics	(3) Eastern periphery	(4) Service oriented
Robot density	0.0453**	0.0419	0.818	0.135**
	(0.0191)	(0.0342)	(0.514)	(0.0554)
Controls	Yes	Yes	Yes	Yes
Kleibergen–Paap F statistic	14.023	6.954	4.202	12.747
Constant	−1.828	−1.571	15.03**	13.13**
	(2.144)	(3.105)	(7.415)	(6.506)
Observations	714	503	420	334
R-squared	0.283	0.423	0.066	0.078

IV estimates. Same as Table 1.

Table 3
Robotization effect across occupational groups.

	(1) Managers	(2) Clerks	(3) Craft workers	(4) Manual workers
Robot density	0.213***	−0.0101	−0.0605	−0.120*
	(0.0740)	(0.0899)	(0.0569)	(0.0652)
Controls	Yes	Yes	Yes	Yes
Kleibergen–Paap F statistic	17.276	17.940	16.940	16.994
Constant	−7.794	20.57	20.86**	2.520
	(8.884)	(15.06)	(8.979)	(8.503)
Observations	1454	1056	1687	1631
R-squared	0.064	0.048	0.036	0.046

IV estimates. Same as Table 1. We define professional groups by aggregating ISCO 1-digit occupations: Managers (Managers, Professionals and Technicians), Clerks (Clerks, Service and sales workers), Craft workers (Skilled agricultural workers and Craft and related trade workers) and Manual workers (Plant and machine operators and Elementary occupations).

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