Automation and the Rise of Superstar Firms

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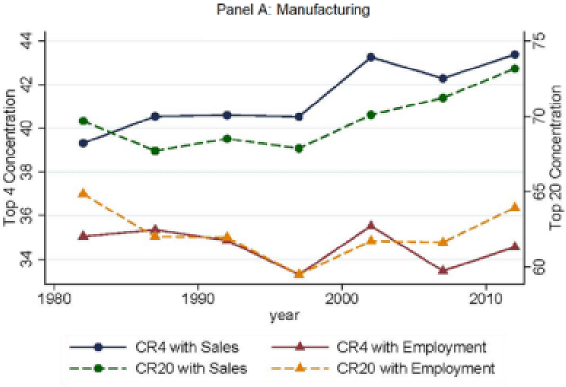
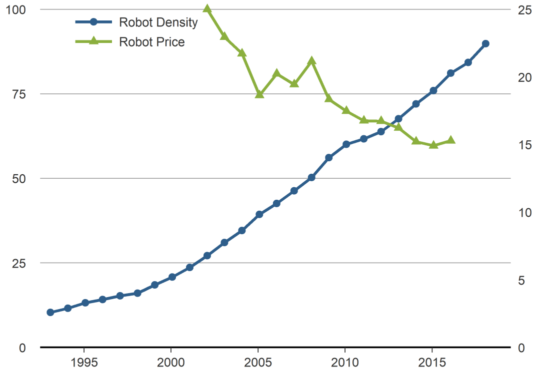
The rise of superstar firms



Source: Autor et al. (2020)

- Sales concentration rose, employment concentration flat

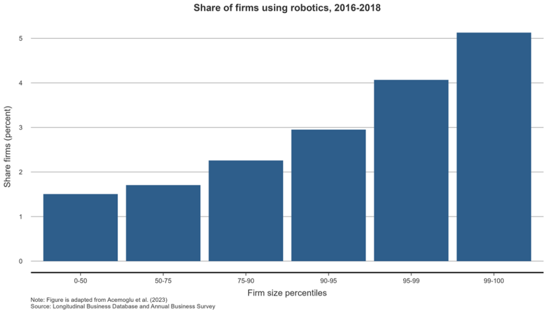
Automation also rising



Robot density and robot price. Source: IFR and BLS

- Robot density rising while robot prices declining

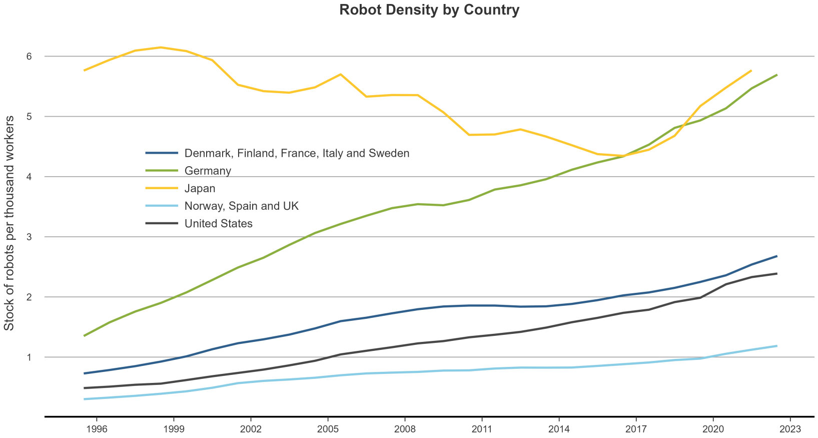
Automation highly skewed toward large firms



Source: 2019 Annual Business Survey, Acemoglu, et al (2023)

- 2% of firms (economy-wide) adopted robots in 2016-18; those firms are large, employing 15.7% of all workers (2019 ABS)
- 8.7% of manufacturing firms adopted robots and those firms employed 45.1% of manufacturing workers

US not a leader in robot adoption



Source: International Federation of Robotics, Bureau of Labor Statistics & OECD via Haver Analytics

How is automation related to industry concentration?

- Industry evidence suggests automation has sizable effects on sales concentration, but smaller effects on employment concentration
- GE model with heterogeneous firms, automation, and variable markup $\Rightarrow$ Rise in automation explains
  - 49% of rise in manufacturing sales concentration
  - 25% of divergence between sales and employment concentrations
- Calibrated model suggests that modest subsidy for automation improves welfare

Model Mechanism

- Fixed costs of operating automation technology $\Rightarrow$ large, productive firms more likely to automate
  - Consistent with ABS evidence (Zolas et al., 2020; Acemoglu et al., 2022)
- Automation improves labor productivity, enabling large firms to become even larger
- Automation has smaller effects on employment share of top firms: labor-substituting technology

Related Literature

1. **Industry concentration:** Autor et al. (2020), Furman and Orszag (2018), Akcigit and Ates (2019), Hsieh and Rossi-Hansberg (2019)
   - Importance of economy of scale: Hubmer and Restrepo (2022), Kwon et al. (2022), Aghion et al. (2019), Lashkari et al. (2022),
2. **Automation and labor market:** Acemoglu and Restrepo (2018, 2020), Aghion et al. (2021), Leduc and Liu (2023)
3. **Automation and tax policy:** Costinot and Werning (2022), Guerreiro et al. (2022), Beraja and Zorzi (2022)

Contributions to literature

- Establish new evidence that automation contributes to rise of industry concentration

- Propose quantitative GE framework for studying the economic mechanism

- Use quantitative framework to evaluate macro and welfare effects of automation taxes/subsidies

Data

- Industry concentration: sales (or employment) share of top 1% Compustat firms in 2-digit industries
- Robot density: operation stock of industrial robots per thousand manufacturing employees in 2-digit industries robot def.
  - Alternative measure: robots per million labor hours
  - Source: IFR, NBER-CES, EUKLEMS
- Sample: unbalanced panel of 13 industries, 2007-2018

summary statistics

Robot density corr. with sales concentration, not with employment concentration

	top 1% share of sales		top 1% share of emp	
	(1)	(2)	(3)	(4)
ln(robot/thousand emp)	0.021**		0.002	
	(0.007)		(0.015)	
ln(robot/million hours)		0.021**		0.002
		(0.007)		(0.015)
Observations	117	117	104	104
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Note: Industry variables are weighed by sales shares in 2007. Standard errors clustered by industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Instrumental-variable (IV) approach

- Following Acemoglu and Restrepo (2020), use lagged robot density in Europe as IV for same-industry robot density in US

$$robot_{jt}^{EURO5} = \frac{1}{5} \sum_{k \in EURO5} \frac{\text{robot stock}_{kjt}}{\text{thousands of employees}_{kjt}}$$

  - EURO5 countries: Denmark, Finland, France, Italy, and Sweden

- IV relevance: global advancement of automation technology and earlier robot adoptions in EURO5 than in US

- IV exclusion: lagged robot density in EURO5 does not have direct effects on US industry concentration except through advancement of automation technology

IV estimation results (second stage)

	top 1% share of sales		top 1% share of emp	
	(1)	(2)	(3)	(4)
ln(robot/thousand emp)	0.038**		0.012	
	(0.019)		(0.016)	
ln(robot/million hours)		0.036*		0.014
		(0.020)		(0.016)
Observations	117	117	104	104
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Anderson-Rubin *p*-value	0.000	0.001	0.474	0.401

Note: Industry variables are weighed by sales shares in 2007. Standard errors clustered by industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

- 1 std ↑ robot density raises top 1% sales share by 10 pp (from 30% to 40%)
  - Estimates significant at 5% level and robust to weak instruments
- Effects on top 1% employment share small and insignificant

Potential challenges for identification

1. Unobserved shocks common to EU and US markets could violate IV exclusion
   - EU robot adoptions uncorrelated with other major global trends, such as offshoring, declines of routine jobs, and capital deepening (Acemoglu and Restrepo, 2022)
2. IV exclusion could also be violated if EU robot adoption raised US concentration by increasing global sales of US multinationals
   - Sales of U.S. affiliates in EU are small relative to US parents' total sales (e.g., 3.4% in 2020)
   - Results are robust to using domestic sales details
3. Concentration might be rising before robot adoptions (pre-trends)
   - Placebo IV regressions using lags of concentration as dependent variable $\rightarrow$ no effects from robot adoptions details

Final Goods Production

- Final goods a Kimball aggregate of differentiated intermediate goods

$$\int_0^1 \Lambda(q(j))dj = 1$$

- Monopolistic competition in intermediate goods market and perfect competition in final goods market
- With Klenow-Willis (2016) specification, demand elasticity and markup given by

$$\sigma(q(j)) = \sigma q(j)^{-\frac{\varepsilon}{\sigma}} \quad \mu(j) = \frac{\sigma(q(j))}{\sigma(q(j)) - 1}$$

- Super-elasticity $\varepsilon \neq 0 \rightarrow$ firm's markup depends on its relative output

Intermediate Goods Producers (Firms)

- Face monopolistic competition in product markets and perfect competition in input markets
- Production function

$$y = \phi \left[\alpha_a A'^{\frac{\eta-1}{\eta}} + (1-\alpha_a) N^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}$$

  where $\phi =$ persistent idiosyncratic productivity; $A' =$ robot input; and $N =$ labor input.

- A firm chooses from one of the two technologies
  1. Automation technology: incurs i.i.d., per-period fixed cost $s \sim F(s)$
  2. Labor-only technology ($A' = 0$): no fixed costs

Production decisions

- Bellman equation for firm

$$
\begin{aligned}
V(\phi, A; s) \;\; &= \max_{p,y,N,I_a \geq (\delta_a - 1)A} \Big[py - WN - Q_a I_a - s\phi \mathbb{I}\{A' > 0\} \\
&+ \;\; \beta E_{\phi'|\phi} \int_{s'} V(\phi', A'; s') dF(s') \Big],
\end{aligned}
$$

subject to

$$A' = (1 - \delta_a)A + I_a$$

taking as given competitive wages W and exogenous robot price Q_a

Technology choices

- Firm's Bellman equation can be written as

$$V(\phi, A; s) = Q_a(1-\delta_a)A + \max\{V^a(\phi) - s\phi, V^n(\phi)\},$$

where

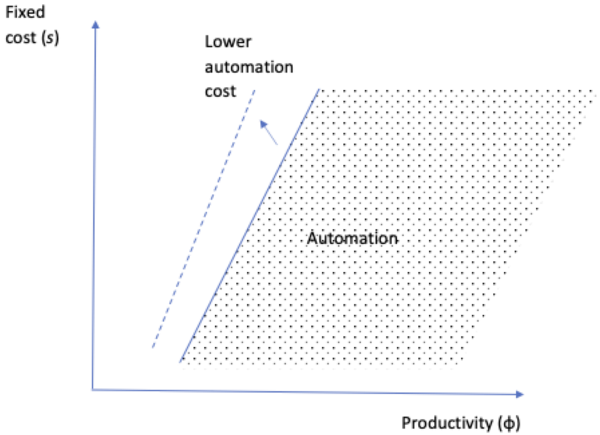
$$V^a(\phi) = \max_{p,y,N,A'>0}\left[py - WN - Q_aA' + \beta E_{\phi'|\phi}\int_{s'} V(\phi', A'; s')dF(s')\right],$$

$$V^n(\phi) = \max_{p,y,N}\left[py - WN + \beta E_{\phi'|\phi}\int_{s'} V(\phi', 0; s')dF(s')\right].$$

- Firm automates iff fixed cost below the threshold

$$s^*(\phi) \equiv \frac{V^a(\phi) - V^n(\phi)}{\phi}$$

Automation Decision



Automation decisions

- Automation incurs fixed cost but reduces marginal cost
- Firm automates iff fixed cost is below threshold $s^*(\phi)$
- Economy-of-scale effect: At given fixed cost s, larger firms (with higher ϕ) more likely to automate
- Declines in Q_a shifts indifference line upward:
  - More firms choose to automate (extensive margin): reducing concentration
  - Existing automating firms use more robots (intensive margin): increasing concentration

Stationary Equilibrium

- Rep household chooses C and N to maximize utility
- Final goods market clears

$$C + Q_a I_a + \int_{\phi} \int_0^{s^*(\phi)} s\phi \; dF(s) \; dG(\phi) = Y$$

- Labor market clears

$$N = \int_{\phi} N(\phi) dG(\phi)$$

- Robot market clears

$$A' = \int_{\phi} A'(\phi) F(s^*(\phi)) dG(\phi)$$

- In stationary equilibrium, $A' = A$

Calibration

- Calibrate 4 non-standard parameters:
  1. Q_a: relative price of robots
  2. σ_a: std of fixed cost of operating automation tech
  3. α_a: robot input weight
  4. η: sub elasticity b/n robots and workers

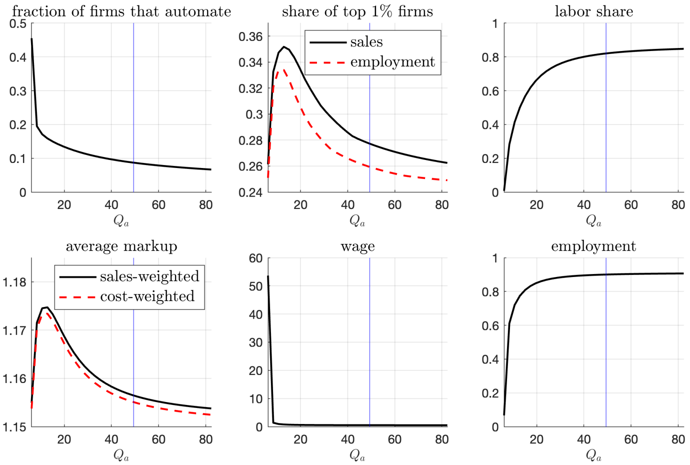
- Match 4 moments in data:
  1. Share of automating firms in manufacturing: 8.7% (2019 ABS)
  2. Employment share of automating firms in manufacturing: 45.1% (ABS)
  3. Robots per manufacturing worker in 2016: $A/N = 0.02$ (IFR and NBER-CES)
  4. Cumulative increase in A/N from 2002 to 2016 of 300% (IFR and NBER-CES)

- Calibrated values: $Q_a = 49.39$, $\sigma_a = 3.38$, $\alpha_a = 0.37$, and $\eta = 2.03$

Full calibration results

Parameter	Notation	Value	Sources/Matched Moments
Panel A: Assigned Parameters			
Discount factor	β	0.99	4% annual interest rate
Inverse Frisch elasticity	ξ	0.5	Rogerson and Wallenius (2009)
Utility weight on leisure	χ	1	Normalization
Robot depreciation rate	δ_a	0.02	8% annual depreciation rate
Productivity persistence	γ	0.95	Khan and Thomas (2008)
Productivity standard dev.	σ_ϕ	0.1	Bloom et al. (2018)
Demand elasticity parameter	σ	10.86	Edmond et al. (2021)
Super-elasticity	ϵ/σ	0.16	Edmond et al. (2021)
Panel B: Parameters from Moment Matching			
Relative price of robots	Q_a	49.39	Fraction of automating firms
SD of log automation fixed costs	σ_a	3.38	Employment share of automating firms
Elasticity of substitution	η	2.03	Growth rate of robot density
Robot input weight	α_a	0.37	Robot density

Macro effects of changes in robot price



Automation and Industry Concentration

- Increased automation explains about 49% of the observed increase in sales concentration (1.48 pp out of 3 pp)
- Automation also explains about 25% of observed divergence between sales and employment concentration (0.46 pp out of 1.8 pp)
- Non-monotonic effect of automation on concentration
  - At high Q_a, only top firms automate $\rightarrow$ more automation raises concentration
  - At sufficiently low Q_a, automation is widespread $\rightarrow$ more automation reduces concentration
- Automation differs from general-purpose equipment

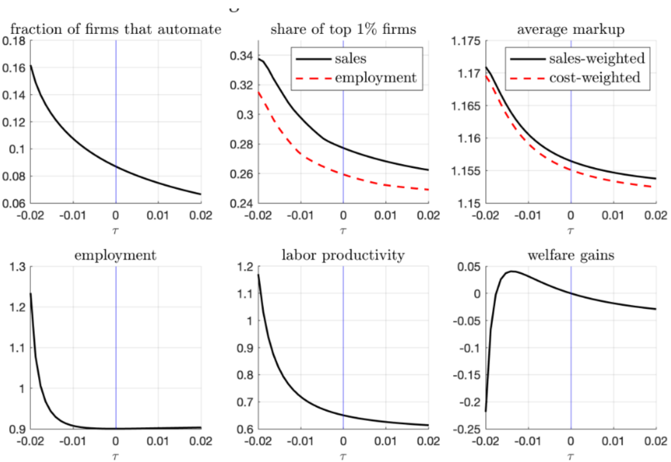
Policy Analysis

- Source of inefficiency: market power

- Trade-off for taxing automation: markups vs. productivity

- Is taxing robots a good idea?

Effects of taxing robots



- Optimal subsidy for robots of 1.4%: raises welfare by 4.07% of CE relative to benchmark

Conclusion

- Empirical evidence: automation raises manufacturing sales concentration, but not employment concentration
- A quantitative GE framework of automation helps explain these facts
  - Key channels: Economy-of-scale and labor-substituting technology
  - Rise of automation explains 50% of the observed rise in sales concentration and 25% of the gap b/w sales and employment concentration
  - Calibrated model implies a modest subsidy for robots improves welfare
    - Policy faces tradeoff between productivity and markup

Additional Slides

IFR Definition of Robots

Industrial robots are automatically controlled, reprogrammable, and multipurpose manipulators with several axes.

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Summary Statistics

	#obs	mean	min	p25	p50	p75	max	s.d.
robots/thousand employees	156	30.42	0.00	0.24	2.26	10.90	419.92	87.96
robots/million hours	156	19.58	0.00	0.18	1.72	7.72	243.54	52.42
top 1% share of sales	121	0.30	0.08	0.22	0.30	0.36	0.77	0.13
top 1% share of employment	106	0.27	0.11	0.21	0.28	0.32	0.46	0.08

Source: Authors' calculations using IFR, Compustat, and NBER-CES.

- Large variations of robot density
- Sales concentration is higher and more variable than employment concentration

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Results for Domestic Sales

	top 1% share of domestic sales			
	OLS		IV	
	(1)	(2)	(3)	(4)
ln(robot/thousand emp)	0.021^{**}		0.038^{**}	
	(0.007)		(0.020)	
ln(robot/million hours)		0.021^{**}		0.037^{*}
		(0.007)		(0.020)
Observations	117	117	117	117
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Anderson-Rubin *p*-value			0.000	0.000

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Pre-Trend Test

	five-year lagged top 1% share					
	sales		domestic sales		employment	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: OLS regressions					
ln(robot/thousand emp)	0.006		0.007		0.002	
	(0.011)		(0.010)		(0.008)	
ln(robot/million hours)		0.005		0.006		0.002
		(0.011)		(0.010)		(0.008)
	Panel B: IV regressions					
ln(robot/thousand emp)	-0.024		-0.016		-0.010	
	(0.041)		(0.034)		(0.002)	
ln(robot/million hours)		-0.025		-0.017		-0.013
		(0.045)		(0.037)		(0.021)
Observations	122	122	122	122	102	102
Industry, Year FE	✓	✓	✓	✓	✓	✓

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