What do we know about robot automation?

Displacement, productivity, and the comparison that identifies an effect

Sergio Ocampo
ECON 3399 · AI and Robots at Work

A machine can affect labour in different ways

A robot

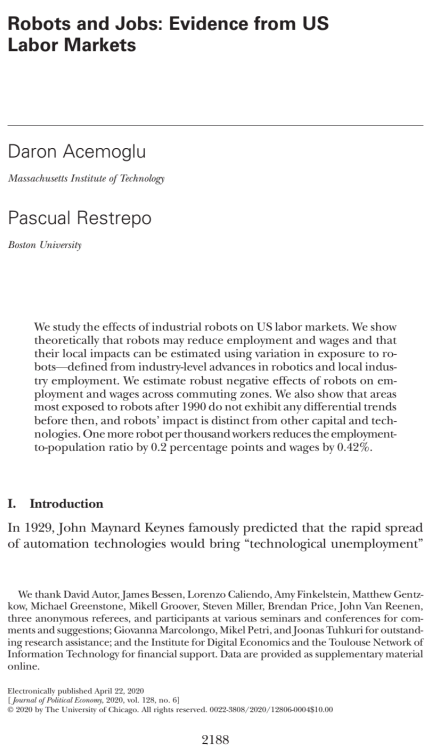
An autonomous machine performs an activity that a worker previously carried out.

A tool

A machine helps the worker perform a task.

Both can increase output. Their effects on labour demand need not be the same.

Robots and Jobs



Robots and Jobs: Evidence from US Labor Markets

Daron Acemoglu

Massachusetts Institute of Technology

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We study the effects of industrial robots on US labor markets. We show theoretically that robots may reduce employment and wages and that their local impacts can be estimated using variation in exposure to robots—defined from industry-level advances in robotics and local industry employment. We estimate robust negative effects of robots on employment and wages across commuting zones. We also show that areas most exposed to robots after 1990 do not exhibit any differential trends before then, and robots' impact is distinct from other capital and technologies. One more robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%.

I. Introduction

In 1929, John Maynard Keynes famously predicted that the rapid spread of automation technologies would bring "technological unemployment"

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Evidence from US labor markets

Daron Acemoglu and Pascual Restrepo

Journal of Political Economy · 2020

Open the paper

Published article · First page

Do industrial robots reduce local employment and wages?

Question: How do outcomes change in more exposed U.S. places relative to less exposed places?

Unit: a commuting zone—counties linked by commuting within a local labour market.

Design: initial industry employment × later industry robot adoption.

> Compare changes in employment/population and hourly wages, 1990–2007.
> The outcome includes the whole local labour market, not just adopting firms.

Exposure combines initial jobs with industry robot adoption

$$E_c = \sum_i s_{ci,0} \, \Delta\text{Robots}_i$$

Symbol	Measurement
c, i	Commuting zone and industry.
$s_{ci,0}$	Industry i's share of the zone's 1970 employment.
ΔRobots_i	Adjusted industry penetration: additional robots per 1,000 workers.

> A place is more exposed when it initially specializes in robot-adopting industries.

The same industry shock produces different local exposure

Teaching example: autos add **4 robots per 1,000 workers**; all other industries add zero.

Place	Initial auto-employment share	Predicted exposure
A	25%	$0.25 \times 4 = 1.0$
B	5%	$0.05 \times 4 = 0.2$

> A is five times as exposed because of its initial industry mix.
> The shares predate adoption; they do not measure where workers move later.

Bartik (shift-share) instruments

Objective: the causal effect of robot exposure on local jobs & wages.
Adoption also responds to demand ⟶ ordinary correlations can mislead.

$$Z_c = \sum_i \underbrace{s_{ci,0}}_{\text{initial industry share}} \times \underbrace{g_i}_{\text{European robot adoption}}$$

- **First stage:** predict region c's robot exposure using Z_c + controls
- **Second stage:** regress jobs & wages on predicted exposure + the same controls

> **Assumption, conditional on controls:**
> Shocks or initial shares are unrelated to other drivers of local outcomes.
> Z_c affects jobs & wages only through robot exposure.

Applications of Bartik instruments

Application	**Baseline exposure × shifter**
Robots · Acemoglu–Restrepo	Industry employment mix × European robot adoption
Trade · Autor–Dorn–Hanson	Industry employment mix × Chinese exports to other countries
Immigration · Card	Origin-country settlement mix × national inflows by origin
Local labour demand · Bartik	Industry employment mix × national industry employment growth
Credit supply · Greenstone et al.	Local bank lending shares × bank-specific credit supply shocks
Demand & innovation · Jaravel	Product sales shares by consumer group × group population growth

Using robot adoption in Europe

European adoption supplies instrument Z_c for U.S. exposure E_c^{US}.

$$\text{Measures:} \quad Z_c = \sum_i s_{ci,0}\, \Delta\text{Robots}_i^{Europe}, \qquad E_c^{US} = \sum_i s_{ci,0}\, \Delta\text{Robots}_i^{US}$$

$$\text{First stage:} \quad E_c^{US} = \pi_0 + \pi_1 Z_c + X_c'\gamma + v_c$$

$$\text{Second stage:} \quad \Delta y_c = \alpha + \beta\, \hat{E}_c^{US} + X_c'\delta + \varepsilon_c$$

- Δy_c: employment/population or log-wage change; X_c: controls
- $\hat{E}_c^{US}$: U.S. robot exposure predicted by the first stage

> Assumption: Z_c affects local outcomes only through U.S. robot exposure.
> β: relative local outcome changes per unit of U.S. robot exposure.

Employment and wages fall more in exposed places

Employment

Wages

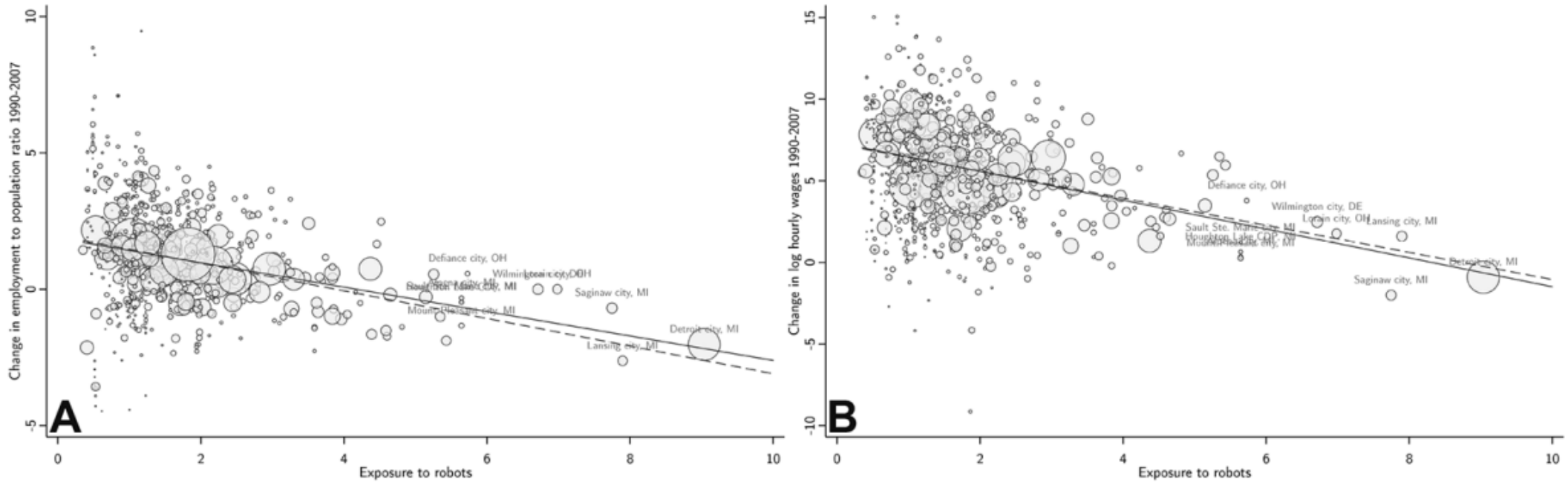


Figure 6A,B: European-based robot exposure versus U.S. employment/population (left) and hourly wages (right), 1990–2007.

> More exposed places have worse relative employment & wage changes.
> Each dot is a commuting zone, after accounting for the controls.

The IV coefficients measure relative local losses

Outcome-change difference per +1 robot / 1,000 workers	IV estimate	SE
Change in employment/population, percentage points	-0.388	0.091
Change in log hourly wages, × 100	-0.768	0.148

Table 7A, cols. 3 and 6; 722 zones. 1990–2007 changes, rescaled to a 14-year equivalent. pretrends

$\Delta \log w = \log(w_{\text{end}}/w_{\text{start}})$: cumulative wage growth.

> One additional robot per 1,000 workers, relative to less-exposed areas:
> Employment/population falls **0.39 percentage points** more.
> With the same starting wage, hourly wages end about **0.77% lower**.

Relative local losses extend beyond manufacturing

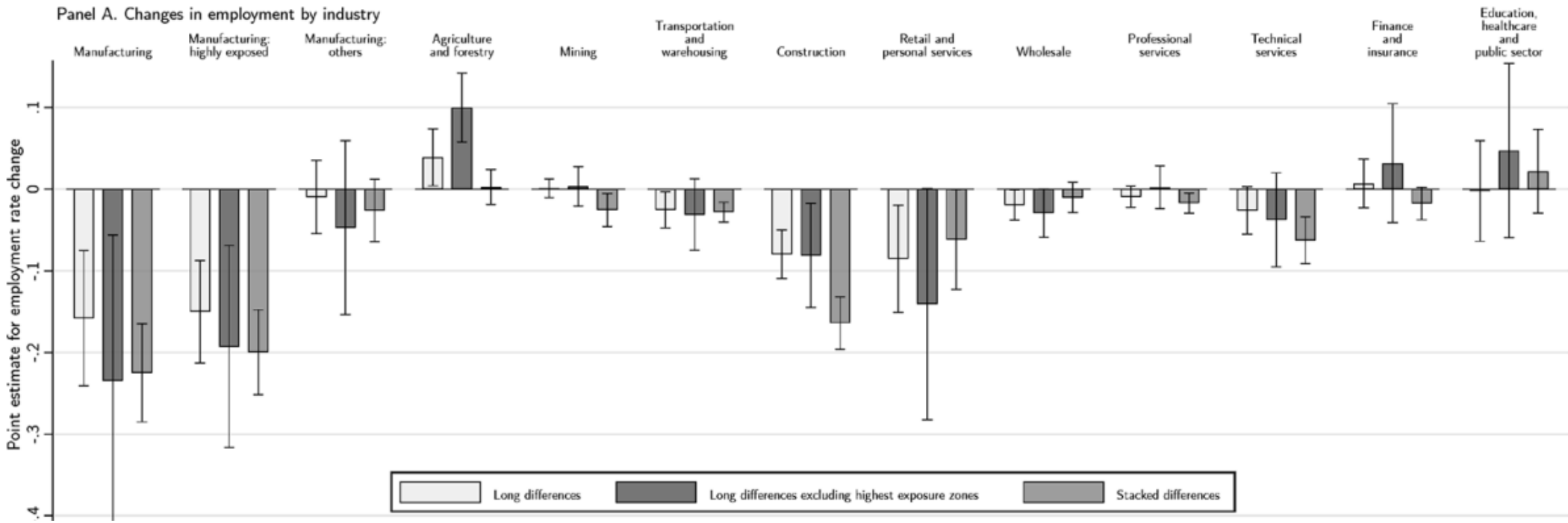


Figure 8: local robot-exposure effects on employment/population by industry (panel A).

> More exposed zones fare worse in manufacturing, construction, and local services.
> Local demand can transmit the shock beyond factories.

The occupational burden is concentrated in routine manual work

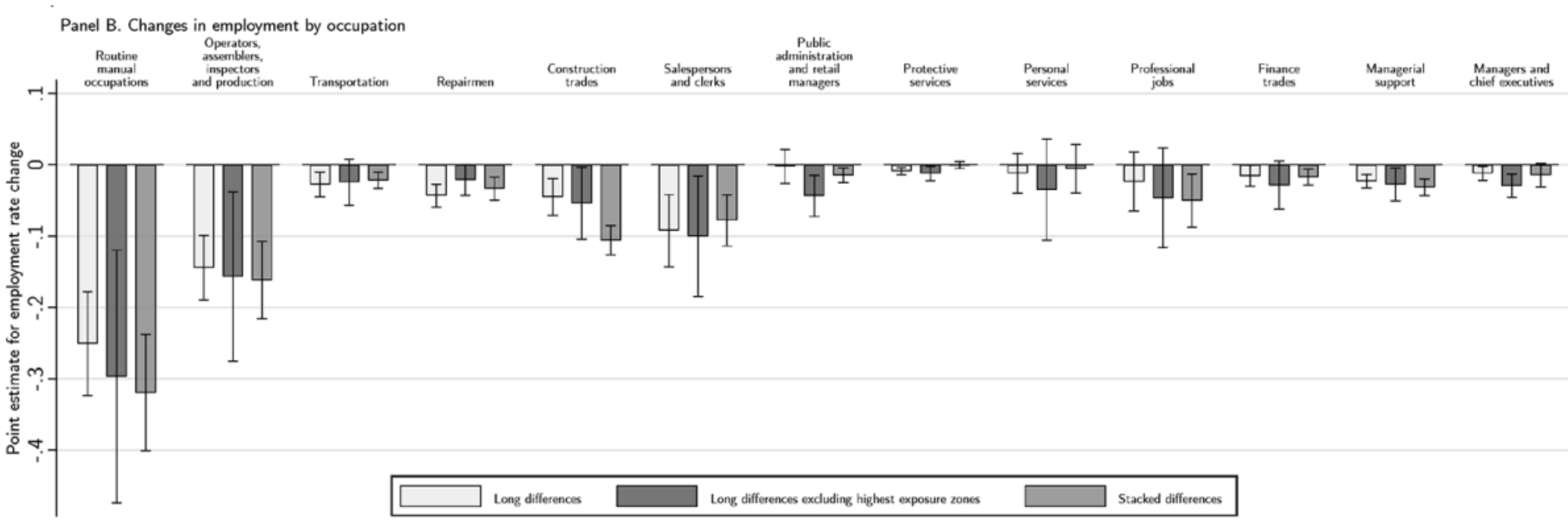


Figure 8B: local robot-exposure effects on employment/population by occupation.

> Routine manual and production jobs show the largest relative local losses.
> The estimates for professional and managerial jobs are much smaller.

The missing intercept problem

Δy_c^R: change in zone c's outcome caused by robots.

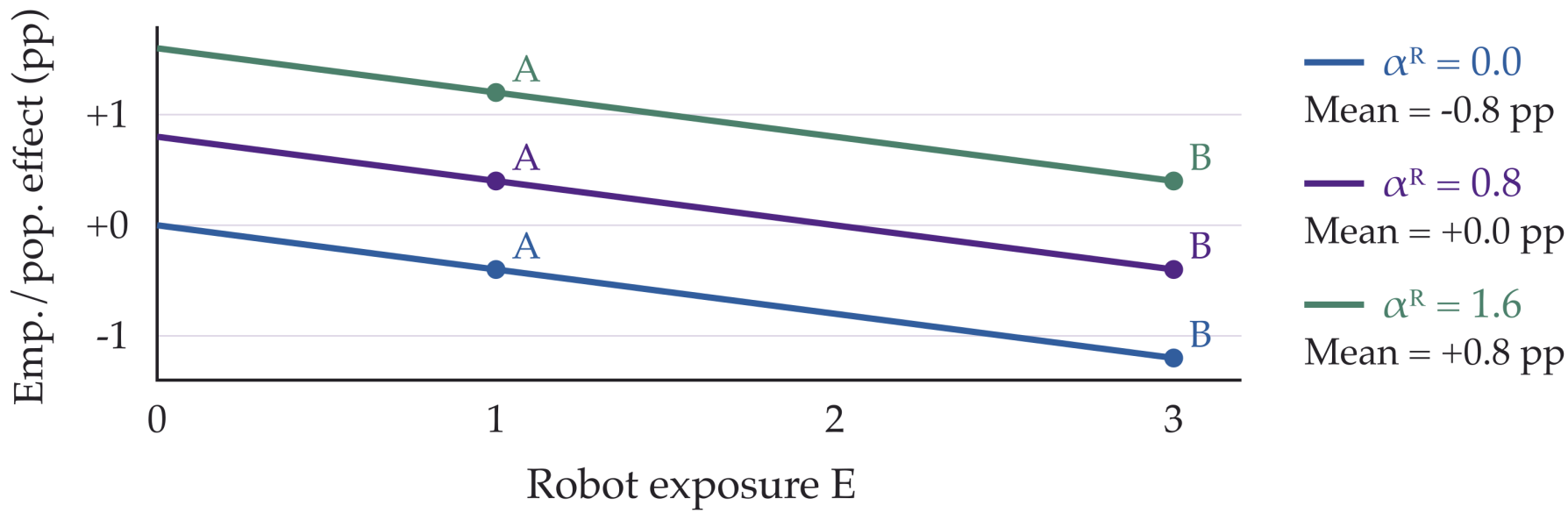
$$\Delta y_c^R = \alpha^R + \beta E_c$$

- β: exposure gradient identified by cross-zone comparisons
- α^R: common robot effects through prices, demand & income
- National mean: $\Delta \bar{y}^R = \alpha^R + \beta \bar{E}$

> The regression has an intercept.
> It does not isolate the robot-caused change in that intercept.

The same relative loss can imply different national effects

Illustration: $\beta = -0.4$; equal-size regions with $E_A = 1$, $E_B = 3$.



Invented robot-caused effects: the relative slope is fixed.
The common effect changes; these are not observed regression lines.

> Every line has the same B - A gap: -0.8 percentage point.
> The national mean can be negative, zero, or positive.

Aggregate numbers require additional assumptions

Use a **task-assignment model** (details) with trade across local labour markets.

- Use outside evidence for cost savings, goods substitution & spending shares; fit labour/robot supply to local IV estimates
- Assume costless trade & mobile capital: cheaper goods and capital income benefit other regions

Per +1 robot / 1,000 workers	**Employment/population**	**Wages**
Relative cross-zone IV comparison	-0.39 percentage point	-0.77%
Paper's model-based U.S. aggregate calculation	-0.20 percentage point	-0.42%

> Under this calibration, aggregate losses are smaller than relative local losses.

Robot Adoption and Labor Market Dynamics



Robot Adoption and Labor Market Dynamics

Anders Humlum*
University of Chicago

November 28, 2021

Abstract

I study the distributional impact of industrial robots using administrative data that link workers, firms, and robots in Denmark. I estimate a dynamic model of how firms select into and reorganize production around robot adoption. I find that firms expand output, lay off production workers, and hire tech workers when they adopt robots. I embed the firm model into a general equilibrium framework that endogenizes the dynamic choice for workers to switch occupations in response to robots. To this end, I develop a fixed-point algorithm for solving the general equilibrium that features two-sided (firm and worker) heterogeneity and dynamics. I estimate that robots have increased average real wages by 0.8 percent but have lowered the real wages of production workers by 5.4 percent. Welfare losses from robots are concentrated on old production workers, as younger workers benefit from the option value of switching into tech.

Keywords: automation, robot adoption, labor market dynamics, earnings inequality
JEL codes: D22, J23, J24, J31, O14, O33

*E-mail: humlum@uchicago.edu. I am extremely grateful to my advisor Stephen Redding for his guidance in this project, and to my committee Bo Honoré and Alex Mas for invaluable suggestions and encouragement. I am indebted to Jan De Loecker, Gene Grossman, Henrik Kleven, and Eduardo Morales for insightful comments. I thank University of Copenhagen for providing data access, and I acknowledge financial support from the International Economics Section at Princeton University.

Anders Humlum

Denmark · firms, workers & robots

Who gains when an adopting firm grows?

Open the paper

Working paper · November 28, 2021

Who gains inside a robot-adopting firm?

Question: Does firm expansion benefit production and technical workers alike?

Linked Danish data, 1995–2015	**What is observed**
Robots	Customs purchases + Statistics Denmark adoption survey
Firms	Sales, wage bills and workforce composition
Workers	Employer–employee registers: occupations and earnings

> Follow the firm and the composition of its labour payments.

- **Key difference:** Humlum observes individual firms' adoption choices & links them to employees; the U.S. study uses local labour-market aggregates

Compare adopters with similar non-adopters

Match before adoption	Compare around adoption
Same two-digit industry	One firm adopts; the other is a comparison firm
Similar sales and production wage-bill shares	Match levels + trends in the preceding three years
Event-study window: years -4 to +4	Track differences relative to year -1

Identification: matched firms would otherwise have followed similar paths.

> Compare results to a dynamic model of robot adoption & production/technical hiring.
> Firms weigh a one-off adoption cost against expected future profit gains.
> Larger firms spread the fixed cost over more output ⟶ stronger incentives to adopt.

Adopters expand sales faster than their wage bill

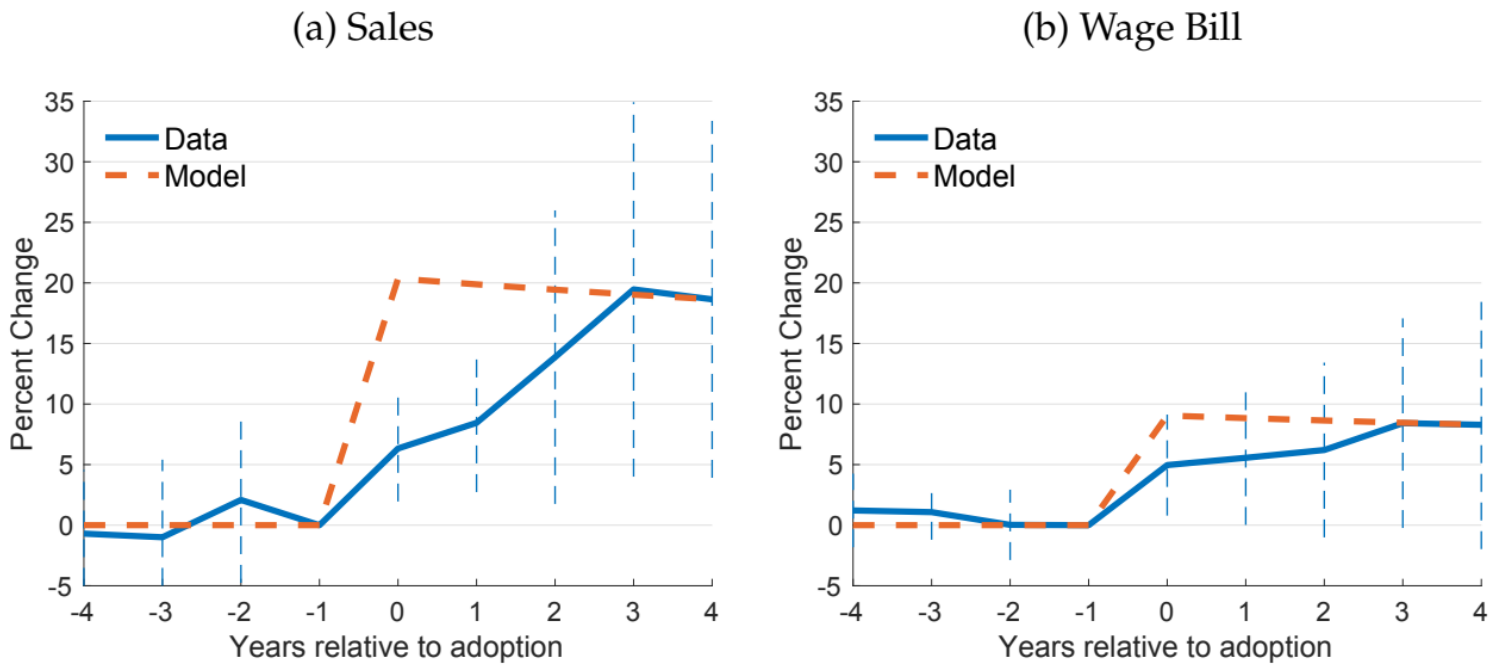


Figure 1. Blue: matched DiD; orange: model fit. Bars: 90% confidence intervals.

> Sales: about +20%; total wage bill: about +8%.

Production and technical labour payments move apart

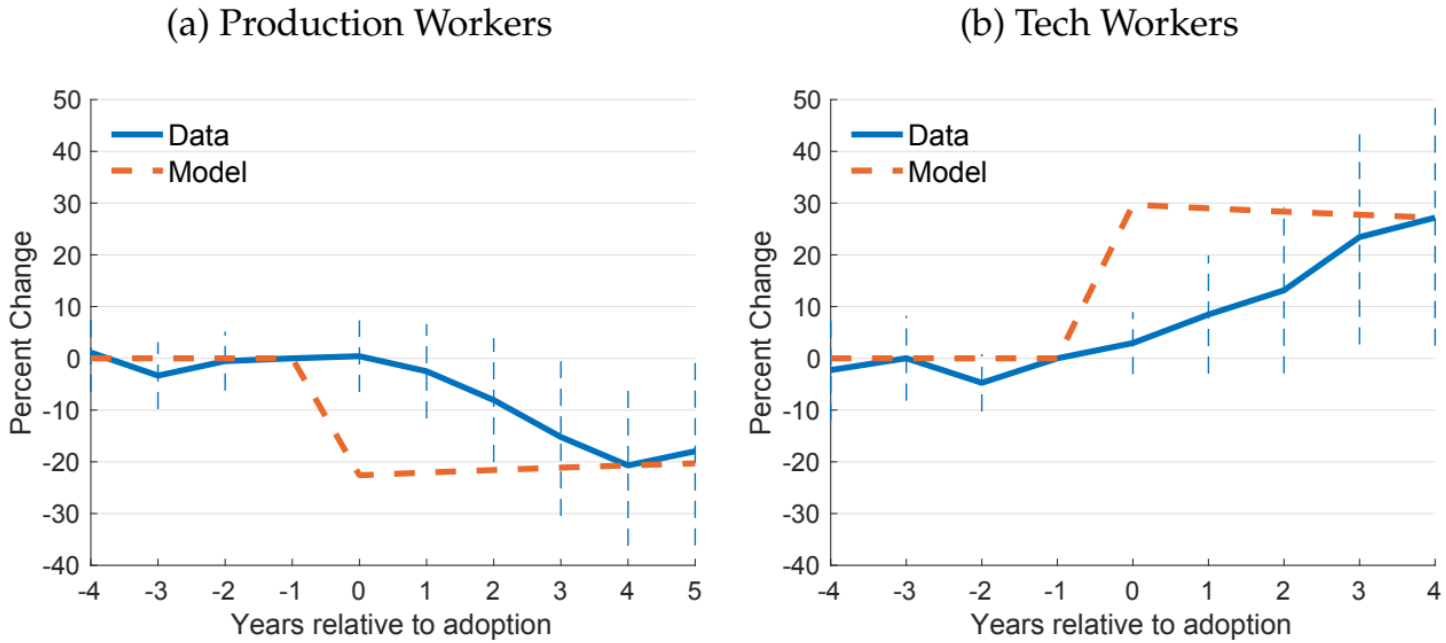


Figure 2. Wage-bill responses relative to matched controls. Bars: 90% confidence intervals.

> Production wage bill: about -20%; technical wage bill: about +30%.
> Robots change the composition of labour demand inside expanding firms.

A national counterfactual needs firms, workers and prices

Firms

- Pay a fixed cost to adopt robots
- Choose worker inputs and production
- Compete through costs, prices and sales

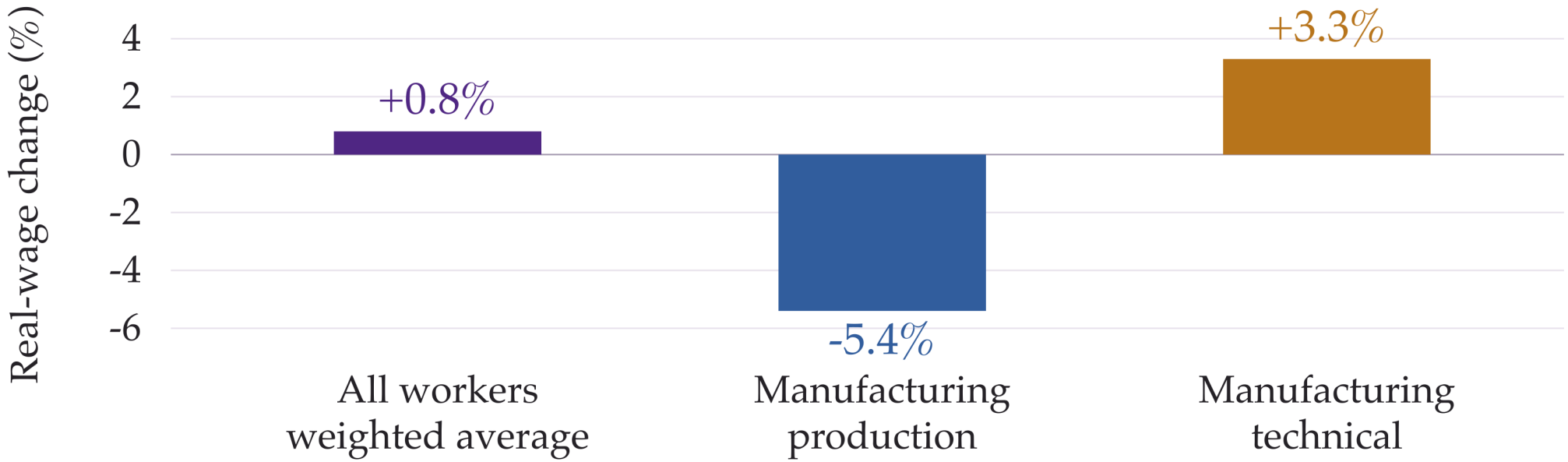
Workers

- Choose an occupation
- Accumulate occupation-specific skills
- Face costs of switching occupations

Comparison: robot diffusion versus no robots, with wages and prices adjusting.

> Real wage = nominal wage ÷ consumer price index.

Model real-wage effects differ across occupations



2019 model baseline versus no robots. Rounded values from Figure 5; this chart shows no sampling confidence intervals.

> The average gain includes lower consumer prices.
> Manufacturing production workers still lose in this counterfactual.

Younger workers have more scope to change occupations

Model welfare: change in remaining-lifetime earnings equivalent.

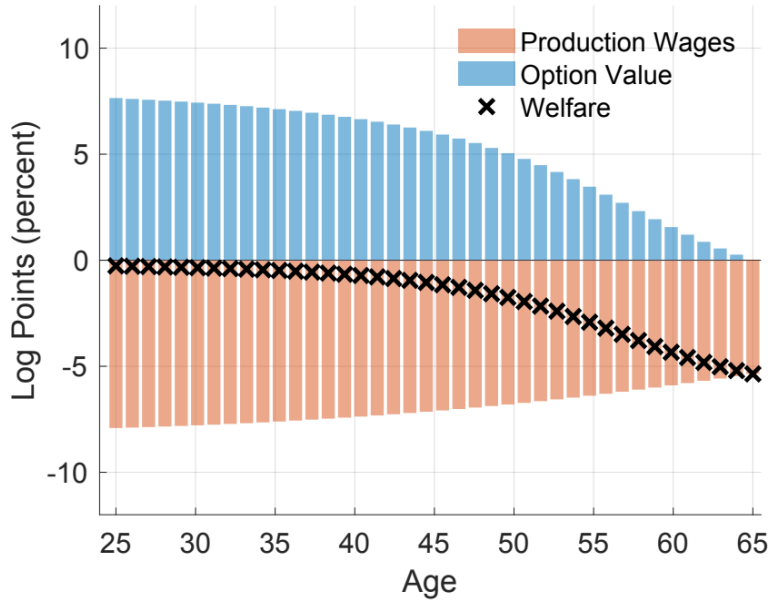
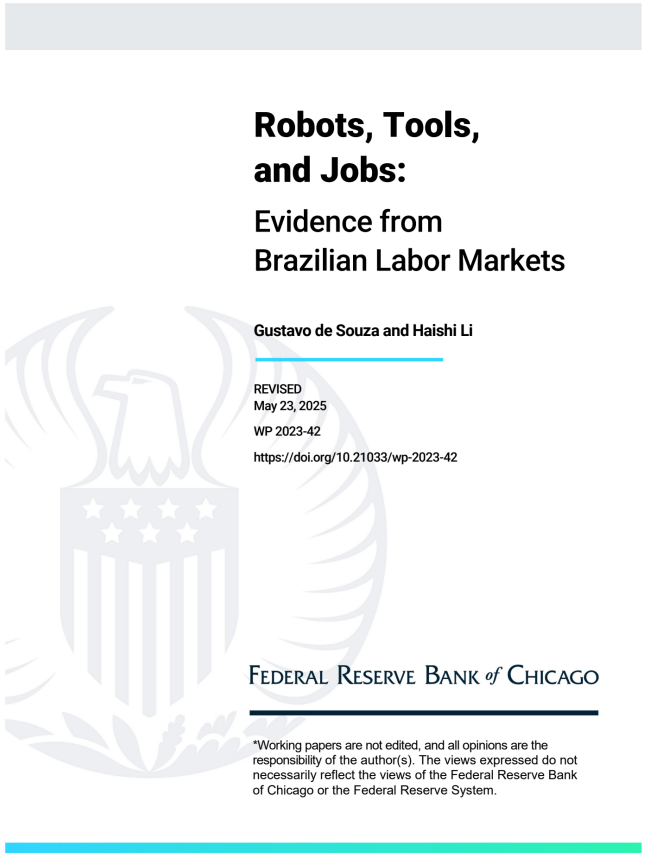


Figure 8: manufacturing production workers in 2019.
Horizontal: age. Vertical: welfare-equivalent change, log points (≈%).

> Lower future wages hurt this occupation.
> The opportunity to switch cushions younger workers more.

Robots, Tools, and Jobs



Working paper · May 23, 2025 revision · First page

Evidence from Brazilian labor markets

Gustavo de Souza and Haishi Li

Federal Reserve Bank of Chicago · WP 2023-42

Open the paper

Do robots and worker-operated tools have different effects?

Object	What the authors measure
Robots / tools	Autonomous machinery / machinery requiring a worker to operate it.
Adoption	Dollar value of machine imports, not the number of machines.
Unit and outcomes	Region × industry; formal employment and monthly earnings.
Variation	Five-year log changes; instruments based on machinery tariffs.

Design: Separate robot and tool imports; link both to Brazil's formal region–industry employment; use tariff-based instruments.

- **Import instrument:** Mercosur negotiations cut machinery tariffs; industries' initial machine mixes imply different price cuts.
  Combine tariff cuts with initial routine/manual task content to predict robot/tool imports

Industries faced different cuts in robot and tool tariffs

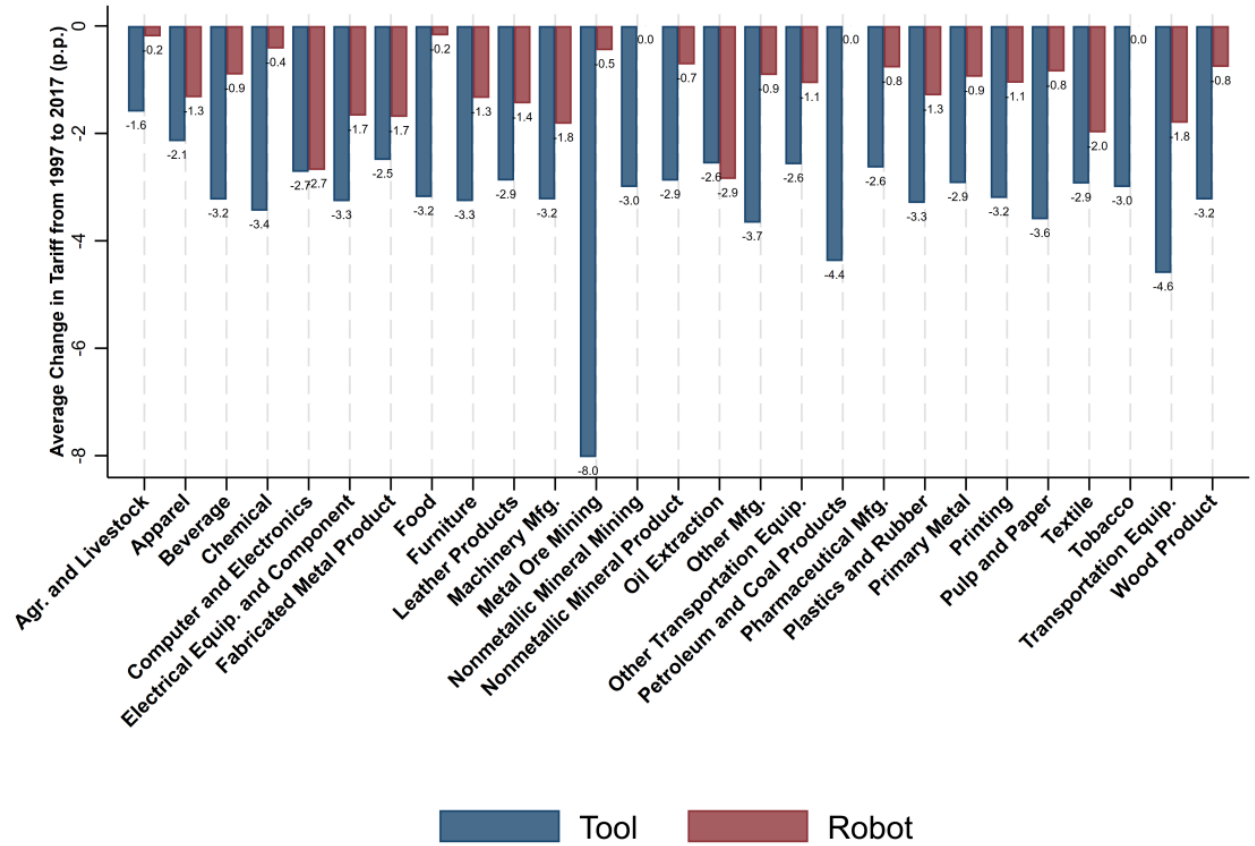


Figure 1 (Case 8, Exhibit 1). Industry tariff changes, percentage points.
Blue: tools; red: robots. Industries use different mixes of machines.

Controlling for tools changes the robot coefficient

Outcome: Δ log employment	**Robots only**	**Robots and tools**
Δ log robot imports	0.004 (0.02)	-0.22 (0.03)
Δ log tool imports	—	+0.17 (0.02)
Region–sector–period observations	204,069	204,069

Tables 4/2, col. 4. Five-year changes; year, region + sector effects; baseline controls; tariff IVs. Clustered SEs.

> 10% more robot imports: about 2.25% lower relative employment growth.
> 10% more tool imports: about 1.74% higher relative employment growth.

Workers with less schooling bear the largest robot losses

Employment elasticity	Below high school	High school	Some college+
Robot imports	-0.23	-0.04	-0.02
	(0.03)	(0.03)	(0.02)
Tool imports	+0.17	+0.09	+0.05
	(0.02)	(0.03)	(0.03)

Table 5, employment cols. 1, 3, 5. Same joint IV design; samples differ by education group.

> The negative robot effect is concentrated below high school.
> Tools raise employment most for that same group.

Employment and earnings move in the same direction for the most exposed group

Monthly earnings elasticity	Below high school	High school	Some college+
Robot imports	-0.05	-0.02	-0.01
	(0.010)	(0.01)	(0.01)
Tool imports	+0.04	+0.008	+0.02
	(0.007)	(0.01)	(0.01)

Table 5, cols. 2, 4, 6. "Wage" in the source table is monthly earnings; it is not an hourly wage.

> Below high school, robot imports reduce both employment and earnings; tools increase both. The effects concern people's incomes, not just job counts.

Managers and professionals: smaller, less precise effects

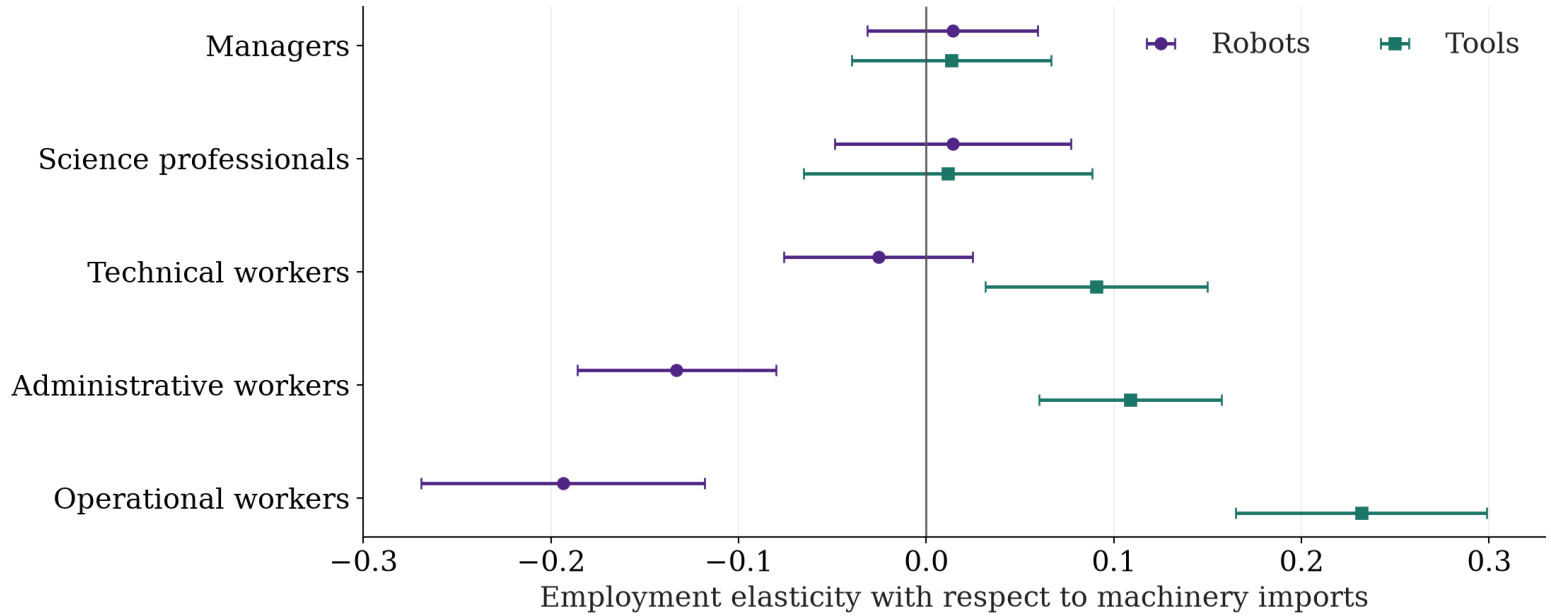


Table 6, all five occupation groups. Dots: joint IV estimates; lines: approximate 95% confidence intervals.

> Administrative and operational jobs show the clearest robot losses.
> Manager and science-professional estimates are near zero, with intervals spanning both gains and losses.

Other evidence: productivity and local adjustment

Paper	Data origin	Main result
Graetz–Michaels (2018) *Robots at Work*	IFR robots + EU KLEMS. 17 countries; 1993–2007.	Authors' scaling calculation: ≈0.36 pp/year productivity growth. No clear total-hours decline; low-skill hours share falls.
Dauth et al. (2021) *Adjustment to Robots*	German regions, 1994–2014. IFR + linked worker–firm registers.	Relative manufacturing losses offset by services. Incumbents change roles; entrants shift sectors.

Other evidence: adopters, competitors and selection

Published paper	Data origin	Main result
Acemoglu–Lelarge–Restrepo (2020) *Competing with Robots*	French robot-purchase records + firm accounts. 2010–2015.	Adopters expand; competitors contract. The industry employment association is negative.
Bonfiglioli et al. (2024) *Robot Imports and Firm-Level Outcomes*	French customs + manufacturing firm accounts. 1994–2013.	Demand growth can raise both adoption and jobs. Predetermined-exposure estimates indicate job losses.

Other evidence: worker losses and domestic industry gains

Paper / version	Data origin	Main result
Bessen et al. (2025) *Workers at Firms that Automate*	Dutch worker registers + integrator-service expenses. 2000–2016.	More separations and fewer days worked. Five-year earnings loss ≈9% of one pre-event year's pay.
Aghion et al. November 2025 draft	French accounts + customs, 1995–2017. Foreign supplier-shock IV.	Employment elasticities: firm ≈0.18; industry ≈0.41. Industry gains concentrate in import-competing sectors.

Appendix: Prior trends are a useful diagnostic

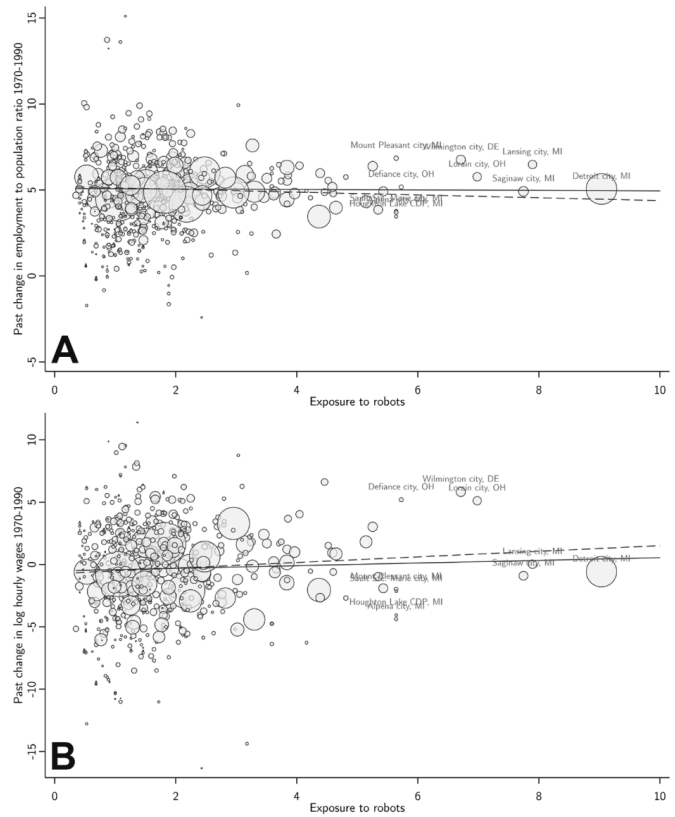


Figure 7. A design check using outcomes before the main robot-adoption period.

Appendix: Task assignment and the automation frontier

Industry i needs all tasks $s \in [0,1]$. Choose inputs for one unit of task s:

- ℓ, m: labour & robots; W_c, R_c^M: wage & robot rental price
- γ_L, γ_M: output per worker/robot; θ_i: last robot-feasible task

$$\min_{\ell,m\geq 0} \; W_c\ell + R_c^M m$$

$$\text{s.t. } \gamma_L\ell + \gamma_M m \geq 1, \qquad m = 0 \text{ if } s > \theta_i$$

Automation shock: $\theta_i \uparrow \longrightarrow$ more robot-feasible tasks.
They switch to robots when $R_c^M/\gamma_M < W_c/\gamma_L$.

Appendix: The production model gives competing forces

- Displacement: fewer human tasks
- Lower costs ⟶ potential demand expansion
- Other firms + sectors respond to prices & income
- Worker mobility across occupations & locations

> A labour-market effect includes responses beyond the adopting establishment.

Appendix: An illustrative exposure calculation

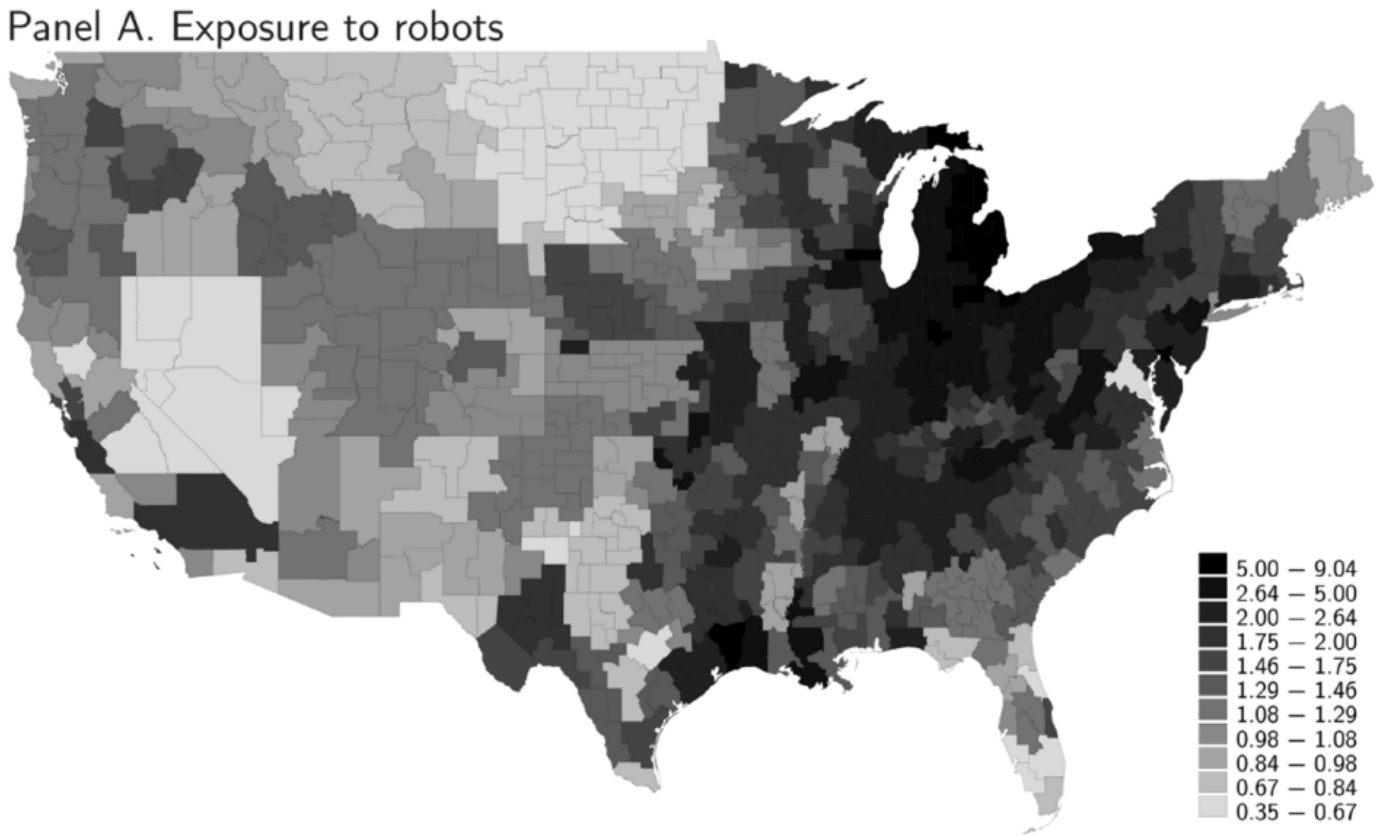
Baseline industry share	Place A	Place B
Automobiles	40%	10%
Other industries	60%	90%

Suppose robot penetration grows by 4 units in automobiles and 1 elsewhere.

$$E_A = 0.4(4) + 0.6(1) = 2.2, \qquad E_B = 0.1(4) + 0.9(1) = 1.3$$

Invented values illustrating the weighting. They are not observations from the study.

Appendix: The geography of exposure



Acemoglu–Restrepo Figure 4(a). Darker areas have greater predicted exposure.

Appendix: The empirical comparison

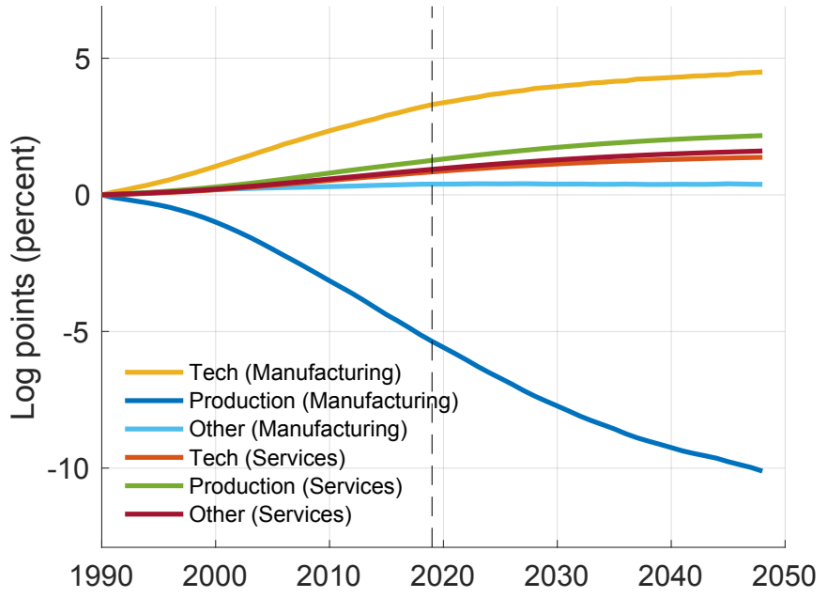
$$\Delta y_c = a + bE_c + X_c' d + u_c$$

Compare places with different predicted robot exposure, after accounting for observed baseline differences and other shocks.

A negative slope could still reflect an omitted industry trend.

Appendix: Humlum's full real-wage simulation paths

Figure 5: Real Wage Effects of Industrial Robots
(Weighted Average in 2019: +0.82 percent)



Original Figure 5. Difference between baseline and no-robots simulations; dashed line marks 2019.

> These are conditional model paths, including years beyond the estimation sample.

Appendix: Robots at Work



The Review *of* Economics *and* Statistics

VOL. C DECEMBER 2018 NUMBER 5

ROBOTS AT WORK

Georg Graetz and Guy Michaels*

Abstract—We analyze for the first time the economic contributions of modern industrial robots, which are flexible, versatile, and autonomous machines. We use novel panel data on robot adoption within industries in seventeen countries from 1993 to 2007 and new instrumental variables that rely on robots' comparative advantage in specific tasks. Our findings suggest that increased robot use contributed approximately 0.36 percentage points to annual labor productivity growth, while at the same time raising total factor productivity and lowering output prices. Our estimates also suggest that robots did not significantly reduce total employment, although they did reduce low-skilled workers' employment share.

I. Introduction

ROBOTS' capacity for autonomous movement and their ability to perform an expanding set of tasks have captured writers' imaginations for almost a century.[1] But more recently, robots have emerged from the pages of science-fiction novels into the real world, and discussions of their possible economic effects have become ubiquitous. These discussions reflect both high expectations and deep concerns. There is a particularly lively debate on the implications of recent and anticipated developments in robotics and closely related technologies (see, e.g., Brynjolfsson & McAfee, 2014, and Autor, 2015).

This growing interest reflects a profound change in robot capabilities over the past few decades. Creating robots that are autonomous, flexible, and versatile was a major engineering challenge, but remarkable progress has been made. Robots can now perform a fairly wide range of tasks, including welding, painting, and packaging, with very little human intervention. These capabilities set robots apart from earlier waves of automation and more conventional information and communication technologies (ICT), which left flexible movement in three dimensions firmly in human hands. As robots take on more tasks, many people worry that large-scale job losses are looming. In one survey carried out in the United Kingdom, 30% of respondents believed that their job could be replaced by a robot in the next twenty years.[2]

Yet despite the widespread interest and concern, there is relatively little evidence on the implications of increased robot use for labor productivity, total factor productivity, output prices, and the employment of workers with different skills across the developed world. Our study begins to remedy this problem by shedding light on how industrial robots are changing the economy. To frame our analysis, we construct a simple model of firms' decision to adopt robots. By paying a fixed cost of adoption, firms can employ robots alongside workers to perform a range of tasks, whose scope varies by industry. Declines in robot prices increase robot adoption, which raises productivity and wages and decreases output prices.

Our main contribution is to study industrial robots empirically, using new data from the International Federation of Robotics (IFR). The IFR measures deliveries of "multipurpose manipulating industrial robots," based on the definitions of the International Organization for Standardization (ISO), which allow us to compare robot delivery numbers across country-industry pairs and over time. Specifically, the IFR definition refers to a "manipulating industrial robot as defined by ISO 8373: An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation

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* Graetz: Uppsala University; Michaels: London School of Economics.

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A supplemental appendix is available online at http://www.mitpress journals.org/doi/suppl/10.1162/rest_a_00754.

[1] Discussions of automata and physical construction of working machines go back to the ancient world. But according to the *Oxford Online Dictionary*, the word *robot* comes from *robota*, the Czech word for forced labor. The term was coined in Čapek's 1920 play, *Rossum's Universal Robots* (http://www.oxforddictionaries.com/definition/english/robot). Robots gained in popularity following the work of Asimov (1950).

[2] The survey was carried out by the British TV station Sky News. See results and an accompanying article at http://interactive.news.sky.com/Robots_Tabs_FULL.pdf and http://news.sky.com/story/1544448/robot-revolution-40-percent-fear-wipeout-by-machines, respectively.

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Appendix: Can robot adoption raise industry productivity?

Question: Do robot-adopting industries produce more per hour, and does pay rise?

Unit: 224 country–industry cells in 17 countries, 1993–2007.

Instrument: the initial share of industry hours in robot-replaceable tasks.

> Robot density = robots per million hours worked.
> The regressions rank the change in density on a 0–1 scale.

Appendix: Read a rank coefficient before comparing it with other papers

Object	Example
Rank change	Moving from the 40th to the 50th percentile = +0.10.
Productivity coefficient: 1.05	$0.10 \times 1.05 = 0.105$ log points.
Interpretation	About 10.5% higher output per hour for that rank difference.

> A rank change does not mean 10% more robots.
> Compare the direction and outcome across papers, not their raw coefficients.

Graetz and Michaels (2018) · Table 1 col. 4, PDF p. 10; Table 3 col. 4, PDF p. 14 · Return to comparison

Appendix: Across countries, robot-intensive industries become more productive

Outcome, 1993–2007	OLS	IV: replaceable hours
Δ log value added/hour	0.66 (0.24)	1.05 (0.38)
Δ log mean hourly wage	0.039 (0.017)	0.087 (0.021)

Table 1 and Table 3, col. 4. 224 country–industry cells; controls differ by outcome. Regressor: robot-densification percentile divided by 100.

> Productivity and wages rise, with much larger productivity estimates.
> The paper's conservative calculation attributes 0.36 percentage point of annual productivity growth to robots.

Appendix: The productivity relationship is visible in the data

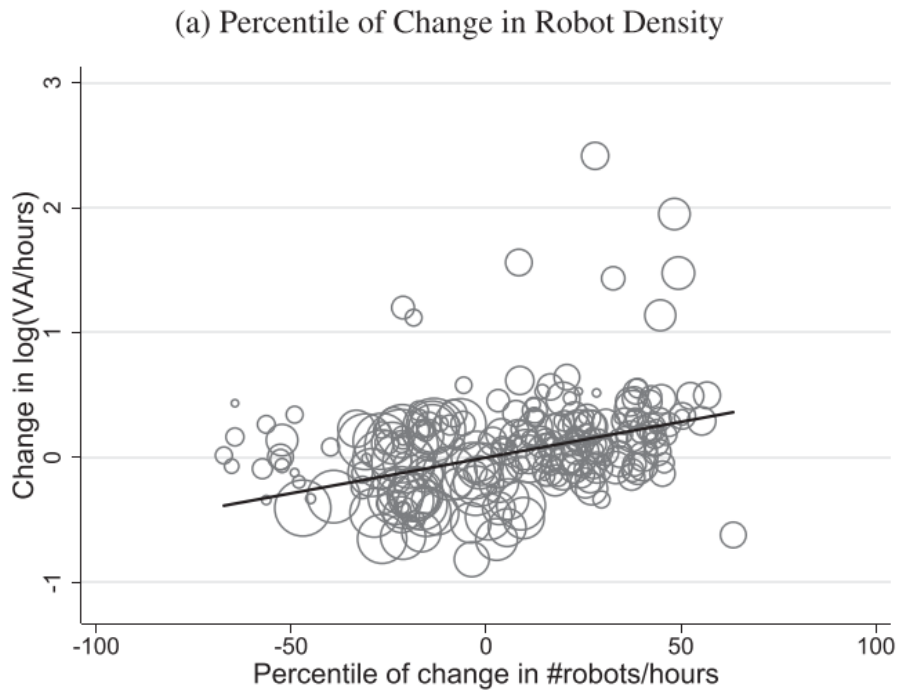


Figure 2(a): labour-productivity growth versus the percentile of robot densification, net of country trends.

> Industries with greater robot adoption have larger productivity gains.
> A positive productivity effect can coexist with losses in exposed local labour markets.