Digital technologies and their impact on EU employment and production

Catarina Midões [†]   Georgios Petropoulos [‡]

[†]Bruegel, catarina.midoes@bruegel.org.

[‡]Massachusetts Institute of Technology and Bruegel, georgios.petropoulos@bruegel.org

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Technological progress and employment

Two channels:

1. Displacement Effect: directly displacing workers from tasks
2. Productivity Effect: increasing demand for labour in industries or jobs that arise due to technological progress

Industrial Robots as a case study

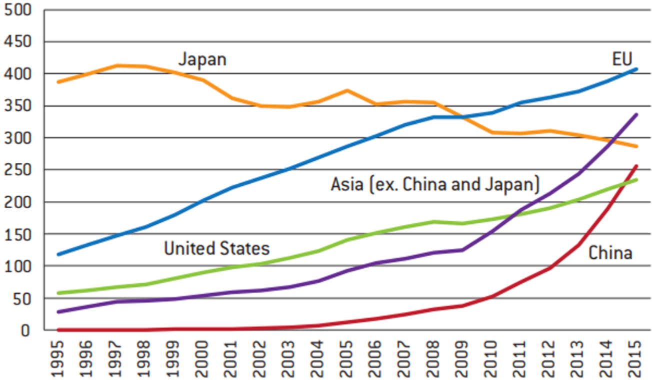
- Consistent definition of Industrial Robots across countries and years by the International Federation of Robots (IFR):

  > *"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"*

- Example of technology which can replace certain human tasks entirely without supervision, as opposed to ICT or other machines

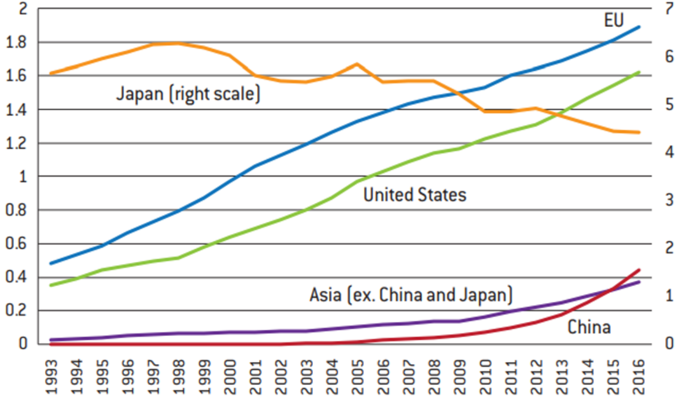
Empirical trends

Thousands of robots per region



Source: IFR.

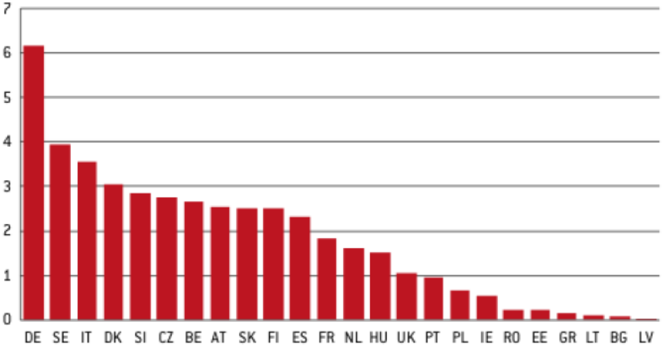
Thousands of robots per worker, per region



Source: IFR and ILO.

Empirical trends

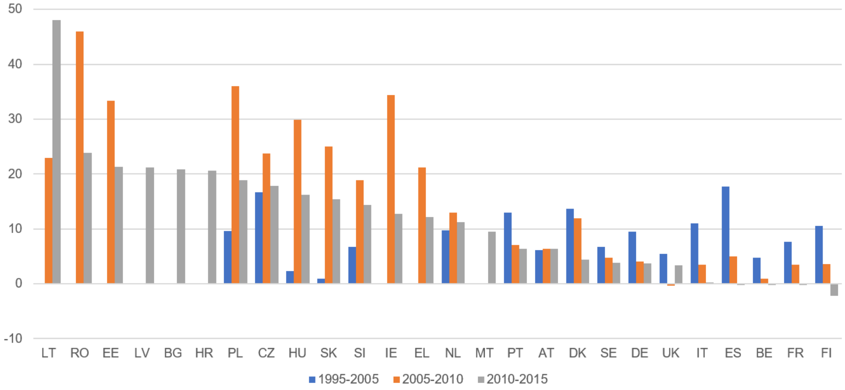
Robots per thousand workers, by country



Source: IFR and Eurostat.

Empirical trends

Median annual growth rate of operating industrial robots, by country



Literature

- Graetz and Michaels (2018), EU subsample, 1993-2007, by country-sector:
  - Increase in use of robots per hour raised the annual growth of labour productivity by 0.37 p.p.
  - Increase in use of robots per hour reduced the share of hours worked by low-skilled workers relative to middle and high-skilled
- Acemoglu and Restrepo (2019): one more robot per thousand workers reduces the employment to population ratio by 0.18 - 0.34 percentage points (US, 1990-2007, by commuting zone)

Literature

- Chiacchio et al (2018): *a la* Acemoglu and Restrepo, one additional robot reduces the employment rate by by 0.16-0.20 (6 EU countries, 1995-2007, by NUTS2 region)
- Dauth et al (2017) in Germany, 1994-2014 by NUTS3 region find:
  - Positive effect on growth rate of employment when considering only location dummies and local manufacturing employment shares
  - No significant effect on local employment after controlling for demographic characteristics

Our work

- Extending the sample period to 2015 (1995-2015) for all European countries possible
  - Applying country-sector specifications
  - Applying regional specifications
- Possible short-run and long-run effects
- Potential spillover effects coming from 'competition' through robotisation

Data

Robot Stock

- World Robotics Database (IFR) provides stock of robots by country-sector
- Reporting issues: some EU countries only start reporting sectorial breakdown in 2004
- Attempt to use the least stringent assumptions:
  1. Keeping only country-sectors for which data is available in both 1995 and 2015, 14 countries, "NOIMP" models OR
  2. For missing years, allocating robots to a sector based on its average proportion of total stock (of the years reported) [1], 23 countries, "IMP" models

Demographic/Education groups

- EU KLEMS March 2008 release: only available for a subset of EU countries

[1] If in the first year of reporting at the sector level there are any robots. Otherwise, a zero is assumed.

Specifications: country-sector model

For each country i and sector j, the first specification of interest is thus:

$$\Delta emp_{ij} = c_i + s_j + \beta \Delta r_{ij} + u_{ij} \tag{1}$$

where:

- Δemp_{ij} is the growth rate between 1995 of 2015 of the number of employees in country i, sector j
- Δr_{ij}: growth rate between 1995 and 2015 of robot stock in country i, sector j.[1]

(Some) Disadvantages

- Not possible to disentangle from country-sector simultaneous trends
- Limited sample (to answer an EU question)

[1] Since several country-sectors start by having zero robots, the growth rate for country i sector j is calculated as the difference between $log(1 + r_{ij2015}) - log(1 + r_{ij1995})$ where r_{ijt} is the robot stock in country i in sector j in year t.

Specifications: country-sector model

Demographic groups

$$\Delta emp_{ij} = c_i + s_j + \beta_1 \Delta r_{ij} + \beta_2 Prop_{ijk} + \gamma \Delta r_{ij} \times Prop_{ijk} + u_{ij}, \tag{2}$$

where $Prop_{ijk}$ is the proportion of employees in 1995 belonging to group k: different sex, age, and skill groups.

Short-run and Long-run effects

$$\Delta emp_{ij} = c_i + s_j + \beta_1 \Delta r_{ij} 1[Intro <= 2005] + \beta_2 \Delta r_{ij} 1[Intro > 2005] + u_{ij}, \tag{3}$$

as well as sample separation for additional flexibility.

Spillover effects

$$\Delta emp_{ij} = c_i + s_j + \beta_1 \Delta r_{ij} + \beta_2 \Delta (W_j \setminus r_{ij}) + u_{ij} \tag{4}$$

where $W_j \setminus r_{ij}$ is the stock of robots in sector j elsewhere in the world, i.e., excluding country i

Summary Statistics

Sector	Avg Growth rate of workers	Avg Growth rate of robots
Mining and quarrying	-47.1%	124.9%
Food, beverages and tobacco	-18.8%	289.5%
Textiles and leather	-94.6%	88.2%
Wood	-36.0%	170.1%
Paper and publishing	-42.7%	164.9%
Coke, chemicals and plastic	-10.1%	253.3%
Other non-metallic	-36.4%	196.6%
Basic metals	-36.6%	237.9%
Machinery	3.0%	228.2%
Fabricated metals	-17.2%	279.7%
Electrical equipment	-24.0%	206.0%
Motor vehicles	3.6%	235.8%
Other transport	-29.5%	176.8%
Other manufacturing	-11.3%	171.4%
Utilities	-3.2%	114.2%
Construction	7.8%	281.2%
Business services	30.6%	323.5%

Average over countries in sample, with imputations. Only sectors included. Several non-manufacturing activities missing.

Specifications: regional model

$$Exp_{ri} = \sum_{j \in J} l_{rj} APR_{ij} \tag{5}$$

where:

r: NUTS2 region

i: country

l_{rj} is the portion of workers of region r which work in sector j

and APR_{ij} is adjusted penetration of robots in country i sector j

$$APR_{ij} = \frac{\Delta R_{ij}}{L_{ij}} - \frac{\Delta Y_{ij}}{Y_{ij}} \frac{R_{ij}}{L_{ij}} \tag{6}$$

where:

R_{ij} is the robot stock in country i in sector j in 1995

L_{ij} is the number of employees in country i in sector j in 1995

Y_{ij} is GVA in country i in sector j in 1995

ΔV_{ij} is the different between 1995 and 2015 in the variable V_{ij}

Specifications: regional model

The specifications of interest in the regional model are thus:

$$\Delta emp_{ri} = c_i + \beta Exp_{ri} + \gamma X_{ri} + u_{ij} \tag{7}$$

where X_{ri} is a $(K \times 1)$ vector with control variables, including demographic changes in the labor force; routinisation and offshorability indices; exposure to Chinese imports; and the growth rate of capital stock.

Spillover effects To represent possible spillover effects, an Exposure to foreign robots is built, using the adjusted penetration of robots in all other EU countries.

(Some) Disadvantages

- Labour shares not necessarily exogenous to local employment movements
- Proxy variable, and, if effects depend on timing, particularly problematic

Results: country-sector model

	(1)	(2)	(3)	(4)
	Δemp_{ij}	Δemp_{ij}	Δemp_{ij}	Δemp_{ij}
Δr_{ij}	0.0469***	0.0361**	0.0253**	0.0135
	(0.0159)	(0.0154)	(0.0122)	(0.0156)
Δ Value Added		0.257***	0.191***	
		(0.0619)	(0.0593)	
Δ Comp.Employees		0.179***	0.452***	
		(0.0516)	(0.0588)	
Δ GFCF		-0.0348	-0.00472	
		(0.0426)	(0.0372)	
Country Effects	no	no	yes	yes
Industry Effects	no	no	no	yes
N	238	152	152	238
adj. R^2	0.03	0.30	0.62	0.34

SE in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Results: Long-run/short-run

	Δemp_{ij} *ALL* *NOIMP*	Δemp_{ij} 10*ormore*, *NOIMP*	Δemp_{ij} 10*less*, *NOIMP*	Δemp_{ij} *ALL*, *IMP*	Δemp_{ij} 10*ormore*, *IMP*	Δemp_{ij} 10*less*, *IMP*
Δr_{ij}	0.0135	0.0320*	-0.106*	0.0168	0.0356**	-0.0336
	(0.86)	(1.94)	(-1.69)	(1.39)	(2.51)	(-0.77)
Country Effects	yes	yes	yes	yes	yes	yes
Industry Effects	yes	yes	yes	yes	yes	yes
N	238	162	76	391	260	131
adj. R^2	0.34	0.47	0.26	0.40	0.44	0.37

t statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Results: Long-run/short-run

	Δemp_{ij} *NOIMP*	Δemp_{ij} *IMP*
$\Delta r_{ij} 1[Intro > 2005]$	-0.0208	-0.00728
	(-0.87)	(-0.46)
$\Delta r_{ij} 1[Intro <= 2005]$	0.0301*	0.0314**
	(1.69)	(2.32)
Country Effects	yes	yes
Industry Effects	yes	yes
N	238	391
adj. R^2	0.35	0.41

t statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Results

VARIABLES	(1) Δemp_{ij}	(2) Δemp_{ij}	(3) Δemp_{ij}	(4) Δemp_{ij}
Δr_{ij}	0.837***	0.825***	0.884***	0.796***
	(0.181)	(0.186)	(0.218)	(0.243)
prop_female		0.0578	0.213	0.306
		(0.408)	(0.413)	(0.405)
prop_female*Δr_{ij}		0.0309	0.00686	-0.0264
		(0.0981)	(0.103)	(0.107)
prop_lowmid	0.665	0.545	0.871	2.534*
	(1.180)	(1.151)	(1.168)	(1.328)
prop_lowmid*Δr_{ij}	-0.874***	-0.869***	-1.037***	-0.938***
	(0.198)	(0.199)	(0.275)	(0.335)
prop_young			-1.602	-1.608
			(0.976)	(1.248)
prop_young*Δr_{ij}			0.377	0.352
			(0.266)	(0.375)
spillover				-0.123**
				(0.0601)
Country Effects	yes	yes	yes	yes
Industry Effects	yes	yes	yes	yes
N	208	208	208	181
adj. R^2	0.667	0.667	0.672	0.692

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Results: regional model

	(1)	(2)	(3)	(4)	(5)	(6)
	Δemp_{ri}	Δemp_{ri}	Δemp_{ri}	Δemp_{ri}	Δemp_{ri}	Δemp_{ri}
Exp_{ri}	0.0186	0.0472*	0.0440*	0.0232	0.0572**	0.0520**
	(0.66)	(1.82)	(1.95)	(0.77)	(2.15)	(2.31)
Spillover				-0.0288	-0.0747	-0.0802**
				(-0.61)	(-1.58)	(-2.13)
Share of working pop. 1995	-0.462	-0.133	1.281**	-0.0288	-0.0747	-0.0802**
	(-0.80)	(-0.29)	(2.22)	(-0.61)	(-1.58)	(-2.13)
Share of employment in manufacturing, 1995	-0.0439	-0.322	-0.583**	-0.549	-0.363	1.076*
	(-0.20)	(-1.41)	(-2.15)	(-0.88)	(-0.76)	(1.88)
Exp Chinese Imports	0.0875***	0.0961***	-0.00583	0.0948***	0.113***	0.00689
	(2.92)	(3.23)	(-0.12)	(2.92)	(3.60)	(0.14)
OFF1995	0.119	-0.00125	0.261*	0.122	-0.00235	0.267*
	(0.87)	(-0.01)	(1.67)	(0.89)	(-0.01)	(1.75)
RTI1995	0.0289	0.218*	-0.168	0.0363	0.248**	-0.146
	(0.27)	(1.80)	(-1.20)	(0.34)	(2.06)	(-1.06)
Population in 1995		-0.000187	0.00759		-0.00232	0.00598
		(-0.01)	(0.66)		(-0.18)	(0.52)
Share of highly educated		0.0563**	-0.00709*		0.00578**	-0.00690*
		(2.13)	(-1.83)		(2.19)	(-1.77)
Women Participation rate		1.934***	0.465		2.110***	0.670
		(3.42)	(0.82)		(3.59)	(1.15)
Share of Young Actives (15-24)		-0.853	-2.683***		-0.713	-2.454***
		(-1.51)	(-3.81)		(-1.23)	(-3.37)
Δ Capital Stock			0.292**			0.299**
			(2.45)			(2.52)
N	134	130	117	134	130	117
adj. R^2	0.04	0.24	0.32	0.03	0.24	0.33

t statistics in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Includes north dummy

Concluding remarks

- The growth rate of robots appears positively related to employment in the long-run ($>$10years after intro of the first robot)
  - Though it has not been fully disentangled from Country-Industry movements
- The period is relevant also in the regional approach: negative results of robotisation for the 1995-2007 period in Europe, but positive ones for 1995-2015
- We confirm the skills composition matters: the effect of robots are positively related to the proportion of highly-skilled individuals in a sector
- Competition between countries appears to play a role: the decision to robotise might attract / impede businesses from rellocating

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