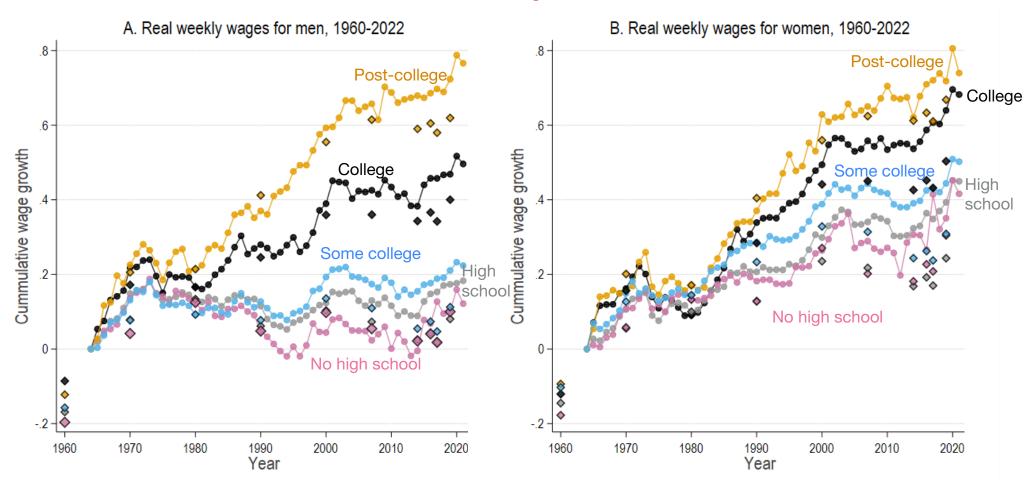


Pascual Restrepo, Yale University

### **IEA Lectures 2025**

# How Computer Automation Transformed the Work Landscape

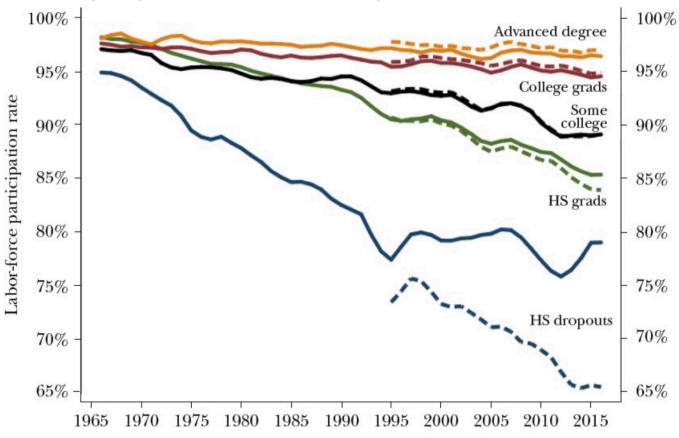
#### Trends in US Labor Markets: Real Wages



Cumulative wage growth by group, 1963–2022 (lines, from CPS) and 1960-2022 (diamonds, from Census/ACS)

#### Trends in US Labor Markets: Employment

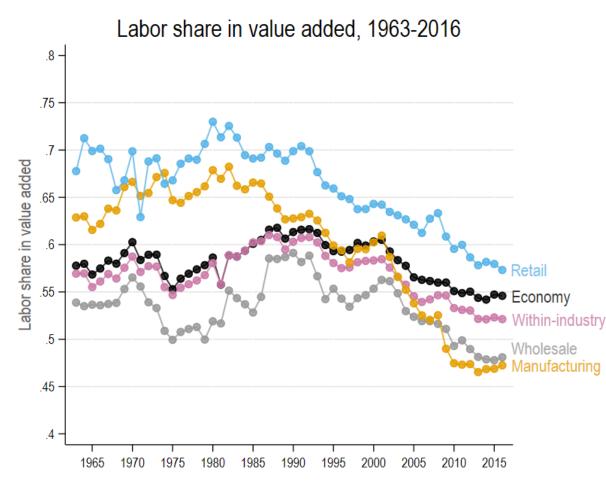
Labor-force participation rate, Men 25-54 years of age



Labor force participation declined since 1970s -1980s

- More so for men with no college or advanced degrees
- Is this a cause for concern?
  - Bad news if people discouraged from work
  - Good news if working less because satiated, a-la Keynes (seems unlikely!)

#### Trends in US Labor Markets: Declining Labor Shares



Labor share in value added went from being stable to declining for important sectors in 1980–2020

- Decline pronounced in manufacturing, retail, wholesale
- Less pronounced on aggregate due to reallocation of laborintensive sectors

Labor share in value added by sector, BLS and BEA industry accounts

#### What Explains these Trends?

Potential explanations: institutions, globalization...

**Computer-powered automation**—Technologies that replace labor in a widening range of work tasks

Industrial robotics  $\Rightarrow$  Technology to handle welding and assembly

CNC machinery  $\Rightarrow$  Technology to handle metal and wood-working processes

Software systems  $\Rightarrow$  Technology to handle sales, logistics, and clerical tasks

We automated many of the work tasks performed by non-college workers in the 1970s-80s

**Keep in mind:** Not all technologies automate work

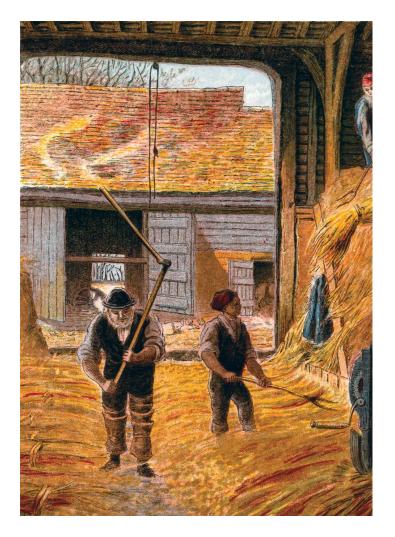
e.g., new products, new energy sources, improvements in materials

**Today:** framework for thinking about impact of automation technology + evidence for US

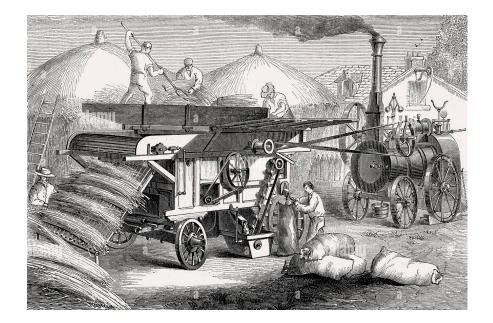
### Moravec's Work Landscape



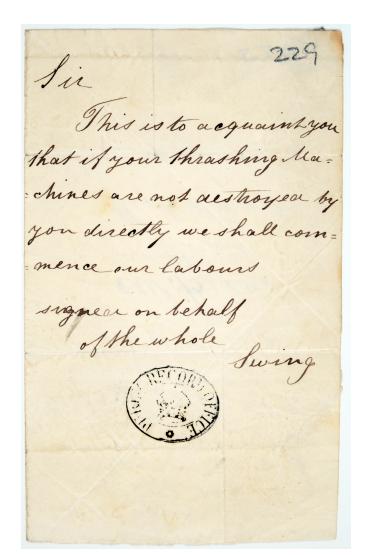
Historically, we figured out ways to mechanize and *automate* work



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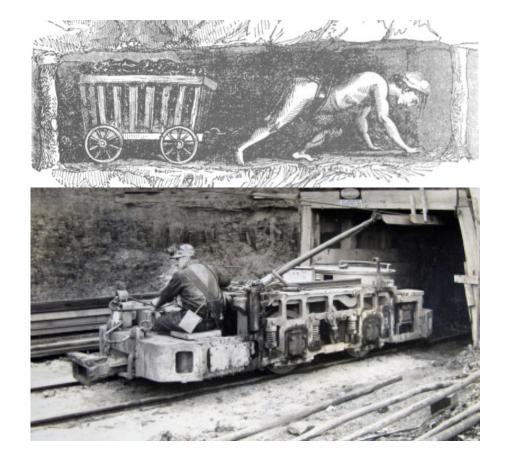
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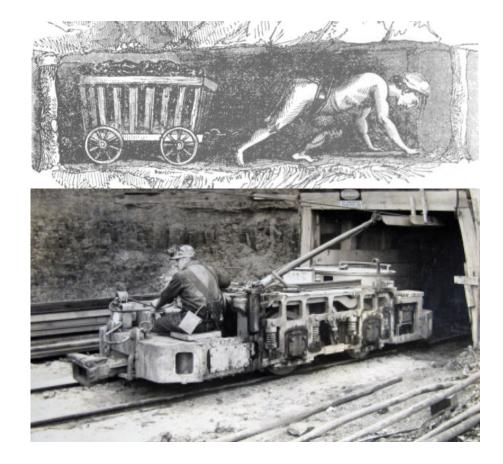
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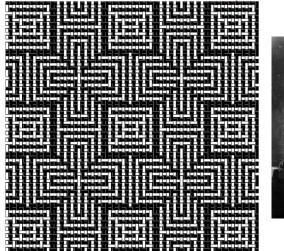
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- Automation: use of machines or systems that can perform complex work on their own, replacing human input.



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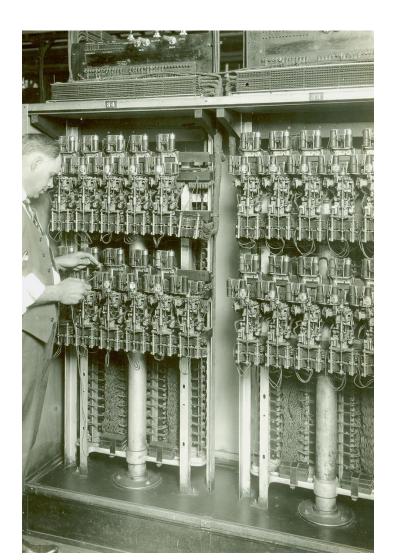
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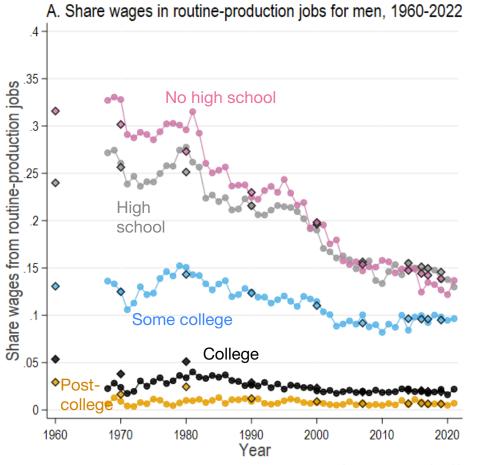
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#### **One commonality:** routine (codifiable) work

(Autor-Levy-Murnane 2003)

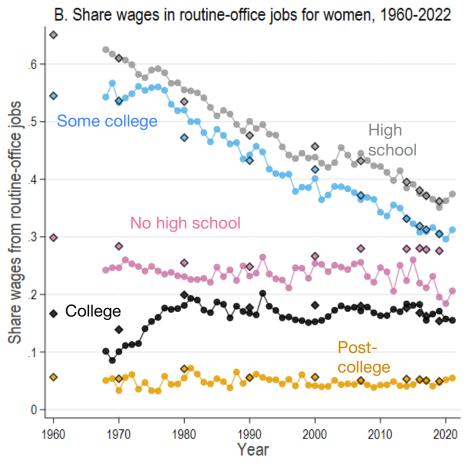
#### Shifts in Work Tasks for Men



Employment in routine jobs, 1963–2022 (lines, from CPS) and 1960-2022 (diamonds, from Census/ACS)

- Decline in production jobs intensive in routine work tasks
  - Welding, assembly, painting
  - Machining
  - Metal and wood working
  - Palletizing
  - Tasks can be codified and automated with industrial robots and CNC machines
- For non-college men, decline in routinemanual jobs from 25 % to 12 % of employment

#### Shifts in Work Tasks for Women



Employment in routine jobs, 1963–2022 (lines, from CPS) and 1960-2022 (diamonds, from Census/ACS)

- Decline in office jobs intensive in routine work tasks
  - Sales and placing orders
  - Time-keeping and handling payroll
  - Keeping records and tabulation
  - Dispensing cash and verifying paperwork
  - Tasks that can be codified and automated with software and computer systems
- For non-college women, decline in routine-office jobs from 55 % to 35 % of employment

The Task Model (Acemoglu and Restrepo, 2022)

Output

$$\ln y = \int_0^1 \ln y(x) \, dx$$

~1

Tasks

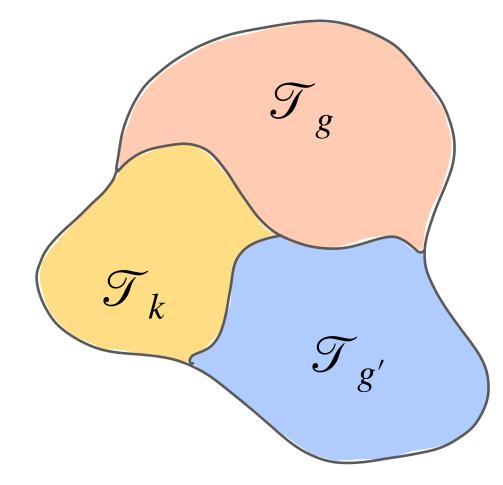
$$y(x) = \sum_{g} \psi_{g}(x) \ell_{g}(x) + \psi_{k}(x) k(x)$$
  
Task-specific technologies ( $\psi_{k}(x) = 0$  if not automated and  $\psi_{k}(x) > \underline{\psi}$  otherwise)

• capital produced from final good one-to-one

Factors' supply and equilibrium

- supply of group labor fixed at  $\ell_g$  (focus on wages)
- Equilibrium given by cost-minimizing task allocation

#### Equilibrium Assignment and Wages



**Real wages:** 

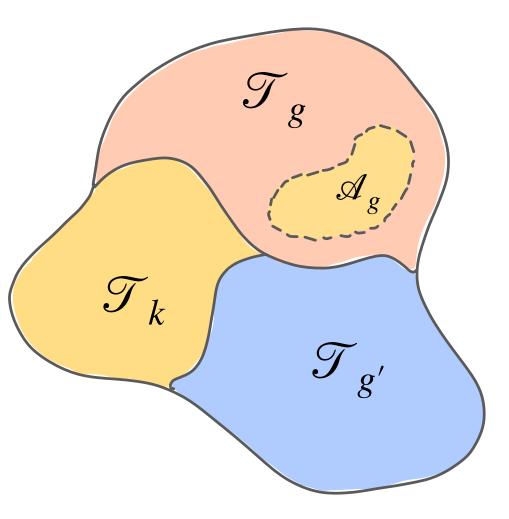
$$w_g = \frac{y}{\ell_g}$$
 Task mass<sub>g</sub>

- Mass of tasks assigned to group g:
  - Share of work landscape dominated by group
  - wages higher for groups whose skills needed for more tasks

Labor share given by  $\sum_{g}$  Task mass<sub>g</sub>

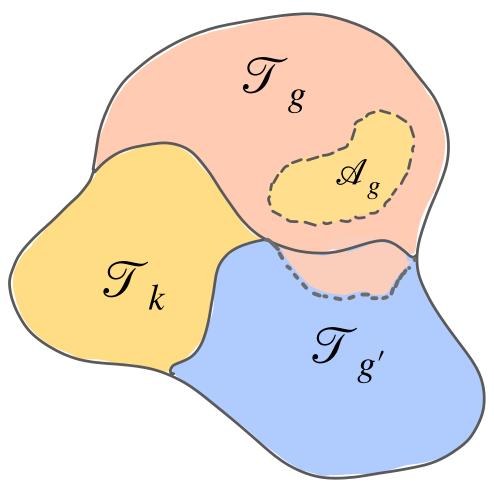
- Share of work landscape dominated by labor

#### **Automation**



- Creation of *new machine* or *computer* system capable of replacing labor in some of the tasks it performs
  - i.e., we figured out ways to mechanize and automate work
- Extensive margin advances: direct effect of automation is to displace workers from  $\mathcal{A}_g$
- Different from advances at intensive margin improving existing systems
  - i.e., improved cranes or conveyors, electricity substituting for steam...

#### **Effects of Automation**



- Task displacement: group g workers substituted away from tasks in  $\mathcal{A}_g$ 
  - Outcompeted by new machines or computer systems
- **Ripples:** reassignment of boundary tasks in response to wage changes
- Cost-savings: reduced cost of completing tasks in  $\mathcal{A}_g$

### Effects of Automation on Wages: No ripples

Recall  $w_g = (y/\ell_g)$  Task mass<sub>g</sub>.

Change in real wages due to automation:

$$\Delta \ln w_g = \begin{array}{c} \text{output growth} \\ \text{``Productivity'' effect} \\ (+) \end{array} \\ \begin{array}{c} \text{``Task-displacement'' effect} \\ (-) \end{array}$$

- Direct effect of automation is to:
  - Shift employment away from automated tasks
  - Reduce relative (and in some cases real) wages of displaced groups
  - Reduce the labor share

#### Effects of Automation on Wages: Ripples

Change in real wages due to automation:

$$\Delta \ln w_g = \begin{array}{c} \text{output growth} \\ \text{``Productivity'' effect} \\ (+) \end{array} - \begin{array}{c} \sum_{j} \theta_{gj} \text{ share tasks automated}_{j} \\ \text{``Task-displacement'' effect} \\ \text{spread across groups with} \\ \text{weights } \theta_{gj} \in [0,1] \end{array}$$

•  $\theta_{gi}$  is extent to which groups compete for tasks, both directly and indirectly

- Uniform  $\Theta$ : groups highly substitutable and can reallocate with ease, incidence shared equally
- Diagonal  $\Theta$ : groups highly specialized and cannot reallocate with ease, incidence on exposed groups

#### Effects of Automation on Wages: Productivity effect

• TFP gains from automation

TFP gains = 
$$\sum_{g}$$
 Share g in GDP × Share tasks automated<sub>g</sub> × Cost savings<sub>g</sub>

- Can be small for "so-so" automation technologies
- TFP gains pin down average wage growth

TFP gains = 
$$\sum_{g}$$
 Share g in GDP ×  $\Delta \ln w_g$ 

- Average wage necessarily rises, but some workers might lose

# How Computer-Automation Transformed Manufacturing



Computer-numerically-controlled (CNC) Machinery

**Industrial Robots** 

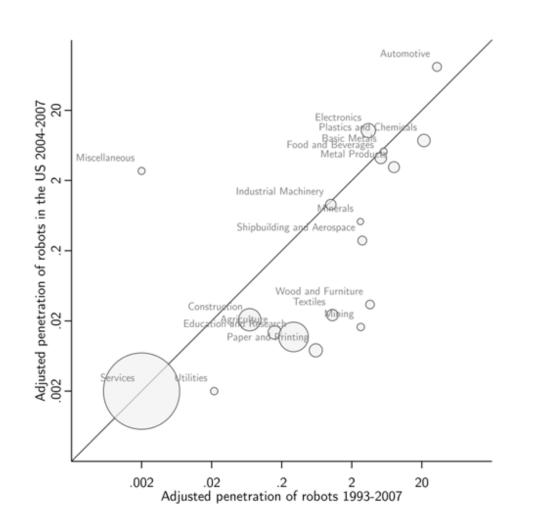
- How did adoption of industrial robots affect US local labor markets during 1990-2007? (Acemoglu-Restrepo 2020)
- Measure of robot exposure across US commuting zones *z*:

$$\mathsf{R}_{z} = \sum_{i} s^{E}_{z,i,1990} \cdot \mathsf{APR}^{US}_{i,93-07}$$

- APR: ∆ robots per thousand workers (adjusting for industry expansion)
- Instrumented using historical differences in industry location and advances in Europe

$$\mathsf{R}_{z}^{IV} = \sum_{i} s_{z,i,1970}^{E} \cdot \mathsf{APR}_{i,93-07}^{EURO}$$

• Industries with greater penetration: increasing output; falling labor shares and employment



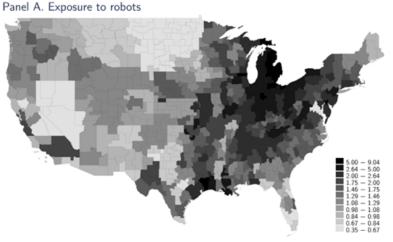
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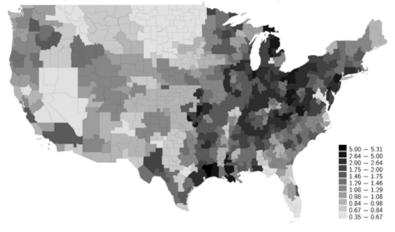
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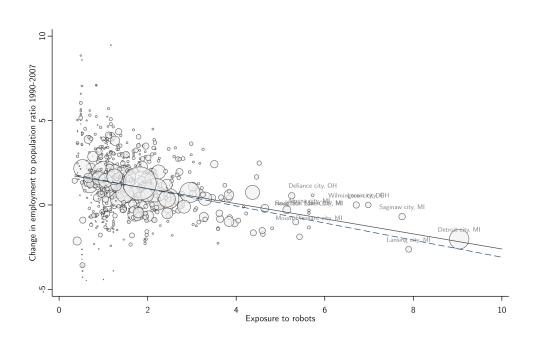


Panel B. Exposure to robots outside automotive industry



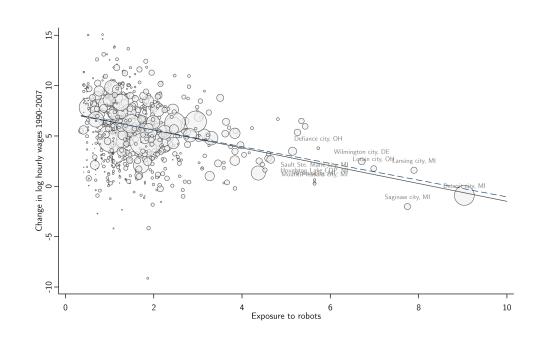
- Consequences of displacement effects in exposed regions:
  - I extra industrial robot leads to 3 fewer manufacturing jobs in exposed commuting zone relative to others
    - Decrease in overall employment rates, especially for non-college men
  - I robot per thousand workers reduces wages in commuting zone by 0.7% relative to others
  - Estimate small aggregate gains (0.3% GDP expansion per robot per thousand workers)

$$\Delta y_{z,90-07} = \beta \cdot \mathsf{R}_z^{IV} + \mathsf{controls}_z + \epsilon_z$$



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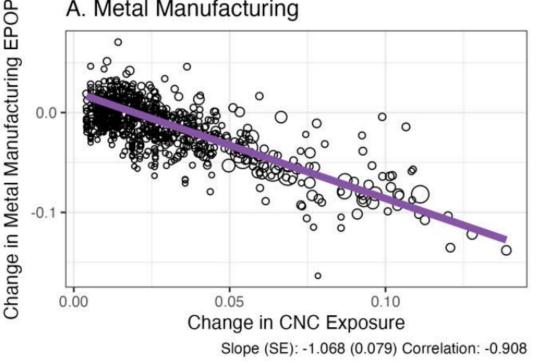


# **CNC** Machinery and Jobs

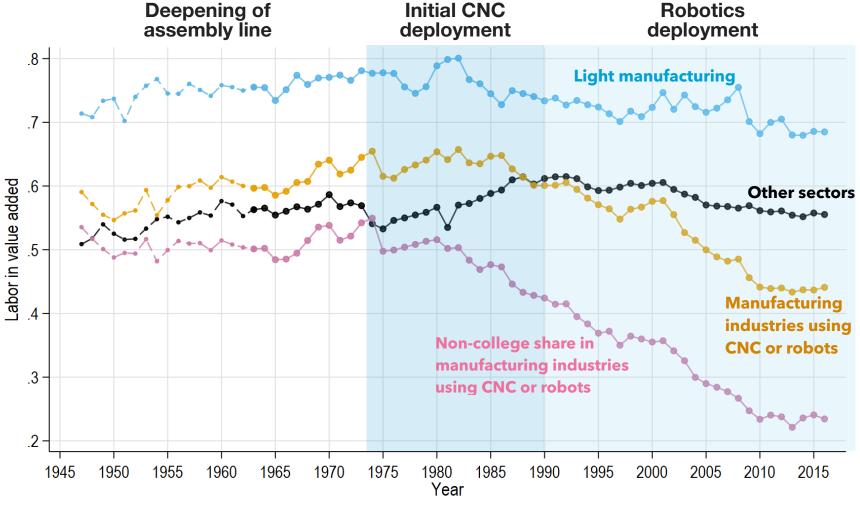
Estimating the effects of CNC machinery in metal-working industries (Boustan-Choi-Clingingsmith)

- Effects on exposed industries (post 1970)
  - Higher value added and investment -
  - Reduced labor shares and employment -
  - Shift towards more educated workers -
- Effects on commuting zones housing these industries
  - Reallocation away from metal manufacturing
  - No overall employment effects -

#### A. Metal Manufacturing



# **Computer-Powered Automation in Manufacturing**



Data from BEA integrated industry accounts for 1947-2016

- How did automation affect the US wage structure nationally? (Acemoglu-Restrepo 2022)
- Share tasks lost to automation by group g

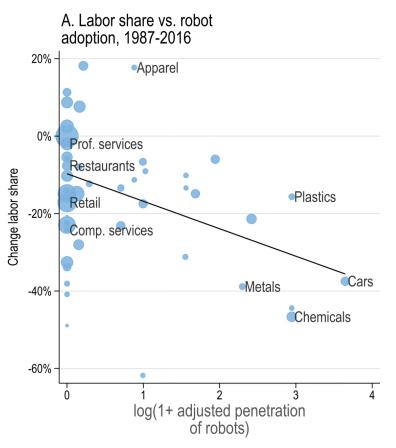
$$td_g = \sum_{i} \omega_{gi} \cdot \mathsf{RCA}_{g,i}^{rout} \cdot \text{automation-driven} \\ \text{declines in } d \ln s_{\ell i}$$

- First two terms from 1980 Census, using routine work measure (Acemoglu-Autor)
- $d \ln s_{\ell i}^d$  from industry regression of labor share changes 1980-2016 on automation proxies
  - In **black:** percent labor share decline
  - In **orange:** component due to automation

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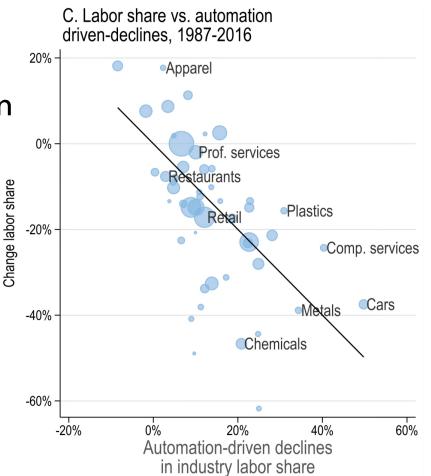
B. Labor share vs. specialized software and dedicated machinery, 1987-2016 20% - Apparel 0% Prof. services Restaurants Change labor share Retailastics -20% Comp. services Cars Metals -40% Chemicals -60% -5 Change in share of specialized software services

and dedicated machinery services (in pp)

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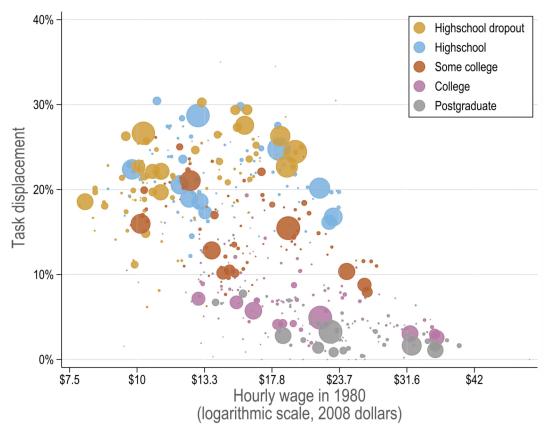
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Transportation pipelines Chemical products Petroleum and coal products Transportation by rail Primary metals Transportation by air Motor vehicles Legal services Communications Nonmetallic mineral products mputers and electronics Computer services Printing and publishing Wholesale Accommodation Food manufacturing Transportation by water ransportation equipment Retail Plastic and rubber products Machinery Finance and insurance Construction Transportation by truck Transportation of transit Furniture Paper products Educational services Textiles Ambulatory health care Wood products Miscellaneous manufacturing Appliances Restaurants Oil and gas extraction Metal products Transportation services Hospitals Professional services Real estate Social assistance Warehousing and storage Administrative services Percent labor Utilities share decline Personal services Recreation Direct task Apparel and Leather displacement Agriculture and farming -20% 20% 40%60% 80% Industry task displacement, 1987-2016

# Who Won, Who Lost?

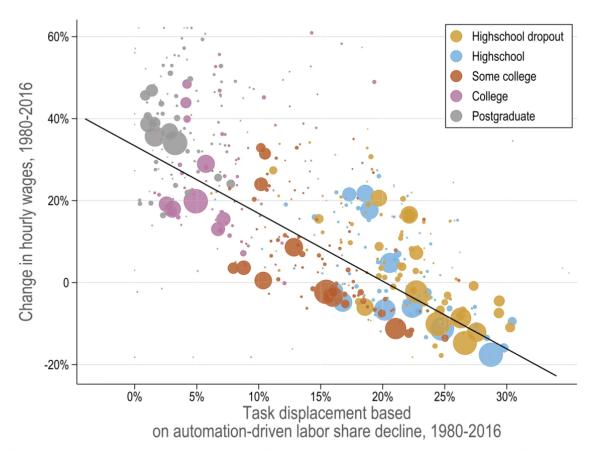
- Measured rate of task displacement from computer-powered automation:
  - Average US worker lost 15% of their initial tasks in 1980-2016
  - US workers with college degrees shielded
  - US workers with no college lost 25% of terrain to automation
  - Men lost 17%, women 10%

Task displacement from computer-powered automation, US worker groups, 1980–2016



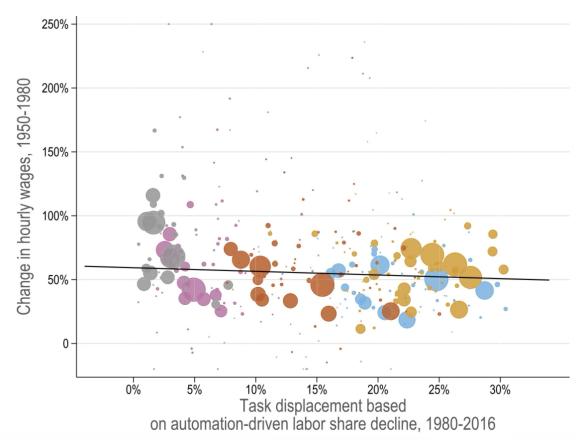
# Task-displacement Rates and Labor Market Outcomes

- Consequences of higher task-displacement rates:
  - A 10pp increase in rate of task displacement associated with relative wage decline of 17%
  - Real wage <u>declines</u> for highly exposed groups
  - Rates of displacement account for 70% of wage trends across groups
  - Reduction in employment (people discouraged from working)
  - Relationship absent before computer era



# Task-displacement Rates and Labor Market Outcomes

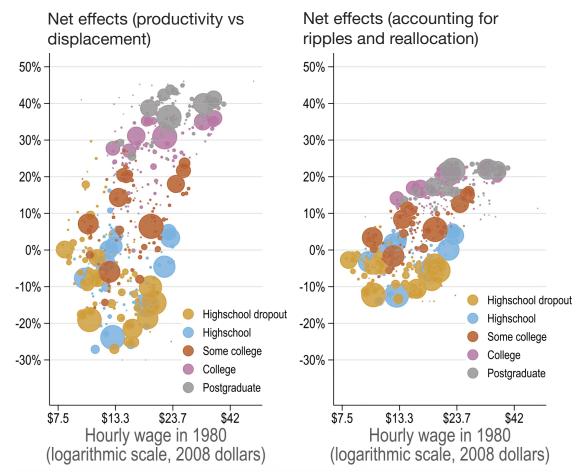
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# Net Effects Accounting for Ripples and TFP Expansion

But what about the size of the pie and ripples?

- Reallocation plays equalizing role
  - Half incidence shared
- Increase in pie (productivity gains) from computer-powered automation not huge...
  - For cost savings of  $30\,\%$  ,TFP gains of 4% over 1980-2016.
  - Net effect of computer-powered automation is negative for various groups

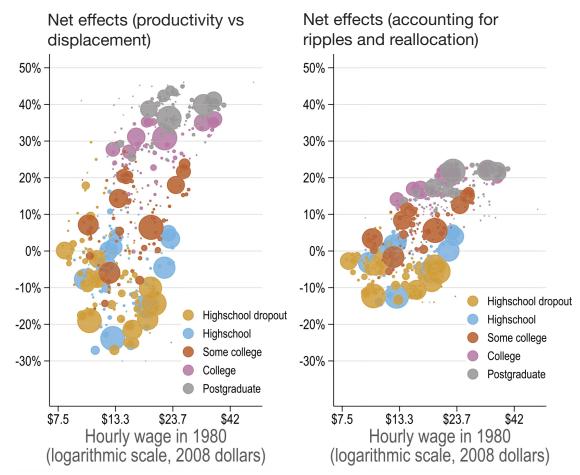


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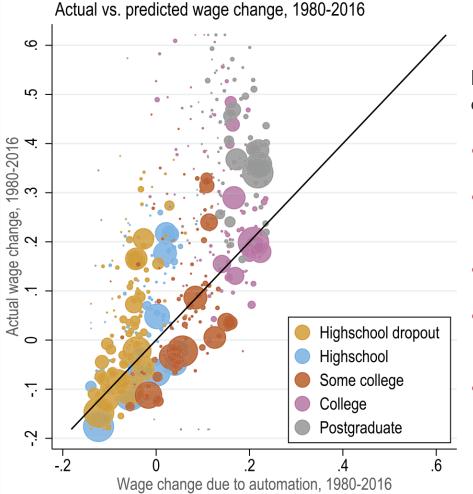
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Ultimate source of TFP growth are **new ideas** on products and goods. Automating what we have can only take us so far!



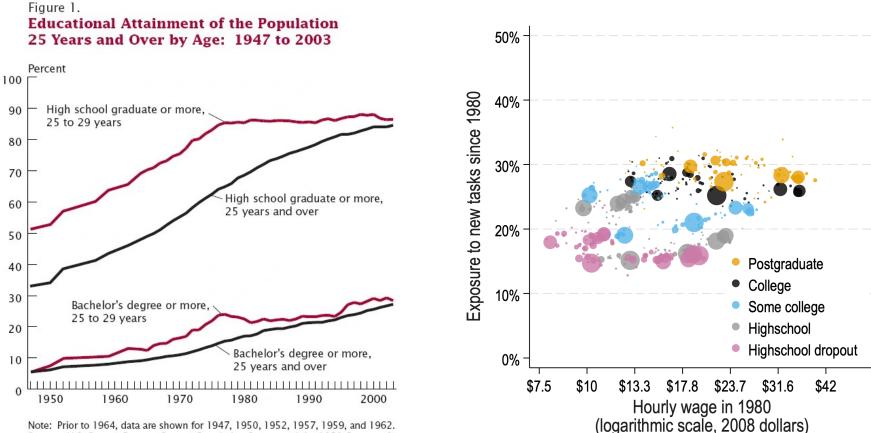
### The Bottom Line



Measured **rates of task displacement** due to computer-powered technology:

- Explain 48% of observed wage changes
- Explain 80% of rise in college premium and 60% of rise in post-college premium
- Explain 80% of real wage declines
- Miss wage growth at top (other forces or direct complementarities with technology?)
- Predict increase in GDP of 20%, mean wage of 6%, and TFP of 4% (for cost savings of 30%)

# Limited Offsetting Role of Supply Responses and New Work



Source: U.S. Census Bureau, Current Population Survey and the 1950 Census of of Population.

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  - Previous wave of computer-powered automation confined to routine work
  - Polani's paradox "we know more than we can tell"
  - Al and LLM as a technology for extracting what is it that we knew but could not tell and then deploying tacit knowledge at scale
  - Potential to replicate human expertise (even if tacitly acquired) across many domains

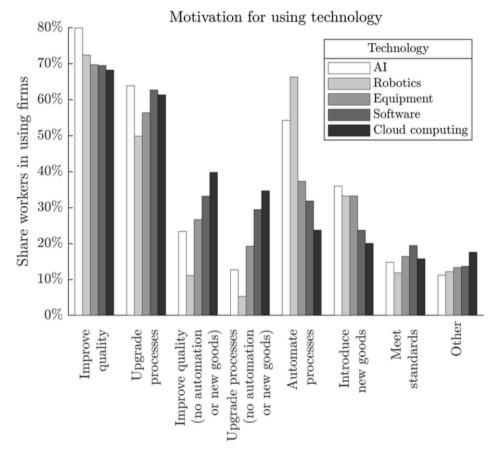


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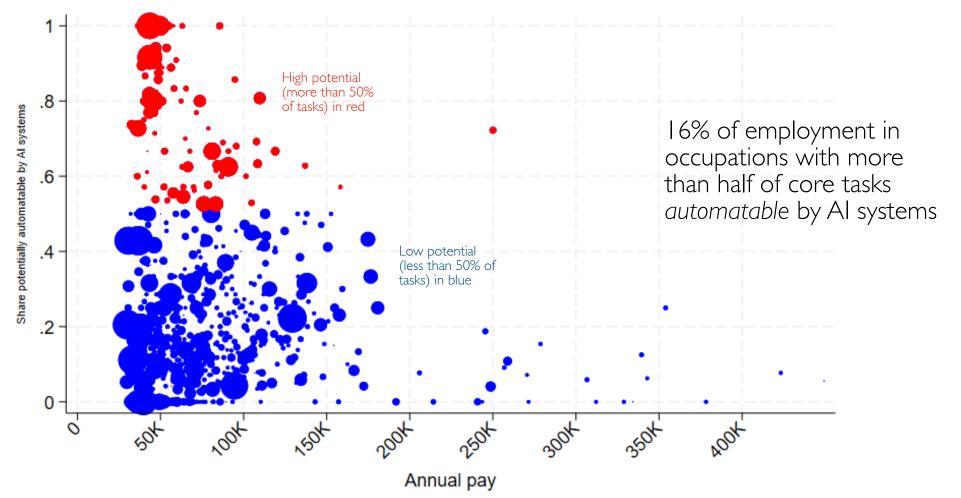
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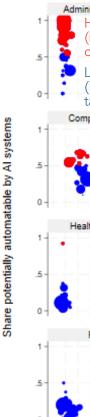


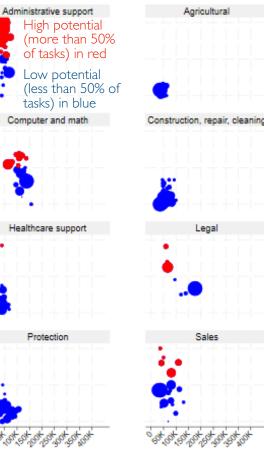
See "Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey" by Acemoglu et al.

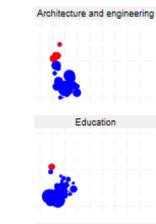
### Work that can Potentially be Automated with LLM-powered Systems From Eloundou et al. (2024)



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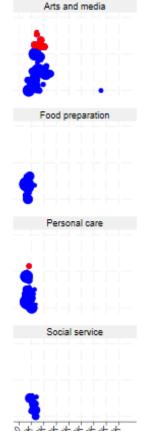


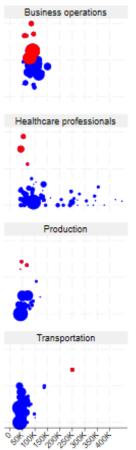
Managers



Sciences

Annual pay





### Implications for Developing Countries

**Inappropriate technology:** benefits of automation greater for countries with scarce labor and abundant computing capabilities.

**FDI:** if multinationals automate their production, FDI less effective at generating local employment and benefits

**Offshoring:** automation reduces pressure on multinationals to reallocate production to low-wage countries

**Shifting locus of competitive advantage:** as production in a sector automated, production shifts towards countries abundant in capital (and away from countries abundant in labor)

### Conclusions

Computer-powered automation has been an important force reshaping the work landscape since 1970s-80s

- By displacing workers from tasks they used to perform, automation can reduce wages and employment opportunities for exposed segments of workforce
- Measured **rates of task displacement** due to computerpowered technology explain broad wage trends in US:
  - Explain 48% of observed wage changes
  - Explain 80% of rise in college premium and 60% of rise in post-college premium
  - Explain 80% of real wage declines
- Yet, automation of existing work brought modest TFP gains.
- Al and LLMs have potential to automate areas of the work landscape shielded by *Polani's paradox*.

