MACROECONOMICS AND INEQUALITY

TASKS, AUTOMATION, AND WAGE INEQUALITY

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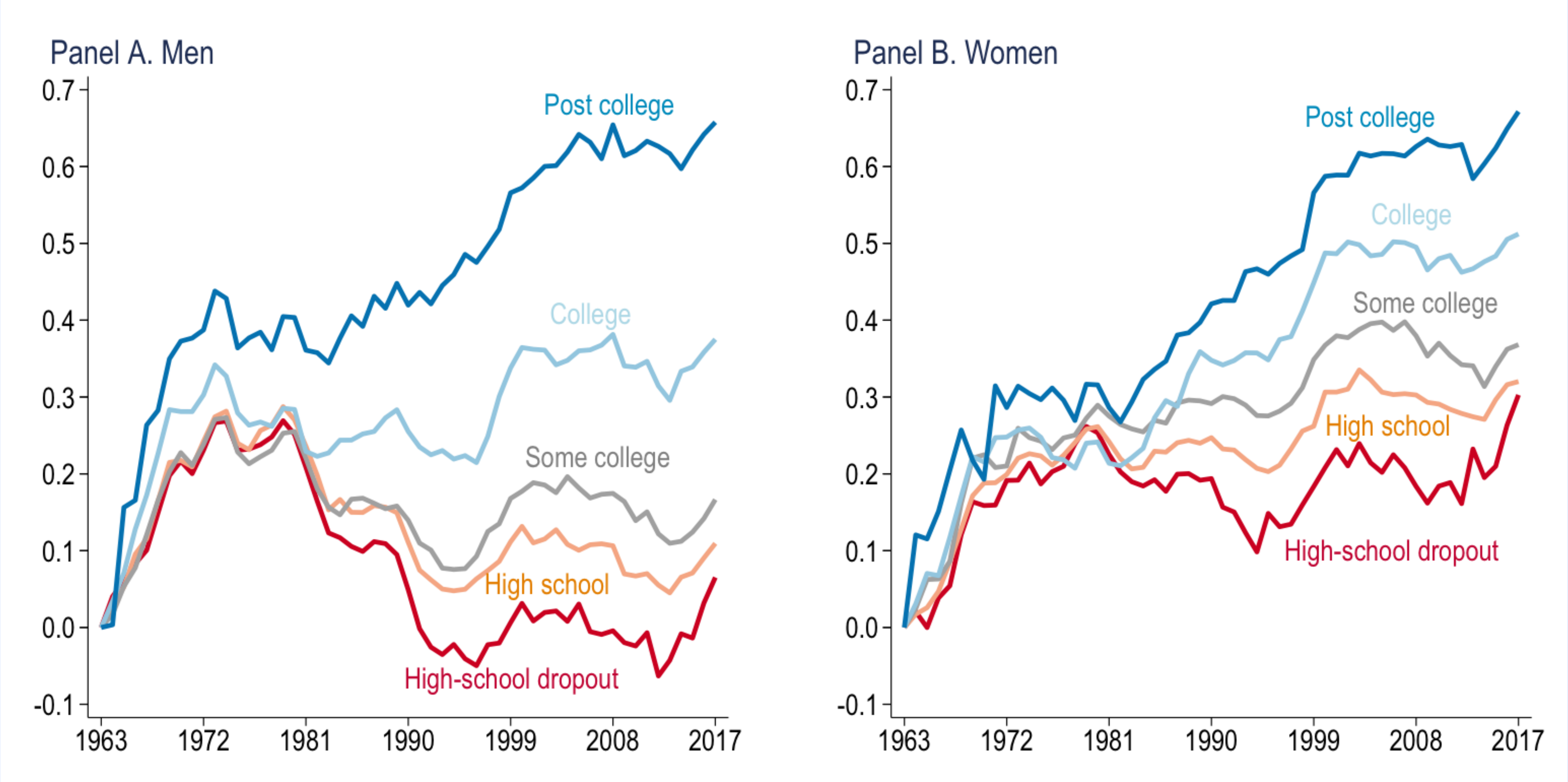
CONTENT

1. The task model of automation
2. Evidence of the displacement effect
3. Measuring task displacement
4. Quantifying the effect of task displacement
5. Research questions

THE RISE IN US WAGE INEQUALITY



Cumulative wage growth by group, 1963–2017. From Autor (2020)

THE CANONICAL MODEL

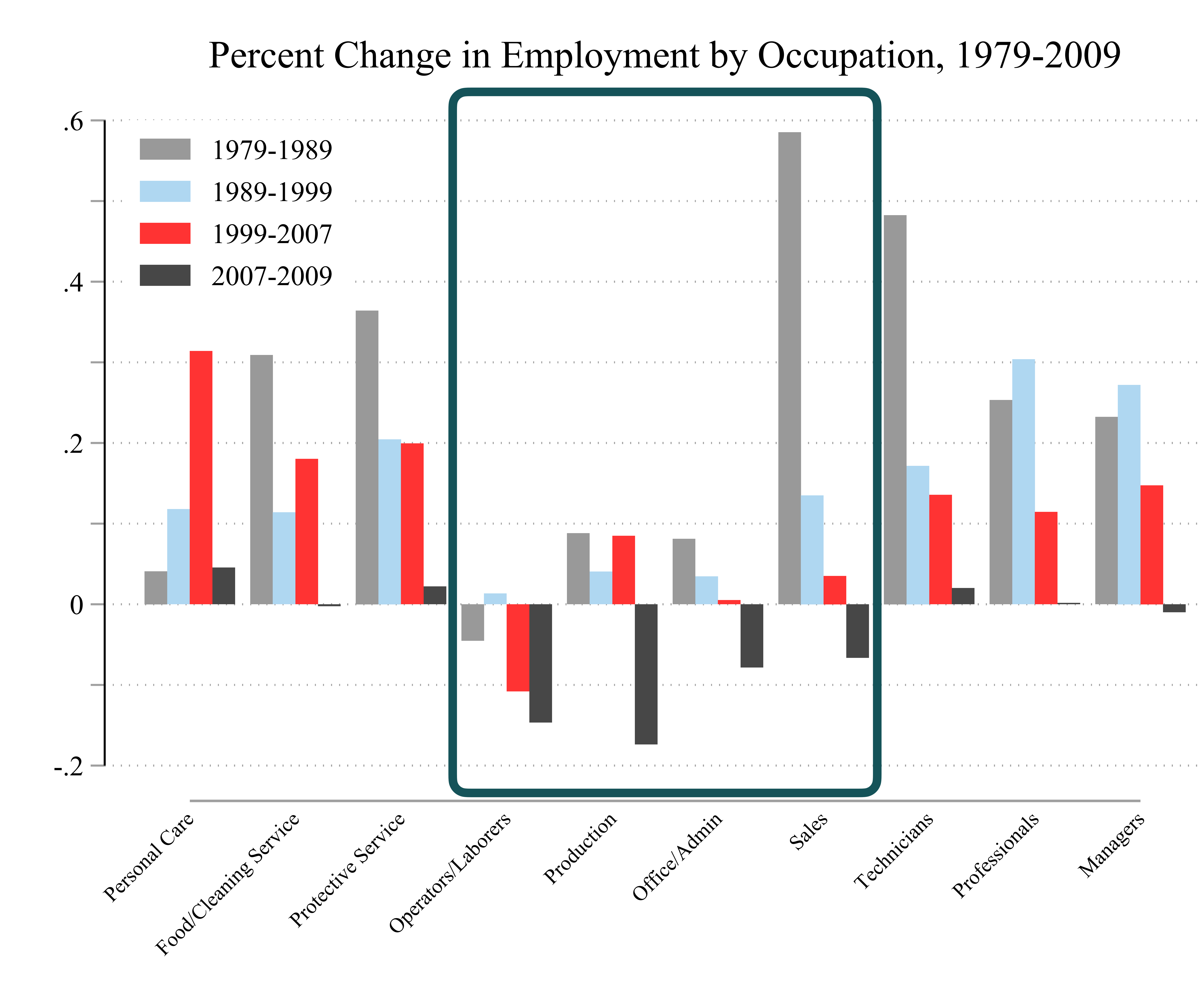
- Existing models of wage inequality emphasize **direct complementarities** between technology and skilled labor or capital and skilled labor:

$$y = f(A_h \cdot h, A_\ell \cdot \ell); \quad \sigma > 1; \quad A_h \uparrow$$

- direct complementarities with technology
- capital skill complementarity and lower capital prices

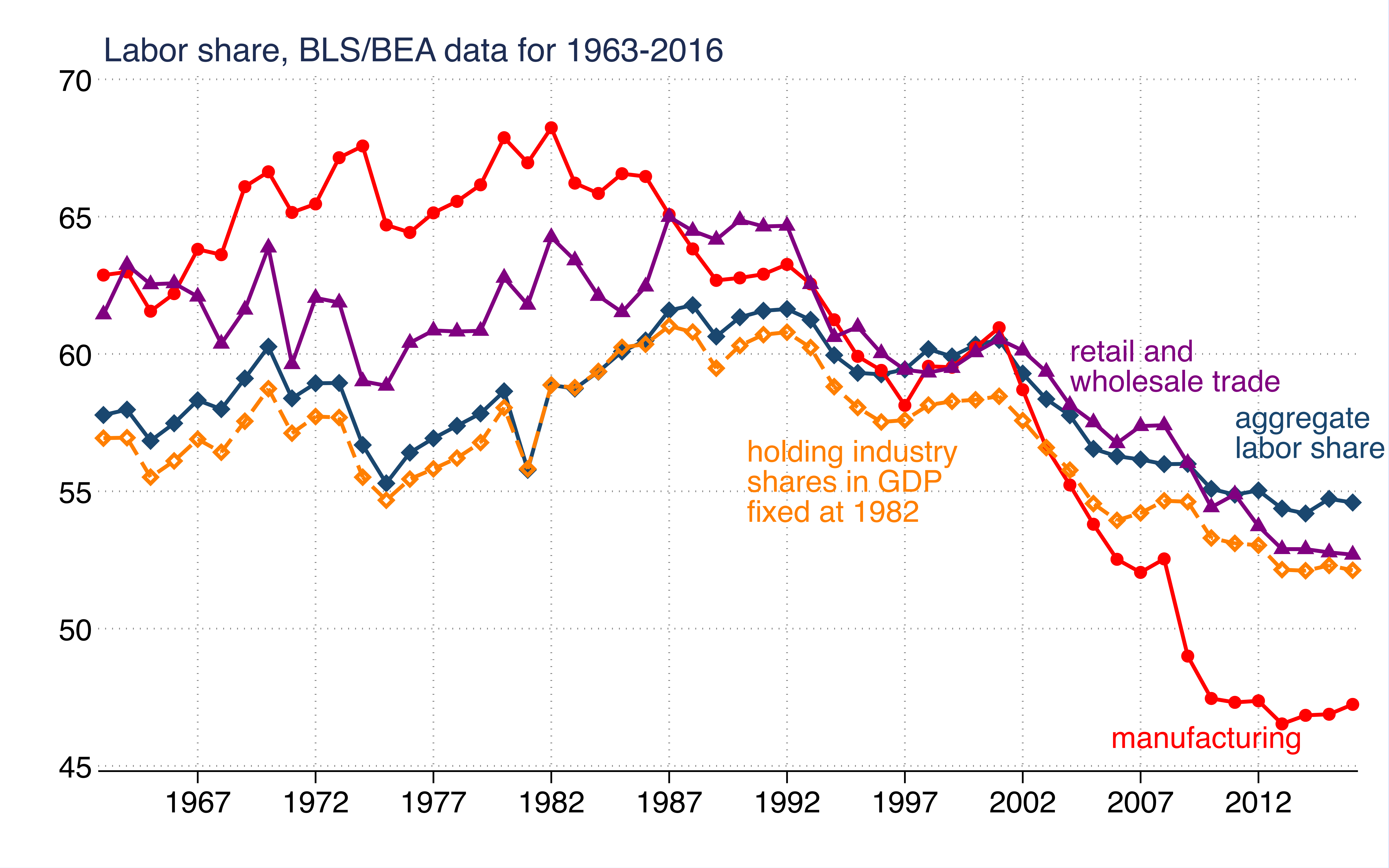
- These models imply **rising wages for all**, unless $A_\ell \downarrow$ …
- But what does it mean for technology to make some workers less productive?
- Standard model miss possibility that technology substitutes for labor in some tasks and sectors—automation or replacement.

LARGE CHANGES IN OCCUPATIONS AND TASKS PERFORMED BY WORKERS



- Decline in jobs intensive in **routine tasks**
- Not driven by changes in college completion or changes in workforce composition
- Observed within industries and sectors (not a corollary of decline in manufacturing)
- Visible in all decades (exception is sales in 80s)
- And in most OECD countries

LARGE DECLINE IN LABOR SHARE IN SOME SECTORS

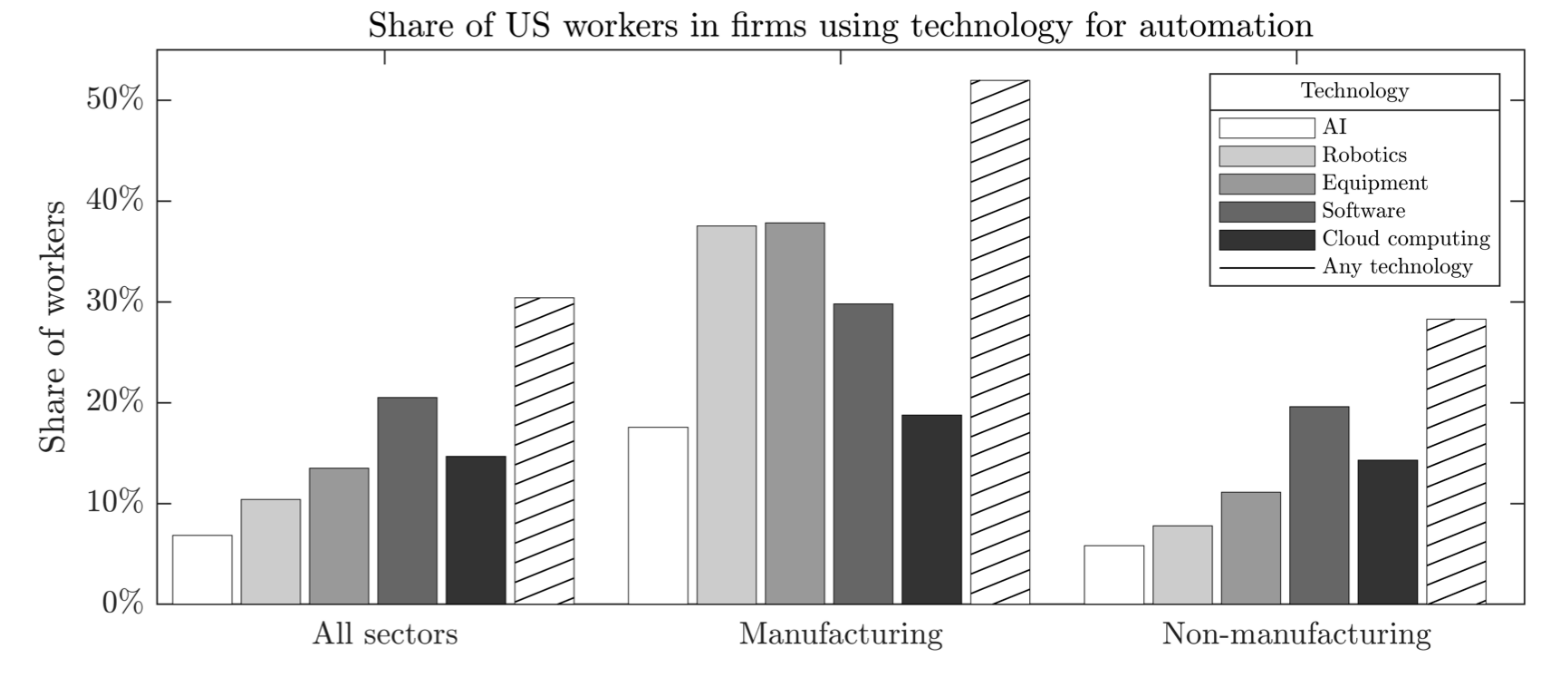


- Labor shares:

$$s_{\ell,i} = \frac{\text{wages}_i}{\text{value added}_i}$$

- If no changes in markups, labor shares informative of changes in technology
- Karabarbounis and Neiman (2014) argue that decline seen in most countries

IS AUTOMATION AND IMPORTANT DRIVER OF LABOR MARKET TRENDS?



from *Automation and the Workforce: A firm-level view using the 2019 Annual Business Survey*.

THE TASK MODEL (ACEMOGLU AND RESTREPO, 2022)

Output

$$y = \left(\frac{1}{M} \int_{\mathcal{T}} (M \cdot y(x))^{\frac{\lambda-1}{\lambda}} \cdot dx \right)^{\frac{\lambda}{\lambda-1}}$$

Factor-augmenting technologies

Tasks

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

Task-specific technologies

Factors' supply & Equilibrium

- capital produced from final good $c = y - \int_{\mathcal{T}} k(x)/q(x) \cdot dx$
- supply of labor fixed at $\ell_g = \int_{\mathcal{T}} \ell_g(x) \cdot dx$
- Equilibrium given by unique allocation that maximizes c

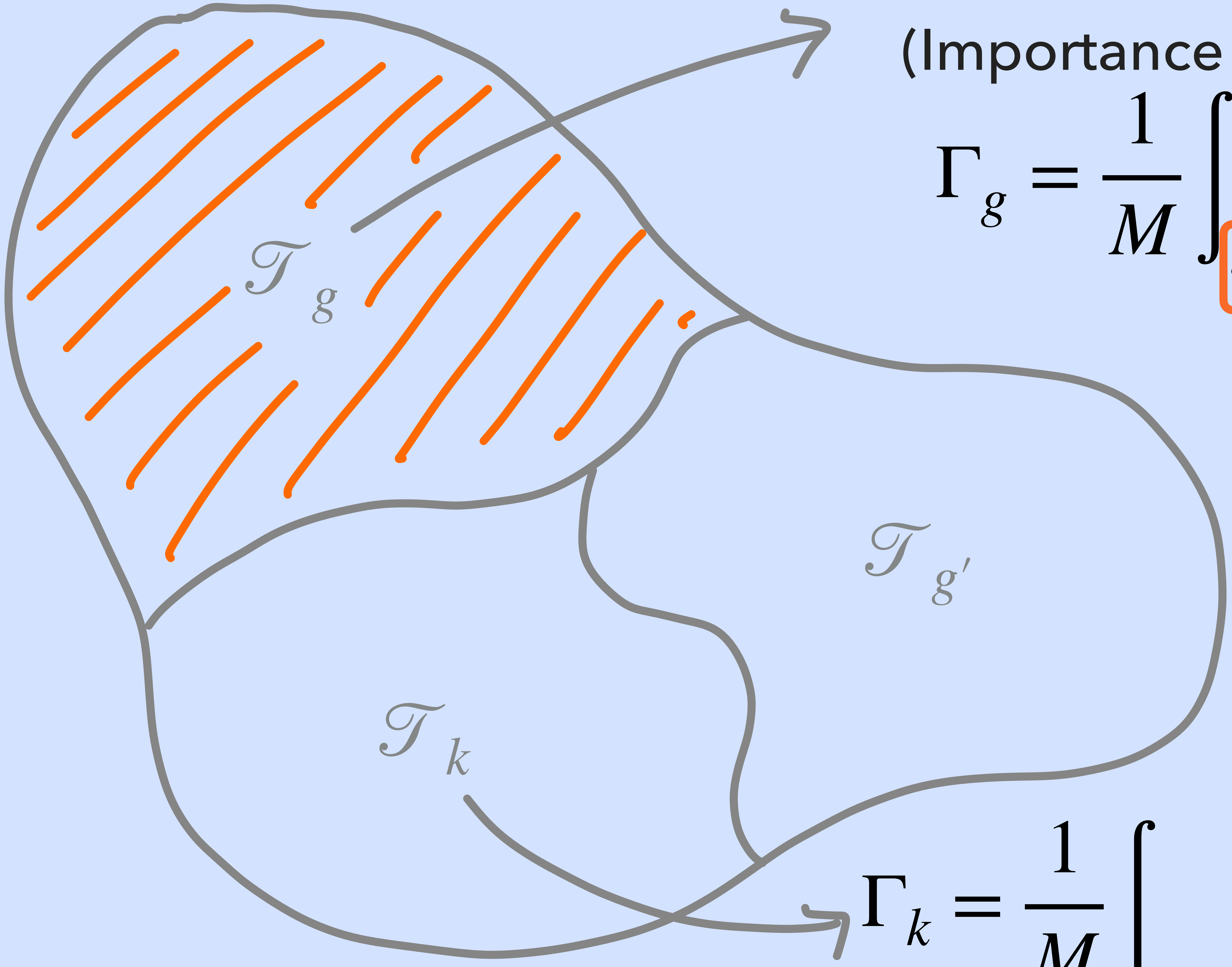
THE ALLOCATION OF TASKS AND TASK SHARES

Task shares, $\{\Gamma_g\}_g, \Gamma_k$

(Importance of tasks allocated to g)

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

Set of tasks allocated to g



$$\Gamma_k = \frac{1}{M}\int_{\mathcal{T}_k} (\psi_k(x) \cdot q(x))^{\lambda-1} \cdot dx$$

EQUILIBRIUM AND TASK SHARES

Output
$$y = \left(1 - A_k^{\lambda-1} \cdot \Gamma_k\right)^{\frac{\lambda}{1-\lambda}} \cdot \left(\sum_g \boxed{\Gamma_g^{\frac{1}{\lambda}}} \cdot (A_g \cdot \ell_g)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}$$

Wages
$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \boxed{\Gamma_g^{\frac{1}{\lambda}}}$$

Labor share
$$s_L = 1 - A_k^{\lambda-1} \cdot \boxed{\Gamma_k}$$

Differences with usual CES:

1. task shares determine CES shares
2. elasticity of subst. j and g, $\sigma_{jg} \geq \lambda$
3. term on front: roundabout production

EQUILIBRIUM AND TASK SHARES

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$$y = \left(1 - A_k^{\lambda-1} \cdot \Gamma_k\right)^{\frac{\lambda}{1-\lambda}} \cdot \left(\sum_g \boxed{\Gamma_g^{\frac{1}{\lambda}}} \cdot \left(A_g \cdot \ell_g\right)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}$$

Wages
$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \boxed{\Gamma_g^{\frac{1}{\lambda}}}$$

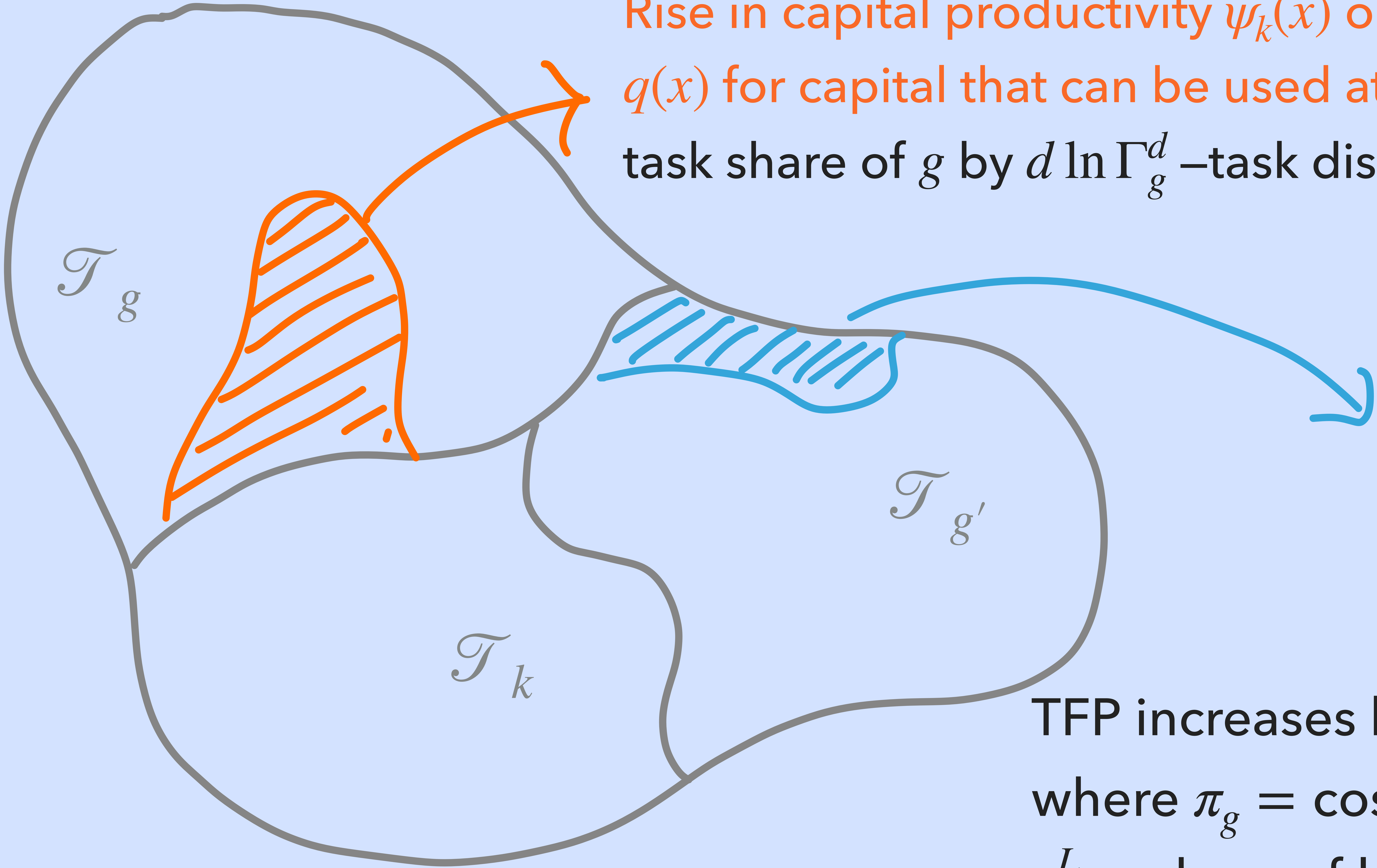
Labor share
$$s_L = 1 - A_k^{\lambda-1} \cdot \boxed{\Gamma_k}$$

Representation result:

Conditional on optimal task allocation, **task shares determine CES shares, wages, and labor share**

Solving for full equilibrium requires finding optimal task allocation.

EFFECTS OF AUTOMATION



Rise in capital productivity $\psi_k(x)$ or investment technology $q(x)$ for capital that can be used at tasks in $\mathcal{T}_g$: reduces task share of g by $d \ln \Gamma_g^d$ –task displacement

Ripple effects on g'

TFP increases by $s_g^L \cdot d \ln \Gamma_g^d \cdot \pi_g$ where π_g = cost-saving gains, and s_g^L = share of labor g in value added

EFFECTS OF AUTOMATION ON WAGES: NO RIPPLE EFFECTS

- To gain intuition start with case with **no ripple effects.**
- Change in wages due to automation technologies:

$$d\ln w_g = \frac{1}{\lambda} \cdot d\ln y - \frac{1}{\lambda} \cdot \boxed{d\ln \Gamma_g^d}$$

Direct effect from task displacement

$$\sum_g s_g^L \cdot d\ln w_g = d\ln \mathsf{tfp} = \sum_g s_g^L \cdot \boxed{d\ln \Gamma_g^d \cdot \pi_g}$$

Productivity effects

- Direct effect of automation is to reduce relative (and in some cases real) wages of displaced workers and reduce the labor share. **Evidence?**

EVIDENCE OF DIRECT DISPLACEMENT EFFECTS

- Robots and Jobs: Evidence from US Labor Markets (Acemoglu-Restrepo, 2020)
- Competing with Robots: Firm-level Evidence from France (Acemoglu-Lelarge-Restrepo, 2020)
- Robot Adoption and Labor Market Dynamics (Humlum, JMP)
- Automation and the Labor Share in the Second Machine Age (Cheng-Drozd-Giri-Taschereau-Xia, 2022)
- Technology, Vintage Human Capital, and Labor Displacement: Evidence from Linking Patents with Occupations (Kogan-Papanikolaou-Schmidt-Seegmiller, 2022)
- New Frontiers: The Origins and Content of New Work, 1940–2018 (Autor-Salomons-Seegmiller, 2021)
- **Not a settled issue!** Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France (Aghion-Antonin-Bunel-Jaravel) finds no evidence of displacement effects and capital-skill complementarity.

ROBOTS AND JOBS

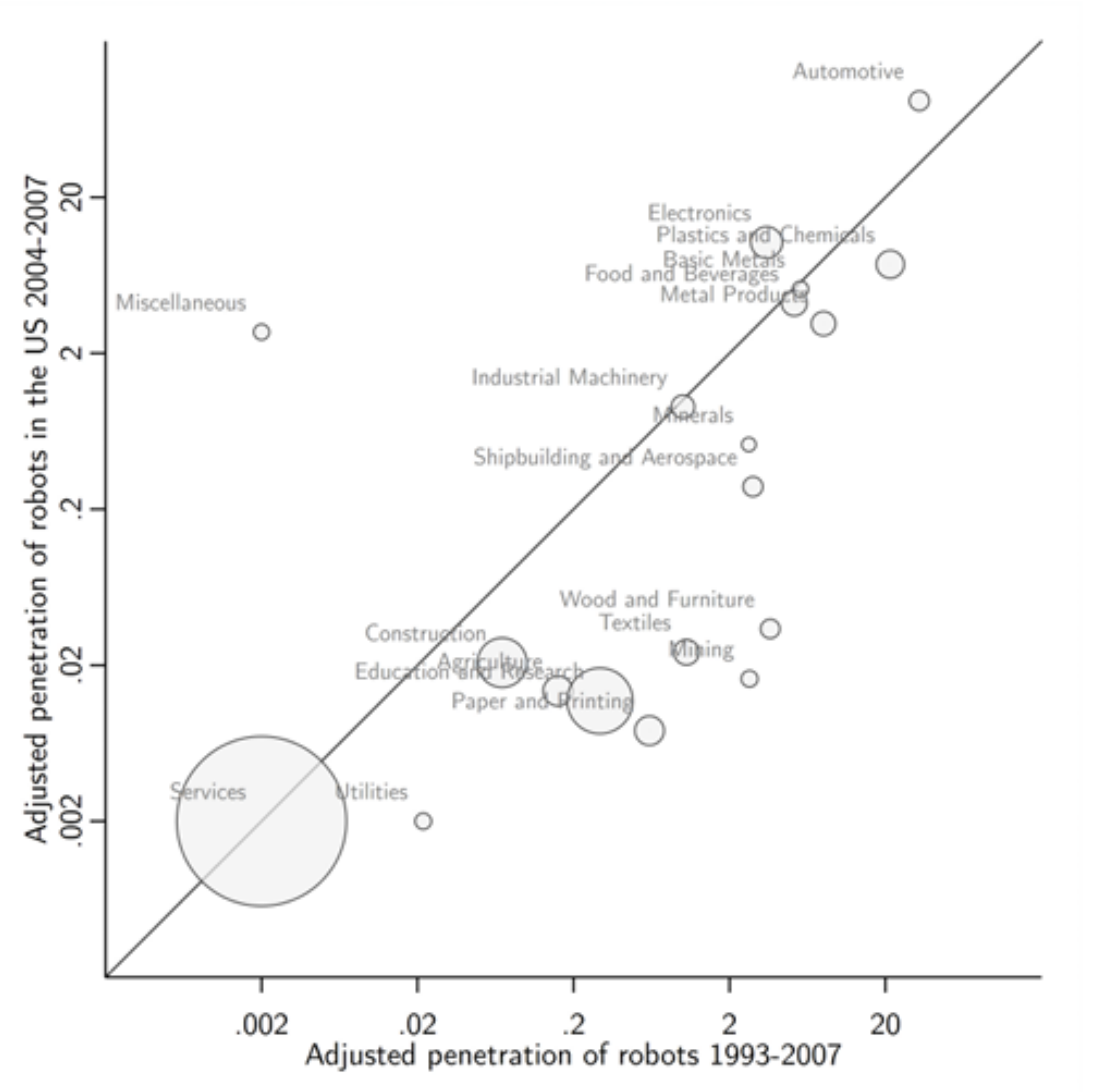
- Measure of robot exposure across US commuting zones:

$$\mathrm{R}_z = \sum_i s^E_{z,i,1990} \cdot \mathrm{APR}^{US}_{i,93-07}$$

- Instrumented using historical differences in industry location and advances in Europe (ahead of the US in robotics)

$$\mathrm{R}^{IV}_z = \sum_i s^E_{z,i,1970} \cdot \mathrm{APR}^{EURO}_{i,93-07}$$

- APRs: Δ robots per 1000 workers (adjusting for industry expansion)



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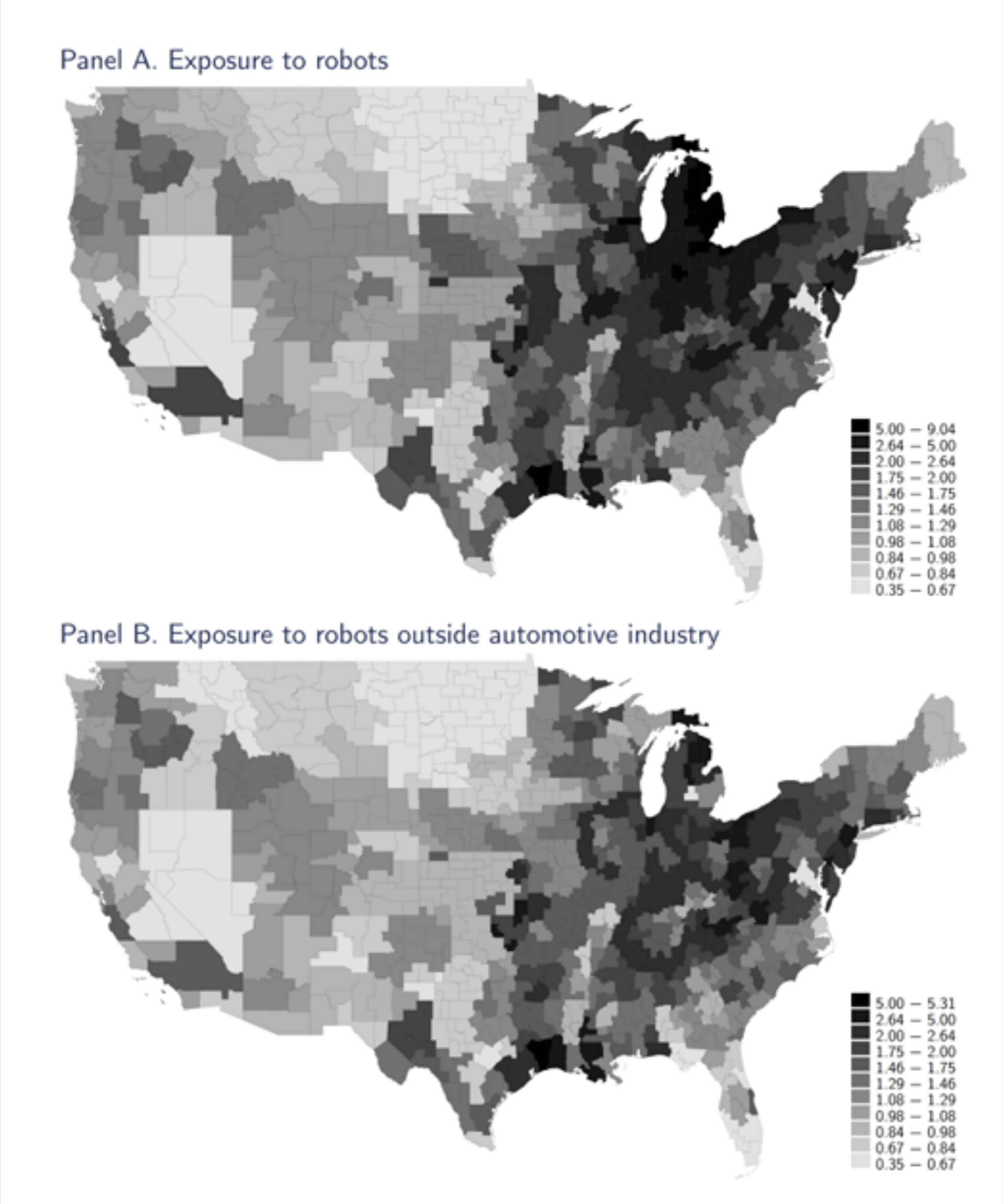
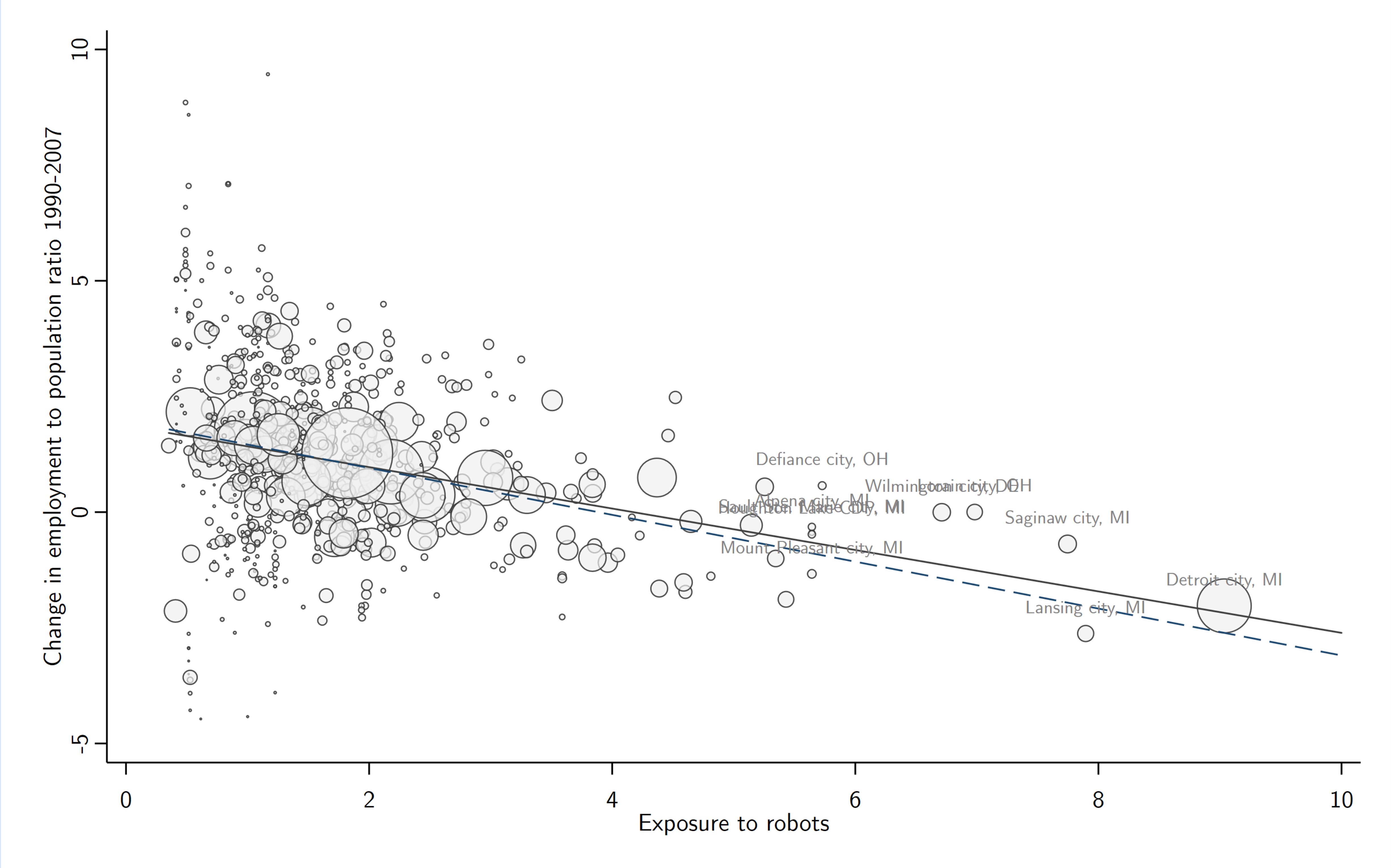


ROBOTS AND JOBS

- Evidence of displacement effects in exposed regions:
  - 1 extra industrial robot leads to **3 fewer manufacturing jobs** in exposed commuting zone relative to others

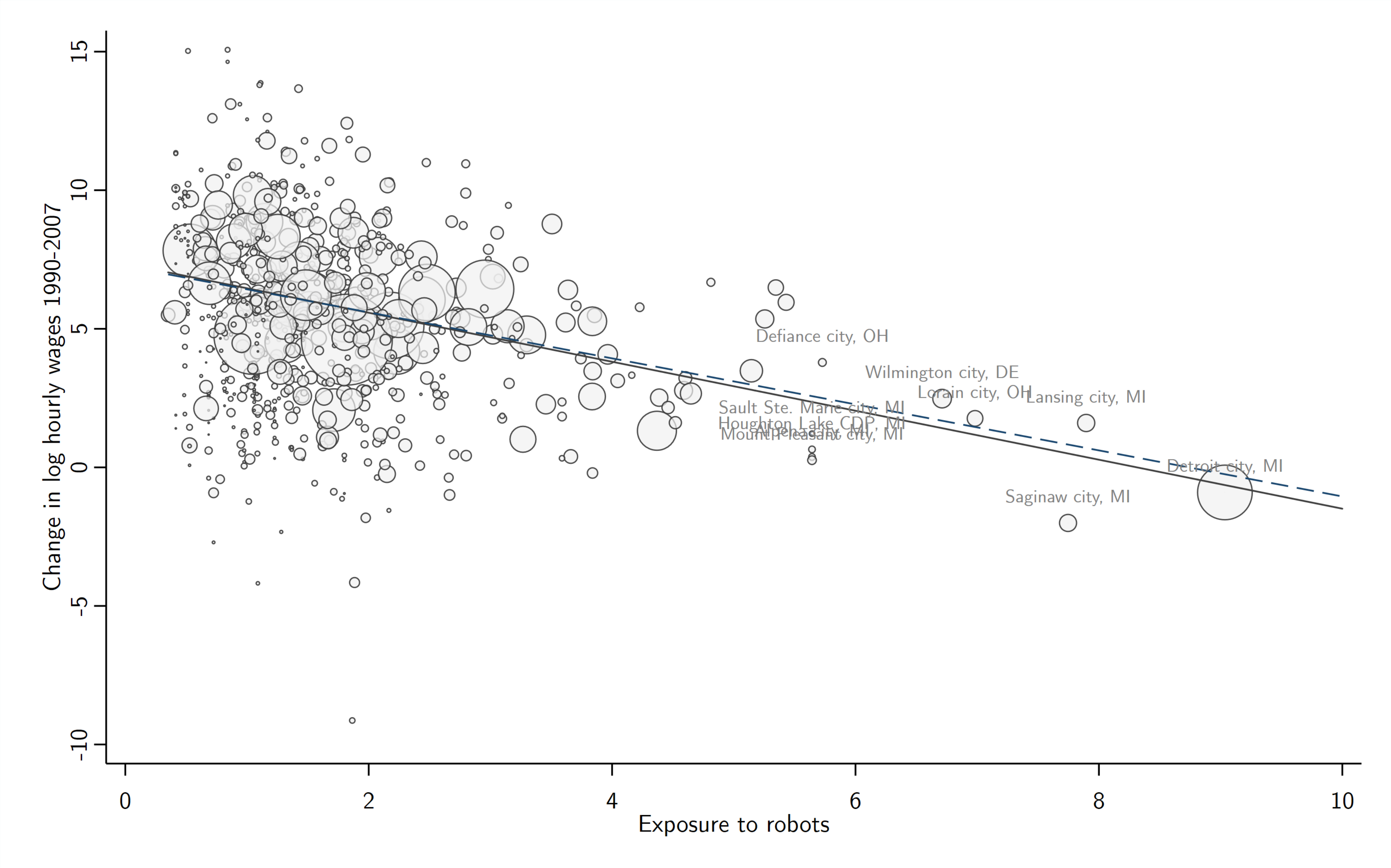
$$\Delta y_{z,90-07} = \beta \cdot \mathrm{R}_z^{IV} + \text{controls}_z + \epsilon_z$$



ROBOTS AND JOBS

- Evidence of displacement effects in exposed regions:
  - 1 extra industrial robot leads to **3 fewer manufacturing jobs** in exposed commuting zone relative to others
  - 1 robot per thousand workers **reduces wages in commuting zone by 0.7%** relative to others
- See paper for computation of aggregate results.

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



EFFECTS OF AUTOMATION ON WAGES: PROPAGATION

- Back to full model with **ripple effects:** how does Γ change in response to indirect effects?

$$d\ln w_g = \underbrace{\frac{1}{\lambda}\cdot d\ln y - \frac{1}{\lambda}\cdot d\ln \Gamma_g^d}_{\text{direct effects } = z_g} + \underbrace{\frac{1}{\lambda}\cdot\frac{\partial \ln \Gamma_g}{\partial \ln w}\cdot \text{stack}(d\ln w_g)}_{\text{ripple effects}_g}$$

Propagation matrix Θ

$$d\ln \boldsymbol{w} = \left(1-\frac{1}{\lambda}\frac{\partial \ln \boldsymbol{\Gamma}}{\partial \ln \boldsymbol{w}}\right)^{-1}\cdot \text{stack}(z_g)$$

$\theta_{gj} \geq 0$: Extent to which j competes for tasks against g

encodes all information on how tasks are reallocated in response to direct effects in stack(z_g)

EFFECTS OF AUTOMATION ON WAGES: PROPAGATION

- Change in wages due to automation: solve system for $\{d\ln w_g\}_g, d\ln y$

$$d\ln w_g = \sum_j \theta_{gj} \cdot \left(\frac{1}{\lambda} \cdot d\ln y - \frac{1}{\lambda} \cdot d\ln \Gamma_j^d\right)$$

Direct and indirect effects from task displacement

$$\sum_g s_g^L \cdot d\ln w_g = d\ln tfp = \sum_g s_g^L \cdot d\ln \Gamma_g^d \cdot \pi_g$$

Productivity effects

- Wages of displaced workers fall when:
  - π_g small (so-so automation)
  - Θ close to diagonal (little room for reallocation and high incidence)

EFFECTS OF AUTOMATION ON WAGES: PROPAGATION

- Two special cases:
  - workers differ in A_g but equal $\psi_g(x)$ across groups

$$\Theta_g = \begin{pmatrix} \theta & \theta & \dots & \theta \\ \theta & \theta & \dots & \theta \\ \vdots & \vdots & & \vdots \\ \theta & \theta & \dots & \theta \end{pmatrix} \Rightarrow d \ln w_g = d \ln tfp > 0$$

  - full market segmentation (groups do not compete for tasks)

$$\Theta_g = \begin{pmatrix} \theta_{1,1} & 0 & \dots & 0 \\ 0 & \theta_{2,2} & \dots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & \theta_{GG} \end{pmatrix} \Rightarrow d \ln w_g = \frac{1}{\lambda} \cdot \theta_{g,g} \cdot (d \ln y - d \ln \Gamma_g^d) \lessgtr 0$$

EXTENSION TO MULTIPLE INDUSTRIES

Industry output

$$y_i = A_i \cdot \left(\frac{1}{M_i} \int_{\mathcal{T}_i} (M_i \cdot y(x))^{\frac{\lambda - 1}{\lambda}} \cdot dx \right)^{\frac{\lambda}{\lambda - 1}}$$

Demand

$$y = \left(\sum_i \alpha_i^{\frac{1}{\eta}} \cdot y_i^{\frac{\eta - 1}{\eta}} \right)^{\frac{\eta}{\eta - 1}}$$

Tasks

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

Factors' supply & Equilibrium

- capital produced from final good $c = y - \int_{\mathcal{T}} k(x)/q(x) \cdot dx$
- supply of labor fixed at $\ell_g = \int_{\mathcal{T}} \ell_g(x) \cdot dx$
- Equilibrium given by unique allocation that maximizes c

EFFECTS OF AUTOMATION ON WAGES: INDUSTRIES

- Change in wages, sectoral output, and GDP due to **automation**:

$$d\ln w_g = \sum_j \theta_{gj} \cdot \left(\frac{1}{\lambda} \cdot d\ln y + \frac{1}{\lambda} \cdot \sum_i \omega_j^i \cdot d\ln \zeta_i - \frac{1}{\lambda} \sum_i \omega_j^i \cdot d\ln \Gamma_{ji}^d \right)$$

$$d\ln \zeta_i = (\lambda - \eta) \cdot d\ln p_i$$

$$d\ln p_i = \sum_g s_{gi}^L \cdot \left(d\ln w_g - d\ln \Gamma_{gi}^d \cdot \pi_{gi} \right)$$

$$0 = \sum_i s_i^Y \cdot d\ln p_i$$

- All that is needed for quantification are measures of $\{d\ln \Gamma_{gi}^d, \pi_{gi}\}$ (forcing variables), estimates of elasticities $\{\lambda, \eta, \Theta\}$, and initial shares $\{\omega_g^i, s_{gi}^L, s_i^Y\}$

DIFFERENT FROM OTHER SECTORAL SHIFTS

- Change in wages, sectoral output, and GDP due to **sectoral shifts**:

$$d\ln w_g = \sum_j \theta_{gj} \cdot \left(\frac{1}{\lambda} \cdot d\ln y + \frac{1}{\lambda} \cdot \sum_i \omega_j^i \cdot d\ln \zeta_i - \frac{1}{\lambda} \sum_i \omega_j^i \cdot d\ln \Gamma_{ji}^d \right)$$

$$d\ln \zeta_i = (\lambda - \eta) \cdot d\ln p_i + (\lambda - 1) \cdot d\ln A_i - d\ln \mu_i$$

$$d\ln p_i = \sum_g s_{gi}^L \cdot \left(d\ln w_g - d\ln \Gamma_{gi}^d \cdot \pi_{gi} \right) - d\ln A_i + d\ln \mu_i$$

$$0 = \sum_i s_i^Y \cdot d\ln p_i$$

- Markups, trade in final goods, and sector-specific changes in TFP affect wage structure through sectoral shifters $d\ln \zeta_i$

MEASURING TASK DISPLACEMENT

- **Assumption:** only routine tasks automated and all workers displaced from routine tasks in an industry at the same rate.

$$d \ln \Gamma^d_{gi} = \frac{\omega^R_{gi}}{\omega^R_i} \cdot \text{automation-driven declines in } d \ln s^L_i$$

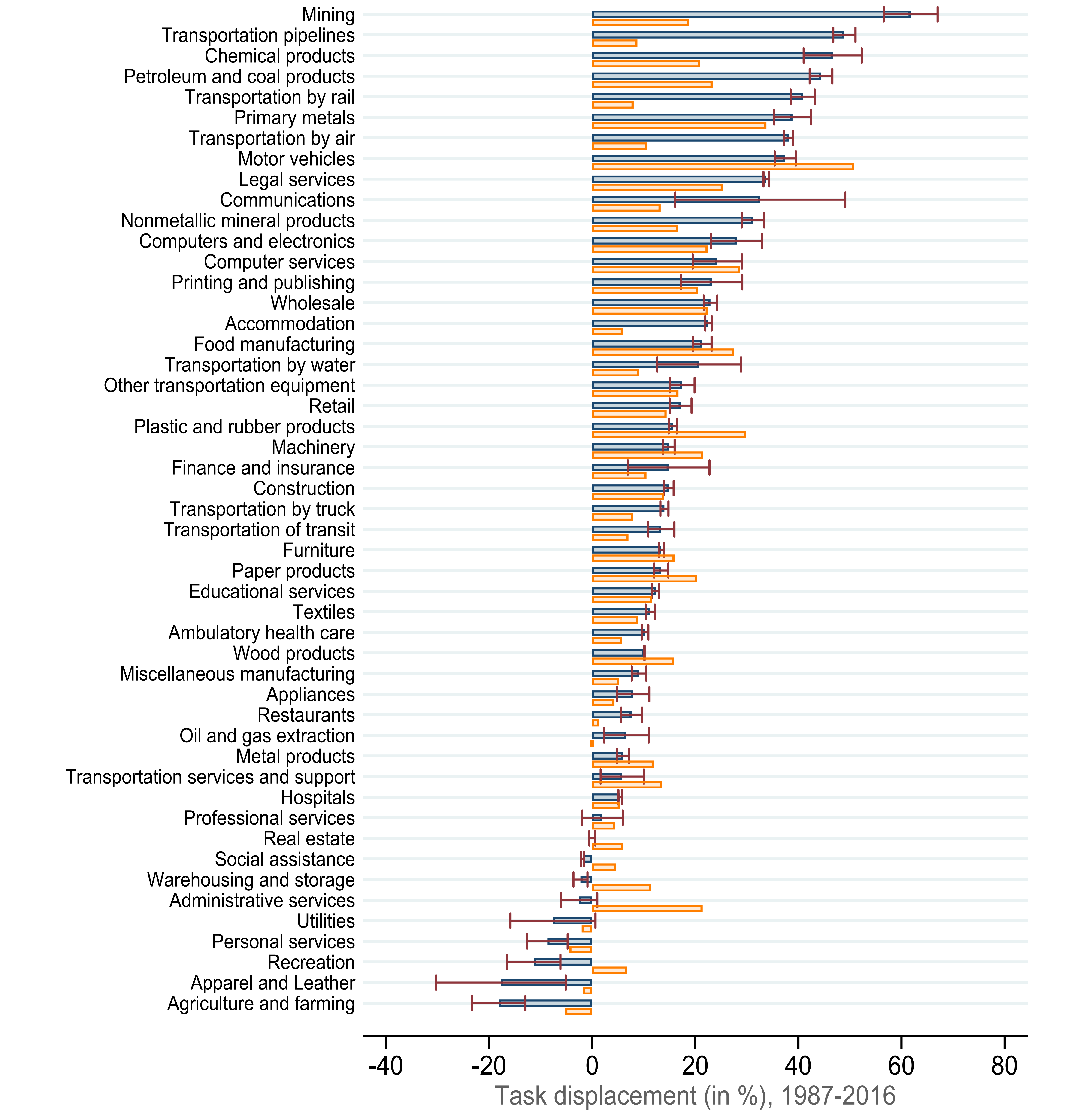
revealed comparative advantage in routine jobs in industry

measures total task displacement in industry i

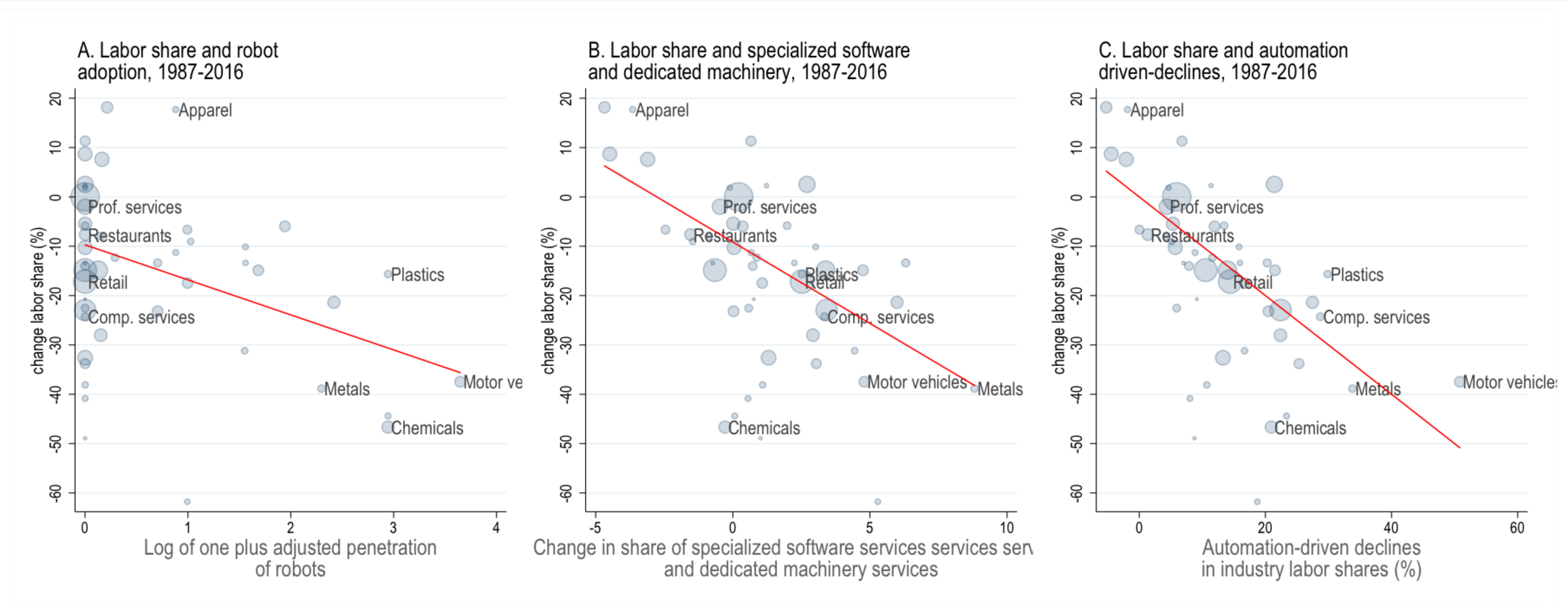
- **Paper:** Use observed $-d \ln s^L_i$ (no markups/monopsony and CD; see paper)
- **Today:** Use industry-level measures of automation (robots, specialized software and machinery) to estimate automation-driven declines $-d \ln s^{L,d}_i$

MEASURING TASK DISPLACEMENT

- Data on labor shares for 49 industries from the BEA from 1987–2016
- In blue, percent labor share decline
- In orange, part **due to specialized software and equipment, and robotics**
- These techs explain 50% of variation in labor share decline across industries



MEASURING TASK DISPLACEMENT



- Estimating the component of the labor share decline due to automation

MEASURING TASK DISPLACEMENT

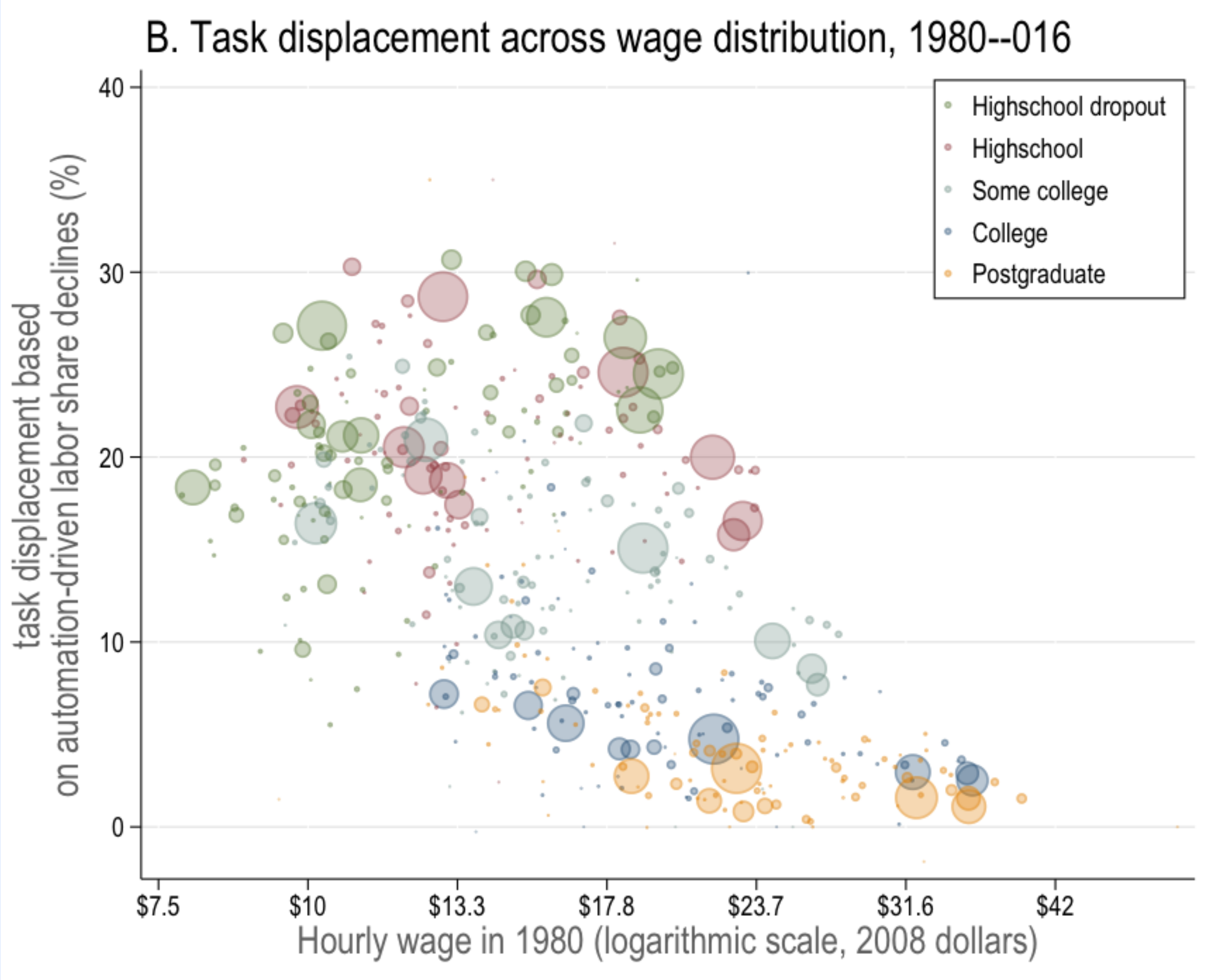
- Compute **direct task displacement** (td) for 500 groups (education, gender, experience, race, immigrant status)

- Total direct displacement across industries:

$$\text{td}_g = \sum_i \omega_g^i \cdot d \ln \Gamma_{gi}^d$$

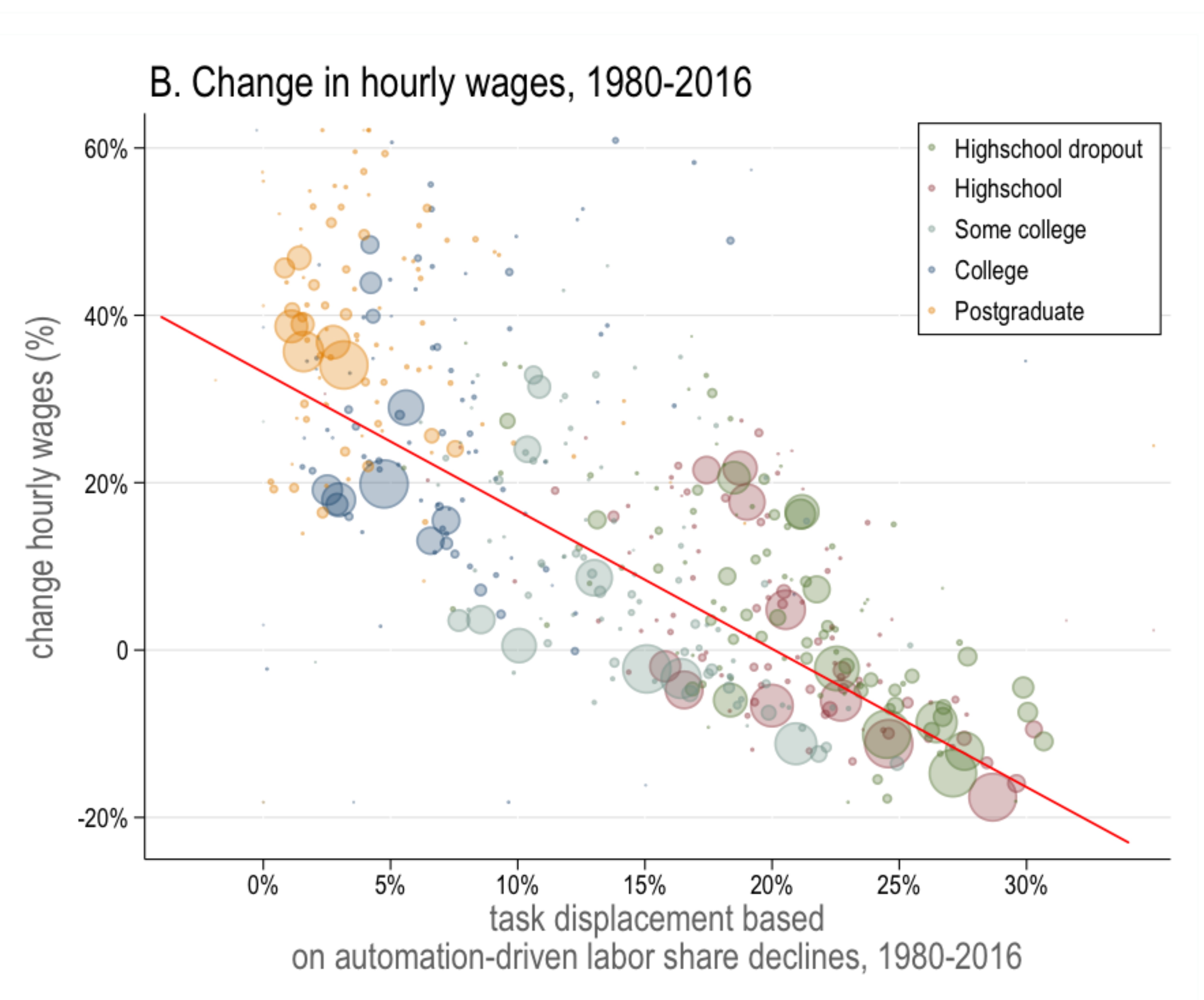
- Baseline wages by industry and in routine jobs from 1980 US Census

- Routine jobs from ONET as in Acemoglu and Autor (2011)



WAGE CHANGES AND DIRECT TASK DISPLACEMENT 1980—2016

$$\Delta \ln w_{g,80-16} = \beta \cdot \text{td}_g + \text{controls}_g + \epsilon_g$$



- **Key role of direct effects:** 10 pp increase in direct task displacement leads to 16% decline in group wages
- Similar relationship within education groups and gender
- Direct task displacement explains 50% of differences across groups; educational dummies only 10%
- Relationship only for workers in routine jobs in automating industries
- Robust to controlling for trade, markups, unions, changes in supply…

ESTIMATING THE KEY ELASTICITIES

- Take $\lambda = 0.5$ from Humlum's JMP and $\eta = 0.2$ from Buera, Kaboski, Rogerson (2015)
- Estimate parametrized version of propagation matrix:
  - Theory restrictions
    $$\varepsilon_g - \frac{\theta_{gj}}{s_j^L} = \varepsilon_j - \frac{\theta_{jg}}{s_g^L}, \qquad \varepsilon_g = \sum_j \theta_{gj}, \qquad \theta_{gj} \geq 0.$$
  - Parametrization
    $$\theta_{gj} = \frac{1}{2}(\varepsilon_g - \varepsilon_j) \cdot s_j^L + \boxed{\sum_n \beta_n \cdot f(d_{gj}^n) \cdot s_j^L,}$$
    $$\theta_{gg} = \beta,$$
    Competition depends on similarity along $n \in$ {occupations, industry, skills}
  - Estimation of β's and ε's
    $$d \ln w_g = \beta_0 - \frac{\beta}{\lambda} \cdot \text{td}_g - \frac{1}{\lambda} \sum_{j \neq g} \left(\frac{1}{2}(\varepsilon_g - \varepsilon_j) \cdot s_j^L + \sum_n \beta_n \cdot f(d_{gj}^n) \cdot s_j^L \right) \cdot \text{td}_j + v_g$$

ESTIMATING THE KEY ELASTICITIES

$$d \ln w_g = \beta_0 - \frac{\beta}{\lambda} \cdot \mathsf{td}_g - \frac{1}{\lambda} \sum_{j \neq g} \left(\frac{1}{2}(\varepsilon_g - \varepsilon_j) \cdot s_j^L + \sum_n \beta_n \cdot f(d_{gj}^n) \cdot s_j^L \right) \cdot \mathsf{td}_j + v_g$$

TABLE A-10: GMM ESTIMATES OF THE PROPAGATION MATRIX.

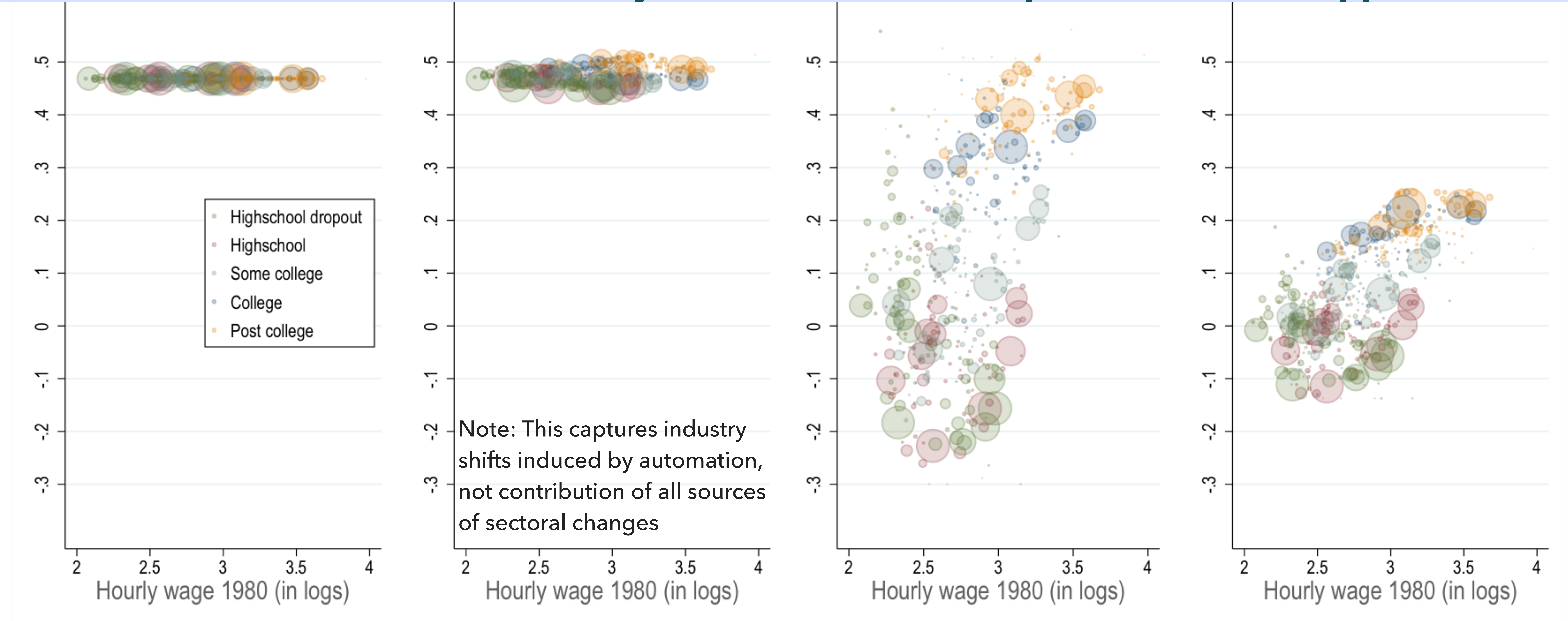
	DEPENDENT VARIABLE: CHANGE IN WAGES 1980–2016					
	TASK DISPLACEMENT MEASURED FROM OBSERVED LABOR SHARE DECLINES			TASK DISPLACEMENT MEASURED FROM AUTOMATION-DRIVEN LABOR SHARE DECLINES		
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A. BASELINE ESTIMATES COMPUTING THE ADJUSTED LABOR SHARE DECLINE WITH $\sigma_i = 1$.						
Own effect, θ/λ	0.88	0.88	0.82	0.89	0.97	0.90
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Contribution of ripple effects via occupational similarity	0.36	0.36	0.31	0.43	0.50	0.45
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)
Contribution of ripple effects via industry similarity	0.22	0.22	0.36	0.35	0.37	0.49
	(0.10)	(0.10)	(0.11)	(0.12)	(0.12)	(0.13)
Contribution of ripple effects via education–age groups	0.18	0.18	0.17	0.17	0.16	0.16
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Covariates:						
Industry shifters		✓	✓		✓	✓
Manufacturing share			✓			✓

Notes: This table presents estimates of the propagation matrix. Ripple effects are parametrized as functions of the similarity of groups in terms of their 1980 occupational distribution, industry distribution, and education×age groups. The table reports our estimates of the common diagonal term θ and a summary measure of the strength of ripple effects operating through each of these dimensions, defined by

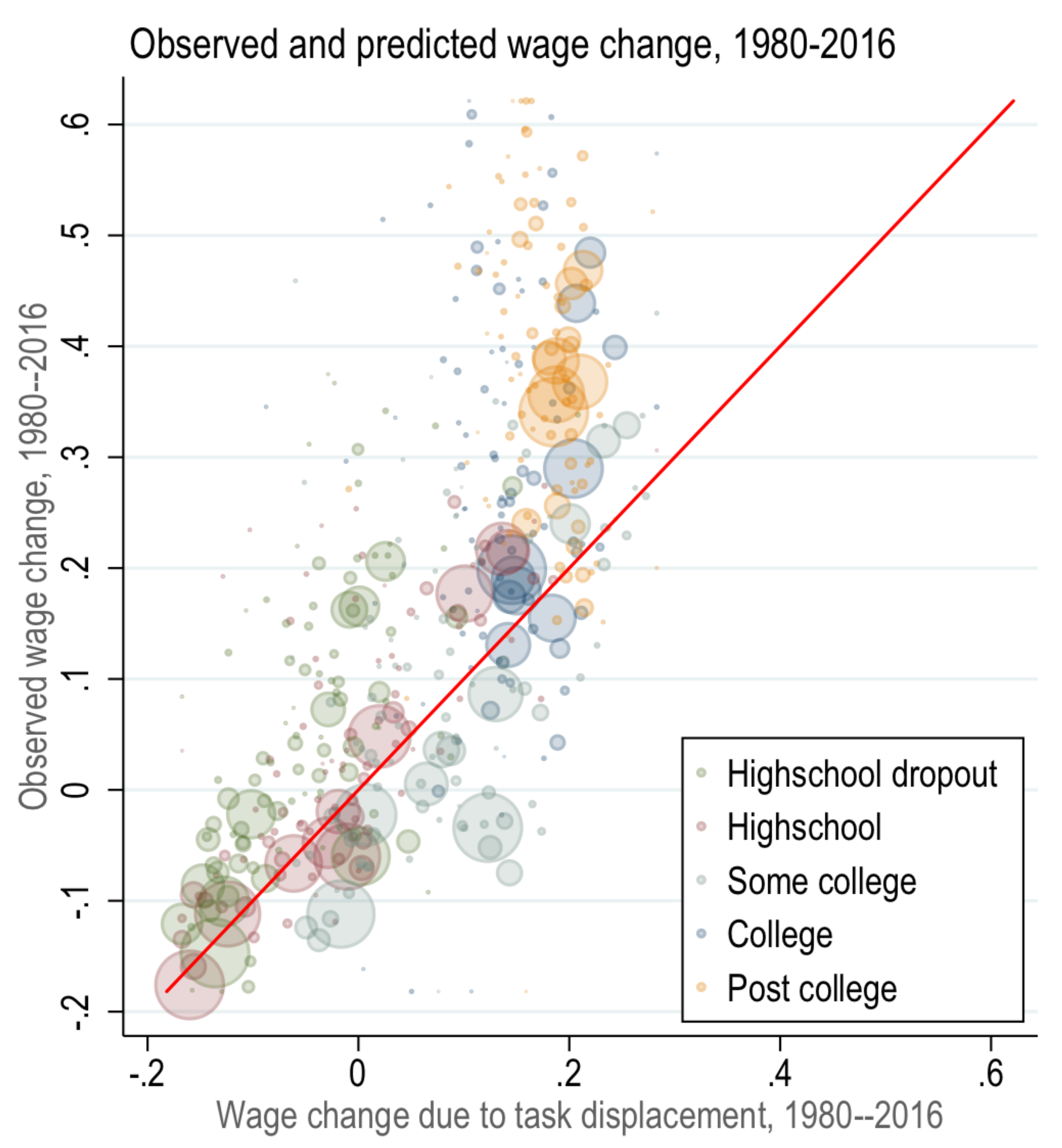
$$\text{Contribution of ripple effects}_n = \frac{\beta_n}{\lambda} \cdot \left(\frac{1}{s^L} \sum_g \sum_{g' \neq g} f(d_{gg'}^n) \cdot s_g^L \cdot s_{g'}^L \right),$$

ACCOUNTING FOR GENERAL EQUILIBRIUM EFFECTS

A. Prod effect B. +Industry shifts C. +Task displacement D. +Ripple effects



ACCOUNTING FOR GENERAL EQUILIBRIUM EFFECTS



Summary of results:

- Explains 48% of observed wage changes
- Explains 80% of rise in college premium and 60% of rise in post-college premium
- Explains 80% of real wage declines
- Misses wage growth at top (other forces or direct complementarities with technology?)
- Increase in GDP of 20%, mean wage of 6%, and TFP of 4%

TAKING STOCK

- Task models capture possibility that capital or new technology can replace workers at certain tasks
- Much of the rise in US wage inequality due to uneven effects of task displacement generated by automation
- Different from canonical explanations of SBTC:
  - emphasizes task displacement and importance of industries and occupations above educational levels in mediating its effects
  - better fit to data and high explanatory power
  - explains lackluster TFP growth and declining real wages

RESEARCH QUESTIONS

- Transitional dynamics: how fast is the reallocation process?
- Does the propagation matrix differ across countries? Perhaps capturing differences in retraining systems?
- Adjustment in economies with frictions: unemployment, sticky wages?
- Quantifying the contribution of task displacement effects for OECD countries
- Introducing capital skill complementarity (or comparative advantage of skill labor in producing automation equipment.
- Much more to be done in terms of estimation. I see our paper as first step in estimating propagation matrix. But I don't think we fully nailed it and that is ok.
- Implications for within-group inequality?