# Automation and New Tasks: How Technology Displaces and Reinstates Labor

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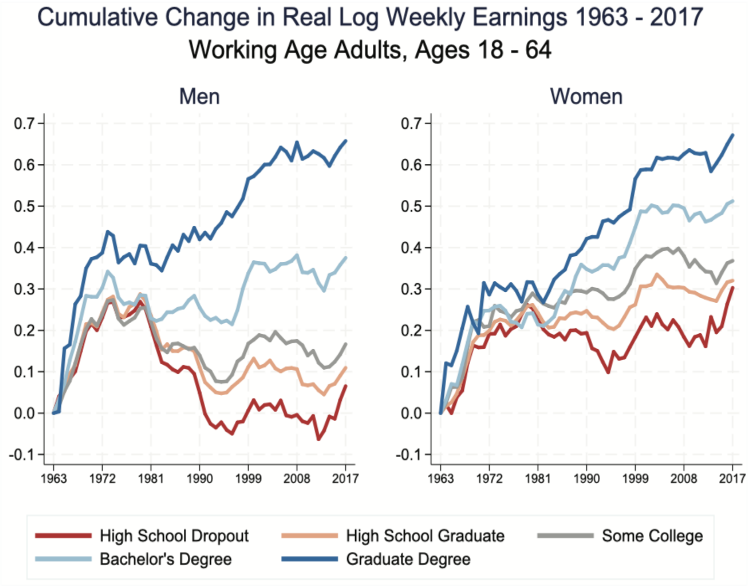

Cumulative Change in Real Log Weekly Earnings 1963 - 2017
Working Age Adults, Ages 18 - 64
Men
Women
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
1963
1972
1981
1990
1999
2008
2017
High School Dropout
High School Graduate
Some College
Bachelor's Degree
Graduate Degree

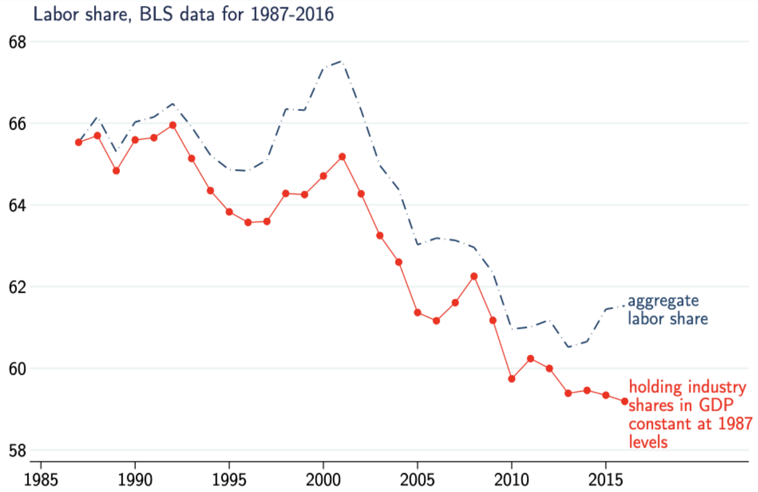
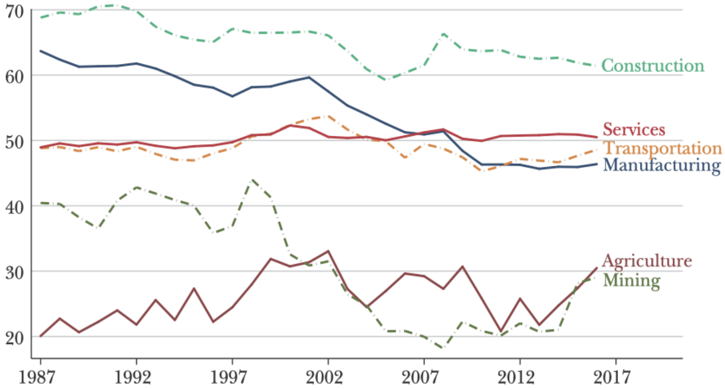

Labor share, BLS data for 1987-2016
68
66
64
62
60
58
1985
1990
1995
2000
2005
2010
2015
aggregate labor share
holding industry shares in GDP constant at 1987 levels

*Figure 4*

**The Labor Share and Sectoral Evolutions, 1987–2017**

A: Labor Share within Each Industry, 1987–2017



# Motivation (Acemoglu & Restrepo [18])

- **2-factor CRS production functions assuming factor-augmenting technological change** pose important problems and puzzles.
- **Capital-augmenting** technological change cannot explain declining wages for some workers or the recent fall in the labor share for realistic parameter values.
- **Labor-augmenting** technological change cannot explain declining wages for realistic parameter values.
- It could explain the recent fall in the labor share for realistic parameter values, but it is not very convincing conceptually.

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# 1. Conceptual Framework

# 1. Conceptual Framework

## Production technology

- Static environment with a unique final good, $Y$.
- $Y$ is produced with a continuum of tasks on the unit interval $[N-1, N]$ with $N$ an exogenous parameter.
- CES technology mapping tasks into the final good:

$$Y = \left[ \int_{N-1}^{N} y(z)^{\frac{\sigma-1}{\sigma}} dz \right]^{\frac{\sigma}{\sigma-1}} \tag{A1}$$

  where $y(z)$ is output of task $z$ and $\sigma \geq 0$ the elasticity of substitution between tasks.
- The final good is the numeraire, $P \equiv 1$.

# The frontier of automation possibilities

**Assumptions**

- Tasks $z \in [N-1, N]$ are ranked such that they become increasingly more difficult for machines to do.
- Assume an exogenous threshold $I$ which is the frontier of automation possibilities.
- All tasks $z \leq I$ can (and will) be automated, and all tasks $z > I$ can only be done by labor.
- An increase in $I$ willl capture automation.

## Supply of labor and capital to tasks

- Task $z$ can be produced by labor, $l(z)$ or by capital, $k(z)$, according to:

$$y(z) = \begin{cases} A^L\gamma^L(z)l(z) + A^K\gamma^K(z)k(z) \text{ if } z \in [N-1, I] \\ A^L\gamma^L(z)l(z) \text{ if } z \in (I, N] \end{cases}$$

  where:

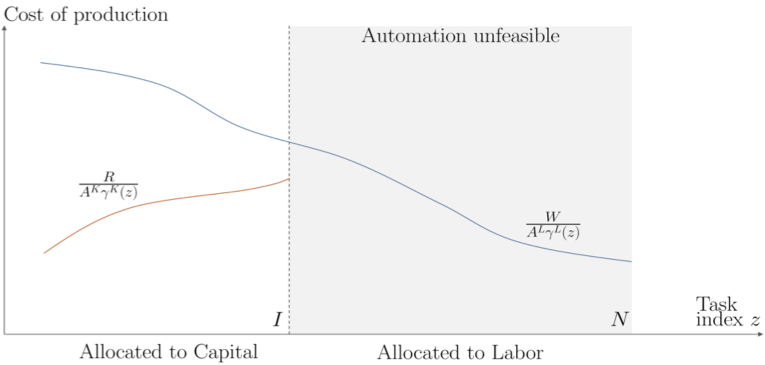
  - $A^L, A^K$ are factor-augmenting technologies
  - $\gamma^L(z), \gamma^K(z)$ are task productivity schedules
  - $l(z), k(z)$ are the number of each factor allocated to task $z$

## Comparative advantage in task production

**Assumption**

$\gamma^L(z)/\gamma^K(z)$ is strictly increasing in $z$.

- This is an assumption about the *relative* productivity of labor and capital in doing different tasks.
- This assumption drives factor allocation across tasks based on comparative advantage (as in Roy [51]).
- All tasks $z \in [N-1, I]$ will be done by capital and all tasks $z \in (I, N]$ will be done by labor.




Allocation of tasks to factors

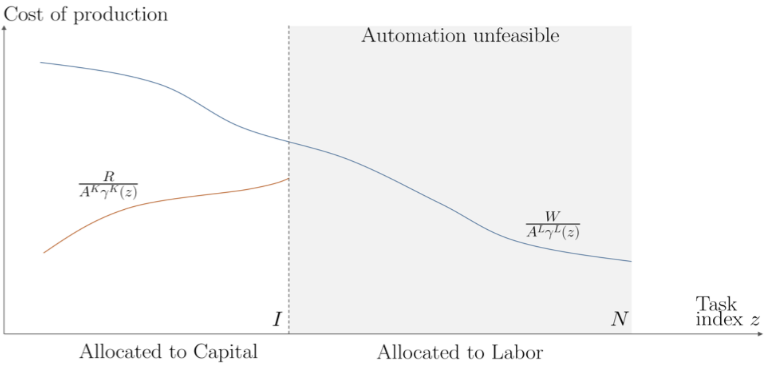
## Clearing factor markets

- Labor and capital are supplied inelastically by $L$ and $K$ respectively (this will no longer hold in section 1.5).
- Labor markets clearing requires:

$$\int_{N-1}^{N} l(z)dz = L \text{ and } \int_{N-1}^{N} k(z)dz = K$$

- In this environment, we can look at:
  - Types of technological change (section 1.2)
  - Equilibrium (section 1.3)
  - Technology and labor demand (section 1.4)
  - Multi-sector economy (section 1.5)

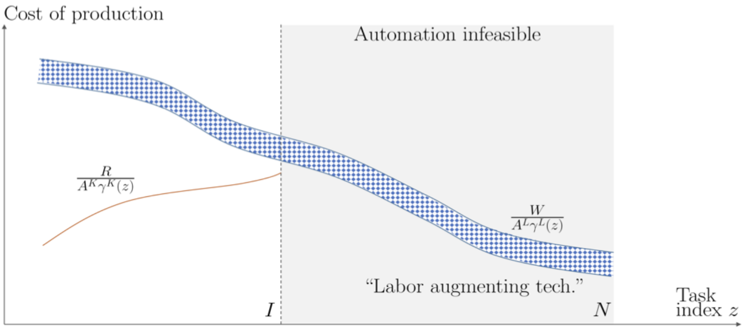
# 1. Conceptual Framework




Allocation of tasks to factors

# Types of technological change

1. **Labor-augmenting technological change**:
   $A^L \uparrow$ or $\gamma^L(z) \uparrow$ for all $z$
2. **Automation (at the extensive margin)**:
   Automation possibility frontier $I \uparrow$
3. **Deepening of automation (at the intensive margin)**:
   $A^K \uparrow$ or $\gamma^K(z) \uparrow$ for all $z < I$
4. **Creation of new labor-intensive tasks**:
   $N \uparrow$ which increases the bounds of the unit interval of tasks ranked by labor's comparative advantage




1. **Labor-augmenting technological change**:
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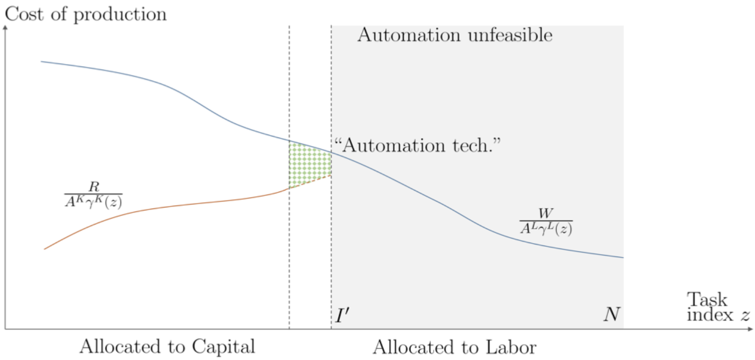
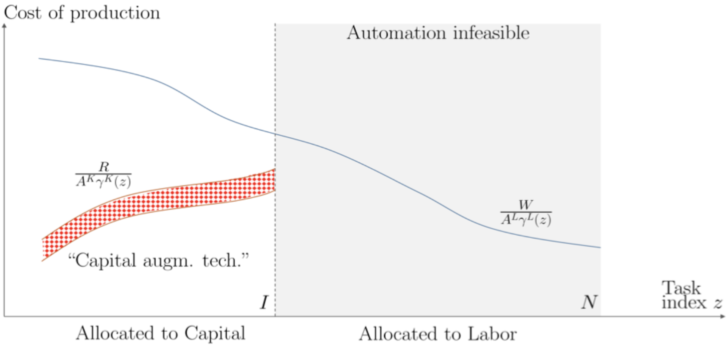
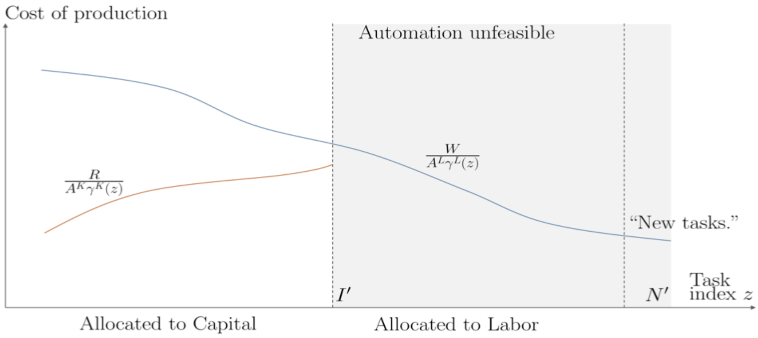



2. **Automation (at the extensive margin)**:
Automation possibility frontier $I \uparrow$




3. **Deepening of automation (at the intensive margin)**:

$$A^K \uparrow \text{ or } \gamma^K(z) \uparrow \text{ for all } z < I$$

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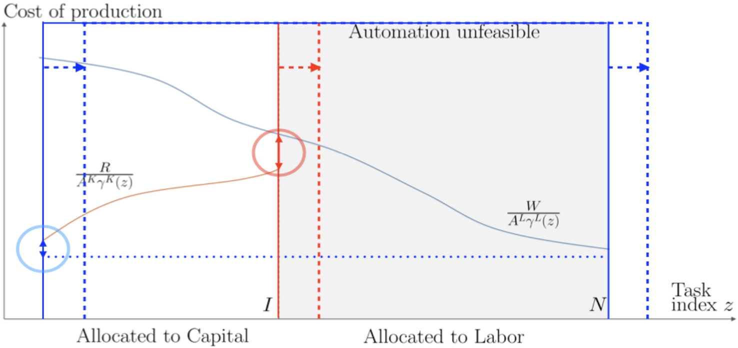
# 1. Conceptual Framework




Efficiencies at marginal tasks: equilibrium assumptions

## Efficiencies at marginal tasks: equilibrium assumptions

- Denote the equilibrium wage rate by $W$ and rental rate by $R$.
- Further assume that in any equilibrium:

$$\frac{A^L \gamma^L(I)}{A^K \gamma^K(I)} < \frac{W}{R} < \frac{A^L \gamma^L(N)}{A^K \gamma^K(N-1)} \qquad \text{(A7)}$$

- First inequality implies that all tasks $z \in [N-1, I]$ will be produced by capital and that an increase in $I$ increases $Y$.
- Second inequality implies that an increase in $N$ increases $Y$.
- We return to these equilibrium assumptions below.

# Task demands

- CES technology mapping tasks into the final good:

$$Y = \left[ \int_{N-1}^{N} y(z)^{\frac{\sigma-1}{\sigma}} dz \right]^{\frac{\sigma}{\sigma-1}} \tag{A1}$$

- Gives demand for task $z$:

$$y(z) = \frac{Y}{p(z)^{\sigma}}$$

- With the price of task $z$, $p(z)$, given by:

$$p(z) = \begin{cases} \frac{R}{A^K \gamma^K(z)} \text{ if } z \in [N-1, I] \\ \frac{W}{A^L \gamma^L(z)} \text{ if } z \in (I, N] \end{cases}$$

## Factor demands in tasks

- Using that $y(z) = A^K \gamma^K(z) k(z)$ for $z \in [N-1, I]$:

$$k(z) = \begin{cases} \frac{Y}{A^K \gamma^K(z)} \left[\frac{R}{A^K \gamma^K(z)}\right]^{-\sigma} \text{ if } z \in [N-1, I] \\ 0 \text{ if } z \in (I, N] \end{cases}$$

  which gives demand for capital in each task $z$.

- Using that $y(z) = A^L \gamma^L(z) l(z)$ for $z \in (I, N]$:

$$l(z) = \begin{cases} 0 \text{ if } z \in [N-1, I] \\ \frac{Y}{A^L \gamma^L(z)} \left[\frac{W}{A^L \gamma^L(z)}\right]^{-\sigma} \text{ if } z \in (I, N] \end{cases}$$

  which gives labor demand in each task $z$.

## Aggregate demand for labor and equilibrium wage

- The market clearing condition for labor is:

$$L = \int_{N-1}^{N} l(z) dz = \int_{I}^{N} \frac{Y}{A^L \gamma^L(z)} \left[ \frac{W}{A^L \gamma^L(z)} \right]^{-\sigma} dz$$

- Re-arranging terms gives the equilibrium wage:

$$\boxed{W = \left[ \frac{Y}{L} \int_{I}^{N} [A^L \gamma^L(z)]^{\sigma-1} dz \right]^{\frac{1}{\sigma}}}$$

- **Sneak preview**: Automation (i.e. an increase in $I$) results in a negative displacement and a positive productivity effect. New tasks (i.e. an increase in $N$) results in positive reinstatement and productivity effects.

## Aggregate demand for capital and equilibrium rental rate

- The market clearing condition for capital is:

$$K = \int_{N-1}^{N} k(z)dz = \int_{N-1}^{I} \frac{Y}{A^K \gamma^K(z)} \left[\frac{R}{A^K \gamma^K(z)}\right]^{-\sigma} dz$$

- Re-arranging terms gives the equilibrium rental rate:

$$\boxed{R = \left[\frac{Y}{K} \int_{N-1}^{I} [A^K \gamma^K(z)]^{\sigma-1} dz\right]^{\frac{1}{\sigma}}}$$

- We can use expressions for $W$ and $R$ above in $P = MC$ to derive an expression for aggregate output $Y$ in equilibrium.

## The aggregate price index in equilibrium

- Profit maximization implies that price equals marginal costs:

$$P = \left[\int_{N-1}^{N} p(z)^{1-\sigma} dz\right]^{\frac{1}{1-\sigma}} \equiv 1$$

- This implies that:

$$\int_{N-1}^{N} p(z)^{1-\sigma} dz = 1$$

- Using the expressions for $p(z)$:

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

# Aggregate output in equilibrium

- Using equilibrium expressions for $W$ and $R$ and rearranging terms gives:

$$Y^{\frac{\sigma-1}{\sigma}} = \left[\int_{N-1}^{I} \gamma^K(z)^{\sigma-1} dz\right]^{\frac{1}{\sigma}} [A^K K]^{\frac{\sigma-1}{\sigma}} + \left[\int_{I}^{N} \gamma^L(z)^{\sigma-1} dz\right]^{\frac{1}{\sigma}} [A^L L]^{\frac{\sigma-1}{\sigma}} \qquad \text{(A2)}$$

- We can define $\Pi(I, N)$ and $\Gamma(I, N)$ such that:

$$Y = \Pi(I, N) \left[ [1 - \Gamma(I, N)]^{\frac{1}{\sigma}} [A^K K]^{\frac{\sigma-1}{\sigma}} + \Gamma(I, N)^{\frac{1}{\sigma}} [A^L L]^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

# A microfounded aggregate CES production function

$$Y = \Pi(I,N)\left[[1-\Gamma(I,N)]^{\frac{1}{\sigma}}\left[A^K K\right]^{\frac{\sigma-1}{\sigma}} + \Gamma(I,N)^{\frac{1}{\sigma}}\left[A^L L\right]^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

with **task content of production** given by:

$$\Pi(I,N) \equiv \left[\int_{N-1}^{I} \gamma^K(z)^{\sigma-1} dz + \int_{I}^{N} \gamma^L(z)^{\sigma-1} dz\right]^{\frac{1}{\sigma-1}} \tag{A4}$$

$$\Gamma(I,N) \equiv \left[\int_{I}^{N} \gamma^L(z)^{\sigma-1} dz\right] \Pi(I,N)^{1-\sigma} \tag{A3}$$

with **factor-augmenting** technological change given by:

$A^K \uparrow$ if capital-augmenting and $A^L \uparrow$ if labor-augmenting

## Microfounded aggregate production functions

- This can be summarized by:

$$Y = \Pi(I, N) F(A^K K, A^L L; \Gamma(I, N))$$

where **technological change** works through:

1. **Changing task content** through a TFP-term $\Pi(I, N)$ and the distribution parameter $\Gamma(I, N) \in (0, 1)$
2. **Factor-augmenting** through $A^K \uparrow$ or $A^L \uparrow$

- We assumed a CES task production function.
- We could also assume a Cobb-Douglas task production function (as in Acemoglu & Restrepo[19]).

## A microfounded aggregate Cobb-Douglas production function

$$Y = \Pi(I,N)\left[\frac{A^K K}{1-\Gamma(I,N)}\right]^{1-\Gamma(I,N)}\left[\frac{A^L L}{\Gamma(I,N)}\right]^{\Gamma(I,N)}$$

with **task content of production** given by:

$$\Pi(I,N) \equiv \exp\left[\int_{N-1}^{I} \ln(\gamma^K(z))dz + \int_{I}^{N} \ln(\gamma^L(z))dz\right]$$

$$\Gamma(I,N) \equiv N - I \text{ and } 1-\Gamma(I,N) = I - N + 1$$

with **factor-augmenting** technological change given by:

$$A^K \uparrow \text{ if capital-augmenting and } A^L \uparrow \text{ if labor-augmenting}$$

# Microfounded aggregate production functions

- We have derived an aggregate production function where differential technological change works through different channels.
- In particular, technological progress changes the distribution parameter and the Hicks-neutral TFP term.
- Task models provide microfoundations for changes in the distribution parameter and TFP due to technical progress.
- It assumes that automation of labor tasks and the creation of new labor-intensive tasks results in a reallocation of factors across tasks and overall productivity effects.

## Factor shares

- The labor share is given by $s_L = WL/Y$.

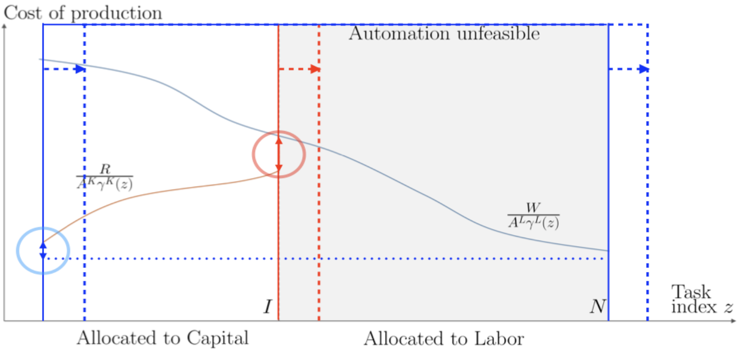
- Using the expressions for $W$ and $Y$ above gives:

$$s_L = \left[1 + [\frac{1-\Gamma(I,N)}{\Gamma(I,N)}]^{\frac{1}{\sigma}} [\frac{A^K K}{A^L L}]^{\frac{\sigma-1}{\sigma}}\right]^{-1} \qquad \text{(A5)}$$

- Using the expression for $W/R$ in equilibrium gives:

$$s_L = \left[1 + [\frac{1-\Gamma(I,N)}{\Gamma(I,N)}][\frac{A^L}{W}\frac{R}{A^K}]^{1-\sigma}\right]^{-1} \qquad \text{(A4)}$$

- Given constant returns to scale, $s_K = 1 - s_L$.




Efficiencies at marginal tasks: equilibrium assumptions

## Equilibrium assumptions revisited

- To ensure that technological progress raises productivity, we assumed that:

$$\frac{A^L\gamma^L(I)}{A^K\gamma^K(I)} < \frac{W}{R} < \frac{A^L\gamma^L(N)}{A^K\gamma^K(N-1)} \tag{A7}$$

- Using the expression for $W/R$, this is equivalent to assuming:

$$\frac{K}{L} > \frac{1-\Gamma(I,N)}{\Gamma(I,N)}\left[\frac{A^L}{A^K}\frac{\gamma^L(I)}{\gamma^K(I)}\right]^{\sigma}$$

$$\frac{K}{L} < \frac{1-\Gamma(I,N)}{\Gamma(I,N)}\left[\frac{A^L}{A^K}\frac{\gamma^L(N)}{\gamma^K(N-1)}\right]^{\sigma} \tag{A6}$$

# 1. Conceptual Framework

## The impact of automation on factor demands

- Using the expression for $W$, the impact of automation on labor demand is given by:

$$\frac{d\ln(W)}{dI} = \underbrace{\frac{1}{\sigma}\frac{d\ln(Y/L)}{dI}}_{\text{Productivity effect}>0} \underbrace{-\frac{1}{\sigma}\frac{\gamma_L(I)^{\sigma-1}}{\int_I^N \gamma^L(z)^{\sigma-1}dz}}_{\text{Displacement effect}<0}$$

- Using the expression for $R$, the impact of automation on capital demand is given by:

$$\frac{d\ln(R)}{dI} = \underbrace{\frac{1}{\sigma}\frac{d\ln(Y/K)}{dI}}_{\text{Productivity effect}>0} \underbrace{+\frac{1}{\sigma}\frac{\gamma_K(I)^{\sigma-1}}{\int_{N-1}^I \gamma^K(z)^{\sigma-1}dz}}_{\text{Expansion effect}>0}$$

## The impact of new tasks on factor demands

- Using the expression for $W$, the impact of new tasks on labor demand is given by:

$$\frac{d\ln(W)}{dN} = \underbrace{\frac{1}{\sigma}\frac{d\ln(Y/L)}{dN}}_{\text{Productivity effect}>0} \underbrace{+\frac{1}{\sigma}\frac{\gamma_L(N)^{\sigma-1}}{\int_I^N \gamma^L(z)^{\sigma-1}dz}}_{\text{Reinstatement effect}>0}$$

- Using the expression for $R$, the impact of new tasks on capital demand is given by:

$$\frac{d\ln(R)}{dN} = \underbrace{\frac{1}{\sigma}\frac{d\ln(Y/K)}{dN}}_{\text{Productivity effect}>0} \underbrace{-\frac{1}{\sigma}\frac{\gamma_K(N-1)^{\sigma-1}}{\int_{N-1}^I \gamma^K(z)^{\sigma-1}dz}}_{\text{Destruction effect}<0}$$

## The productivity effects from automation and new tasks

- Using the equation (A2), the productivity effect from automation is given by:

$$\frac{d\ln(Y)}{dI} = \frac{1}{\sigma-1}\left[\left[\frac{R}{A^K\gamma^K(I)}\right]^{1-\sigma} - \left[\frac{W}{A^L\gamma^L(I)}\right]^{1-\sigma}\right] > 0$$

- Using the equation (A2), the productivity effect from new tasks is given by:

$$\frac{d\ln(Y)}{dN} = \frac{1}{\sigma-1}\left[\left[\frac{W}{A^L\gamma^L(N)}\right]^{1-\sigma} - \left[\frac{R}{A^K\gamma^K(N-1)}\right]^{1-\sigma}\right] > 0$$

## An alternative way to write changes in labor demand

- The labor share is given by:

$$s_L = \frac{WL}{Y} = \left[1 + [\frac{1-\Gamma(I,N)}{\Gamma(I,N)}]^{\frac{1}{\sigma}} [\frac{A^K K}{A^L L}]^{\frac{\sigma-1}{\sigma}}\right]^{-1} \quad \text{(A5)}$$

- Alternative ways to write the change in labor demand due to automation and new tasks therefore are:

$$\frac{d\ln(W)}{dI} = \frac{d\ln(Y/L)}{dI} + \frac{d\ln(s_L)}{dI} \quad \text{(A8)}$$

$$\frac{d\ln(W)}{dN} = \frac{d\ln(Y/L)}{dN} + \frac{d\ln(s_L)}{dN}$$

- To rewrite (A8), totally differentiate $\ln(s_L)$ using (A5).

# Differentiating the labor share

- Totally differentiating the labor share using (A5) gives:

$$d\ln(s_L) = \frac{1}{\sigma}\frac{1-s_L}{1-\Gamma}d\ln(\Gamma(I,N)) - \frac{\sigma-1}{\sigma}[1-s_L]d\ln(\frac{A^K}{A^L}\frac{K}{L})$$

- The first term captures the impact of automation and new tasks, and the second term the impact of factor-augmenting changes (or changes in $K$ and $L$).

- Alternatively, totally differentiating (A4) instead of (A5) gives:

$$d\ln(s_L) = \frac{1-s_L}{1-\Gamma}d\ln(\Gamma(I,N)) - [1-\sigma][1-s_L]d\ln(\frac{A^L}{A^K}\frac{R}{W})$$

# The impact of automation and new tasks on labor demand

- The impact of automation on labor demand is given by:

$$\frac{d\ln(W)}{dI} = \underbrace{\frac{d\ln(Y/L)}{dI}}_{\text{Productivity effect}>0} + \underbrace{\frac{1}{\sigma}\frac{1-s_L}{1-\Gamma}\frac{d\ln(\Gamma(I,N))}{dI}}_{\text{Displacement effect}<0}$$

with $d\ln(\Gamma)/dI < 0$ from equation (A3).

- The impact of new tasks on labor demand is given by:

$$\frac{d\ln(W)}{dN} = \underbrace{\frac{d\ln(Y/L)}{dN}}_{\text{Productivity effect}>0} + \underbrace{\frac{1}{\sigma}\frac{1-s_L}{1-\Gamma}\frac{d\ln(\Gamma(I,N))}{dN}}_{\text{Reinstatement effect}>0}$$

with $d\ln(\Gamma)/dN > 0$ from equation (A3).

## Automation, new tasks, and the labor share

- Assuming only automation and new tasks, we have that:

$$d\ln(s_L) = \frac{1}{\sigma}\frac{1-s_L}{1-\Gamma}\left[\underbrace{\frac{d\ln(\Gamma(I,N))}{dI}}_{<0} + \underbrace{\frac{d\ln(\Gamma(I,N))}{dN}}_{>0}\right]$$

- Automation decreases the labor share (despite productivity effects) whereas the creation of new labor-intensive tasks increases the labor share.

- A constant labor share suggests that both forces balance each other out, a falling labor share suggests that automation is more important than the creation of new labor intensive tasks.

## Factor-augmenting technological progress and labor demand

- The impact of labor-augmenting progress is given by:

$$\frac{d\ln(W)}{d\ln(A^L)} = s_L \qquad \text{(Productivity effect)}$$
$$+ \frac{\sigma - 1}{\sigma}[1 - s_L] \qquad \text{(Substitution effect)}$$

- The impact of capital-augmenting progress is given by:

$$\frac{d\ln(W)}{d\ln(A^K)} = [1 - s_L] \qquad \text{(Productivity effect)}$$
$$+ \frac{1 - \sigma}{\sigma}[1 - s_L] \qquad \text{(Substitution effect)}$$

# 1. Conceptual Framework

# A multi-sector economy

The economy-wide wage bill, $WL$, is given by:

$$WL = \sum_i W_i L_i = \sum_i P_i Y_i s_i^L = \sum_i Y \chi_i s_i^L$$

with $i$ sector $i$ and where

$$s_i^L = \frac{W_i L_i}{P_i Y_i} \qquad \text{the labor share in sector i}$$

$$Y = \sum_i P_i Y_i \qquad \text{economy-wide value added}$$

$$\chi_i = \frac{P_i Y_i}{Y} \qquad \text{sector i's share in total value added}$$

## Decomposing changes in the aggregate wage bill

- Totally differentiating the economy-wide wage bill gives:

$$d(WL) = \sum_i dY \chi_i s_i^L + \sum_i Y d\chi_i s_i^L + \sum_i Y \chi_i ds_i^L$$

- Dividing both sides by $WL$ gives:

$$d\ln(WL) = d\ln(Y) + \sum_i \frac{s_i^L}{s^L} d\chi_i + \sum_i l_i d\ln(s_i^L)$$

with $s^L$ the aggregate labor share and

$$l_i \equiv \frac{W_i L_i}{WL} \text{ such that } \sum_i l_i = 1$$

# Decomposing changes in the aggregate wage bill

- Using the expression for $d\ln(s_i^L)$ above gives equation (A9):

$$
\begin{aligned}
d\ln(WL) = & d\ln(Y) && \text{(Productivity effect)} \\
& + \sum_i \frac{s_i^L}{s^L} d\chi_i && \text{(Composition effect)} \\
& + \sum_i l_i [1-\sigma][1-s_i^L] d\ln\left(\frac{A_i^K W_i}{A_i^L R_i}\right) && \text{(Subst. effect)} \\
& + \sum_i l_i \frac{1-s_i^L}{1-\Gamma_i} d\ln\Gamma_i && \text{(Change task content)}
\end{aligned}
$$

- The last two terms capture changes in $d\ln(s_i^L)$ due to changes in relative effective factor prices (Substitution effect) and $dI$ or $dN$ (Change task content).

# Displacement versus reinstatement effects

- The change in task content due to $dI$ or $dN$ was given by:

$$\sum_i l_i \frac{1 - s_i^L}{1 - \Gamma_i} d \ln \Gamma_i$$

which is measured as a residual using equation (A9).

- It consists of displacement and reinstatement effect given by:

$$\text{Displacement} = \sum_i l_i \min \left[0, \frac{1 - s_i^L}{1 - \Gamma_i} d \ln \Gamma_i \right] \tag{A14a}$$

$$\text{Reinstatement} = \sum_i l_i \max \left[0, \frac{1 - s_i^L}{1 - \Gamma_i} d \ln \Gamma_i \right] \tag{A14b}$$

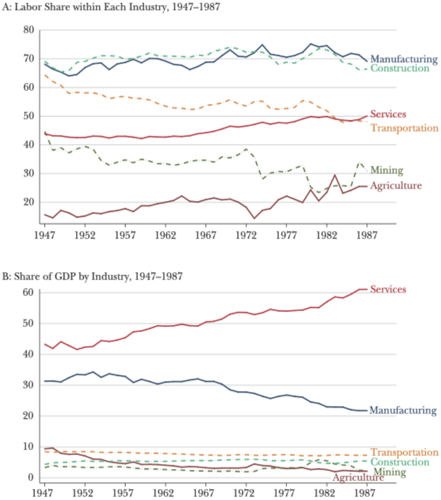
# 2. Sources of Labor Demand Growth in the United States

## Data

- Data for 1987-2017: BEA GDP by Industry Accounts for measures of $P_i Y_i$ and $W_i L_i$, and BLS Multifactor Productivity Tables for measures of $W_i$ and $R_i$ for 61 private NAICS industries.
- Data for 1947-1987: BEA GDP by Industry Accounts for measures of $P_i Y_i$ and $W_i L_i$ for 58 private NAICS industries, and $W_i$ and $R_i$ are computed using a similar procedure as for the period 1987-2017.
- Decompositions above were exact and have to be rewritten for discrete changes (using first-order Taylor approximations).

## 2. Sources of Labor Demand Growth in the United States

*Figure 2*
**The Labor Share and Sectoral Evolutions, 1947–1987**

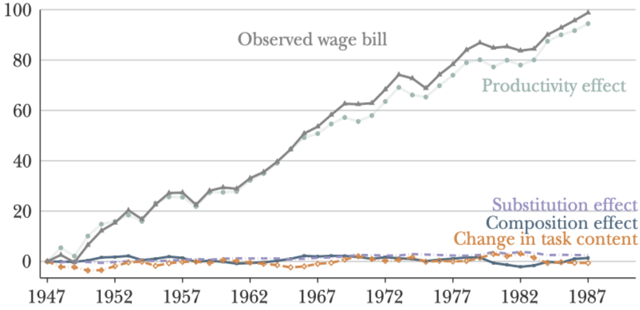



*Source:* Authors using data from the US Bureau of Economic Analysis industry accounts.
*Note:* The top panel shows the labor share in value added in services, manufacturing, construction, transportation, mining and agriculture between 1947 and 1987, while the bottom panel shows the share of value added in these sectors relative to GDP.

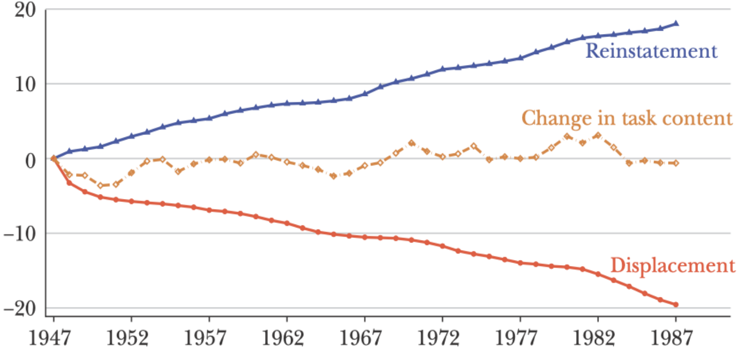
*Figure 3*

**Sources of Changes in Labor Demand, 1947–1987**

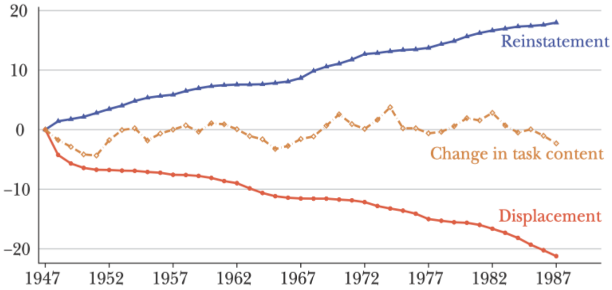
A: Wage Bill, 1947–1987



B: Change in Task Content of Production, 1947–1987



C: Manufacturing Task Content of Production, 1947–1987

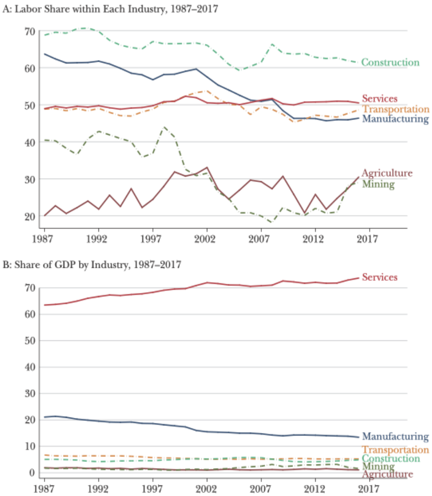



*Source:* Authors' calculations.

*Note:* The top panel presents the decomposition of the wage bill divided by population between 1947 and 1987. The middle and bottom panels present our estimates of the displacement and reinstatement effects for the entire economy and the manufacturing sector, respectively. See text for the details of the estimation of the changes in task content and displacement and reinstatement effects.

## 2. Sources of Labor Demand Growth in the United States

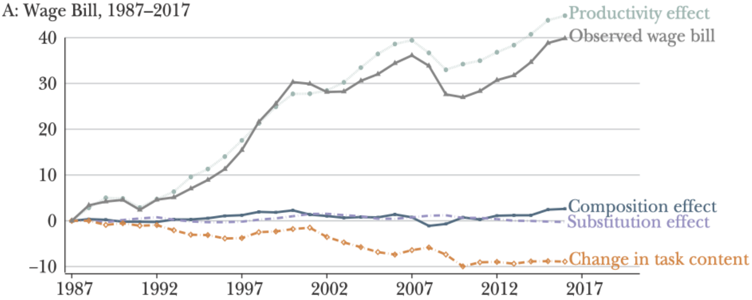
*Figure 4*
**The Labor Share and Sectoral Evolutions, 1987–2017**



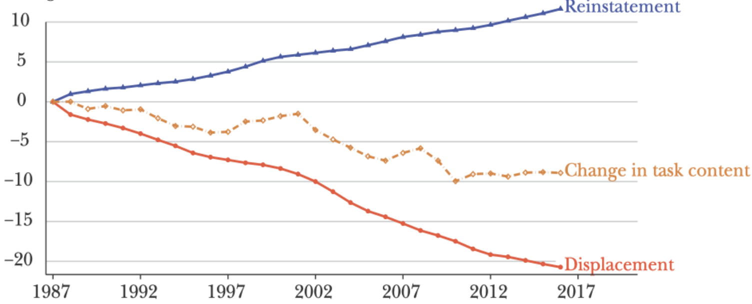

*Source:* Authors using data from the US Bureau of Economic Analysis industry accounts and the Bureau of Labor Statistics.
*Note:* The top panel shows the labor share in value added in services, manufacturing, construction, transportation, mining, and agriculture between 1987 and 2017, while the bottom panel shows the share of value added in these sectors relative to GDP.

*Figure 5*

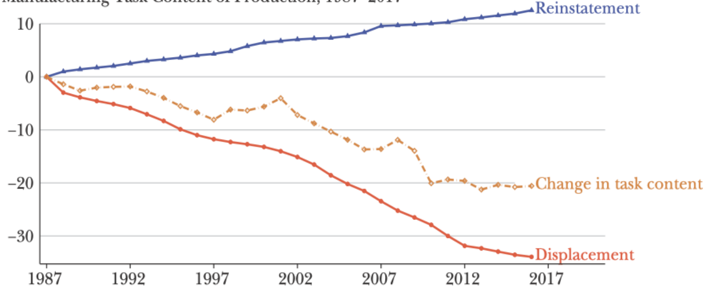
**Sources of Changes in Labor Demand, 1987–2017**



B: Change in Task Content of Production, 1987–2017



C: Manufacturing Task Content of Production, 1987–2017

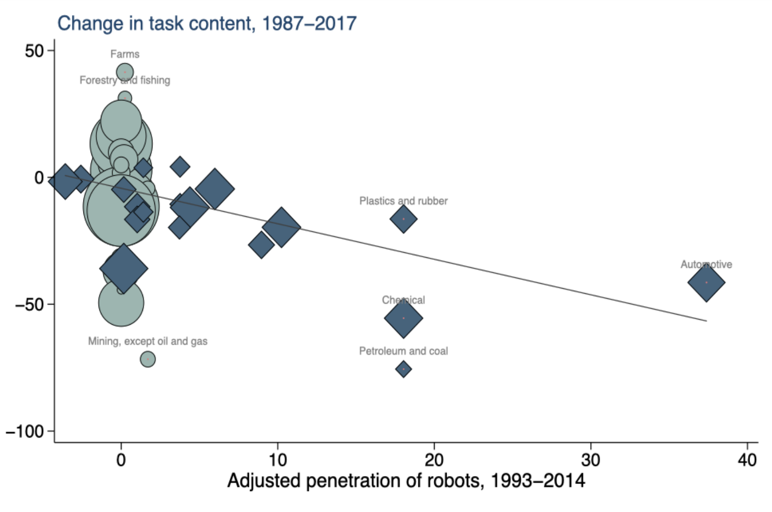


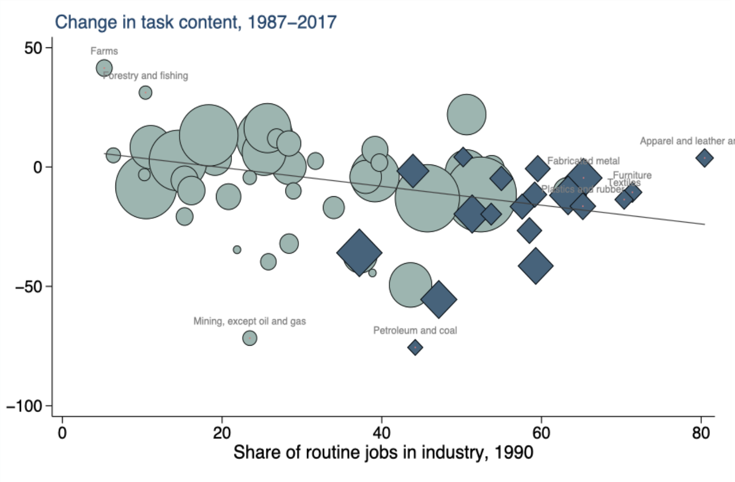

*Source:* Authors' calculations.
*Note:* The top panel presents the decomposition of wage bill divided by population between 1987 and 2017. The middle and bottom panels present our estimates of the displacement and reinstatement effects for the entire economy and the manufacturing sector, respectively. See text for the details of the estimation of the changes in task content and displacement and reinstatement effects.

## 2. Sources of Labor Demand Growth in the United States

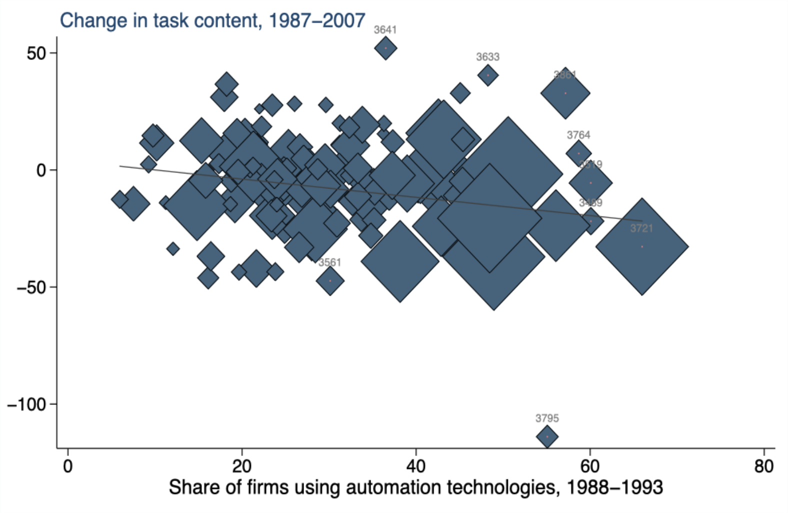
# Changing task content and automation

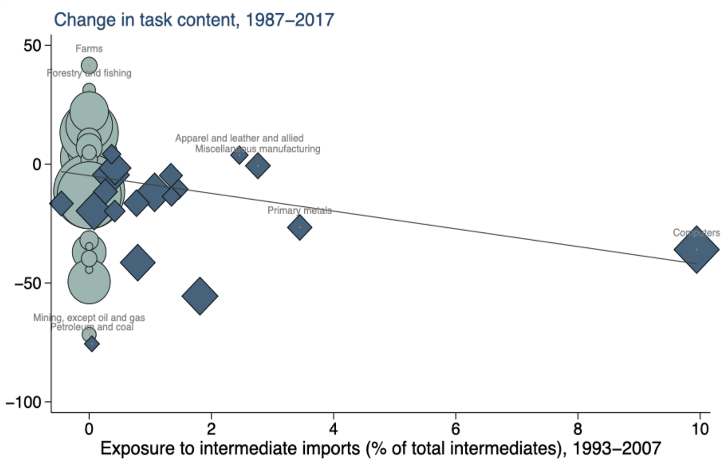
- The measured change in task content might capture something different than the impact of $dI$.
- Correlate changes in task content with other proxies for industry automation for 1987-2014 (Figure A4):
    1. The penetration of robots in 19 (manufacturing) industries.
    2. The share of routine jobs in 1990.
    3. The share of firms across 148 manufacturing industries using automation technologies.


Change in task content, 1987–2017
50
0
−50
−100
Farms
Forestry and fishing
Plastics and rubber
Automotive
Chemical
Mining, except oil and gas
Petroleum and coal
0
10
20
30
40
Adjusted penetration of robots, 1993–2014



Change in task content, 1987–2017
50
0
−50
−100
Farms
Forestry and fishing
Apparel and leather and allied
Fabricated metal
Furniture
Textiles
Plastics and rubber
Mining, except oil and gas
Petroleum and coal
0
20
40
60
80
Share of routine jobs in industry, 1990


Change in task content, 1987–2007
3641
3633
3764
3561
3721
3795
50
0
−50
−100
0
20
40
60
80
Share of firms using automation technologies, 1988–1993



Change in task content, 1987–2017
50
0
−50
−100
Farms
Forestry and fishing
Apparel and leather and allied
Miscellaneous manufacturing
Primary metals
Computers
Mining, except oil and gas
Petroleum and coal
0
2
4
6
8
10
Exposure to intermediate imports (% of total intermediates), 1993–2007

*Table 1*

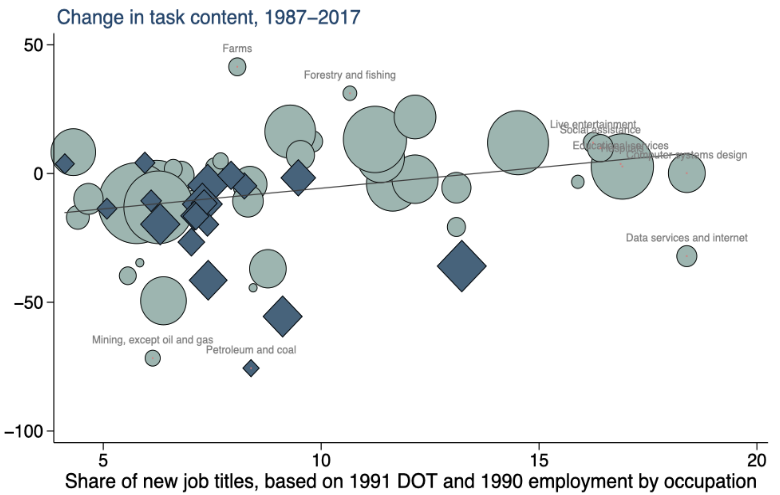
**Relationship between Change in Task Content of Production and Proxies for Automation and New Tasks**

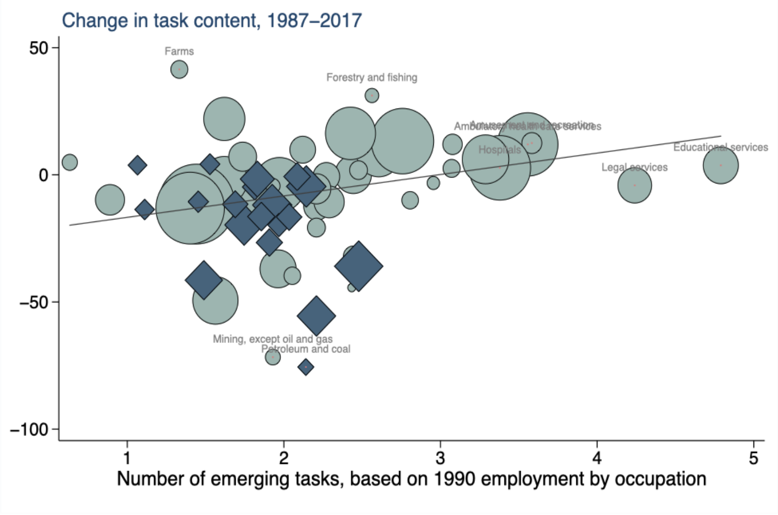
| | *Raw data* (1) | *Controlling for manufacturing* (2) | *Controlling for Chinese import and offshoring* (3) |
|---|---|---|---|
| *Proxies for automation technologies:* | | | |
| Adjusted penetration of robots, 1993–2014 | –1.404 | –0.985 | –1.129 |
| | (0.377) | (0.369) | (0.362) |
| Observations | 61 | 61 | 61 |
| $R^2$ | 0.18 | 0.21 | 0.27 |
| Share of routine jobs in industry, 1990 | –0.394 | –0.241 | –0.321 |
| | (0.122) | (0.159) | (0.164) |
| Observations | 61 | 61 | 61 |
| $R^2$ | 0.14 | 0.19 | 0.27 |
| Share of firms using automation technologies, 1988–1993 (SMT data) | –0.390 | | –0.397 |
| | (0.165) | | (0.166) |
| Observations | 148 | | 148 |
| $R^2$ | 0.08 | | 0.09 |

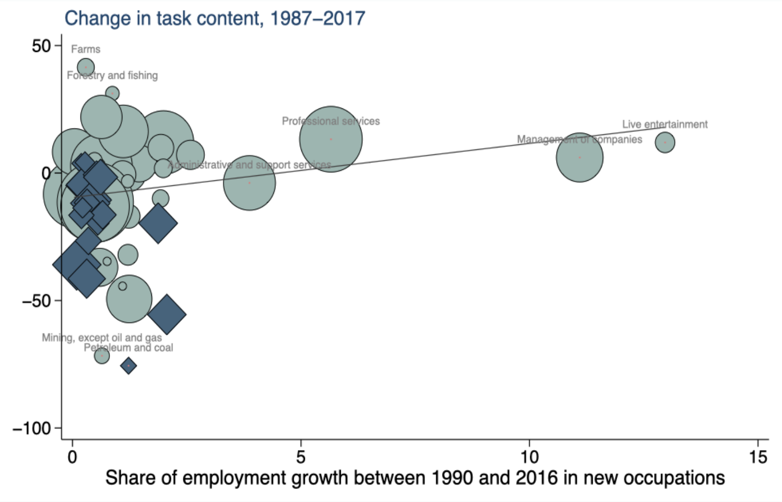
## Changing task content and creation of new tasks

Similarly, correlate changes in task content with proxies for new task creation for 1987-2014 (Figure A5):

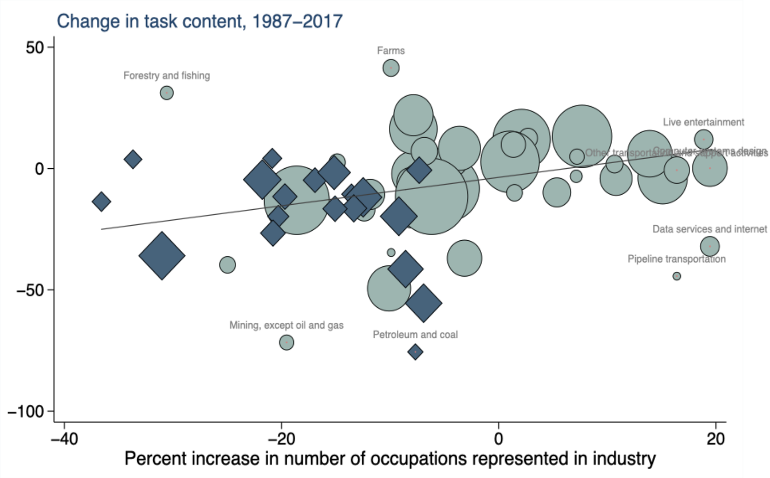
1. The 1990 share of employment in occupations with a large fraction of new job titles using 1991 DOT.
2. The 1990 share of employment in occupations with a large number of “emerging tasks” according to O*NET.
3. The share of employment growth in an industry accounted for by “new occupations” present in 2016 but not in 1990.
4. The percent increase in the number of occupations in an industry between 1990 and 2016.


Change in task content, 1987–2017
50
0
−50
−100
5
10
15
20
Share of new job titles, based on 1991 DOT and 1990 employment by occupation
Farms
Forestry and fishing
Live entertainment
Social assistance
Educational services
Hospitals
Computer systems design
Data services and internet
Mining, except oil and gas
Petroleum and coal


Change in task content, 1987–2017
50
0
–50
–100
Farms
Forestry and fishing
Hospitals
Educational services
Legal services
Mining, except oil and gas
Petroleum and coal
1
2
3
4
5
Number of emerging tasks, based on 1990 employment by occupation



Change in task content, 1987–2017
50
0
−50
−100
Farms
Forestry and fishing
Professional services
Live entertainment
Management of companies
Administrative and support services
Mining, except oil and gas
Petroleum and coal
0
5
10
15
Share of employment growth between 1990 and 2016 in new occupations


Change in task content, 1987–2017
Farms
Forestry and fishing
Live entertainment
Data services and internet
Pipeline transportation
Mining, except oil and gas
Petroleum and coal
50
0
−50
−100
−40
−20
0
20
Percent increase in number of occupations represented in industry

| | | | |
|---|---|---|---|
| *Proxies for new tasks:* | | | |
| Share of new job titles, based on 1991 DOT* and 1990 employment by occupation | 1.609 | 1.336 | 1.602 |
| | (0.523) | (0.530) | (0.541) |
| Observations | 61 | 61 | 61 |
| $R^2$ | 0.12 | 0.23 | 0.32 |
| Number of emerging tasks, based on 1990 employment by occupation | 8.423 | 7.108 | 7.728 |
| | (2.261) | (2.366) | (2.418) |
| Observations | 61 | 61 | 61 |
| $R^2$ | 0.14 | 0.25 | 0.33 |
| Share of employment growth between 1990 and 2016 in new occupations | 2.121 | 1.638 | 1.646 |
| | (0.723) | (0.669) | (0.679) |
| Observations | 61 | 61 | 61 |
| $R^2$ | 0.08 | 0.20 | 0.26 |
| Percent increase in number of occupations represented in industry | 0.585 | 0.368 | 0.351 |
| | (0.156) | (0.207) | (0.215) |
| Observations | 61 | 61 | 61 |
| $R^2$ | 0.14 | 0.19 | 0.25 |

*Source:* Authors.

*Note:* The table reports estimates of the relationship between the change in task content of production between 1987 and 2017 and proxies for automation technologies and new tasks. Each row and column corresponds to a different regression model. Column 1 reports estimates of the bivariate relationship between change in task content of production and the indicated proxy at the industry level. Column 2 includes a dummy for manufacturing industries as a control. In addition, Column 3 controls for the increase in Chinese imports (defined as the increase in imports relative to US consumption between 1991 and 2011, as in Acemoglu et al. 2016) and the increase in offshoring (defined as the increase in the share of imported intermediates between 1993 and 2007, as in Feenstra and Hanson 1999). Except for the third row, which uses the Survey of Manufacturing Technologies (SMT), all regressions are for the 61 industries used in our analysis of the 1987–2017 period. When using the SMT, the regressions are for 148 detailed manufacturing industries. Standard errors robust against heteroskedasticity are in parenthesis. When using the measure of robot penetration, we cluster standard errors at the 19 industries for which this measure is available.

*The DOT is the *Dictionary of Occupational Titles*.

# 2. Sources of Labor Demand Growth in the United States

## Confounding factors

- Trade in final goods is captured by the productivity and composition effects (see Table 1).
- Offshoring changing task content does not seem important (see Table 1).
- Structural change is captured by the composition effect.
- Demographic changes (e.g. skill-upgrading, participation, aging) are captured by the substitution effect.
- Imperfections (e.g. bargaining, rent-sharing) are allowed as long as we remain on the labor demand curve.

# 2. Sources of Labor Demand Growth in the United States

## Why has the nature of technological progress changed?

- The innovation possibilities frontier may have shifted, facilitating automation and making the creation of new labor-intensive tasks more difficult (e.g. AI).
- Tax incentives for automation have increased relative to the creation of new labor-intensive tasks.
- Increasing market power of large tech companies with business models based on automation and small workforces.
- Declining government support for innovation with longer horizons (given that technologies that create new tasks bear fruit more slowly).

# 3. Concluding Remarks

# 3. Concluding Remarks

- This paper develops the most complete (and accessible) task-based model to study the effects of different technologies on labor demand.
- Automation shifts task content against labor, while the creation of new tasks improves it.
- These technologies are qualitatively different from factor-augmenting ones.
- Changes in task content can be inferred from data on labor shares, value added, and factor prices at the industry level.