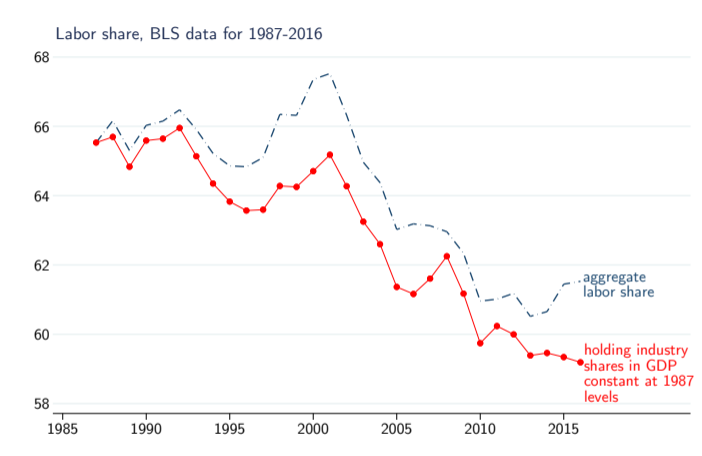# Tasks, Automation and the Labor Market

Daron Acemoglu and Pascual Restrepo

Gorman Lecture 1, October 12, 2020

Shifts Against Labor

Labor share, BLS data for 1987-2016

aggregate labor share

holding industry shares in GDP constant at 1987 levels

- ▶ Declining labor share in the US; similar trends in several advanced economies.
- ▶ Capital deepening? Markups? Monopsony?
- ▶ We argue: much more connected to the changing task content of production.

Some Consequences: Wages

▶ Labor market trends over the last several decades look nothing like a tide lifting all boats.

Cumulative Change in Real Log Weekly Earnings 1963 - 2017
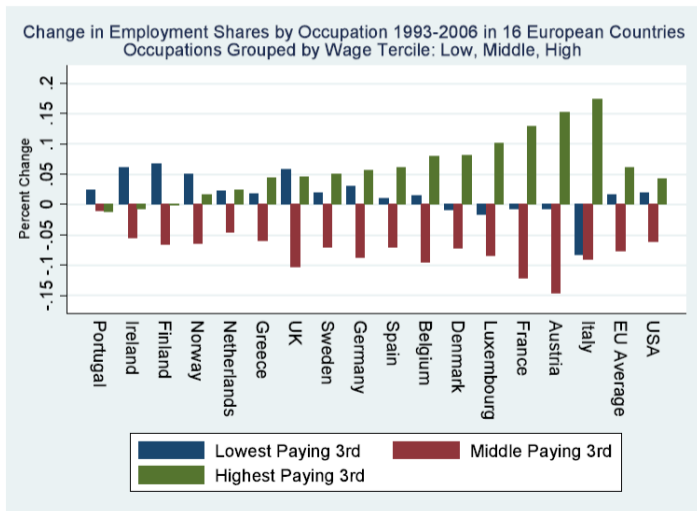Working Age Adults, Ages 18 - 64
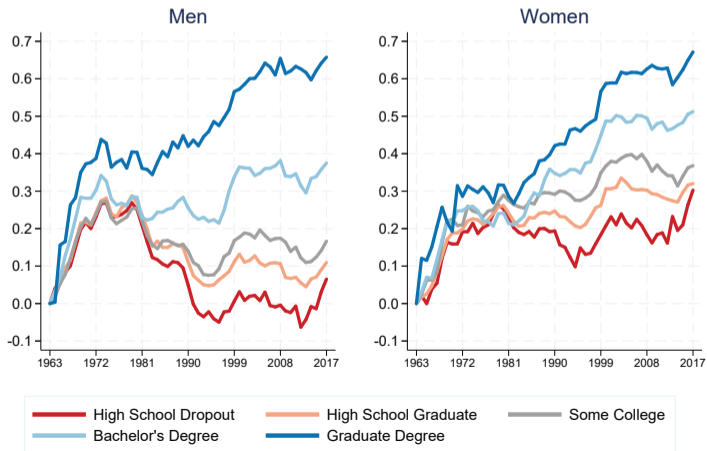
Linked to Changing Task Structure

▶ This isn't because the demand for skills is growing.

Smoothed Changes in Employment by Occupational Skill Percentile 1979-2007
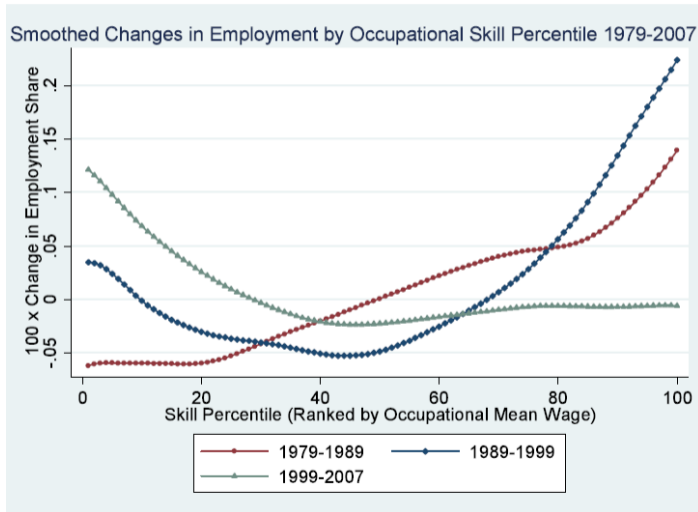
Not Just a US Phenomenon

▶ Similar polarization of employment— but not of wages, indicating an important role for labor market institutions.

Change in Employment Shares by Occupation 1993-2006 in 16 European Countries
Occupations Grouped by Wage Tercile: Low, Middle, High

This Lecture

- **Theory:**
  - automation (e.g., adoption of industrial robots) is at the root of most of the sweeping labor market trends of the last three decades;
  - its impacts can be understood via changes in the labor share, but not using the standard framework with factor-augmenting technologies;
  - a new task-based framework clarifies when automation reduces labor demand and what counterbalances it (in particular new labor-intensive tasks);
  - rise in inequality also intimately linked to changes in task content.

- **Empirics:**
  - in the US the labor share decline is mostly in the manufacturing sector;
  - in manufacturing, decline concentrates in industries undergoing rapid automation;
  - automation technologies closely linked to changes in labor share, employment and wages;
  - in firm-level data from France, labor share increases in firms not adopting robots and declines in firms adopting robots—leading to an overall decline in the labor share in manufacturing.
  - task-displacement and changes in industry labor shares explain most of the changes in inequality in wage structure in the US.

Thinking in Terms of Tasks: Motivation

- Tasks and automation at the center of technological change throughout the last 200 years.
- Machines and computers used for substituting for human labor in a widening range of tasks:
    1. horse-powered reapers, harvesters, and threshing machines replaced manual labor
    2. machine tools replaced labor-intensive artisan techniques
    3. industrial robotics automated welding, machining, assembly, and packaging
    4. software automated routine tasks performed by white-collar workers
- But at the same time, new tasks in which labor has a comparative advantage.

The Need to Think in Terms of Tasks

▶ Hard to map to canonical production function factor-augmenting technologies:

$$Y = F(A_L L, A_K K).$$

▶ Root of the problem:

  ▶ task services are the units of production

  ▶ L and K are inputs that provide task services

  ▶ canonical model abstracts from allocation of tasks to factors

▶ Once we write $F(A_L L, A_K K)$

  ▶ allocation of tasks to factors remain unchanged, and

  ▶ technological change makes capital (or labor) uniformly more productive in all tasks.

Thinking in Terms of Tasks: The Task Content of Production

▶ But technologies other than $\{A_L, A_K\}$ change allocation of tasks:

  ▶ capital outperforms labor in a few tasks and industries
  ▶ it becomes feasible to use capital at certain tasks —automation.

▶ We need to keep track of allocation—the task content of production, Γ—and understand its implications

$$Y = F(A_L L, A_K K; \Gamma).$$

▶ Start from micro-foundations and then aggregate.

Thinking in Terms of Tasks: Framework

$$Y = \left(\int_{N-1}^{N} \mathcal{Y}(z)^{\frac{\sigma-1}{\sigma}} \, dz \right)^{\frac{\sigma}{\sigma-1}}$$

Elast of substitution

Output

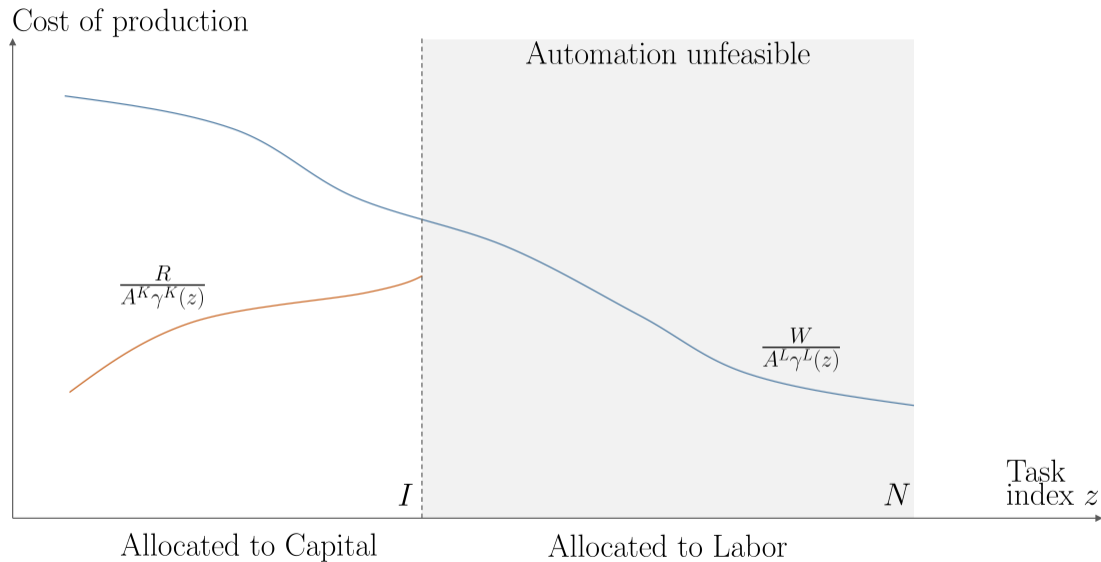Task services

▶ Tasks can be produced using capital or labor:

$$\mathcal{Y}(z) = \begin{cases} A^L \gamma^L(z)\ell(z) + A^K \gamma^K(z)k(z) & \text{if } z \in [N-1, I] \\ A^L \gamma^L(z)\ell(z) & \text{if } z \in (I, N]. \end{cases}$$
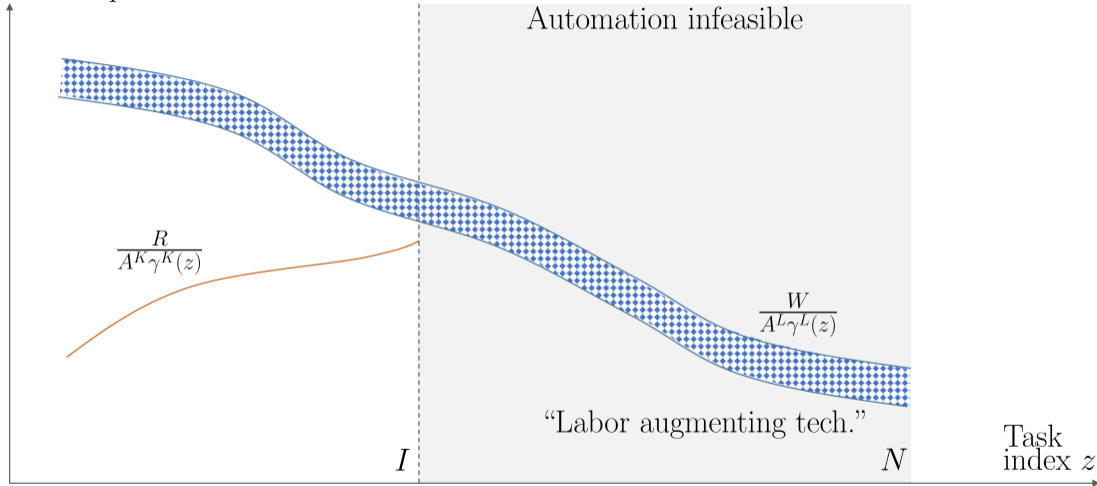
Feasible to automate

New tasks

▶ <u>Comparative advantage:</u> $\gamma^L(z)/\gamma^K(z)$ and $\gamma^L(z)$ increasing in z.

Allocation of Tasks to Factors
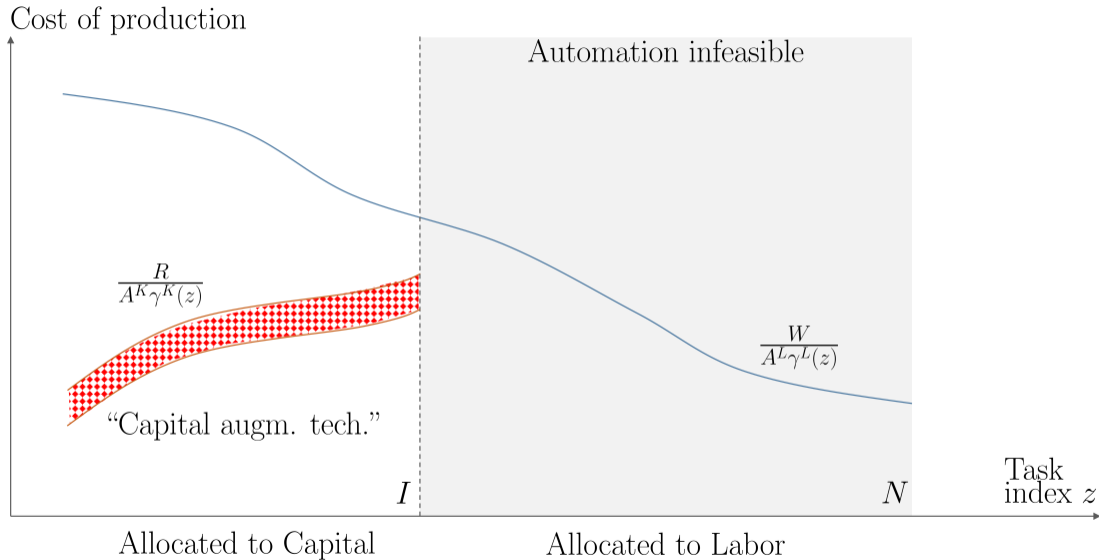

Cost of production

Automation unfeasible

$$\frac{R}{A^K \gamma^K(z)}$$

$$\frac{W}{A^L \gamma^L(z)}$$

I

N

Task index z

Allocated to Capital

Allocated to Labor

Labor-Augmenting Technological Change

Capital-Augmenting Technological Change

Cost of production

Automation infeasible

$$\frac{R}{A^K \gamma^K(z)}$$

"Capital augm. tech."

$$\frac{W}{A^L \gamma^L(z)}$$

I

N

Task index z

Allocated to Capital

Allocated to Labor

Automation: An Increase from I to I'

Cost of production

Automation unfeasible

"Automation tech."

$\frac{R}{A^K \gamma^K(z)}$

$\frac{W}{A^L \gamma^L(z)}$

I' N

Task index z

Allocated to Capital   Allocated to Labor
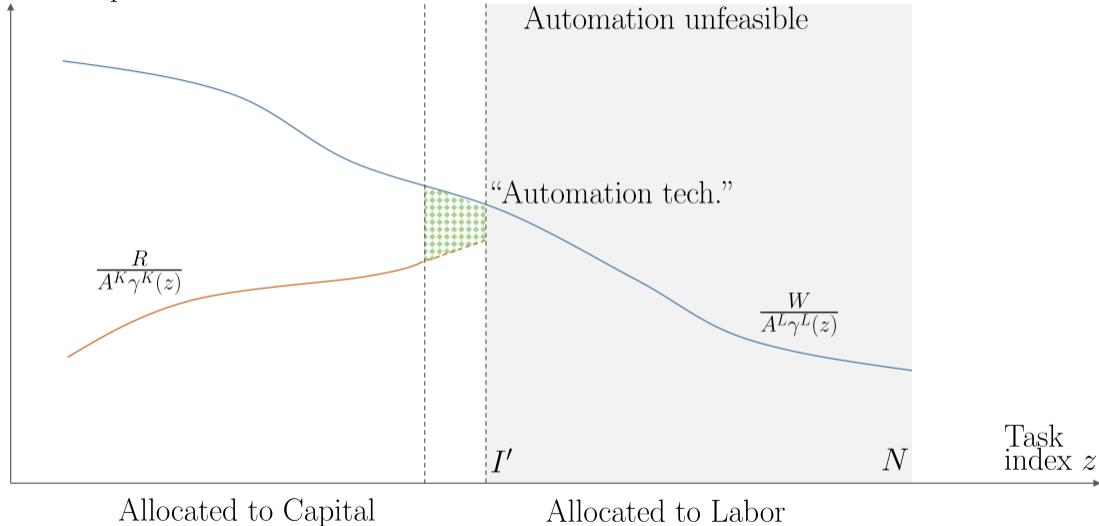
Thinking in Terms of Tasks: Aggregate Representation

$$Y(L, K) = \left(\left(\int_{N-1}^{I} \gamma^K(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (A^K K)^{\frac{\sigma-1}{\sigma}} + \left(\int_{I}^{N} \gamma^L(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (A^L L)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

▶ The labor share is given by

$$s^L = \frac{\Gamma(N, I)(W/A^L)^{1-\sigma}}{(1 - \Gamma(N, I))(R/A^K)^{1-\sigma} + \Gamma(N, I)(W/A^L)^{1-\sigma}}$$

Task content $\Gamma = \frac{\int_{I}^{N} \gamma^L(z)^{\sigma-1} dz}{\int_{N-1}^{I} \gamma^K(z)^{\sigma-1} dz + \int_{I}^{N} \gamma^L(z)^{\sigma-1} dz}$ Task-price subs.

▶ When $\sigma = 1$ or $\gamma^L(z) = \gamma^K(z) = 1$, then $\Gamma = N - I$.

▶ Factor-augmenting technologies and automation work through different channels: task content vs task-price substitution

▶ Automation always reduces the labor share regardless of the value of σ.

Thinking in Terms of Tasks: Labor Demand

▶ The labor share also determines labor demand:

$$WL = Y \times s^L$$

Output

Wage bill as
measure of labor demand

Labor share

▶ For now, ignoring markups and other non-competitive elements.
▶ Let us also postpone a discussion of inequality until later, focusing for now on average wages.

Automation and Labor Demand

$$\frac{\partial \ln WL}{\partial I} = \frac{1}{\sigma - 1} \left[\left(\frac{R}{A^K \gamma^K(I)} \right)^{1-\sigma} - \left(\frac{W}{A^L \gamma^L(I)} \right)^{1-\sigma} \right] \quad \text{(Productivity effect>0)}$$

$$+ \frac{1}{\sigma} \frac{1 - s^L}{1 - \Gamma(N, I)} \frac{\partial \ln \Gamma(N, I)}{\partial I} \quad \text{(Displacement effect<0)}$$

▶ In the absence of the displacement effect, the wage bill changes proportionately to output, and the labor share is constant.

▶ Because the displacement effect is negative, wage bill increases less than output.

▶ Net effect on wage bill depends on technology/context:

  ▶ "brilliant technologies," large displacement effect and large productivity gains
  ▶ "so-so technologies," large displacement effect and small productivity gains

▶ Modest productivity growth does not necessarily signal slowdown of automation.

Factor-Augmenting Technologies and Labor Demand

$$\frac{\partial \ln WL}{\partial \ln A^L} = s^L \qquad\qquad\qquad \text{(Productivity effect)}$$

$$+ \frac{\sigma - 1}{\sigma}(1 - s^L) \qquad \text{(Task-price substitution)},$$

$$\frac{\partial \ln WL}{\partial \ln A^K} = (1 - s^L) \qquad\qquad \text{(Productivity effect)}$$

$$+ \frac{1 - \sigma}{\sigma}(1 - s^L) \qquad \text{(Task-price substitution)}.$$

▶ No displacement or reinstatement effect; task content unchanged.

▶ Task-price subs effect small ($\sigma \approx 1$) relative to productivity effect:

  ▶ affect labor demand through productivity

  ▶ changes in labor share require huge productivity increases

Where Does the Labor Share Decline Comes from? 1947-1987
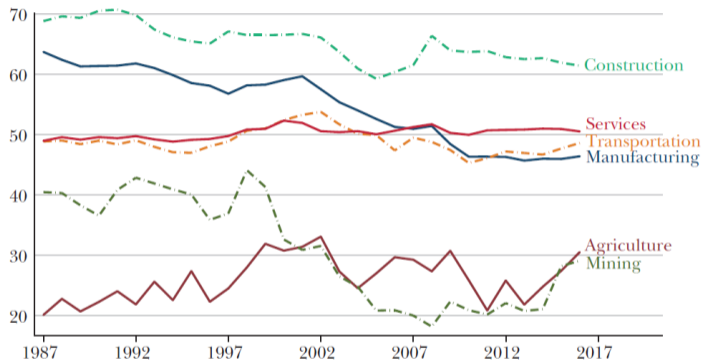

A: Labor Share within Each Industry, 1947–1987
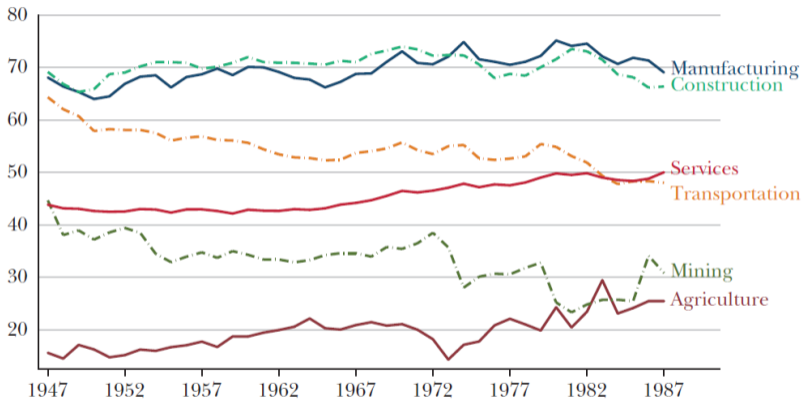
- ▶ Important to look at labor share in value added (not sales, since the share of intermediates in sales is increasing over time).
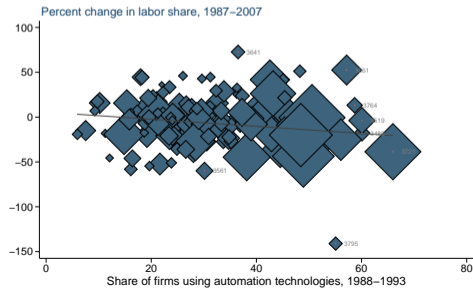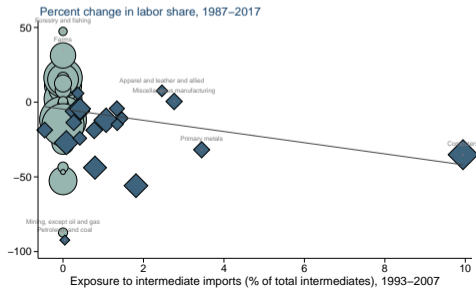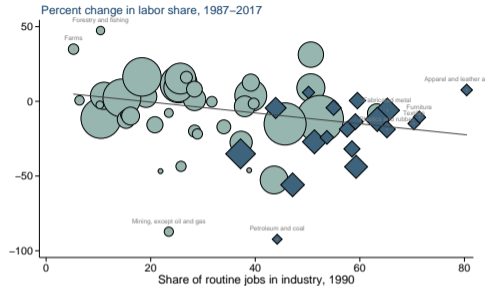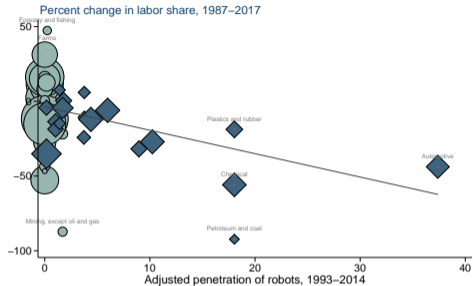
Where Does the Labor Share Decline Comes from? 1987-2017

A: Labor Share within Each Industry, 1987–2017

- ▶ Some declines in labor share in wholesale and retail during this time period.
- ▶ But the decline in the labor share is mostly a manufacturing phenomenon.

Automation and the Labor Share: Industry Evidence

Robustness

Table: Relationship between labor share and proxies for automation.

	Raw data	Controlling for manufacturing	Controlling for Chinese import and offshoring
	(1)	(2)	(3)
Proxies for automation technologies:			
Adjusted penetration of robots, 1993-2014	-1.567	-1.080	-1.149
	(0.429)	(0.385)	(0.394)
Observations	61	61	61
R-squared	0.19	0.23	0.27
Share of routine jobs in industry, 1990	-0.363	-0.157	-0.230
	(0.143)	(0.192)	(0.200)
Observations	61	61	61
R-squared	0.10	0.18	0.25
Detailed manufacturing industries (SMT):			
Share of firms using automation technologies, 1988-1993	-0.396		-0.409
	(0.224)		(0.218)
Observations	148		148
R-squared	0.05		0.10

Quantitative Magnitudes and Interpretation

▶ Let's focus on industrial automation, of which industrial robots are a key component.

▶ Penetration of robots explains 20% of the variation in changes in the labor share across industries (32% within manufacturing).

▶ Each additional robot per thousand workers is associated with a 1% decline in the manufacturing labor share.

▶ Robots are just the tip of a much larger automation iceberg — numerically controlled machines, dedicated automated machines, specialized software and now algorithms.

▶ Increase in robot use of close to 10 robots per thousand workers in manufacturing could account for up to 10% out of the 30% decline in the labor share of the sector.

▶ A sizable portion of the decline in the labor share in US manufacturing seems to be accounted for by industrial automation.

Robots and Jobs: Local Labor Market Effects

- Let's look at the equilibrium effects of automation in a little more detail, focusing on local labor markets affected by robots.
- Data from decennial censuses, ACS and various other sources, plus, crucially, from the International Federation of Robotics (IFR) on industry-level robots data across countries.
- Zero in on labor markets where the distribution of industry employment makes adoption of robots more likely — according to "exposure to robots" measure in Acemoglu and Restrepo (JPE, 2020).
- Loosely speaking, exposure to robots is given by a Bartik measure of baseline industrial structure interacted with the penetration of robots into that industry in countries that are more advanced than the US in robot adoption:

$$\text{exposure to robots}_c = \sum_i \text{robot penetration industry}_i \times \text{baseline industry share}_{ic}$$

$$= \sum_{i \in \mathcal{I}} \overline{APR_i} \times \ell_{zi}^{1970},$$
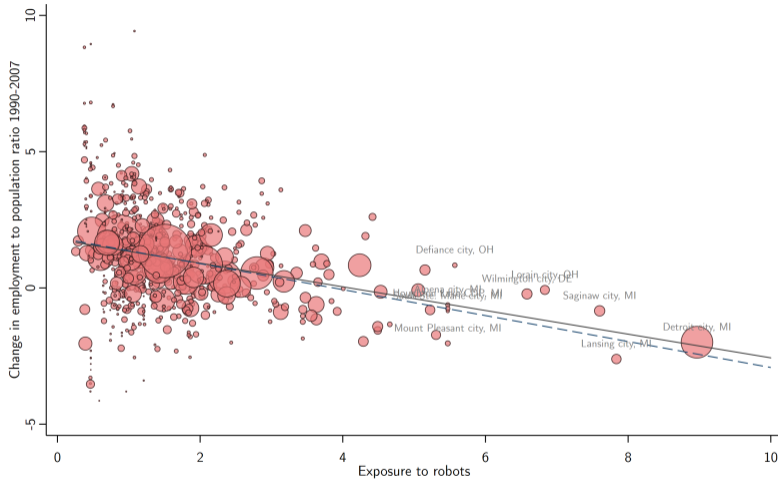
- Then see how this affects employment and wages.

Reality Check: Exposure to Robots and Robotics Activity

▶ No data on robot adoption at the commuting zone level, but we can use robot integrator activity (from Leigh and Kraft, 2017), which is an excellent proxy for local robotics activity.
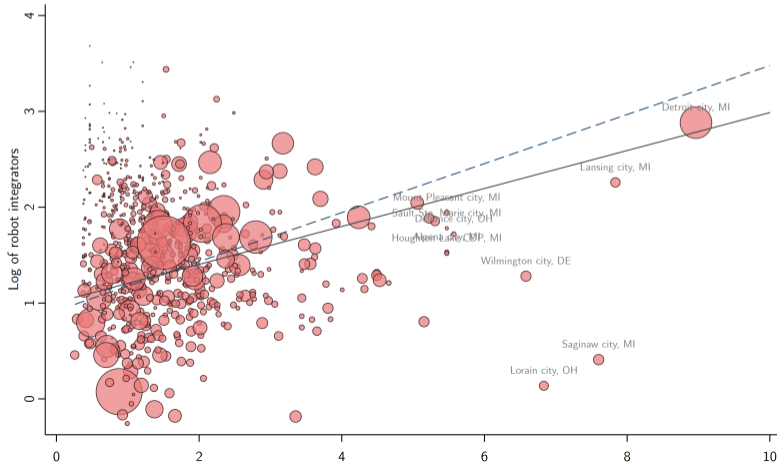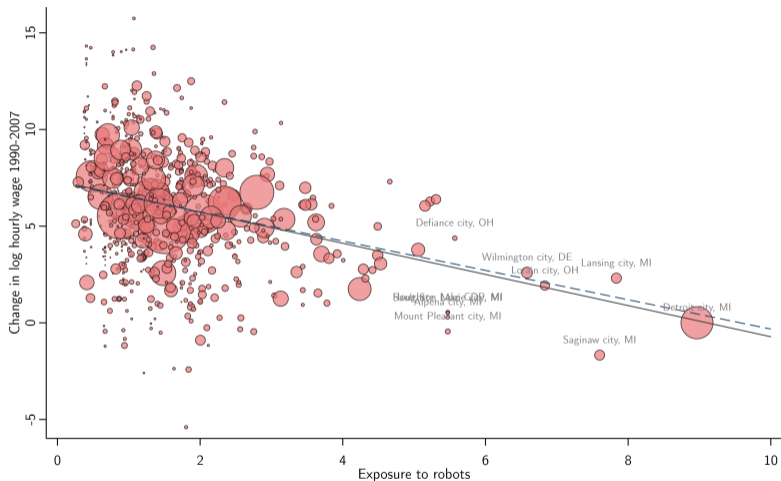
Exposure to Robots and Local Employment

- ▶ Dashed line excludes the most exposed areas; thus the relationship is unchanged without the key parts of the industrial heartland.

Exposure to Robots and Local Wages

- ▶ Dashed line excludes the most exposed areas.

Exposure to Robots and Task Content of Production

Panel B. Changes in employment by occupation

Legend: Weighted by population · Excludes high exposure zones · Unweighted
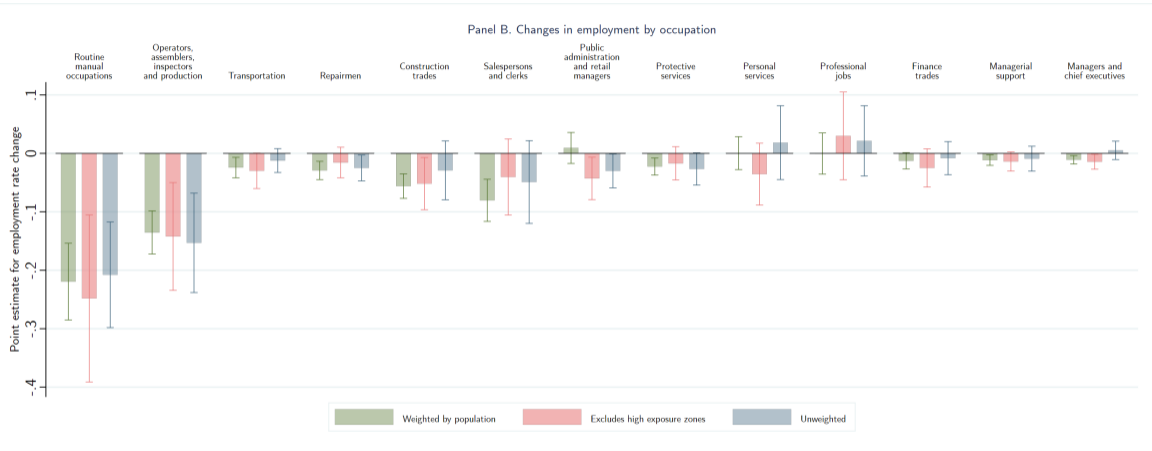
▶ The decline in areas exposed to robots comes from occupations where workers perform tasks that are being replaced by robots.

Robots and Jobs: Recap

▶ The results shown in the previous four figures are highly robust (to various demographic and economic controls, in various subsamples, and most importantly to the inclusion of other technology measures, proxying for non-automation technologies).

▶ Moreover, no pre-trends — more exposed commuting zones were not on differential economic trends before the 1990s.

▶ Overall, this evidence suggests significant displacement effects associated with changes in the task structure.

▶ But the local labor market context is not ideal for seeing changes in labor share and substitution between different types of workers (partly because, as emphasized in Acemoglu and Restrepo, 2020a, there are market-level adjustments in services as well).

▶ For that reason, we now turn to firm-level evidence.

French Data on Robots

- From Acemoglu, Lelarge and Restrepo (AER, P&P 2020).

- Sample of 55,390 firms that were active from 2010 to 2015 in the French manufacturing sector. Subset of 598 firms that purchased industrial robots in this period.

- Identified from several sources:
  - survey by the French Ministry of Industry
  - clients' lists provided by French robot suppliers and integrators
  - customs data on imports of industrial robots by firm
  - fiscal files with information on robot depreciation allowances

- Although only 1% of the firms purchased robots in 2010-2015, these firms account for 20% of total manufacturing employment.

Robot Adoption in French Manufacturing
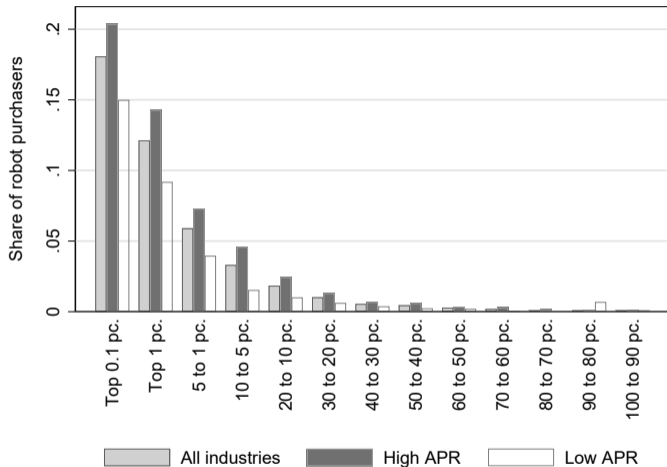
▶ Robot adopters are larger and concentrate in high APR industries—those where there are major advances in robotics technology and rapid spread of robots in other countries.

Estimating Equation

- Estimating equation:

$$\Delta \ln y_f = \beta \cdot \text{Robot}_f + \eta \cdot \text{Adoption by competitors}_f \qquad (1)$$
$$\gamma \cdot X_f + \alpha_{i(f)} + \delta_{c(f)} + \varepsilon_f.$$

where

$$\text{Adoption by competitors}_f = \sum_i m_{fi} \cdot \sum_{f' \neq f} s_{if'} \cdot \text{Robot}_{f'}.$$

- First sum over all 4-digit industries; m_{fi} is the share of firm f sales in industry i.
- The second sum is over all firms other than f and $s_{if'}$ is the share of industry i sales accounted for by firm f'.
- Measure of adoption by competitors gives the overlap in terms of sales across 4-digit industries between a firm and all robot adopters in the economy.
- Unweighted and baseline employment-weighted OLS estimates (no firm-level exogenous source of variation in robot adoption).

Results

Table: Estimates of robot adoption on adopters and competitors

	Unweighted estimates			Employment-weighted estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log employment (in hours)	Δ log value added	Δ labor share	Δ log employment (in hours)	Δ log value added	Δ labor share
Robot adoption by competitors	-0.105	-0.100	0.002	-0.250	-0.209	-0.008
	(0.047)	(0.051)	(0.015)	(0.107)	(0.159)	(0.040)
Robot adopter	0.106	0.201	-0.043	0.035	0.078	-0.027
	(0.020)	(0.030)	(0.009)	(0.022)	(0.029)	(0.012)
R^2	0.093	0.083	0.161	0.190	0.217	0.274

Summary, Quantitative Magnitudes and Interpretation

▶ Most striking result: robot adoption is associated with increases in firm employment but significant declines in the employment of competing firms.

▶ Equally important for our focus: robot adoption associated with a 4.3 pp reduction in the labor share of a firm (and no effect from competitors).

▶ Robot adopters make up 20% of value added, and thus their decline in labor share accounts for a 0.86 pp decline in the manufacturing labor share.

▶ This is approximately the decline in French manufacturing over this time period.

▶ Consistent with theory, competitors' adoption has no impact on own labor share.

Superstar Effects and the Labor Share

▶ The impact of robot adoption on overall labor share is greater than impact on own labor share—because of reallocation documented above.

▶ The issue is very similar to that studied by Autor et al. (2019).

▶ They propose the following decomposition (only for surviving firms here)

$$
\begin{array}{ccc}
\text{Change in} & \text{Within firm change:} & \text{Superstar effect:} \\
\text{labor share} = & \text{Change in} & + \text{Change in covariance between} \\
& \text{unweighted mean} & \text{labor share and value added}
\end{array}
$$

Superstar Effect in French Manufacturing

▶ There is an analogous superstar effect in French manufacturing:

Change in labor share $(-0.7pp)$

Within-firm change $(+1.48pp)$

Superstar effect $(-2.18pp)$

$-2pp$ $-1pp$ $0pp$ $+1pp$
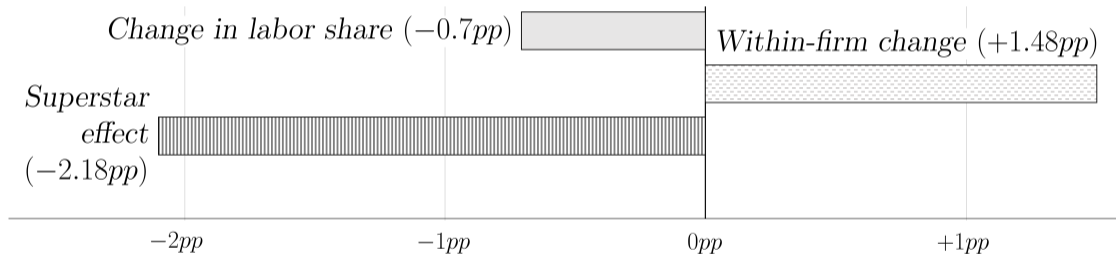
▶ This is quantitatively similar to the findings from the US in Autor et al. (2019).

Robots and Superstar Effects

▶ But we can now further understand the role of automation in this process.
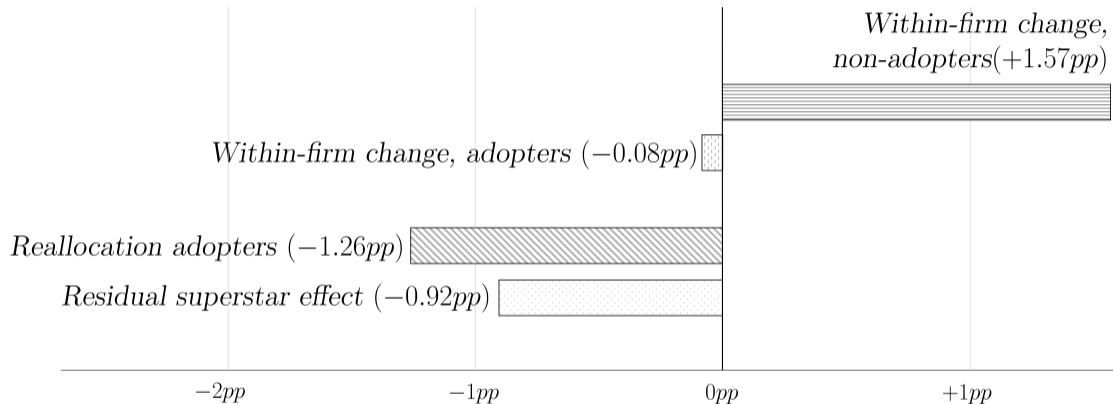
▶ Very different patterns for robot adopters and non-adopters.
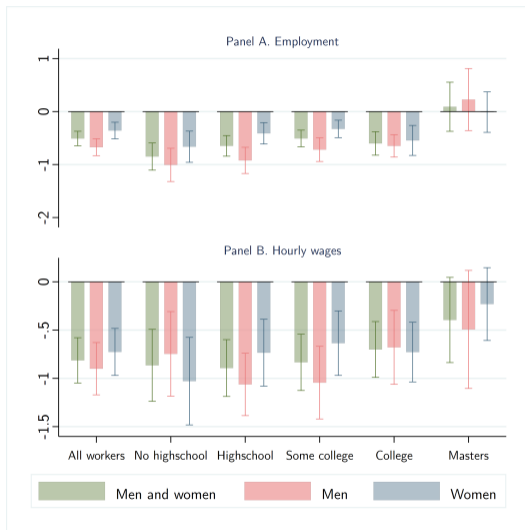▶ Also, changes for these two groups account for two thirds of the superstar effects.

Robots and Superstar Effects (continued)

- The superstar effect for adopters is mostly about the fact that labor share declines in these firms that account for a large fraction of value added.

- No "pure reallocation effect"—driven by shifts in value-added towards lower labor share firms—because no baseline differences in labor share between adopters and non-adopters (74% versus 76% in the two groups).

- This suggests a large role for adoption (and much less for any markup differences or baseline capital efficiency differences).

Inequality

▶ Changes in task content affect different types of workers differently, and thus also have first-order effects on inequality.

▶ How much have these changes impacted changes in wage structure (starting with the US)?

▶ I first present some evidence on the asymmetric effects of changes in task content, focusing on robots.

▶ Then, I outline a framework for estimating the overall contribution of task displacement created by automation technologies (and perhaps offshoring) on changes in wage structure.

▶ Applying this framework to US data, we find that the majority of changes in the US wage structure over the last three decades are driven by task displacement.

Effects on Different Skill Groups

Panel A. Employment

Panel B. Hourly wages

All workers No highschool Highschool Some college College Masters

Men and women   Men   Women

▶ Larger effects on workers with less than college.

Effects on the Distribution of Wages

All workers
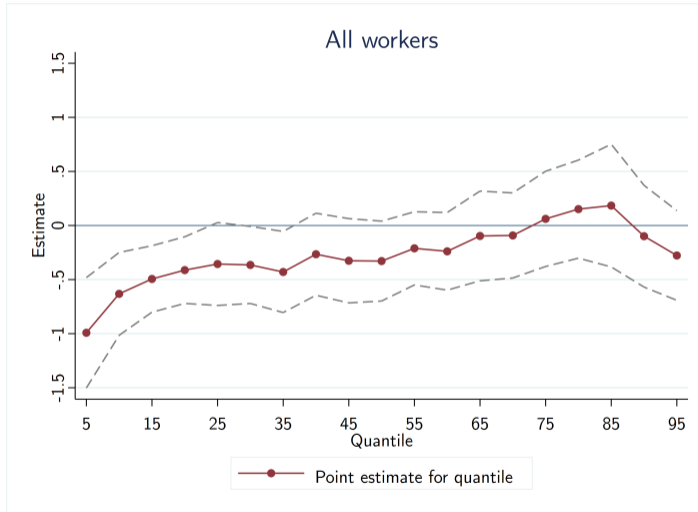
▶ Negative effects concentrate in the bottom seven deciles.

Extended Model: Introducing Different Skill Types

▶ Consider an extension of our task-based framework with skilled and unskilled workers (and a few minor changes) — from Acemoglu and Restrepo (WP, 2020).

Output combines mass M of tasks in $\mathcal{T}$

$$y = \left(\frac{1}{M} \int_{\mathcal{T}} (M \cdot y(x))^{\frac{\lambda-1}{\lambda}} \cdot dx \right)^{\frac{\lambda}{\lambda-1}}, \quad \lambda = \text{task subs.}$$

Tasks produced by capital or different types of labor g

$$y(x) = A_k \cdot \psi_k(x) \cdot k(x) + \sum_g A_g \cdot \psi_g(x) \cdot \ell_g(x).$$

Factor supply and equilibrium

▶ capital $k(x)$ produced from final good at rate $r \cdot q(x)$
▶ labor of type g has fixed supply $\ell_g > 0$
▶ allocation of tasks to factors maximizes $y - r \cdot \int_{\mathcal{T}} k(x) \cdot q(x) \cdot dx$

Model: Allocation of Tasks and Task Shares

Task allocation defined by sets $\mathcal{T}_g$ and $\mathcal{T}_k$

$$\mathcal{T}_g := \left\{ x : \frac{1}{\psi_g(x)} \cdot \frac{w_g}{A_g} \leq \frac{1}{\psi_j(x)} \cdot \frac{w_j}{A_j}, \ \frac{q(x)}{\psi_k(x)} \cdot \frac{r}{A_k} \quad \forall j \right\}$$

$$\mathcal{T}_k := \left\{ x : \frac{q(x)}{\psi_k(x)} \cdot \frac{r}{A_k} \leq \frac{1}{\psi_j(x)} \cdot \frac{w_j}{A_j} \quad \forall j \right\}$$

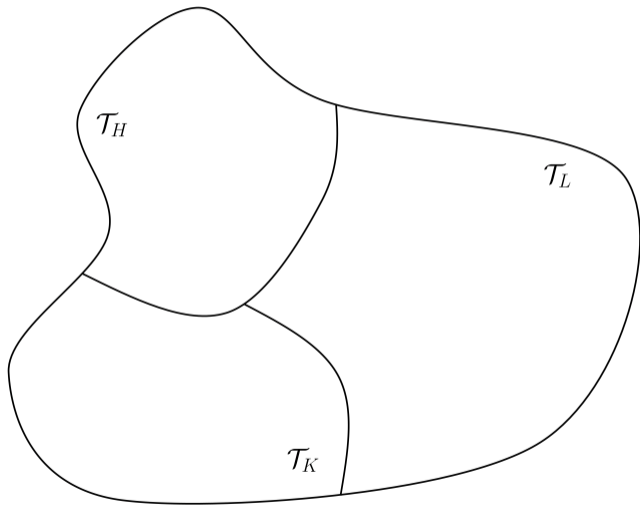Definition of task share of g & task share k

$$\Gamma_g(w^e, \Psi) := \frac{1}{M} \int_{\mathcal{T}_g} \psi_g(x)^{\lambda-1} \cdot dx$$

$$\Gamma_k(w^e, \Psi) := \frac{1}{M} \int_{\mathcal{T}_k} (\psi_k(x)/q(x))^{\lambda-1} \cdot dx.$$
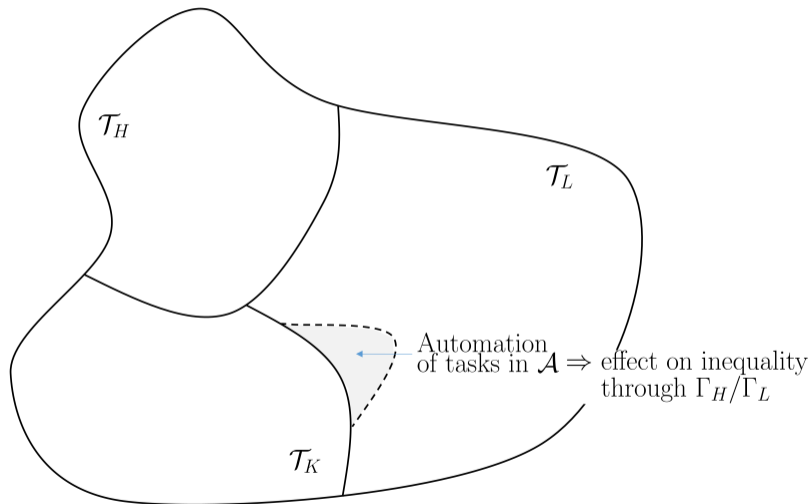
Determinants of Γ_g and Γ_k

▶ wages/rates per efficiency unit $w^e = \{w_1/A_1, \ldots, w_G/A_G, c/A_k\}$.
▶ task-specific technologies $\Psi \Rightarrow$ also affect boundaries $\mathcal{T}_g, \mathcal{T}_k$!

Model: Task Allocations

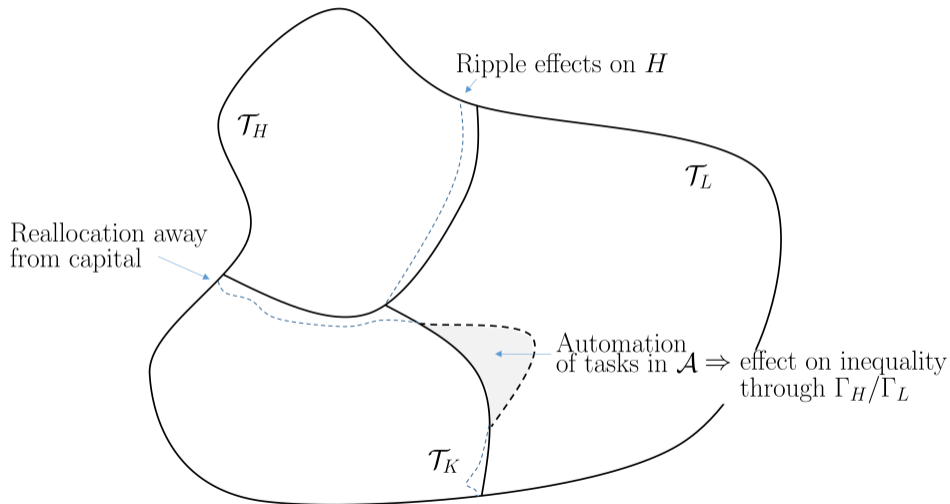# Model: Task-Displacing Technologies

$\mathcal{T}_H$

$\mathcal{T}_L$

Automation of tasks in $\mathcal{A}$ $\Rightarrow$ effect on inequality through Γ_H / Γ_L

$\mathcal{T}_K$

Model: Ripple Effects of Task-Displacing Technologies

Model: Labor-Augmenting Technologies

Increase in $A_H \Rightarrow$ 1. task subs via λ

2. changes in boundaries via w^e

$\mathcal{T}_H$

$\mathcal{T}_L$

Large productivity increase required to get boundary to move

$\mathcal{T}_K$
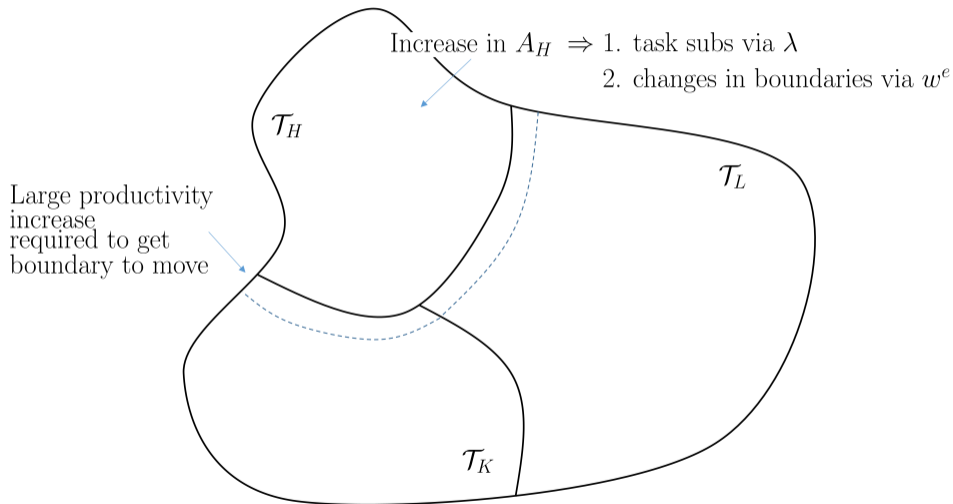
Measuring Task Displacement

- Let us now turn these ideas into an estimating framework.
- Focus on "Cobb-Douglas" case (not necessary for results, but useful for simplification).

A1. Technology and markups
- changes in $\psi_k(x)/q(x)$ leading to task displacement.
- any other form of technology, but no change in markups

A2. Routine tasks in industry i automated at common rate
- Task content for group g in industry i: $\Gamma_{gi} = \Gamma_{gi}^N + \Gamma_{gi}^R$
- $d \ln \Gamma_{gi}^{N,\text{disp}} = 0$ and $d \ln \Gamma_{gi}^{R,\text{disp}} = d \ln \Gamma_i^{R,\text{disp}}$

A1+A2: recover task displacement from industry data on labor shares, s_i^L

$$d \ln \Gamma_i^{R,\text{disp}} = \frac{1}{s_i^R} \cdot d \ln s_i^L \qquad d \ln \Gamma_g^{\text{disp}} = \sum_i \frac{s_{gi}^R}{s_i^R} \cdot d \ln s_i^L$$

- s_{gi}^R: share of group g wages earned in routine jobs at industry i
- s_i^R: share of industry i wages paid in routine jobs

- Summary: task displacement = Bartik measure of change in industry labor share times exposure of a demographic group to routine occupations in that industry.

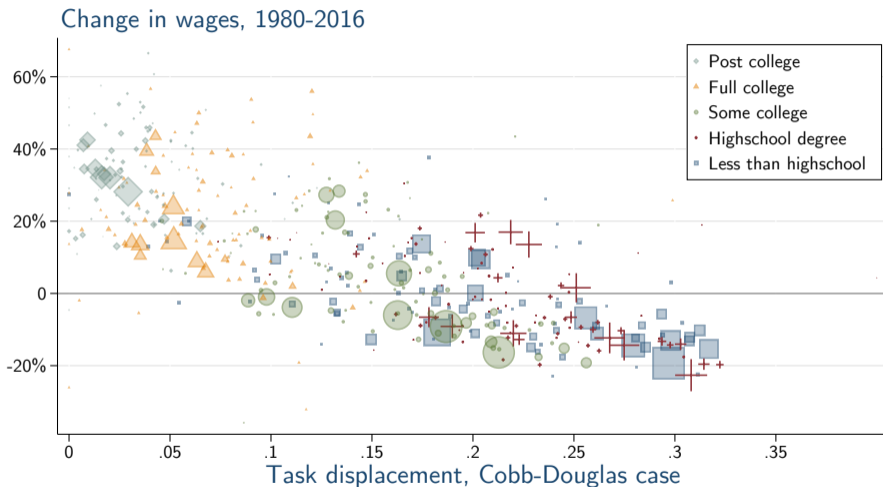# Reduced-Form Evidence: Education Groups

Figure: Reduced-form relation between task displacement and change in wages, 1980–2016.
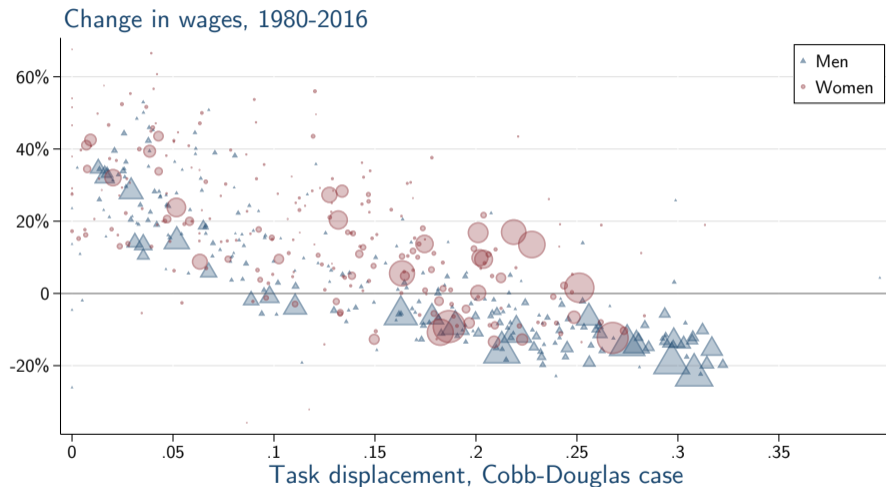
Reduced-Form Evidence: Gender

Figure: Reduced-form relation between task displacement and change in wages, 1980–2016.

Regression Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: change log hourly wages 1980-2016					
Task displacement	-1.482	-1.132	-1.429	-1.243	-1.172	-1.032
	(0.096)	(0.162)	(0.302)	(0.219)	(0.218)	(0.205)
Sectoral expansion		0.214	0.099	0.111	0.117	0.652
		(0.076)	(0.084)	(0.079)	(0.075)	(0.155)
Industries with declining labor share			-0.416			
			(0.404)			
Relative specialization in routine jobs			0.060			
			(0.059)			
R-squared	0.62	0.66	0.70	0.77	0.79	0.81
Observations	500	500	500	500	500	500
Additional covariates:						
Broad group dummies				✓	✓	✓
Regional shares					✓	✓
Broad sectoral shares						✓

Regression Estimates: Task Displacement vs. SBTC

| | Dependent variable: change log hourly wages 1980-2016 | | |
	(1)	(2)	(3)
Education: highschool	0.005	0.017	0.027
	(0.032)	(0.028)	(0.028)
Education: some college	0.032	-0.047	-0.054
	(0.035)	(0.037)	(0.039)
Education: full college	0.247	0.030	-0.045
	(0.029)	(0.053)	(0.060)
Education: more than college	0.395	0.142	0.016
	(0.027)	(0.056)	(0.074)
Gender: women	0.144	0.104	0.070
	(0.026)	(0.022)	(0.023)
Task displacement		-1.174	-1.032
		(0.195)	(0.205)
Sectoral expansion			0.652
			(0.155)
R-squared	0.68	0.76	0.81
Observations	500	500	500
Regional and broad sectoral shares			✓

- Partial R^2 of task displacement is 37.29%.
- In contrast, partial R^2 of education-based SBTC is 15.94%.

Conclusion

▶ A new and richer perspective on wages, employment and inequality.

▶ A lot of the changes in technology are intermediated via changes in labor share.

▶ Major changes in labor share both in the US and other advanced economies. Many candidate explanations, but the role of automation and changes in task content typically ignored.

▶ Evidence suggests a first-order role for automation.

▶ In fact, changes in automation (and task content) seem to account for the bulk of changes in labor share and wage structure in the US.

▶ But what determines automation? How and why has it changed over time? Is this because of technological opportunities? Policy? Inefficiencies?

▶ Next lecture.