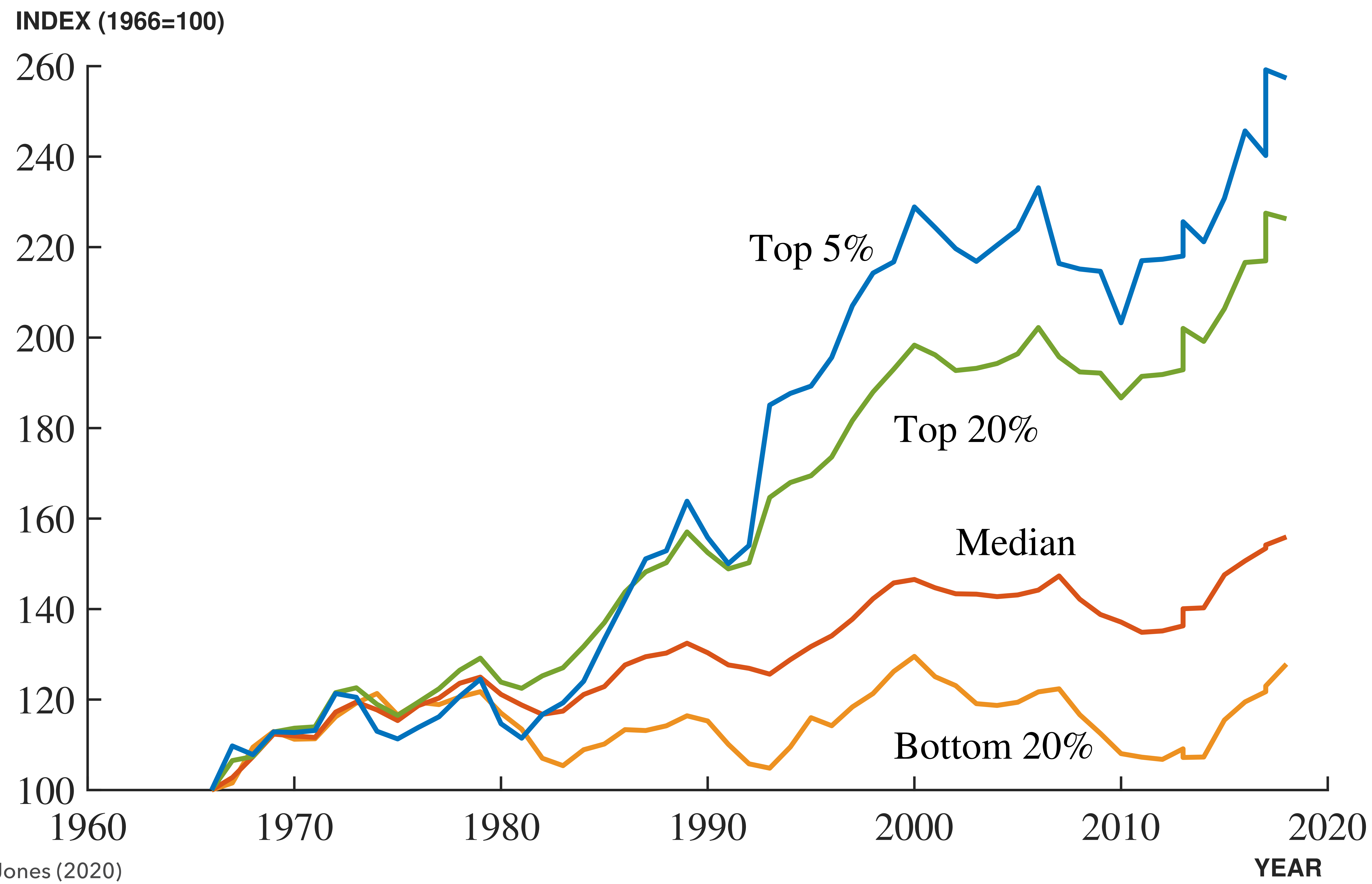
Technological Change and Income Inequality

EC502 Macroeconomics
Topic 6

Masao Fukui

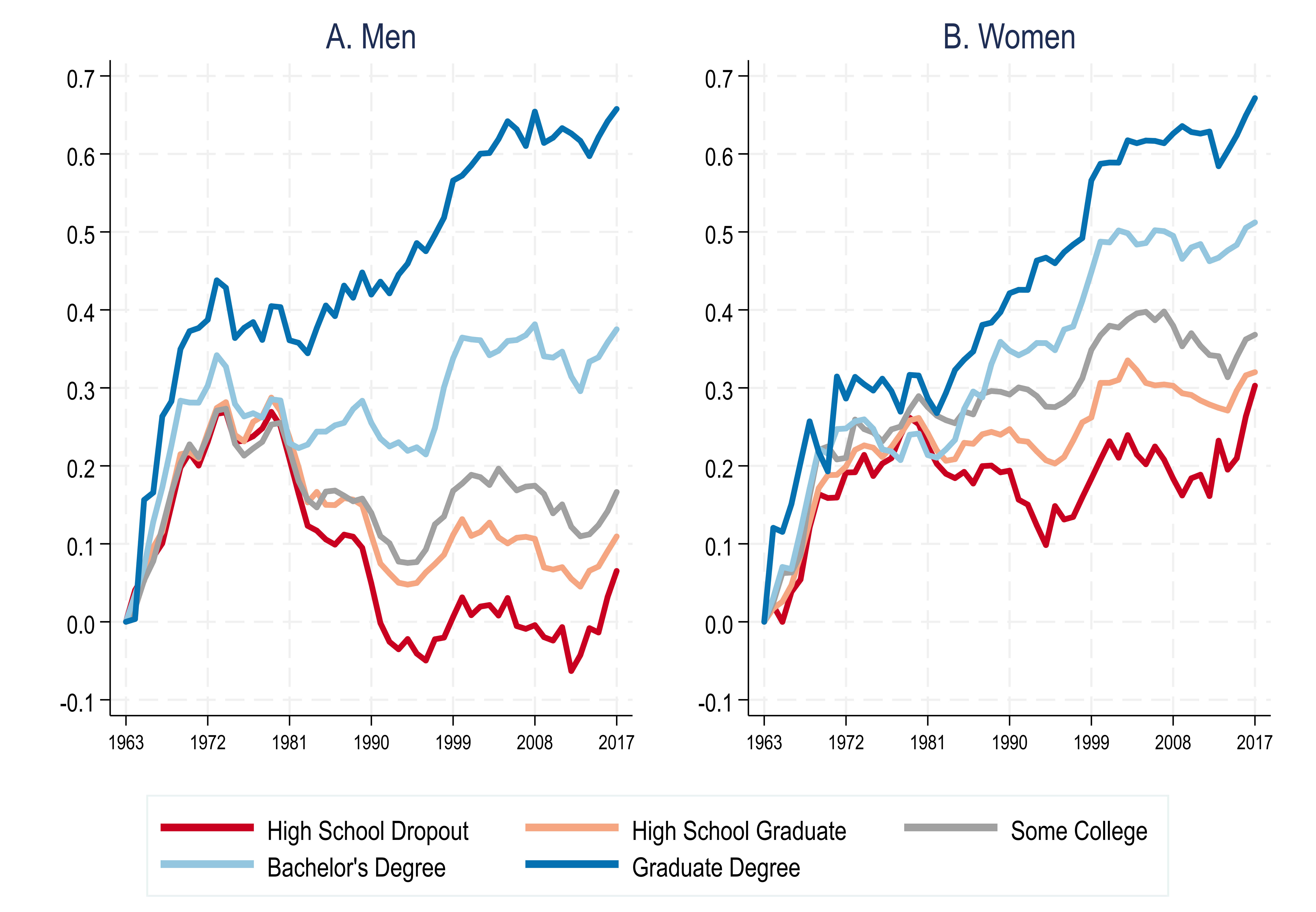
2026 Spring

Growing Income Inequality in the US



Source: Jones (2020)

Rising Real Wage Inequality Across Educational Groups



1. Skill-Biased Technological Change

– Katz and Murphy (1992)

Production Function

- Firms use high- and low-skill labor to produce output:

$$Y = F(L_L, L_H)$$

  - L_L: low-skill labor
  - L_H: high-skill labor
  - F: constant returns to scale

- Assume:

$$F(L_L, L_H) = \left(\alpha^{\frac{1}{\sigma}}(A_L L_L)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)^{\frac{1}{\sigma}}(A_H L_H)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

  - A_L: low-skill augmenting technology, A_H: high-skill augmenting technology
  - $\sigma > 0$: elasticity of substitution between high- and low-skill labor

Three Special Cases

$$F(L_L, L_H) = \left(\alpha^{\frac{1}{\sigma}}(A_L L_L)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)^{\frac{1}{\sigma}}(A_H L_H)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

1. If $\sigma \to \infty$, we have a linear production function:

$$F(L_L, L_H) = A_L L_L + A_H L_H$$

2. If $\sigma = 1$, we have a Cobb-Douglas production function:

$$F(L_L, L_H) = (A_L L_L)^{\alpha}(A_H L_H)^{1-\alpha}$$

3. If $\sigma \to 0$, we have a Leontief production function

$$F(L_L, L_H) = \min\left\{\frac{1}{\alpha}A_L L_L, \frac{1}{1-\alpha}A_H L_H\right\}$$

Firm's Profit Maximization

- Firms take the wage of each skill group as given and decide how many to hire

$$\max_{L_L, L_H} F(L_L, L_H) - w_L L_L - w_H L_H$$

- First-order conditions:

$$\underbrace{\frac{\partial F_L(L_L, L_H)}{\partial L_L}}_{\text{MPL of low-skill labor}} = w_L$$

$$\underbrace{\frac{\partial F(L_L, L_H)}{\partial L_H}}_{\text{MPL of high-skill labor}} = w_H$$

- Assume L_H and L_L are exogenous

Labor Demand

- With our functional form,

$$w_L = \alpha^{\frac{1}{\sigma}} A_L^{\frac{\sigma-1}{\sigma}} (L_L)^{-\frac{1}{\sigma}} \left(\alpha^{\frac{1}{\sigma}} (A_L L_L)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)^{\frac{1}{\sigma}} (A_H L_H)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}}$$

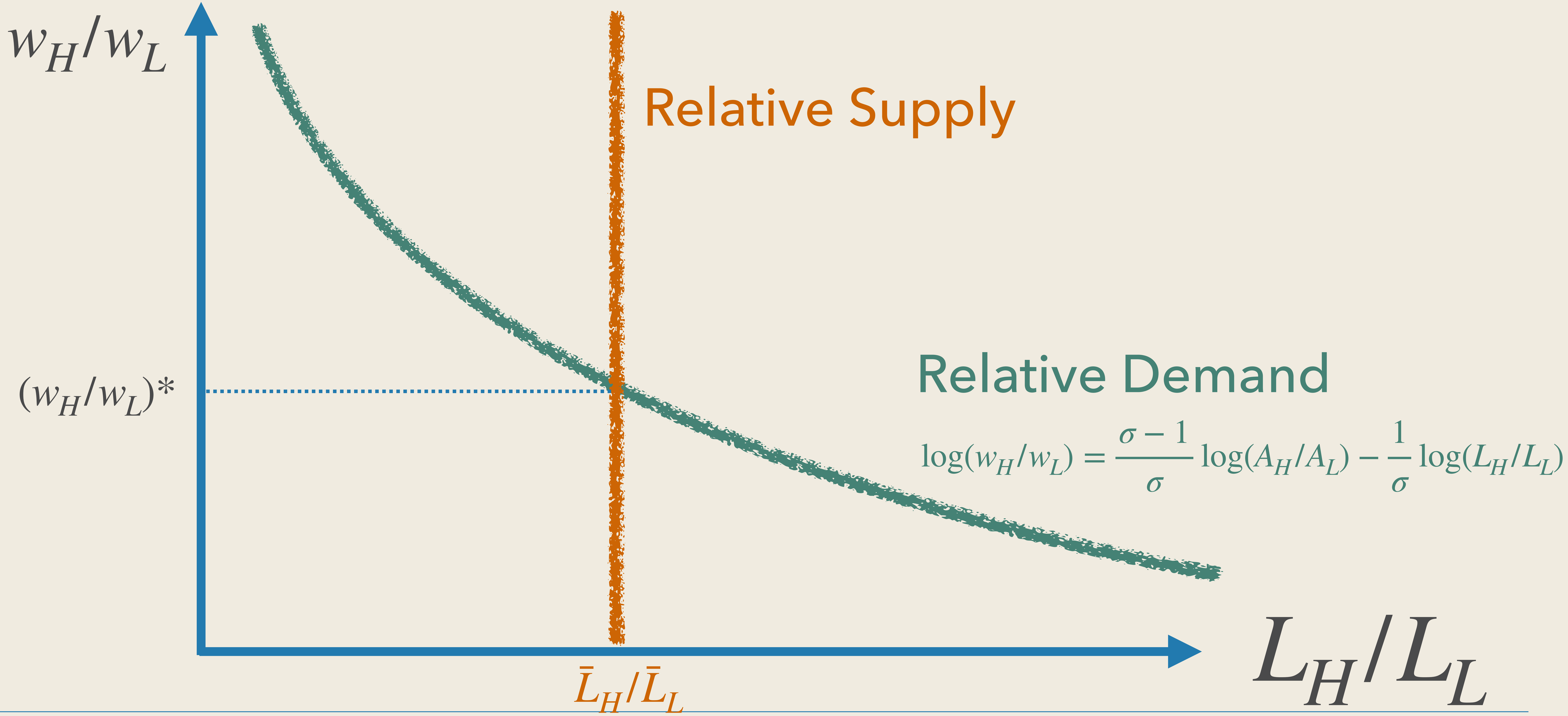
$$w_H = (1-\alpha)^{\frac{1}{\sigma}} A_H^{\frac{\sigma-1}{\sigma}} (L_H)^{-\frac{1}{\sigma}} \left(\alpha^{\frac{1}{\sigma}} (A_L L_L)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)^{\frac{1}{\sigma}} (A_H L_H)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}}$$

- Taking the ratio, relative labor dmeand, L_H/L_L, is

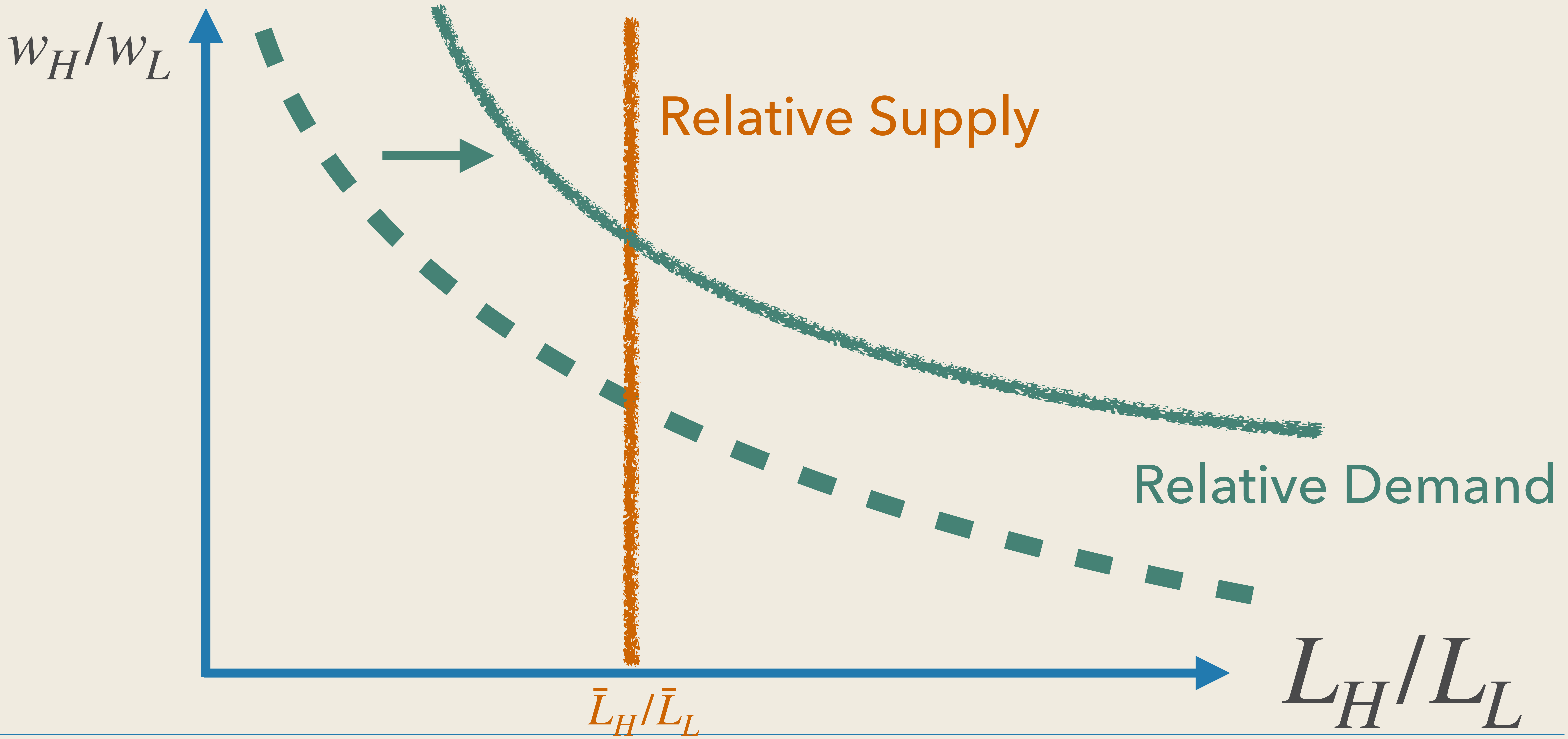
$$\log(L_H/L_L) = (\sigma - 1)\log(A_H/A_L) - \sigma \log(w_H/w_L) + \log((1-\alpha)/\alpha)$$

  - A rise in A_H relative to A_L
    - raises relative labor demand for skilled if $\sigma > 1$ (substitutes).
    - lowerss relative labor demand for skilled if $\sigma < 1$ (complements)

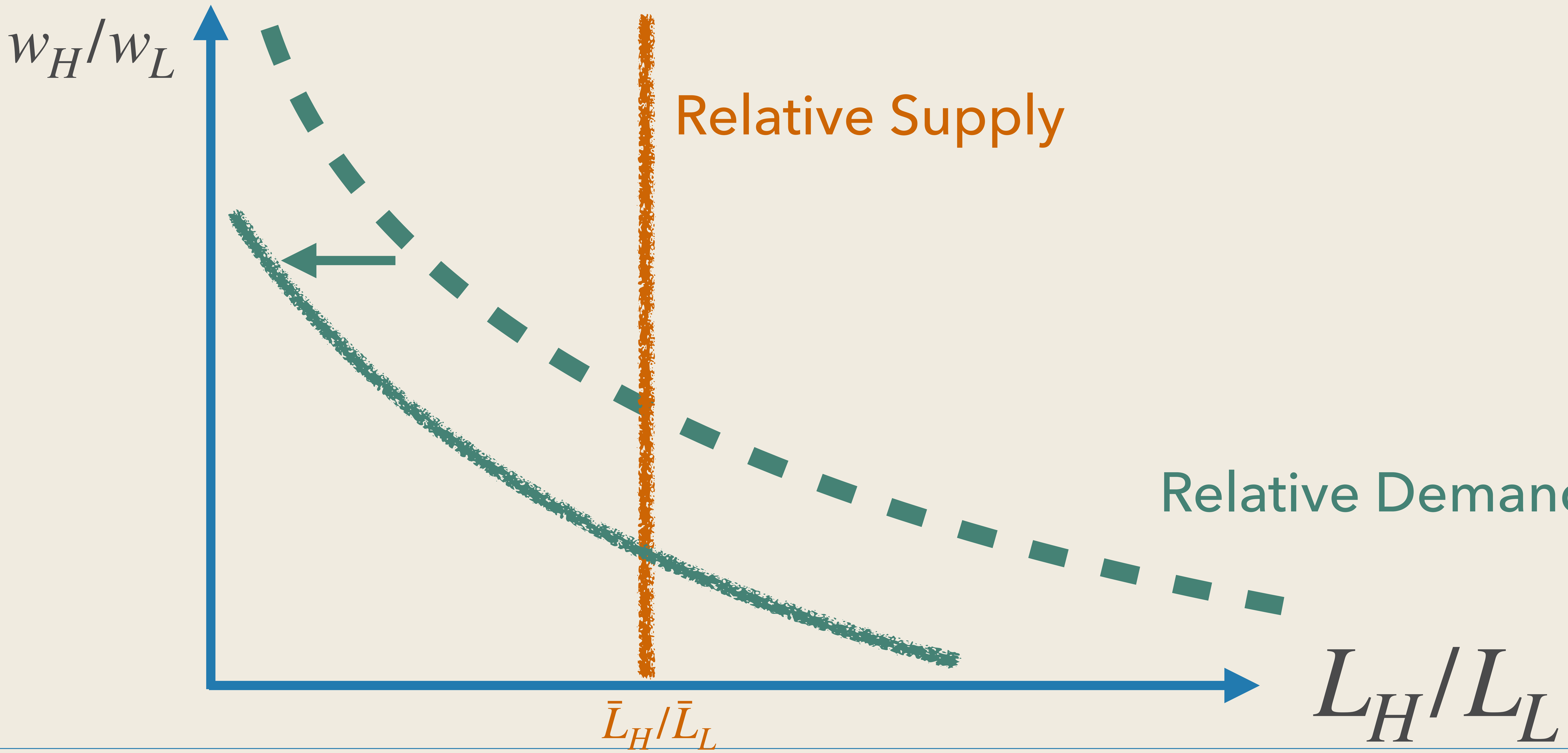
Demand and Supply



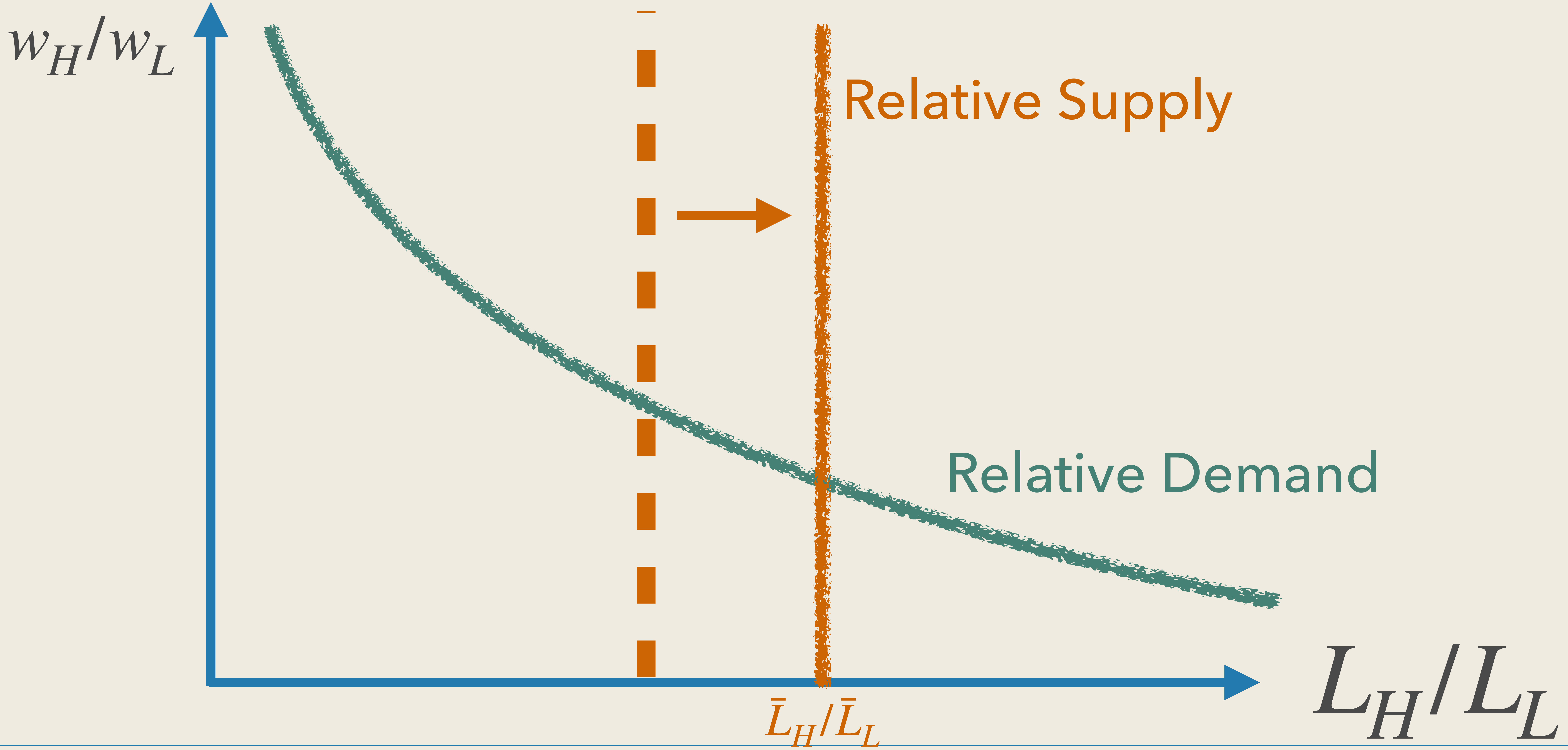
Increase in A_H/A_L if $\sigma > 1$



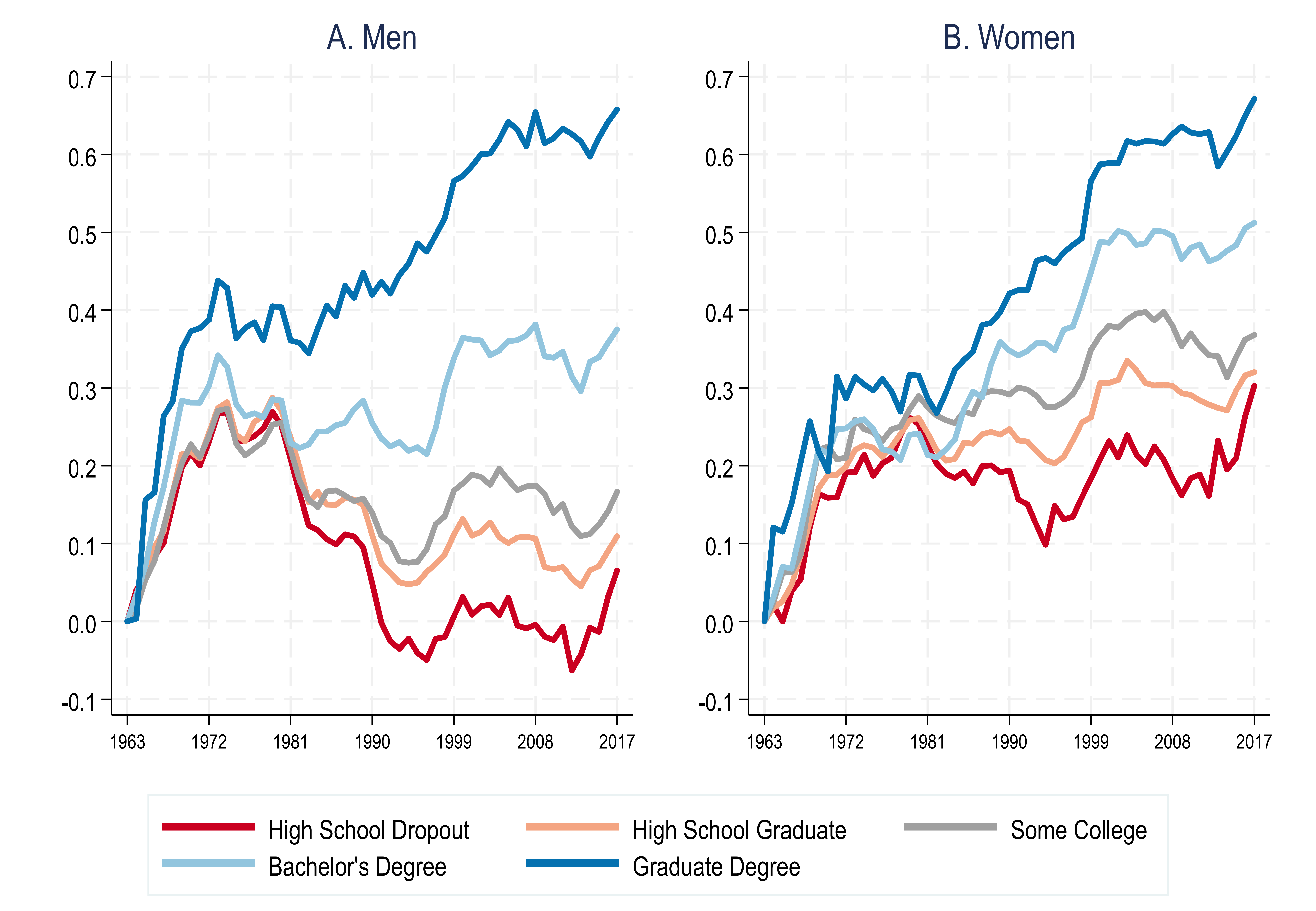
Increase in A_H/A_L if $\sigma < 1$



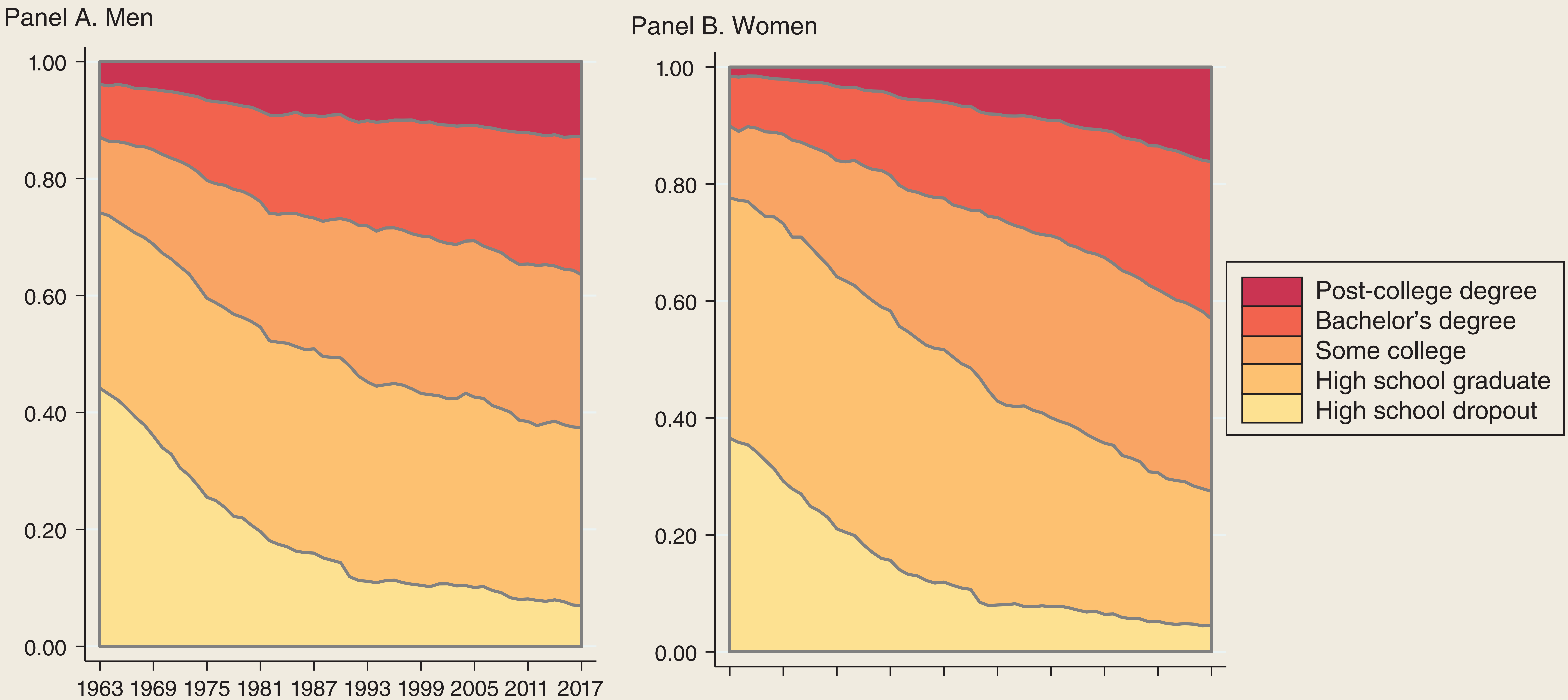
Increase in $\bar{L}_H/\bar{L}_L$



Rising Real Wage Inequality Across Educational Groups



Hours Worked Share



What Has Happened?

$$\log(w_H/w_L) = \frac{\sigma-1}{\sigma}\log(A_H/A_L) - \frac{1}{\sigma}\log(L_H/L_L) + \log((1-\alpha)/\alpha)$$

Went up!

Went up!

- What needs to have happened to A_H/A_L in the past?
- If $\sigma > 1$, A_H/A_L must have been rising (**skill-biased technical change**)
- The consensus among macroeconomists is that $\sigma > 1$

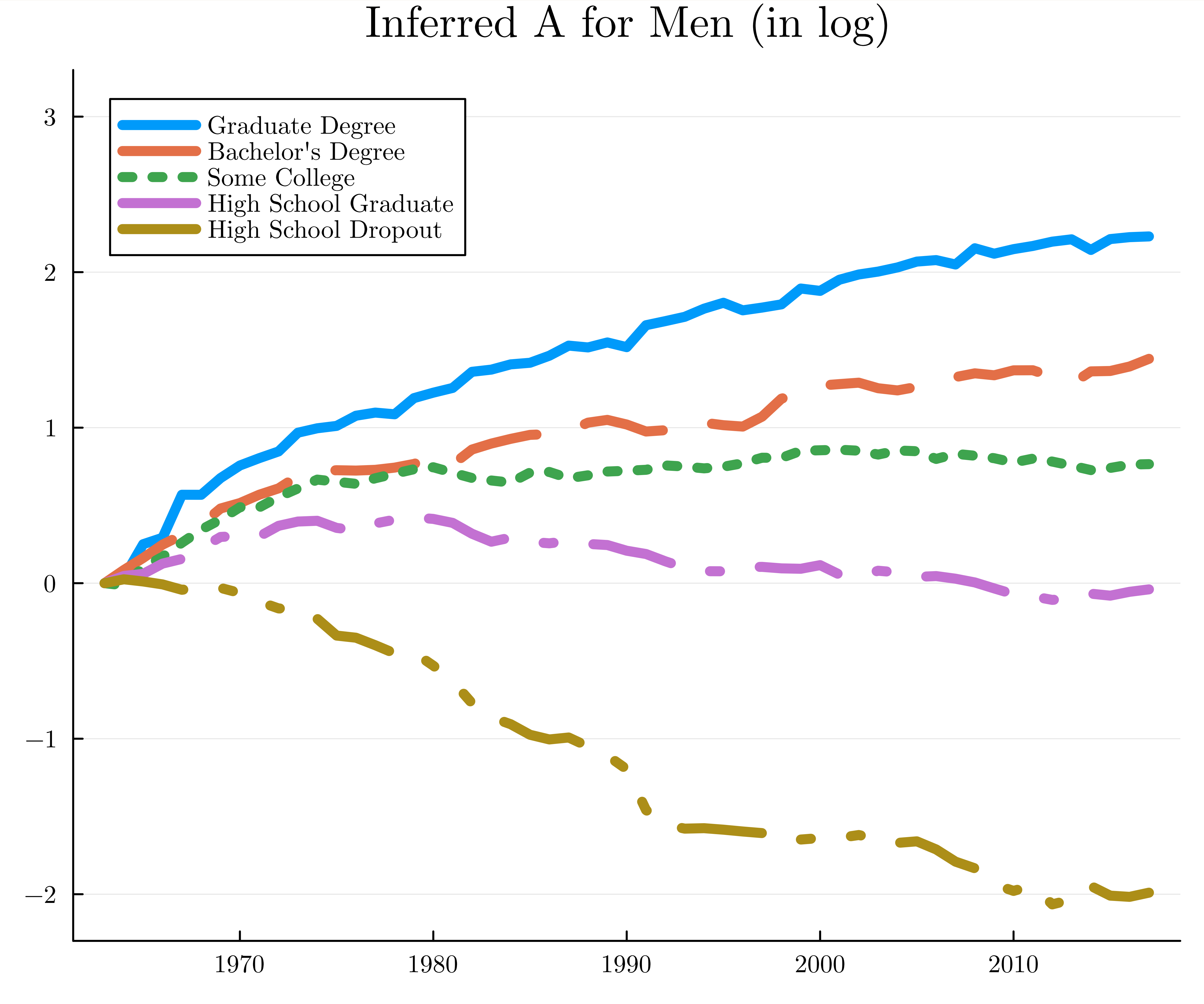
Inferring A_H and A_L

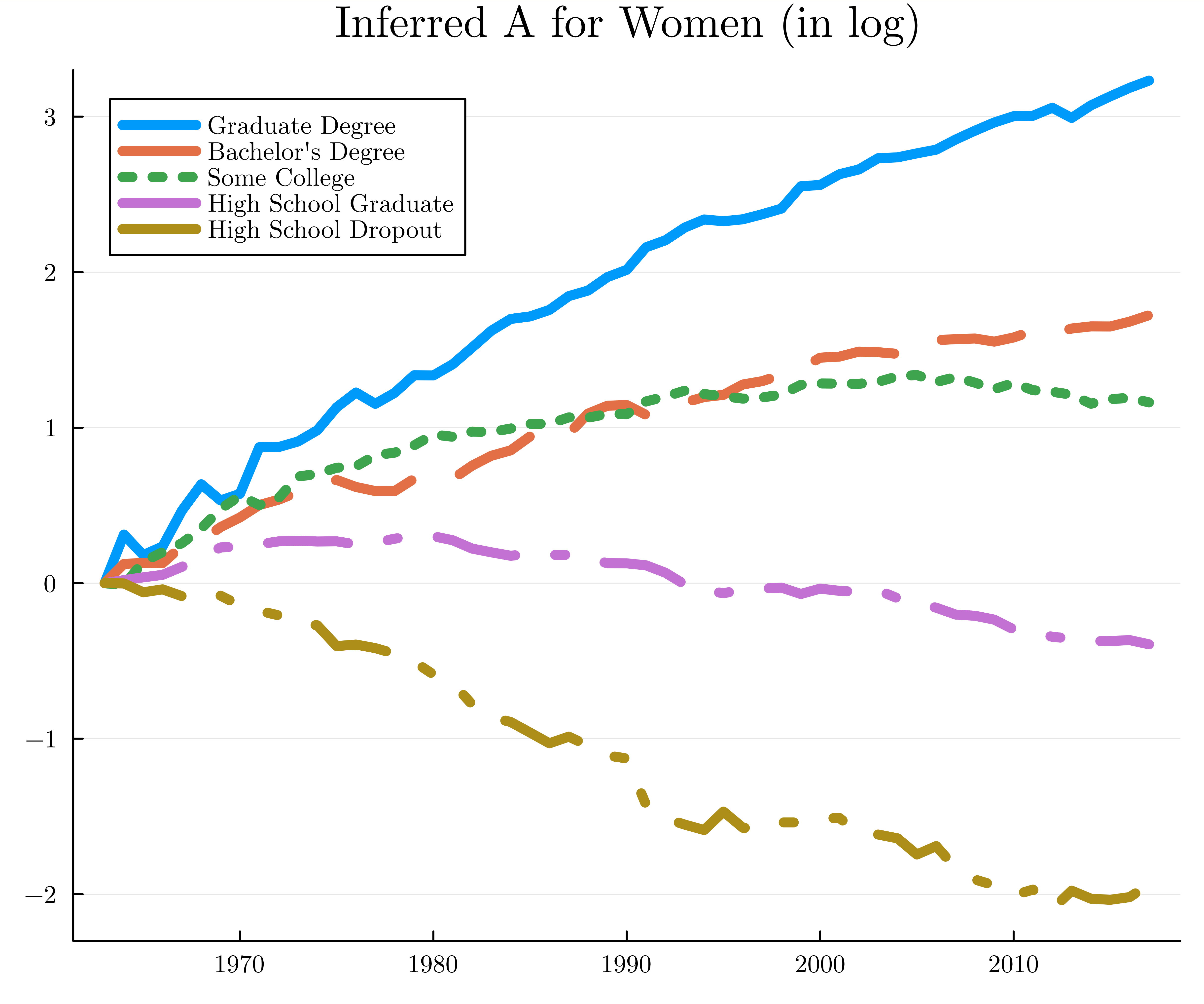
$$w_L = \alpha^{\frac{1}{\sigma}} A_L^{\frac{\sigma-1}{\sigma}} (L_L)^{-\frac{1}{\sigma}} \left(\alpha^{\frac{1}{\sigma}} (A_L L_L)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)^{\frac{1}{\sigma}} (A_H L_H)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}}$$

$$w_H = (1-\alpha)^{\frac{1}{\sigma}} A_H^{\frac{\sigma-1}{\sigma}} (L_H)^{-\frac{1}{\sigma}} \left(\alpha^{\frac{1}{\sigma}} (A_L L_L)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)^{\frac{1}{\sigma}} (A_H L_H)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}}$$

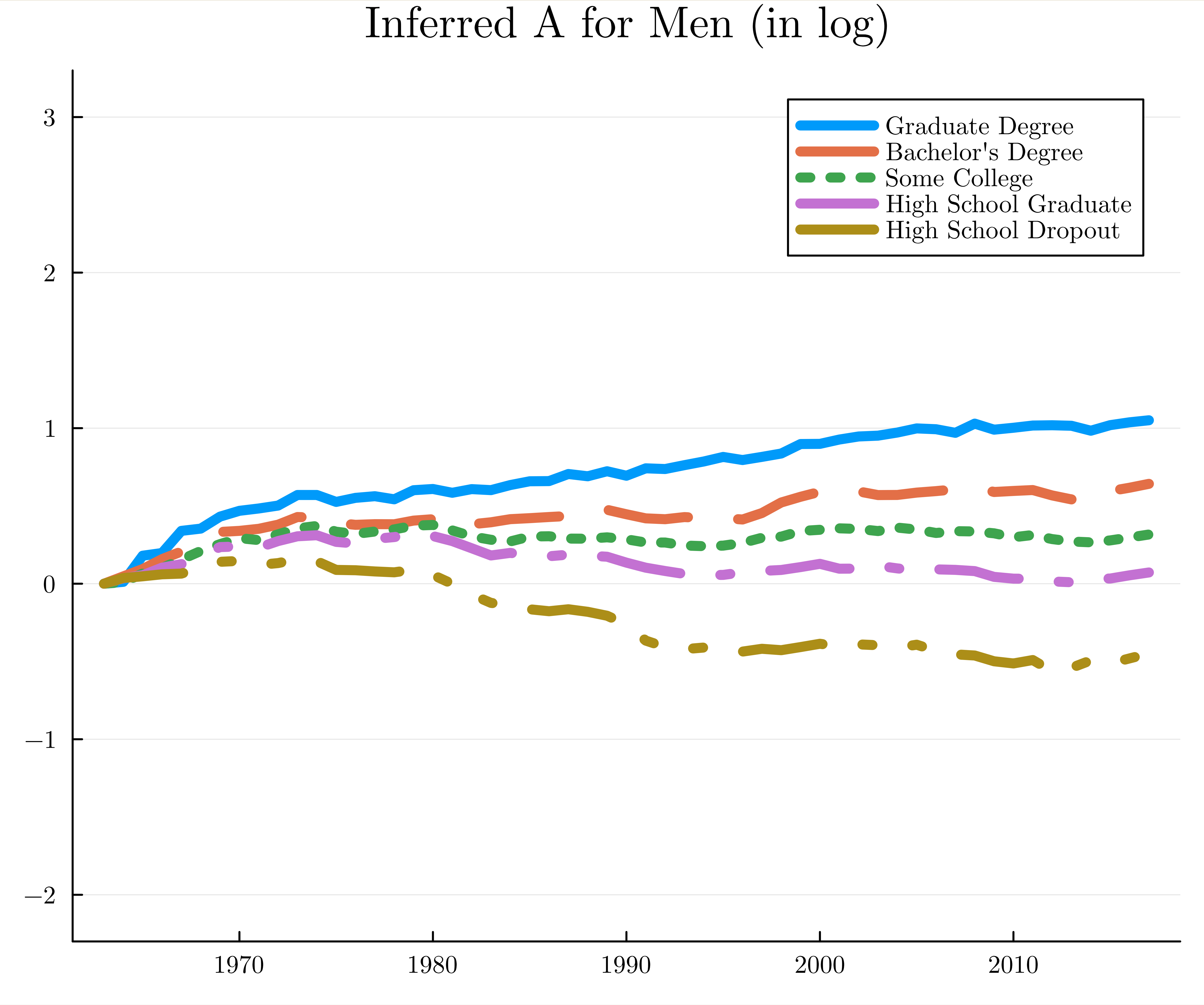
- Suppose we know σ (around $\sigma \in [2,5]$) and fix α
- We observe (L_H, L_L) and (w_H, w_L) in the data
- We can reverse-engineer (A_H, A_L) in the data
  - Just as in how we constructed aggregate TFP (Solow residual)
  - Now each for different groups of people!
- Implement with more than two skill groups:
  - post-college, college, some college, high-school, high-school dropout

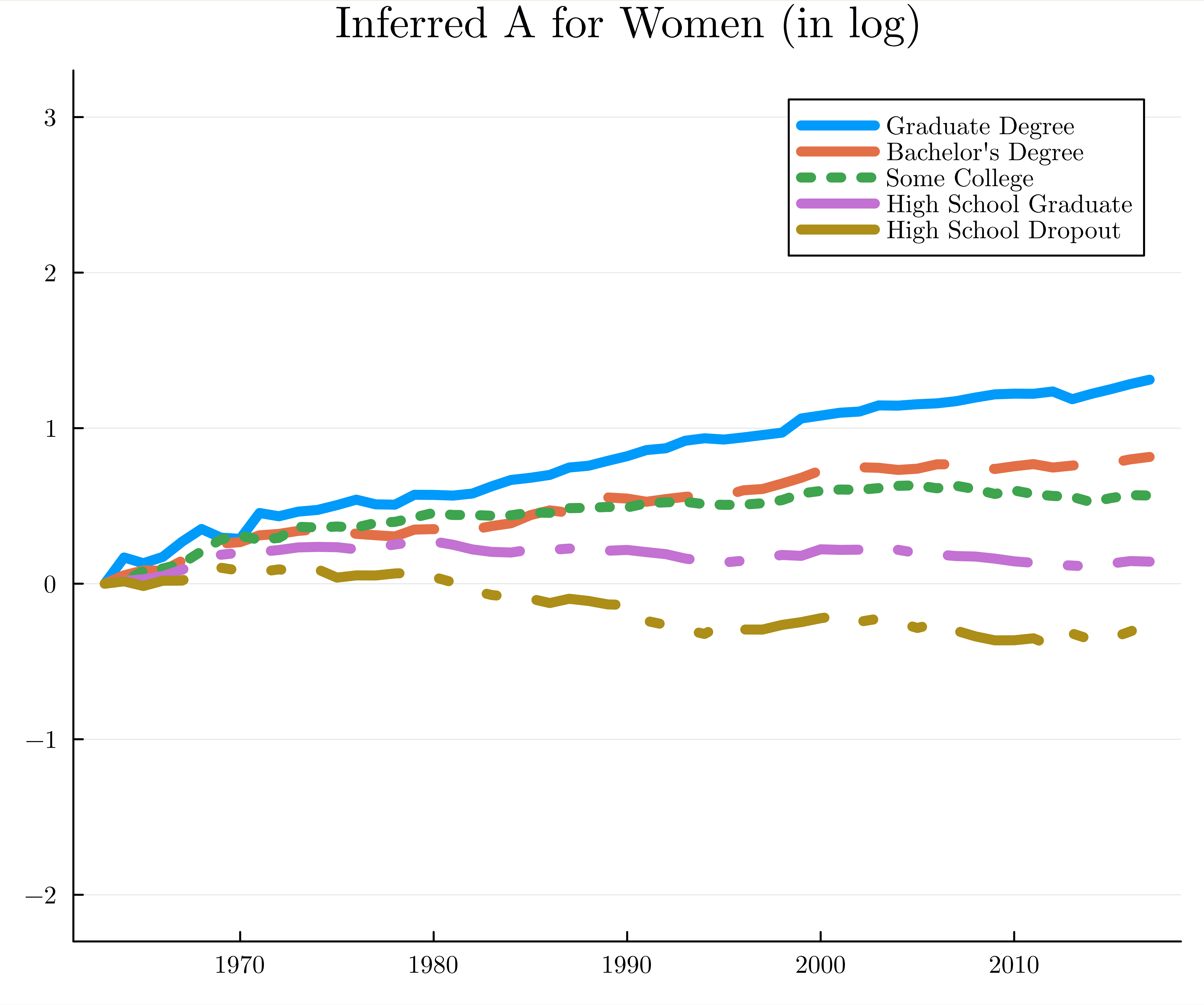
Inferred A with $\sigma = 2$





Inferred A with $\sigma = 5$





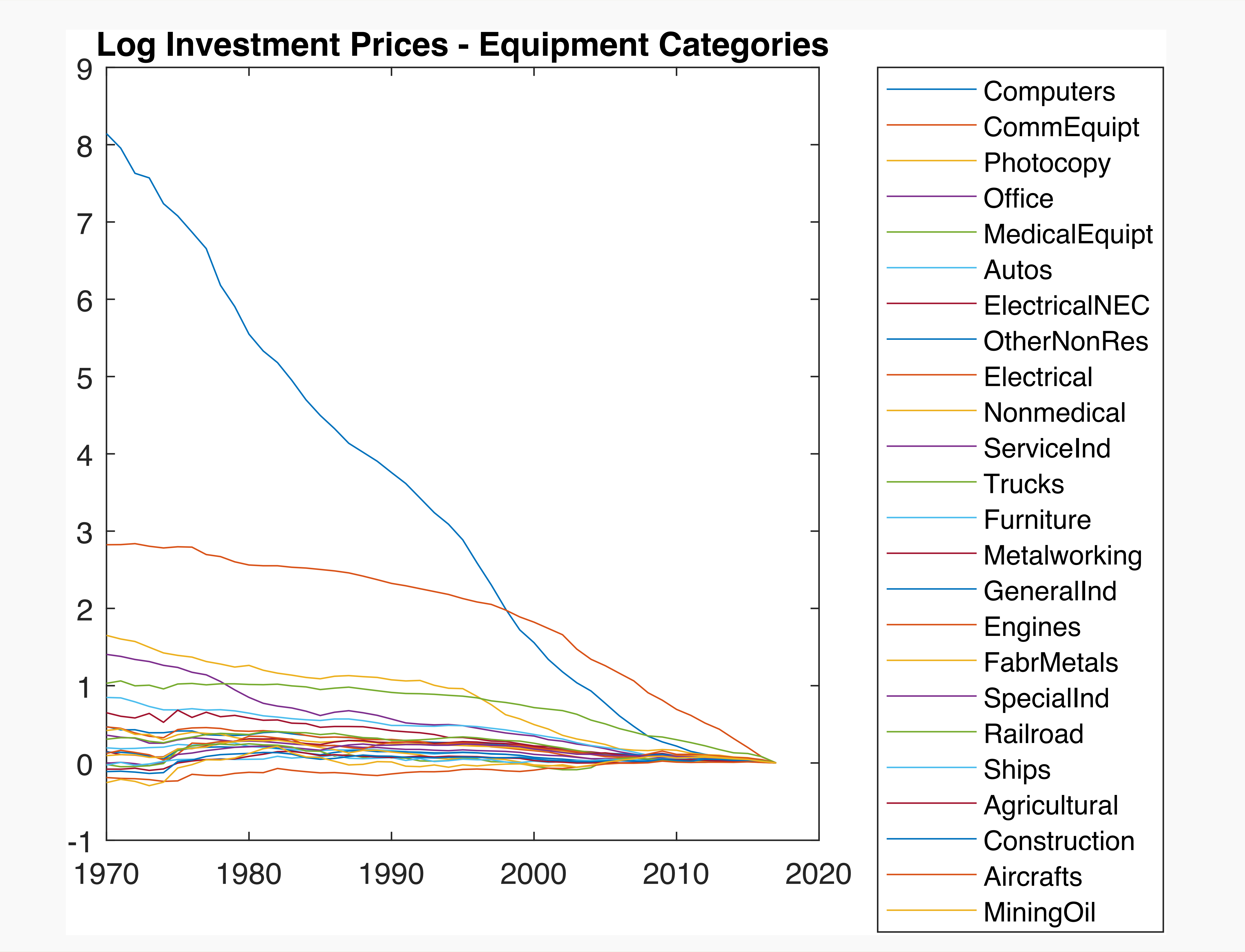
Takeaway

- Productivity of more educated groups sharply increasing over time
  - 50-300% **increase** during 1962-2017
- Productivity of less educated groups sharply declining over time
  - 50-250% **decrease** during 1962-2017
- We infer a substantial degree of "skill-biased technological change"
- What exactly are these technological changes?

Empirical Evidence of the Skill-Biased Technological Change

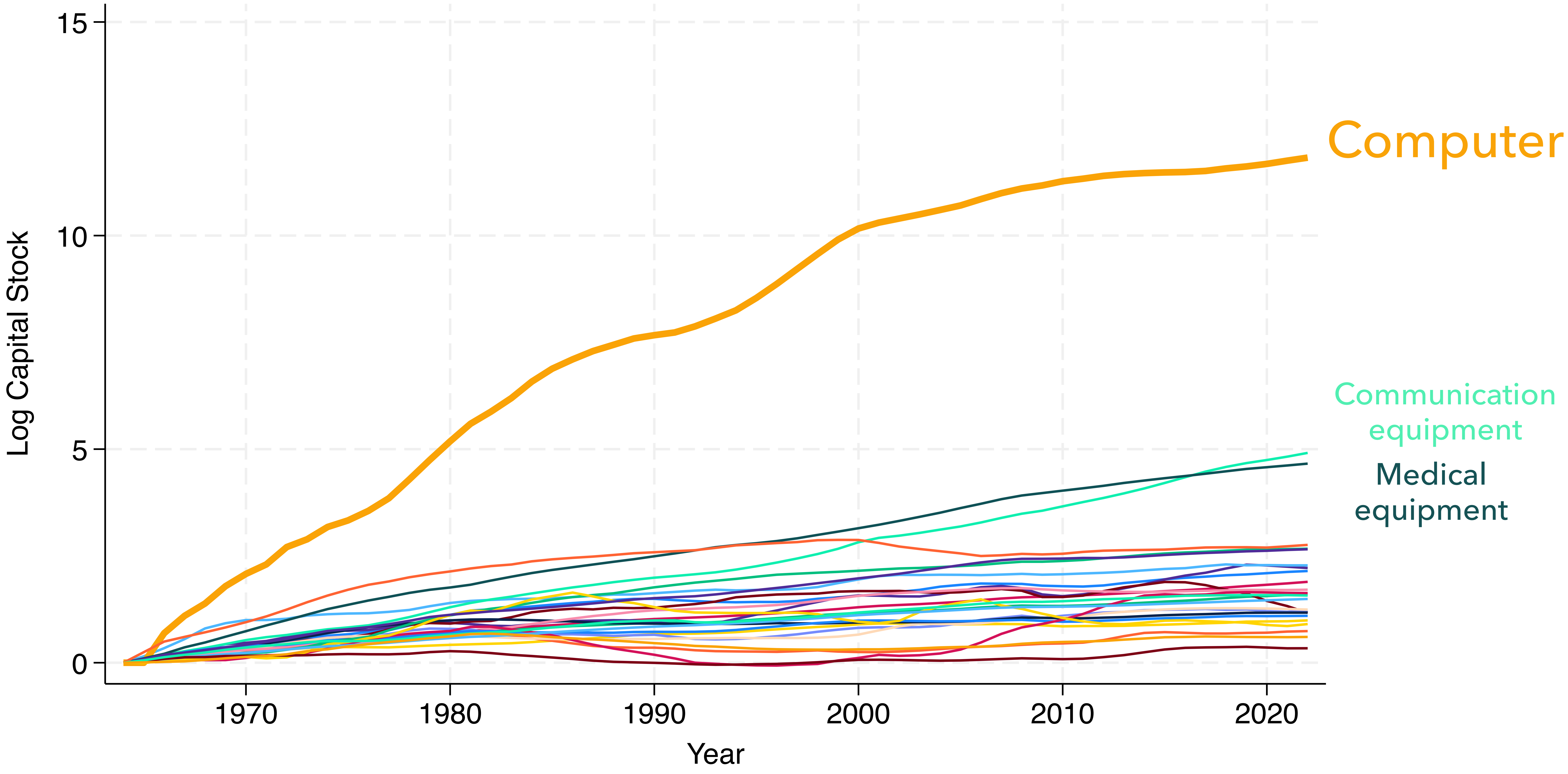
– Akerman, Gaarder & Mogstad (2015)

Declining ICT Equipment Prices



Source: BEA and Gourio and Rognlie (2020)

Surge in ICT Capital Stock



Question

- How do the recent advancements in IC technology affect inequality?
- Setup: Noway 2001-2007
- Institutional background: National Broadband Policy
  - Goal: nationwide broadband access at uniform pricing
  - Means: infrastructure investments, local gov't mandates
- 428 municipalities differed in the timing of the rollout of broadband internet
  - compare municipality with early rollout to the late rollout
- Skill groups: (i) skill (college); (ii) medium (high-school); (iii) low (less than high-school)

Broadband Internet Availability in Norway

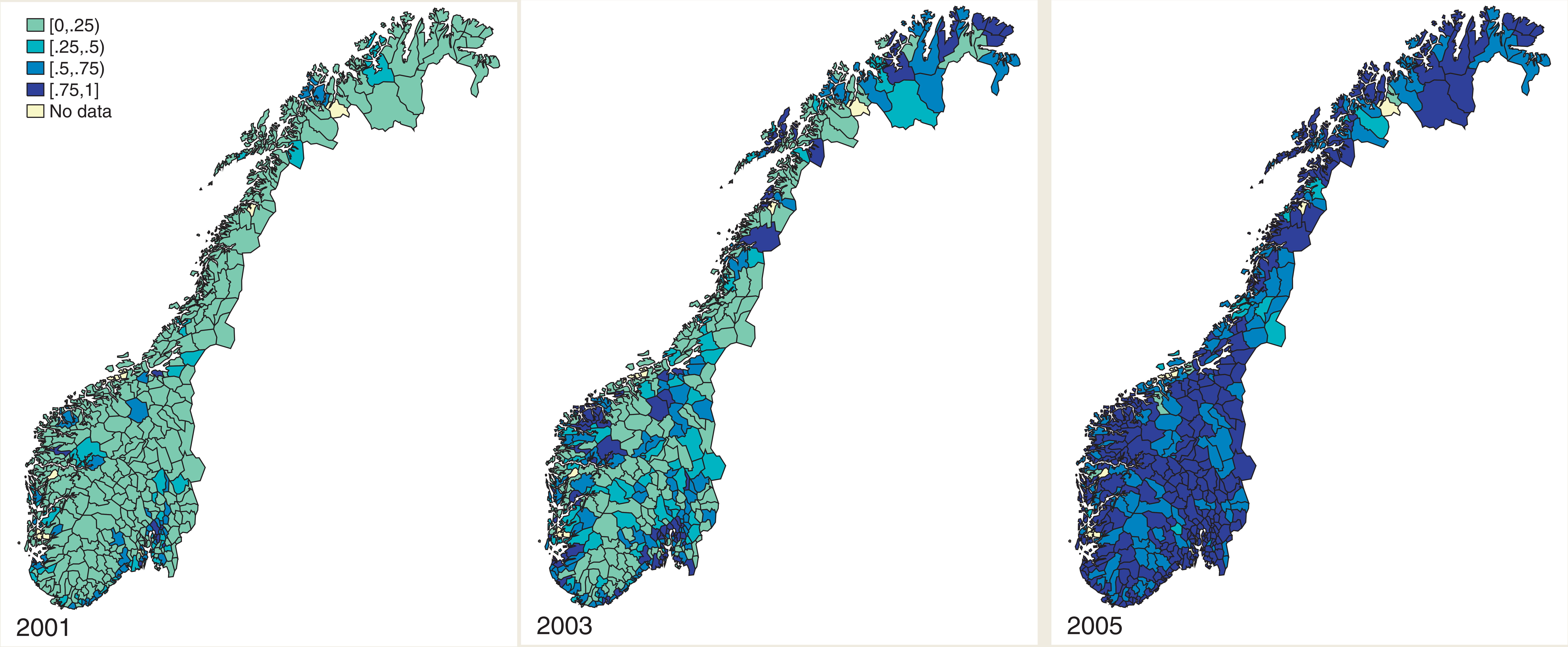
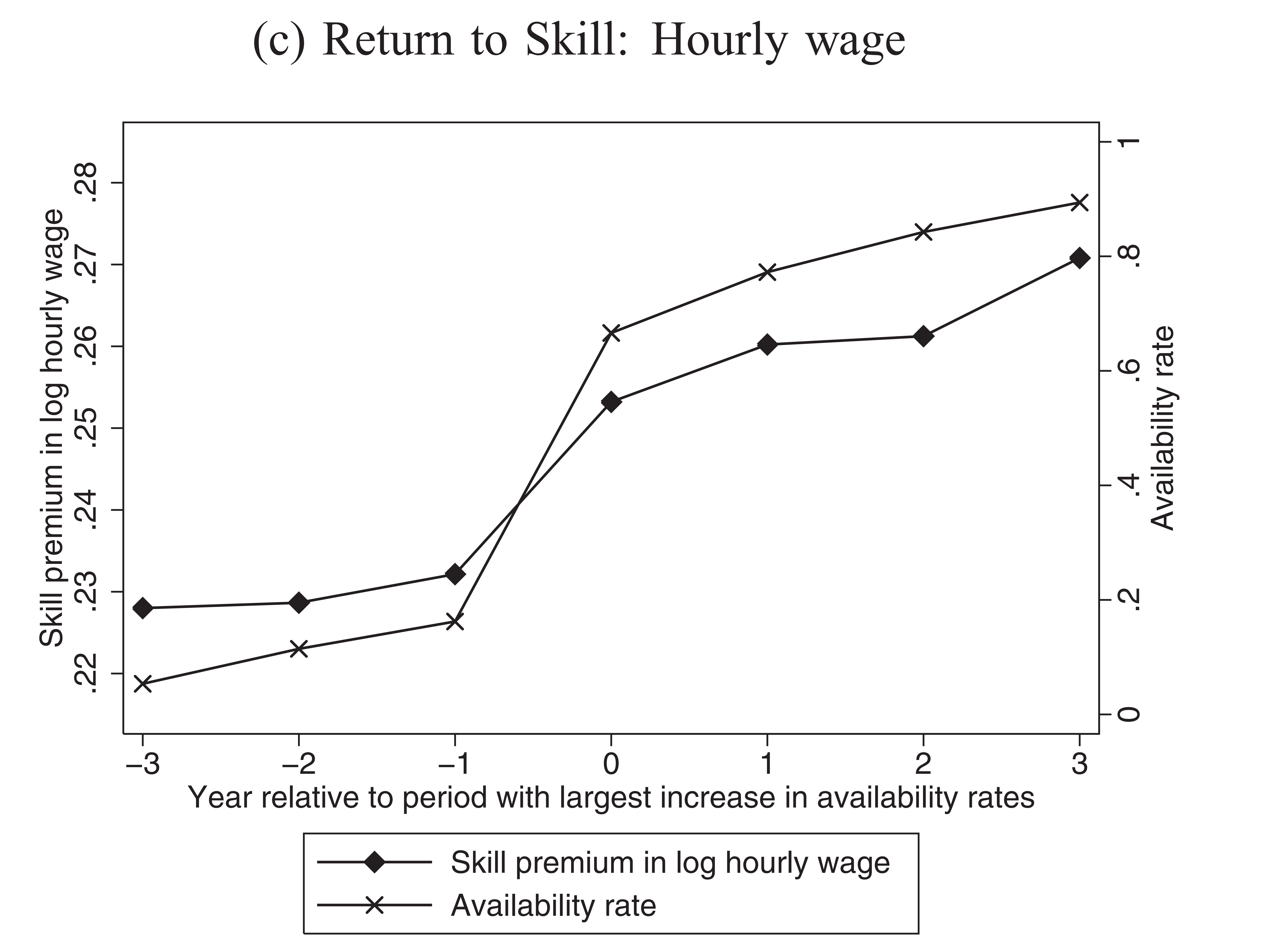


Figure I

Geographical Distribution of Broadband Availability Rates

The graphs show the geographical distribution of broadband availability rates of households in 2001, 2003, and 2005.

Impact of the Broadband Internet on Skill Premium



Impact on Wages and Employment

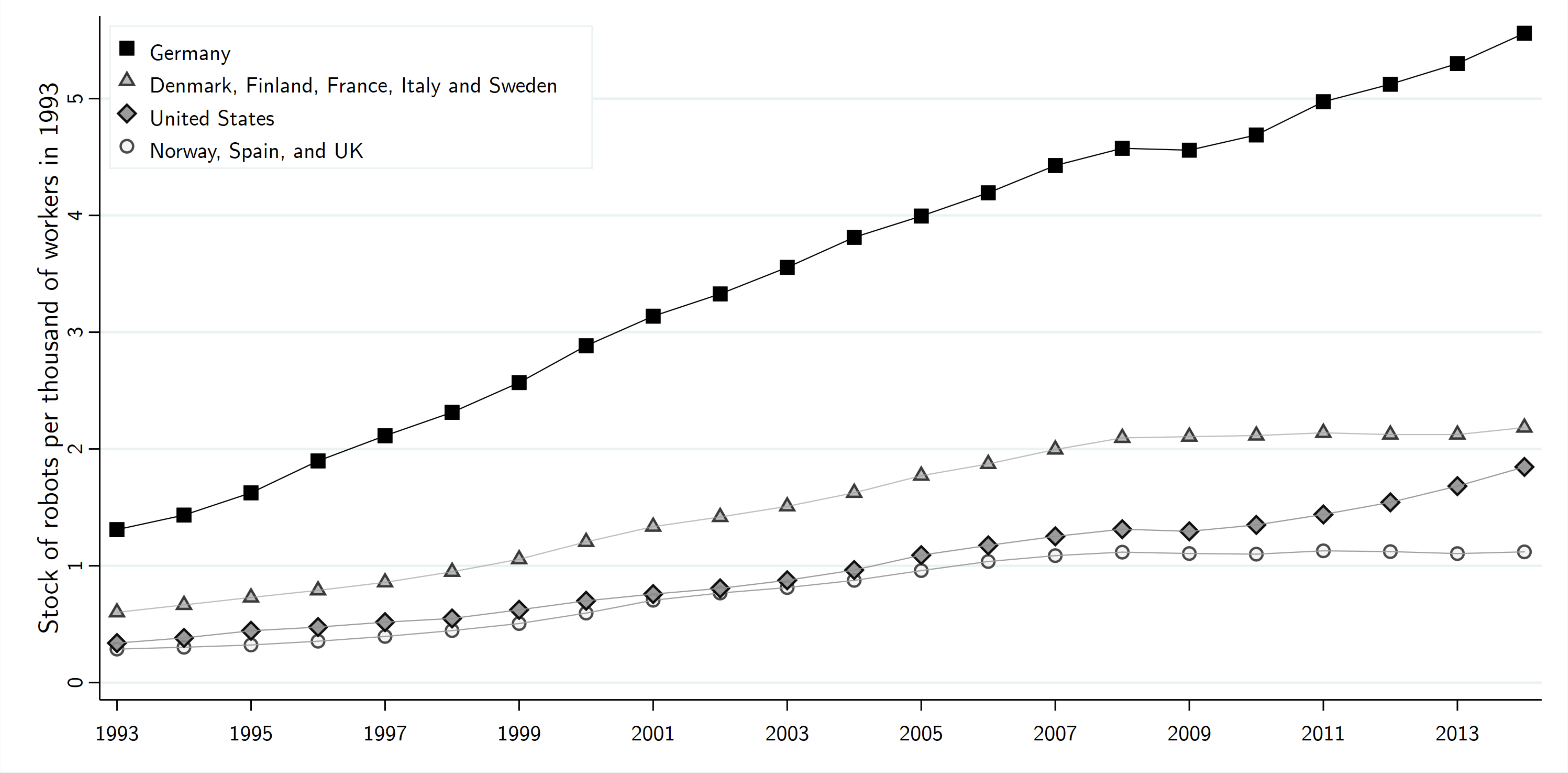
Dependent variable	(1)	(2)	(3)	(4)
	Log hourly wage		Employment	
	2 skills	3 skills	2 skills	3 skills
Availability ×				
Unskilled	−0.00622		0.000794	
	(0.00455)		(0.00252)	
Low skilled		−0.0108***		−0.00392
		(0.00325)		(0.00244)
Medium skilled		−0.00793		0.00388
		(0.00600)		(0.00281)
Skilled	0.0178**	0.0202***	0.0208**	0.0225**
	(0.00720)	(0.00692)	(0.00920)	(0.00892)
Worker-year observations	8,759,388	8,759,388	20,327,515	20,327,515
		p-values		
Test for no skill bias	.000	.000	.012	.001

- Availability of internet...
  (i) raises skilled wage by 2%; (ii) reduces low skilled wage by 1%

2. Automation and Wages

– Acemoglu and Restrepo (2019)

Industrial Robots per Thousand Workers



Robots and Jobs

Labor will become less and less important…More and more workers will be replaced by machines. I do not see that new industries can employ everybody who wants a job.

– Wassily Leontief

Can Robots Reduce Wages?

- Can robots make labor less and less important?
- Consider the production function of the form:

$$F(K, L) = AK^{\alpha}L^{1-\alpha}$$

- As before, wages are given by the marginal product of labor:

$$w = (1-\alpha)AK^{\alpha}L^{-\alpha} = (1-\alpha)\frac{Y}{L}$$

- More robots (higher K) always increase wages!
- What did we miss? Is higher K the right way to think about the automation?

Task-Based Model

- There are N tasks in the economy (cutting, assembling, designing…)
- Suppose that GDP is a combination of task-level output:

$$Y = (X_1)^{1/N} \times (X_2)^{1/N} \times \cdots \times (X_N)^{1/N}$$

- Each task is produced using either labor or robots:

$$X_i = \begin{cases} K_i & \text{if } i \leq I \\ L_i & \text{if } i > I \end{cases}$$

- **Automation**: an increase in I

Back to Cobb-Douglas

- There are L workers and K robots in the economy
- Since all tasks are symmetric, each task employ equal number of workers/robots

$$K_i = \frac{K}{I} \quad \text{for } i \leq I$$

$$L_i = \frac{L}{N - I} \quad \text{for } i > I$$

- Substituting back,

$$Y = \frac{1}{N\alpha^{\alpha}(1-\alpha)^{1-\alpha}} K^{\alpha} L^{1-\alpha}, \quad \alpha \equiv I/N$$

- Back to the Cobb-Douglas production, but α is now the share of automated tasks!

Automation and Wages Revisited

- The wage is given by the marginal product of labor:

$$w = (1-\alpha)\frac{1}{N\alpha^{\alpha}(1-\alpha)^{1-\alpha}}K^{\alpha}L^{-\alpha}$$

$$= (1-\alpha)\frac{Y}{L}$$

- An increase α now appears in two places
  - Displacement effect:
    automation displaces tasks that used to be performed by workers
  - Productivity effect: automation increases the overall output

Automation and Wages Revisited

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Productivity effect

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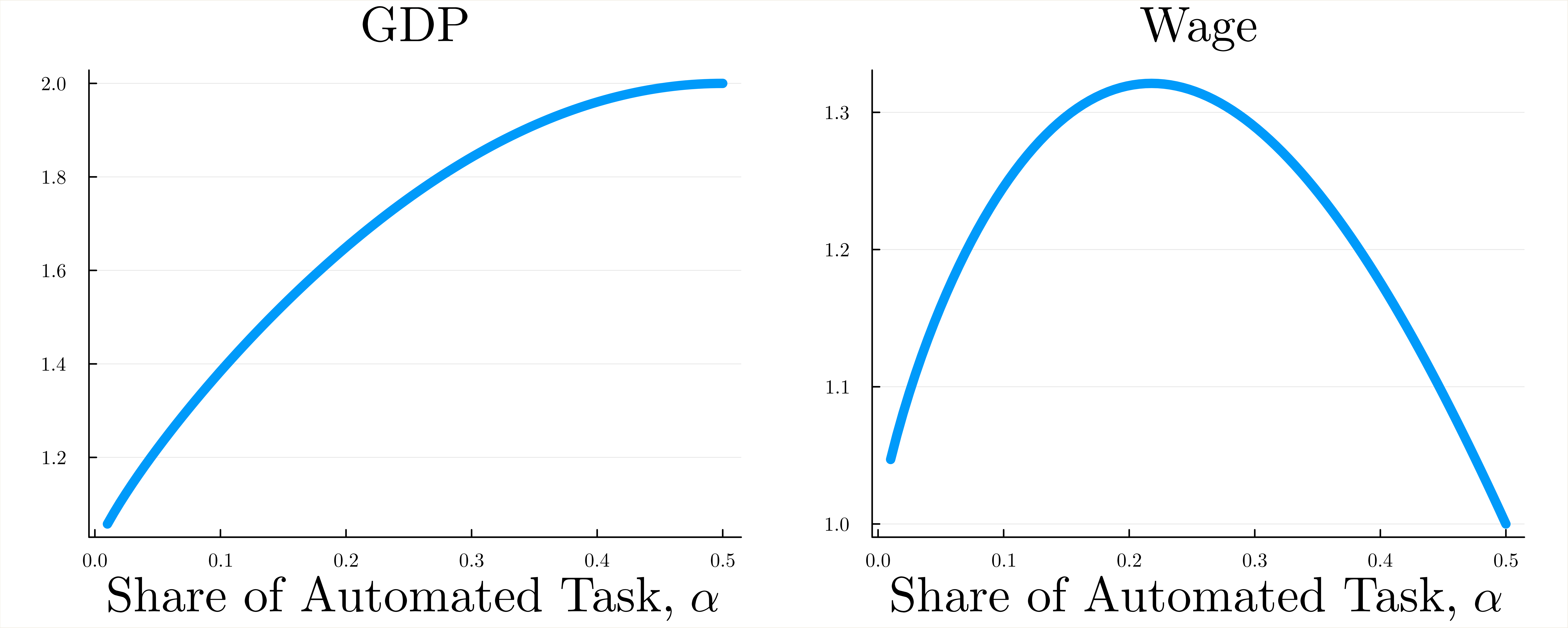
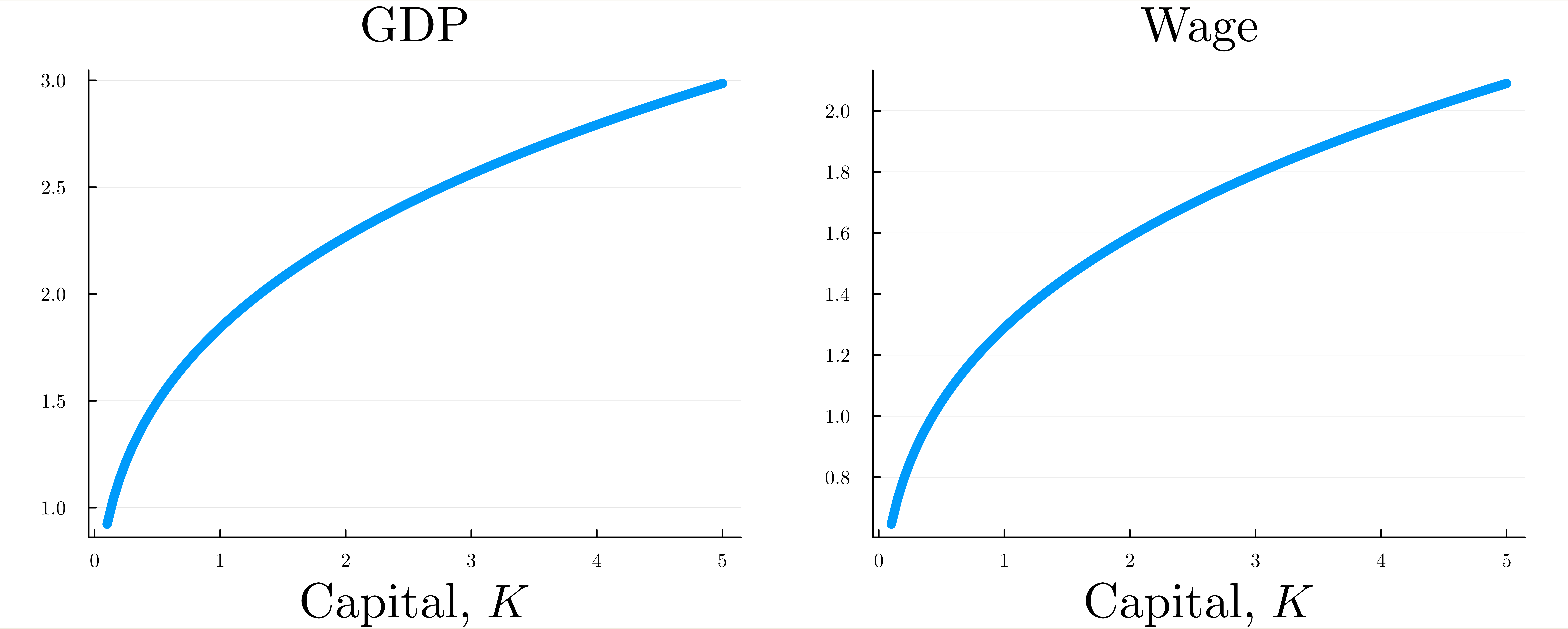
Automatioin can Reduce Wage



Higher K Always Increases Wages



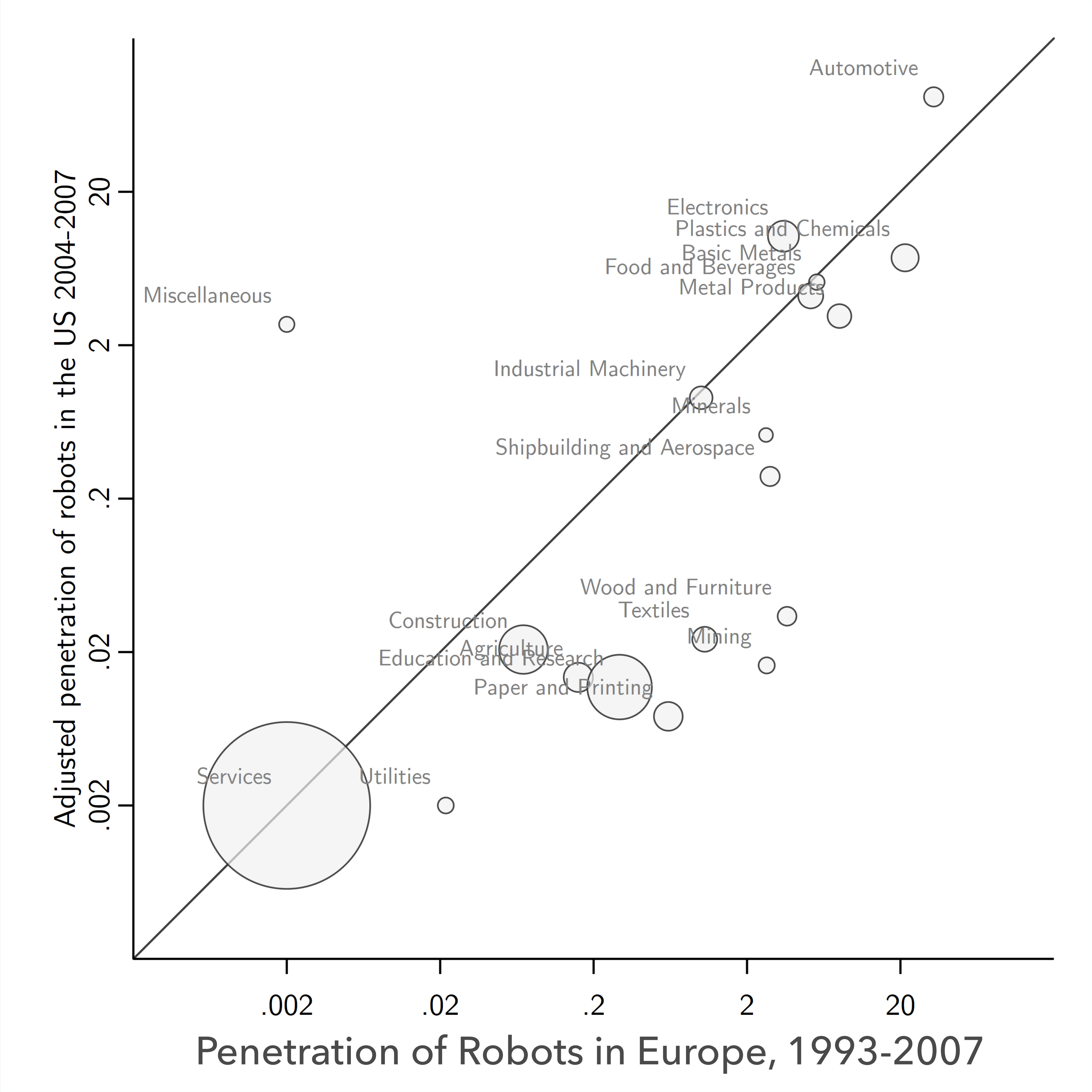
Do Robots Displace Workers?: Empirical Evidence

– Acemoglu and Restrepo (2020)

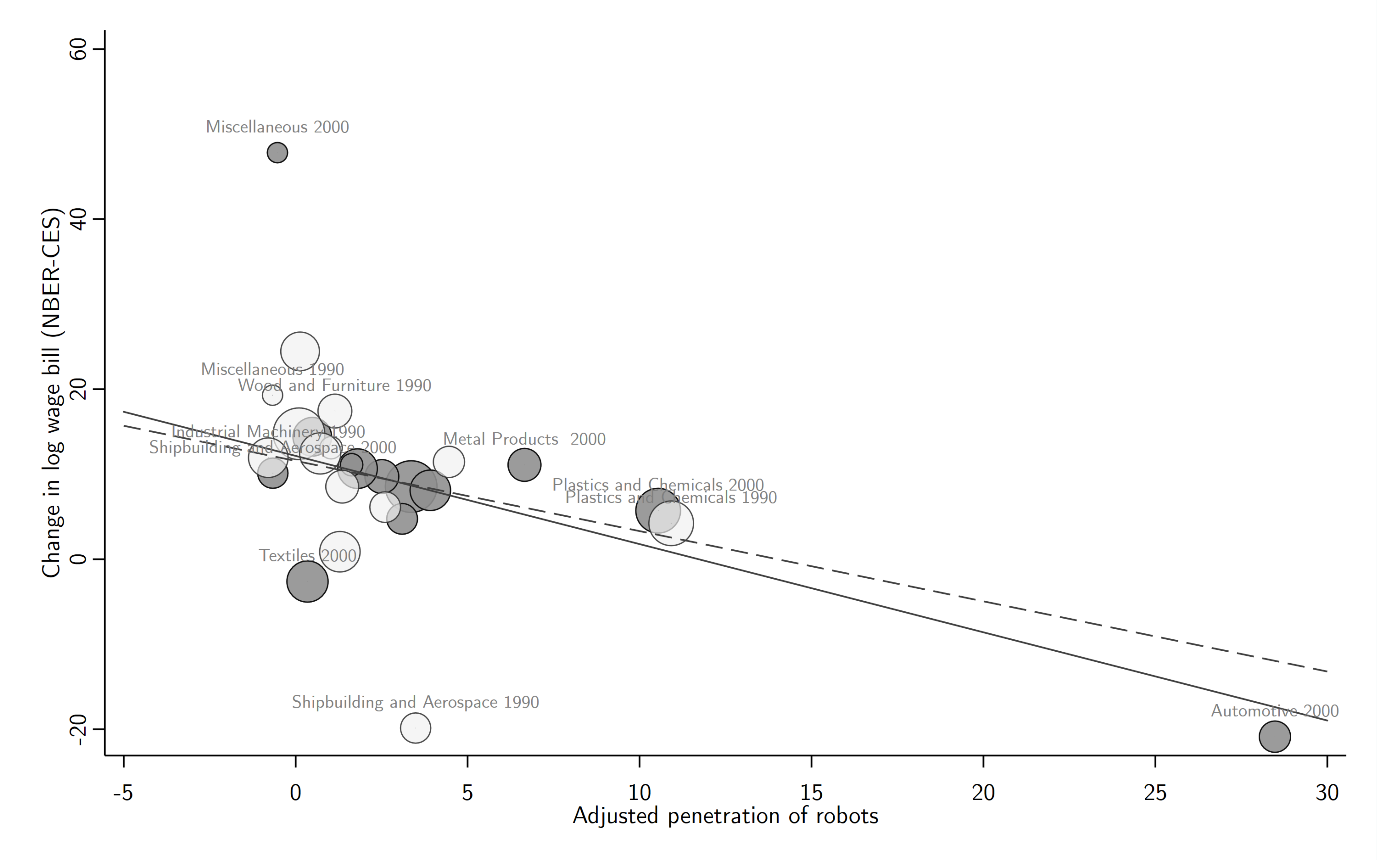
Empirical Strategies

- Different industries experience different degrees of automation
- Regions differ in terms of industrial compositions
  $\Rightarrow$ difference in exposure to automation
- Two strategies:
  1. Compare more exposed industries with less exposed ones
  2. Compare more exposed regions with less exposed regions

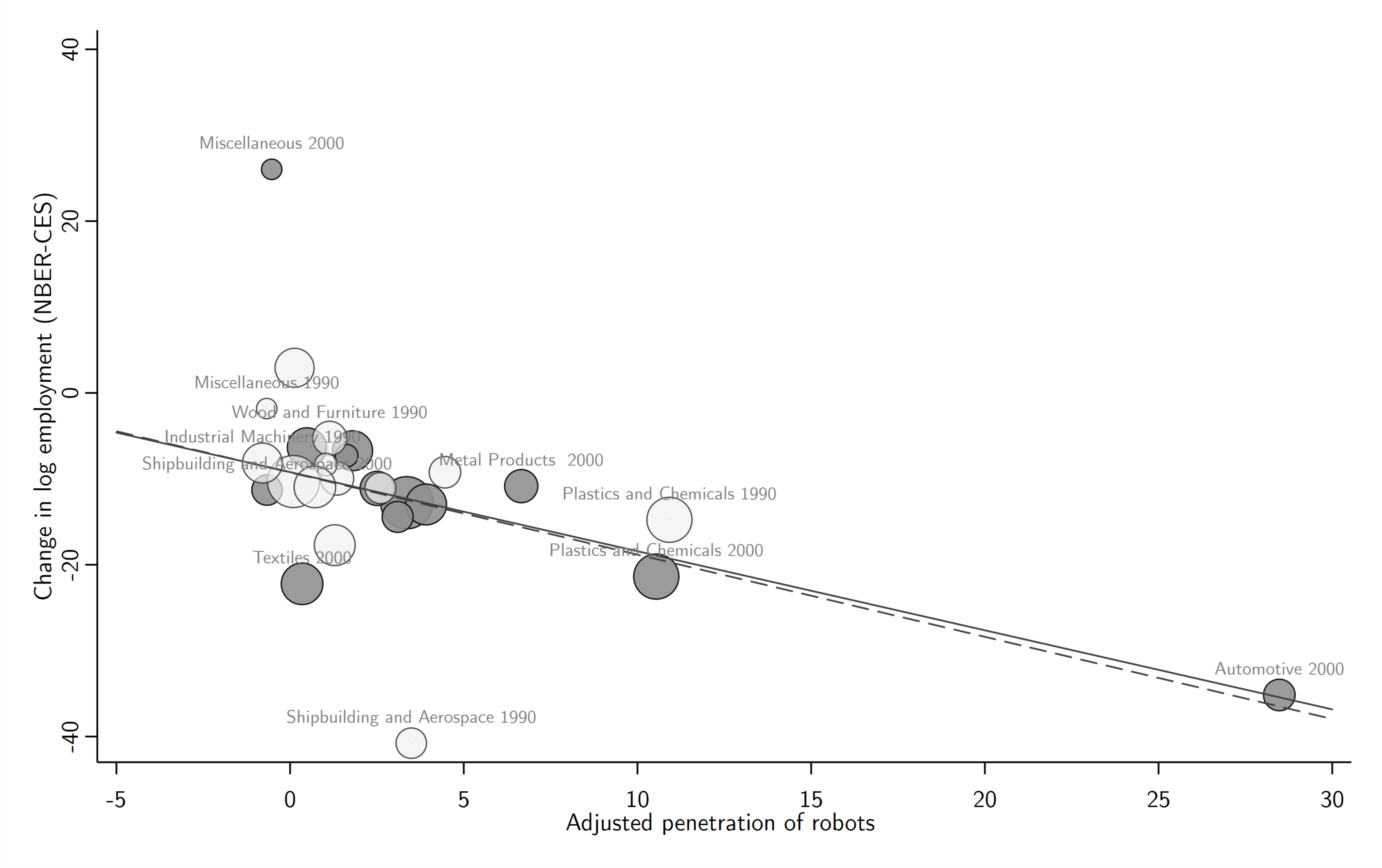
Industry Variation



Robot Penetration and Industry Wages



Robot Penetration and Industry Employment

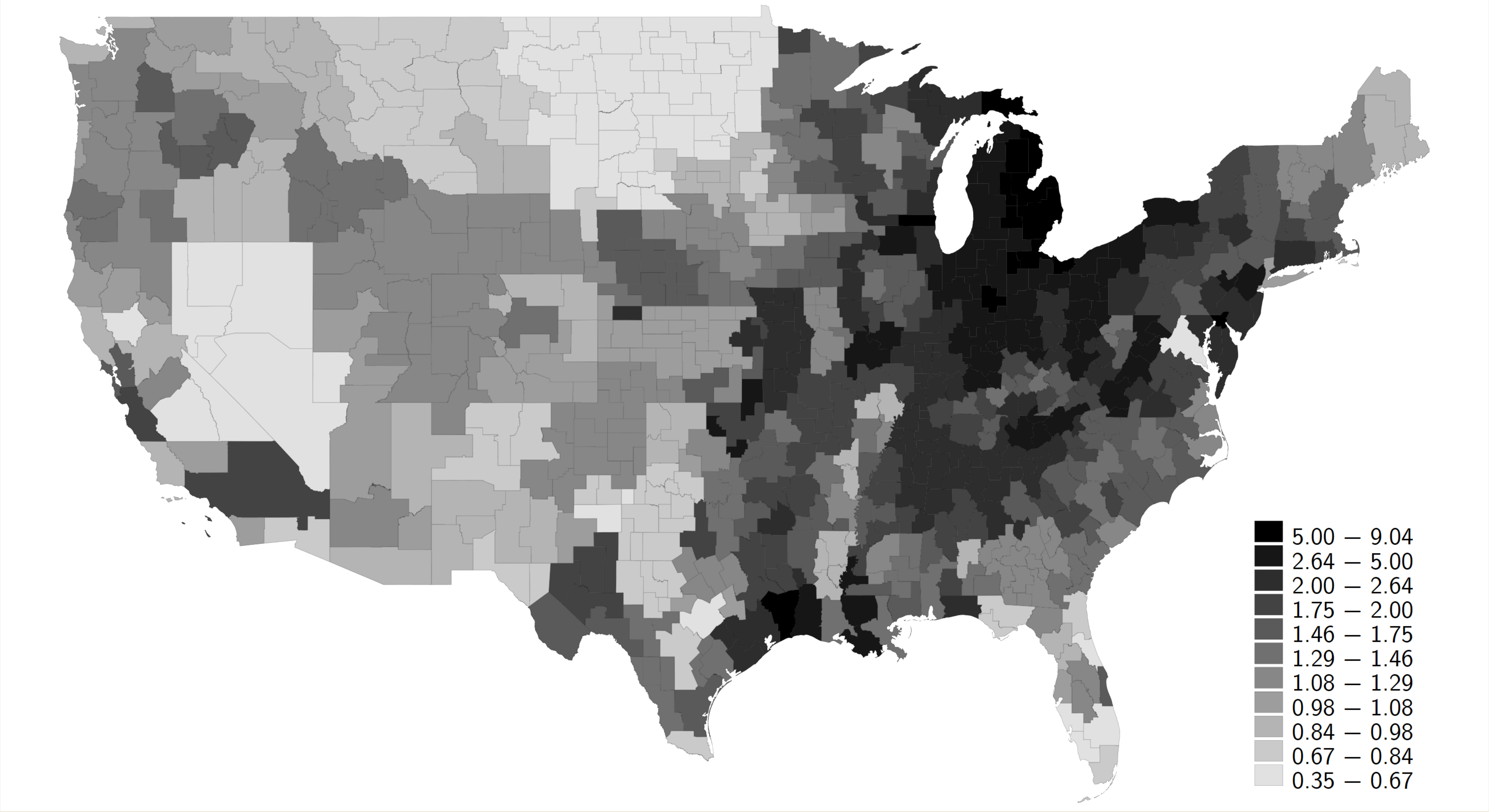


Regional Exposure to Robots

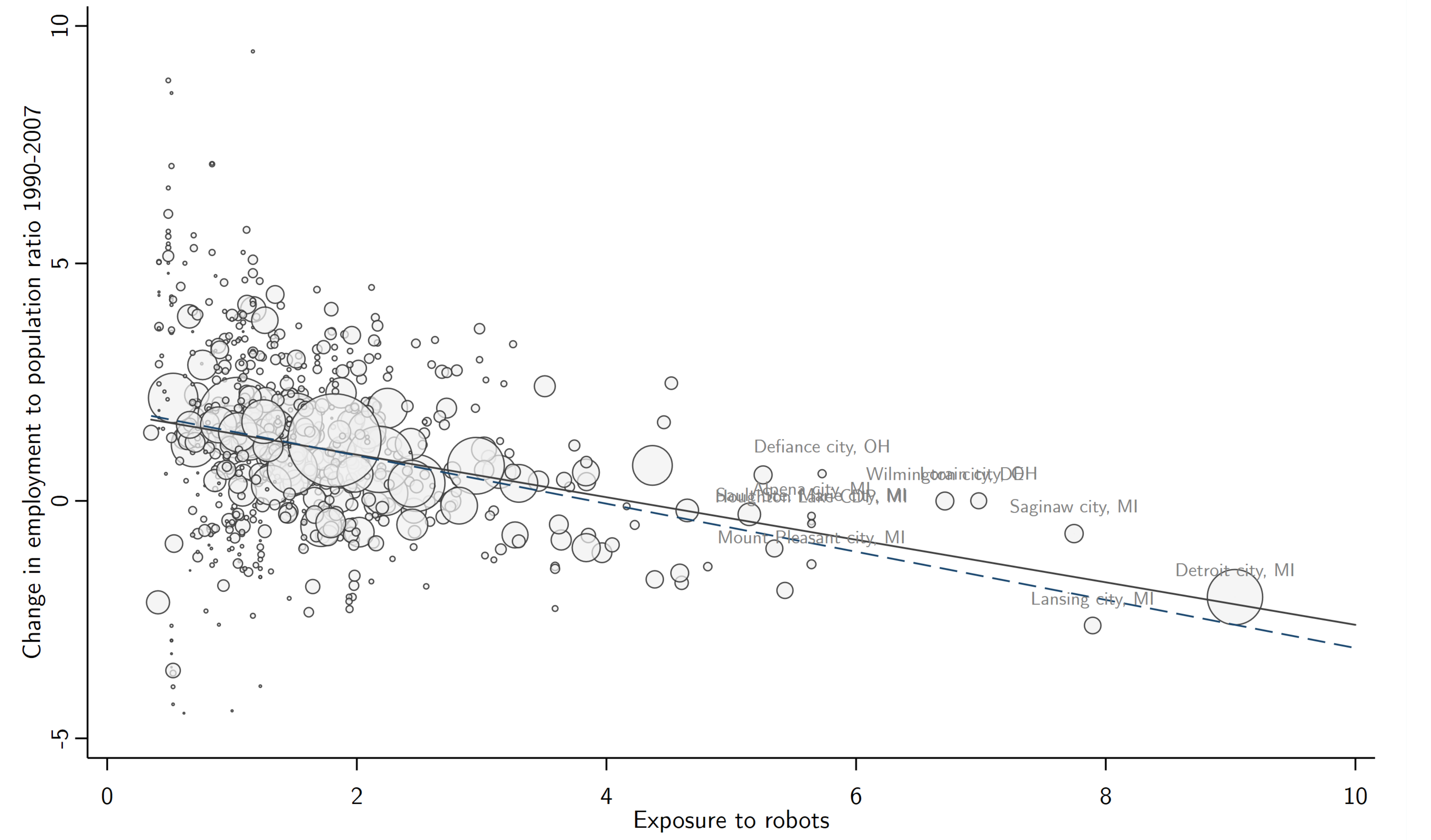
- At the industry level, one more robot per thousand workers is associated with
  - a reduction in wages by 0.9%
  - a reduction in employment by 1.1%

- We now turn to regional analysis. Why regional?
  - It captures the local labor market *equilibrium* effect of automation
    – spillovers to people not working or leaving the directly affected industries
- US regions greatly differed in industry compositions
  $\Rightarrow$ they greatly differed also in exposures to robots

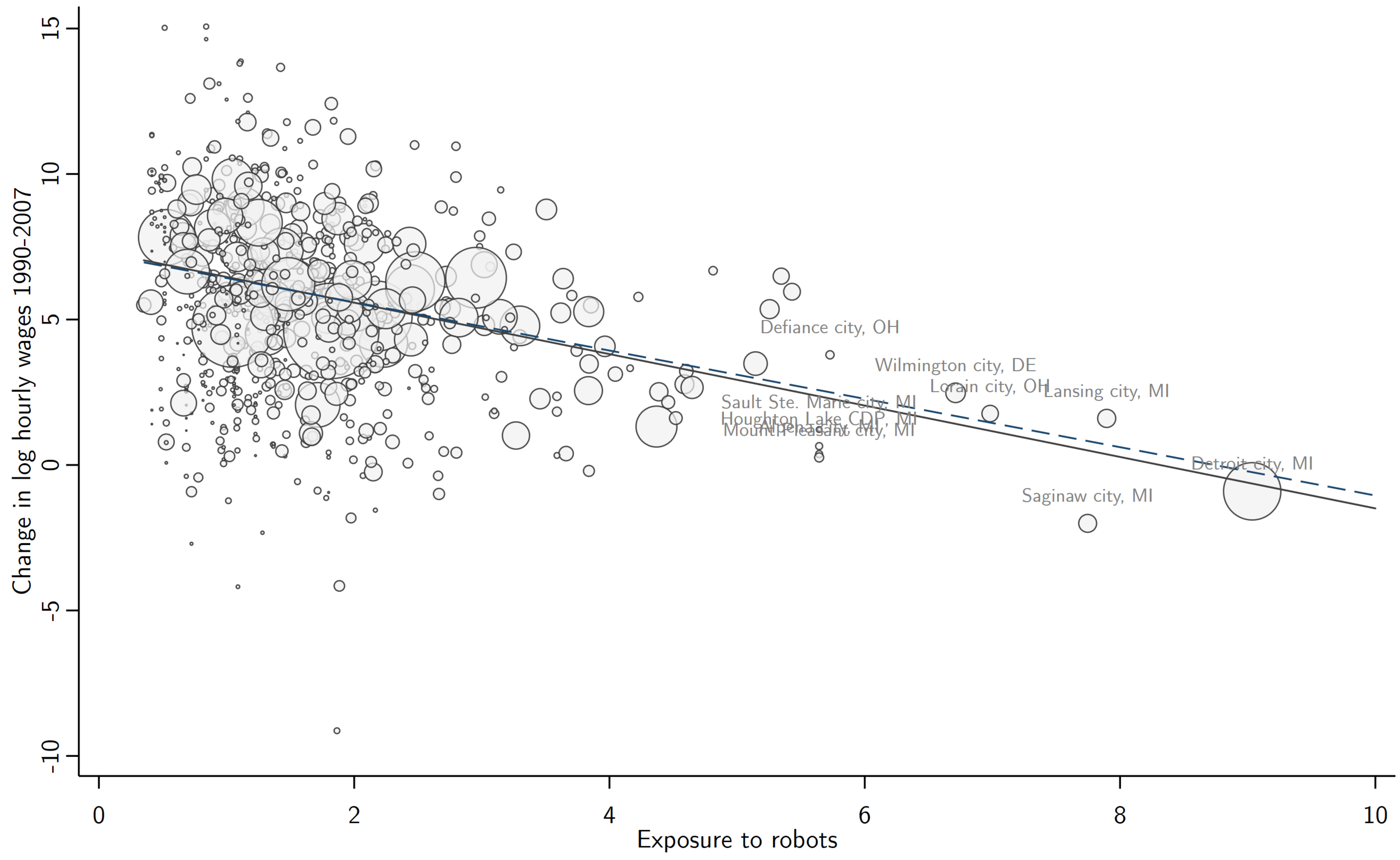
Exposure to Robots



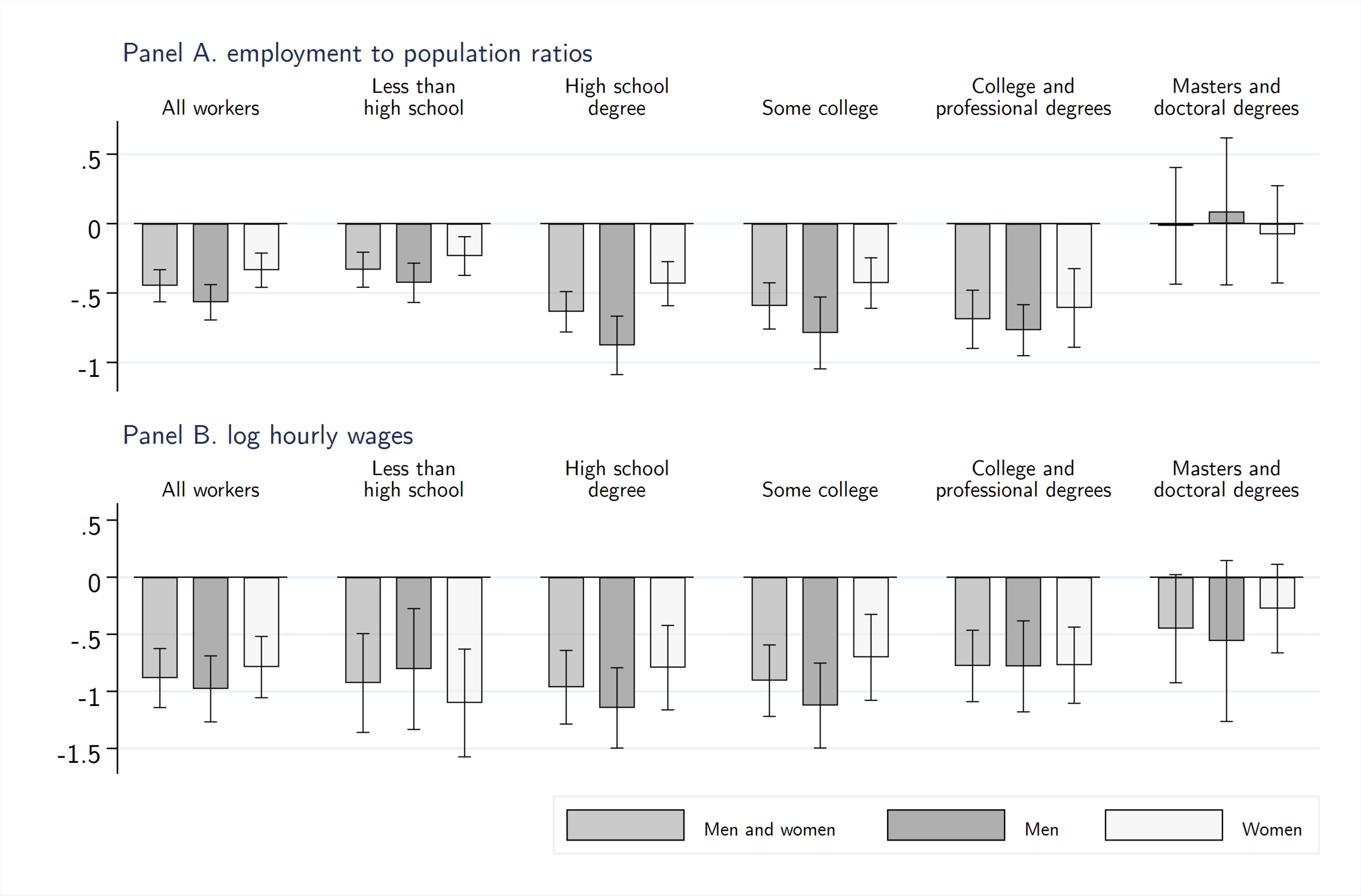
Robots and Regional Employment



Robots and Regional Wages



Effect by Educational Groups



Quantitative Magnitude

- Robots per thousand workers increased by 1.5 in 1993-2014
- This implies
  - 0.3 p.p. decline in employment-to-population ratio
  - 0.42% decline in overall wages