

Robots and the rise of European superstar firms





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Robot Data

- Source: International Federation of Robotics (IFR)
- Adoption of industrial robots across countries and industries
- Yearly surveys of robot suppliers (over 90% of the world market)
- Comprehensive data for 14 (2-digit) ISIC manuf industries



Change in number of robots per thousand workers (2004-2013)

Firm-level Data

Amadeus: Financial data of European firms (Germany, Spain, Finland, France, Italy, Sweden)

Variable	Definition	Mean	Std. dev.	Obs.
Sales	Total operating revenues	12,983.56	38,942.83	1,034,632
Labor	Total number of employees	53.70	118.12	914,900
Materials	Material costs	7,456.90	23,286.33	851,258
Capital stock	Tangible fixed assets	2,620.64	7,897.14	966,819
Average wages	Costs of employees / Labor	37.19	14.12	783,600
Capital investment	Investment in tangible fixed assets	408.89	1,928.41	814,537

Note. The variables are measured annually. The financial variables are given in thousand euros, and are adjusted using industry-level deflators for production, gross fixed capital formation and intermediate inputs from the OECD STAN database. The data includes firms in the manufacturing sector (NACE Rev. 2, 2-digit industry codes 10-30) between 1997 and 2015.

Additional data sources: EUKLEMS, COMTRADE

Empirical Strategy

1. Estimating firm-level TFP and markups

- a. Production function estimation
- b. Markup estimation
- 2. Evaluating the effects of industrial robots
 - a. Industry-level distributions of productivity and markups
 - b. Market concentration and the labor share

Productivity: High vs. low robotized industries



Higher robot exposure is associated with higher TFP growth – only for the already most productive firms

Markups: High vs. low robotized industries



Higher robot exposure is associated with higher markup growth – only for firms with already highest markups

Robots and firm-level productivity

		Dependent variable: Δ_5 In(TFP)			
	-	(1)	(2)	(3)	(4)
Δ_5 ln(Robots)	x Quin1	-0.0030	-0.0046	-0.0025	
-		(0.005)	(0.005)	(0.004)	
	x Quin2	0.0036	0.0020	0.0041	
		(0.005)	(0.005)	(0.004)	
	x Quin3	0.0049	0.0033	0.0054	
		(0.005)	(0.005)	(0.005)	
	x Quin4	0.0068	0.0051	0.0073	
		(0.005)	(0.005)	(0.005)	
	x Quin5	0.0176**	0.0160**	0.0183**	
		(0.008)	(0.008)	(0.008)	
	:				
	x Dec10				0.0241**
					(0.011)
Country, year dummies		\checkmark	\checkmark	\checkmark	\checkmark
Δ_5 other technologies			\checkmark	\checkmark	\checkmark
Δ_5 other industry changes				\checkmark	\checkmark
Initial industry controls				\checkmark	\checkmark

Note. N = 110,710. Standard errors clustered by country x industry in parentheses. Levels of significance: *** 1%, ** 5%, * 10%.

Higher robot exposure is associated with higher TFP growth – only for the already most productive firms

Robots and firm-level markups

		Dependent variable: Δ_5 ln(Markup)			
	-	(1)	(2)	(3)	(4)
Δ_5 In(Robots)	x Quin1	-0.0232*	-0.0224*	-0.0272**	
		(0.014)	(0.013)	(0.010)	
	x Quin2	-0.0277**	-0.0269**	-0.0317***	
		(0.014)	(0.012)	(0.010)	
	x Quin3	-0.0181	-0.0172	-0.0219**	
		(0.013)	(0.012)	(0.010)	
	x Quin4	-0.0188	-0.0179	-0.0228**	
		(0.013)	(0.011)	(0.009)	
	x Quin5	0.0188**	0.0197*	0.0147*	
		(0.011)	(0.010)	(0.008)	
	:				
	x Dec10				0.0422***
					(0.011)
Country, year dummies		\checkmark	\checkmark	\checkmark	\checkmark
Δ_5 other technologies			\checkmark	\checkmark	\checkmark
Δ_5 other industry changes				\checkmark	\checkmark
Initial industry controls				\checkmark	\checkmark

Note. N = 110,710. Standard errors clustered by country x industry in parentheses. Levels of significance: *** 1%, ** 5%, * 10%.

Higher robot exposure is associated with higher markup growth – only for firms with already highest markups

Industry concentration and the labor share

Δ ₅		Δ_5 ln(Sales)		Δ_5 Labor share		
Δ_5 ln(Robots)	x Quin1	-0.0390**		Unweighted	Weighted by firm sales	
	x Quin2	(0.017) 0.0072 (0.018)	Δ_5 In(Robots)	-0.0022 (0.002)	-0.0041** (0.002)	
	x Quin3	0.0250	Country, year dummies Δ_5 other technologies	\checkmark	\checkmark	
	x Quin4	0.0447**	Δ_5 other industry changes Initial industry controls	\checkmark	√ √	
x Quin5 0.0449* (0.025)		N = 326. The labor share is defined as a firm's total labor costs over sales, aggregated to the country-industry- year level. Levels of significance: *** 1%, ** 5%, * 10%.				
Country, year dur	nmies	\checkmark				
Δ_5 other technolo	ogies	\checkmark				
Δ_5 other industry	r changes	\checkmark				
Initial industry co	ntrols	✓				

N = 110,710. Levels of significance: *** 1%, ** 5%, * 10%.

Higher robot exposure is associated with higher industry concentration and a falling aggregate labor share

Conclusion

- Digitalization (robots)
 - boost the productivity and profits of superstar firms
 - Not just in US tech, but also in European manufacturing
 - Rising wage gaps for workers in superstar vs. normal firms
 - Superstar pay best in absolute terms, but have lowest labor shares
 - Re-allocation of market shares towards superstars depresses aggregate labor share
- Challenges
 - Lack of competition → pre-emptive behavior of incumbent superstars
 - Rising inequality in the functional \rightarrow personal income distribution
 - Reason: Extreme concentration of asset ownership
- Policy issues
 - How to spread the asset ownership of robots, digital technologies, superstar firms?
 - *"Who owns the robots rules the world!"* (Richard Freeman)

Appendix

Production Function Estimation

based on Ackerberg et al. 2015

Example: Cobb-Douglas production function

 $q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \boldsymbol{\omega}_{it} + \varepsilon_{it}$ Total factor productivity (TFP)

- Assumptions
 - **1** Scalar unobservable: $m_{it} = f(\omega_{it}, k_{it}, l_{it}, \Delta \text{robots}_{jt-1}, \text{wage}_{it}, C_c, Y_t)$
 - **2** Strict monotonicity: $\omega_{it} = f^{-1}(m_{it}, k_{it}, l_{it}, \Delta robots_{jt-1}, wage_{it}, C_c, Y_t)$
 - **3** Productivity process: $\omega_{it} = g(\omega_{it-1}, \Delta \text{robots}_{jt-1}) + \xi_{it}$
- First stage
 - Let $q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + f^{-1}(\cdot) + \varepsilon_{it} = \Phi(k_{it}, l_{it}, m_{it}, \Delta \text{robots}_{jt-1}, \text{wage}_{it}, \boldsymbol{C}_c, \boldsymbol{Y}_t) + \varepsilon_{it}$
 - OLS to estimate $\widehat{\Phi}_{it}$
- Second stage
 - Use 3 where $\boldsymbol{\omega}_{it} = \widehat{\Phi}_{it} \beta_k k_{it} \beta_l l_{it} \beta_m m_{it}$
 - GMM to identify output elasticities with moment conditions $E\left|\xi_{it}(\beta_k,\beta_l,\beta_m)\begin{pmatrix}l_{it-1}\\l_{it}\\m_{it-1}\end{pmatrix}\right| = 0$

Markup Estimation

De Loecker and Warzynski 2012

- Idea: For cost-minimizing firms and perfect competition: output elasticity of a variable factor of production = expenditure share in total revenue
 - Under *imperfect* competition, the output elasticity exceeds the revenue share
- Production function $Q_{it} = Q_{it}(M_{it}, L_{it}, K_{it}, \Omega_{it}) = F(M_{it}, L_{it}, K_{it}) \Omega_{it}$
- Cost-minimizing producers $\mathcal{L}(M_{it}, L_{it}, K_{it}, \lambda_{it}) = P_{it}^m M_{it} + w_{it}L_{it} + r_{it}K_{it} + \lambda_{it}(Q_{it} Q_{it}(\cdot))$
- Output elasticity of variable input $\theta_{it}^m = \frac{\delta Q_{it}(\cdot)}{\delta M_{it}} \frac{M_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^m M_{it}}{Q_{it}}$
- Define markup $\mu_{it} = \frac{P_{it}}{\lambda_{it}} \rightarrow \mu_{it} = \theta_{it}^m \frac{Q_{it}P_{it}}{P_{it}^m M_{it}} = \beta_m (\alpha_{it}^m)^{-1}$
 - β_m : output elasticity of variable input
 - α_{it}^{m} : share of variable input's expenditure in total sales

Evaluating the effects of industrial robots

Baseline specification derived from the linear version of the assumed productivity process $\Im \omega_{it} = g(\omega_{it-1}, \triangle \operatorname{robots}_{jt-1}) + \xi_{it}$

$\Delta_s y_{ijct} = \gamma_0 + \gamma_1 y_{ijc}$	$h_{t-s} + \delta \Delta_s \text{robots}_{jct-1} + \boldsymbol{\theta} \Delta_s \boldsymbol{Z}_{jct-1} + \boldsymbol{\zeta} \boldsymbol{W}_{jct-s} + \boldsymbol{C}_c + \boldsymbol{Y}_t + \Delta_s \boldsymbol{v}_{ijct}$
$\Delta_s y_{ijct} = y_{ijct} - y_{ijct-s}$	<i>s</i> period change in TFP/markups for firm <i>i</i> in industry <i>j</i> in country <i>c</i> at time <i>t</i>
Z_{jct-1}	Other technologies (ICT, computer software and databases, R&D), imports, exports,
	share of inward FDI, capital-to-labor ratio
W _{jct-s}	Capital-to-labor ratio, average wages
C_c, Y_t	Country and year dummies

Heterogeneous effects

$$\Delta_{s} y_{ijct} = \delta_{1} (\Delta_{s} \text{robots}_{jct-1} \times \text{Quin1}_{ijct-s}) + \dots + \delta_{5} (\Delta_{s} \text{robots}_{jct-1} \times \text{Quin5}_{ijct-s}) + \dots + \Delta_{s} v_{ijct}$$
where $\text{Quin1}_{ijct-s} = \begin{cases} 1, y_{ijct-s} \leq y_{0,2(jct-s)} \\ 0, \text{otherwise} \end{cases}$

OLS, overlapping differences, std. errors clustered at country-industry level

Estimated production function coefficients

		Production function coefficients			
Industry	Code	Labor	Materials	Capital	RTS
Food products, beverages, tobacco	10-12	0.23	0.68	0.10	1.00
Textiles, leather, wearing apparel	13-15	0.41	0.50	0.06	0.96
Wood and wood products	16	0.32	0.61	0.08	1.01
Paper and paper products	17-18	0.41	0.50	0.07	0.98
Other chemical products	19-20	0.29	0.63	0.10	1.01
Pharmaceuticals, cosmetics	21	0.35	0.60	0.03	0.99
Rubber and plastic products	22	0.24	0.65	0.07	0.97
Other non-metallic mineral products	23	0.36	0.56	0.10	1.02
Basic metals	24	0.31	0.62	0.05	0.99
Fabricated metals	25	0.44	0.45	0.10	0.99
Electronics	26-27	0.38	0.56	0.06	1.00
Industrial machinery	28	0.38	0.54	0.07	0.99
Motor vehicles	29	0.32	0.58	0.08	0.99
Other transport equipment	30	0.35	0.57	0.05	0.97

Industry-level evolution of TFP



Note. The figure displays the evolution of average firm-level TFP by ISIC Rev. 4 industries, where the average TFP is weighted by firm sales. For each each industry and year, I calculate the average log change in TFP relative to 2004.

Industry-level evolution of markups



Note. The figure displays the evolution of average firm-level markups by ISIC Rev. 4 industries, where the average markup is weighted by firm sales.

Robustness checks

- Robot density
- Industry-specific trends
- Timing (lag structure, regression in differences)
- Translog production function
- Instrumental variable estimation

Related Literature

Rise of superstar firms

- Increasing industry concentration [e.g. Grullon et al. forthcoming, Andrews et al. 2016]
- Productivity divergence [e.g. Andrews et al. 2016]
- Markup divergence [e.g. De Loecker and Eeckhout 2017, 2018; Weche and Wambach 2018]
- Falling aggregate labor share [e.g. Autor et al. 2017a,b; Kehrig and Vincent 2018]

Drivers of superstar phenomenon

- Technology [e.g. Bessen 2017, Autor et al. 2017b, Dinlersoz and Wolf 2018, Lashkari and Bauer 2018]
- Globalization [e.g. Autor et al. 2017b], regulation and antitrust [e.g. Gutiérrez and Philippon 2018]
- Drivers of productivity dispersion within narrow industries [e.g. Syverson 2011]
- Effects of industrial robots [e.g. Acemoglu and Restrepo 2017, Graetz and Michaels 2018, Dauth et al. 2018]

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