

# 14.452 Economic Growth: Lecture 10, Inequality: The Canonical Approach

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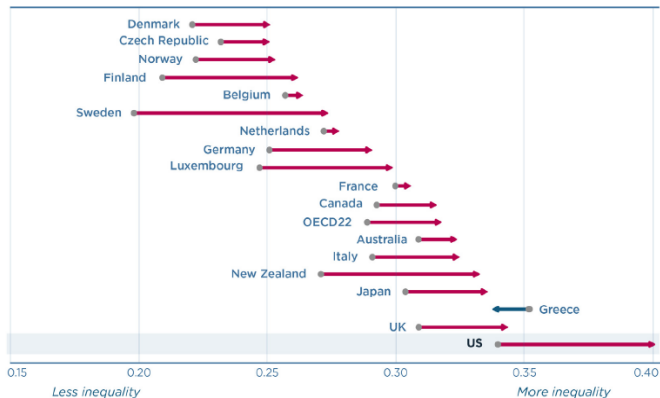
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# Introduction

- We saw the major changes in inequality in the first lecture.
- Do basic growth models, or approaches building on them, have insightful things to say about these inequality patterns?
- Are these inequality trends driven by technology, supply and demand? What else?
- Let me briefly review some of the facts from Lecture 1.

# Surge in Inequality

Figure 1: Change in Gini coefficient, 1985 to 2013

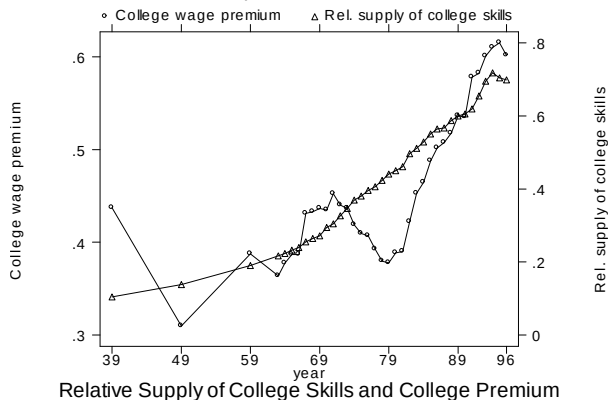


**Note:** 1985 data refer to 1985 or closest available year. 2013 data refer to 2013 or nearest available year. The Gini coefficient measures how equally income is distributed across a population, from 0 (perfectly equal) to 1 (all income to one person).

**Source:** Organization for Economic Cooperation and Development (OECD), "In It Together: Why Less Inequality Benefits All."

# Increased Skill Premia with Growing Supplies: College Premium in the US

- A common pattern across countries is that greater skill and college premia have coincided with rapidly rising supplies (and it is not supplies responding to premia). For example for the US:



# Skill-Biased Technological Change

- Standard explanation based on Jan Tinbergen's seminal work: build on neoclassical growth insights but extend them to incorporate growing demand for skills.
- Key idea: technological change is *skill-biased*, raising demand for more skilled workers.
- Model this as factor-augmenting technological change, as in basic neoclassical approaches.
- Then perhaps also an acceleration that coincided with the changes in the relative supply of skills (though this is secondary, since the behavior of skill supplies is rather complex).
- Important question: skill bias is endogenous, so, why has technological change become more skill biased in recent decades?
- Let us first formalize these ideas.

# Constant Elasticity of Substitution Production Function I

- CES production function case:

$$Y(t) = \left[ \gamma_L (A_L(t) L(t))^{\frac{\sigma-1}{\sigma}} + \gamma_H (A_H(t) H(t))^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where

- $A_L(t)$  and  $A_H(t)$  are two separate technology terms.
- $\gamma_i$ s determine the importance of the two factors,  $\gamma_L + \gamma_H = 1$ .
- $\sigma \in (0, \infty)$  = elasticity of substitution between the two factors.
  - $\sigma = \infty$ , perfect substitutes, linear production function is linear.
  - $\sigma = 1$ , Cobb-Douglas,
  - $\sigma = 0$ , no substitution, Leontieff.
  - $\sigma > 1$ , "gross substitutes,"
  - $\sigma < 1$ , "gross complements".
- Clearly,  $A_L(t)$  is  $L$ -augmenting, while  $A_H(t)$  is  $H$ -augmenting.
- Whether technological change that is  $L$ -augmenting (or  $H$ -augmenting) is  $L$ -biased or  $H$ -biased depends on  $\sigma$ .

# Constant Elasticity of Substitution Production Function II

- Relative marginal product of the two factors:

$$\frac{MP_H}{MP_L} = \gamma \left( \frac{A_H(t)}{A_L(t)} \right)^{\frac{\sigma-1}{\sigma}} \left( \frac{H(t)}{L(t)} \right)^{-\frac{1}{\sigma}}, \quad (1)$$

where  $\gamma \equiv \gamma_H / \gamma_L$ .

- substitution effect*: the relative marginal product of  $H$  is decreasing in its relative abundance,  $H(t) / L(t)$ .
- The effect of  $A_H(t)$  on the relative marginal product:
  - If  $\sigma > 1$ , an increase in  $A_H(t)$  (relative to  $A_L(t)$ ) increases the relative marginal product of  $H$ .
  - If  $\sigma < 1$ , an increase in  $A_H(t)$  reduces the relative marginal product of  $H$ .
  - If  $\sigma = 1$ , Cobb-Douglas case, and neither a change in  $A_H(t)$  nor in  $A_L(t)$  is biased towards any of the factors.
- Note also that  $\sigma$  is the elasticity of substitution between the two factors.

# Constant Elasticity of Substitution Production Function III

- Intuition for why, when  $\sigma < 1$ ,  $H$ -augmenting technical change is  $L$ -biased:
  - with gross complementarity ( $\sigma < 1$ ), an increase in the productivity of  $H$  increases the demand for labor,  $L$ , by more than the demand for  $H$ , creating “excess demand” for labor.
  - the marginal product of labor increases by more than the marginal product of  $H$ .
  - Take case where  $\sigma \rightarrow 0$  (Leontieff): starting from a situation in which  $\gamma_L A_L(t) L(t) = \gamma_H A_H(t) H(t)$ , a small increase in  $A_H(t)$  will create an excess of the services of the  $H$  factor, and its price will fall to 0.

# Empirical Implementation (Katz and Murphy)

- Combining these equations (and of course assuming competitive markets), we have:

$$\ln \omega = \frac{\sigma - 1}{\sigma} \ln \left( \frac{A_H}{A_L} \right) - \frac{1}{\sigma} \ln \left( \frac{H}{L} \right).$$

- Now following Tinbergen, posit:

$$\ln \left( \frac{A_{H,t}}{A_{L,t}} \right) = \gamma_0 + \gamma_1 t,$$

- Then:

$$\ln \omega_t = \frac{\sigma - 1}{\sigma} \gamma_0 + \frac{\sigma - 1}{\sigma} \gamma_1 t - \frac{1}{\sigma} \ln \left( \frac{H_t}{L_t} \right).$$

- Estimating this for 1963–1987, following Katz and Murphy (1992), we obtain

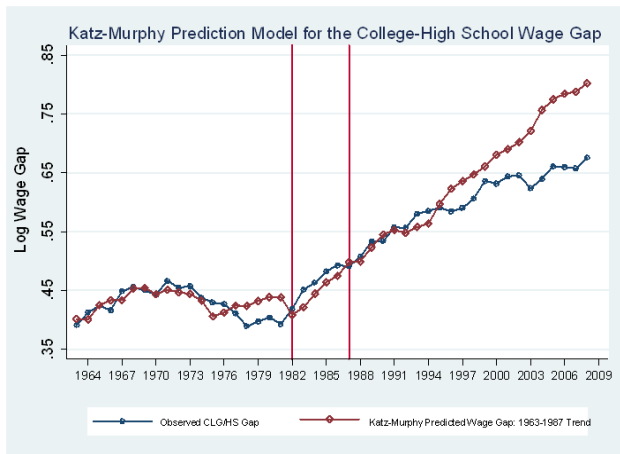
$$\ln \omega_t = \text{constant} + \underset{(0.005)}{0.027 \times t} - \underset{(0.128)}{0.612 \cdot \ln \left( \frac{H_t}{L_t} \right)}$$

# Problem 1

- Factor-augmenting technologies lack descriptive realism.
- Are computers skill biased?
- This would literally mean that they increase the productivity of labor uniformly in everything. But they clearly do not do that. Skilled laborers performing manual tasks will not experience such an increase, nor will workers providing entertainment.
- What about robots? It is difficult to imagine robots as directly increasing the productivity of any type of worker — they are meant to perform tasks that were previously performed by labor.

## Problem 2

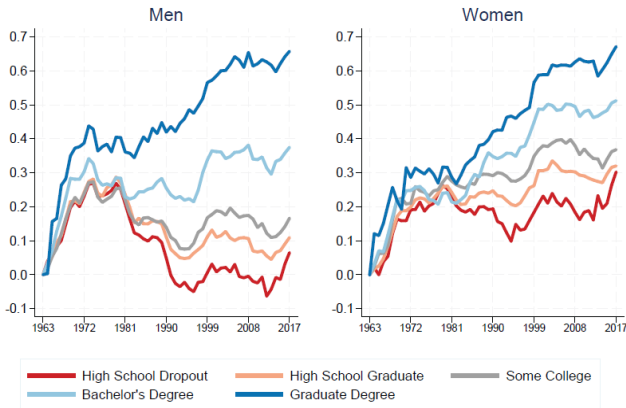
- Bad out of sample prediction of Katz-Murphy type regressions.



## Problem 3

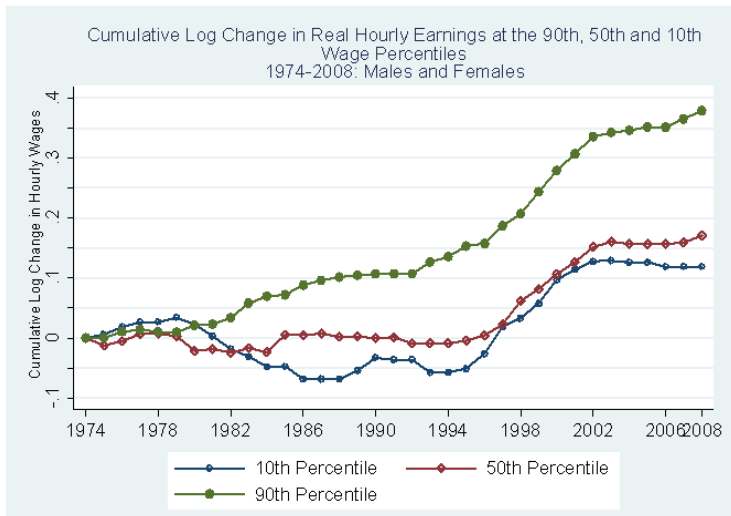
- Declining real wages (without technological **regress**, there should be no wage declines for any group). Recall:

Cumulative Change in Real Log Weekly Earnings 1963 - 2017  
Working Age Adults, Ages 18 - 64



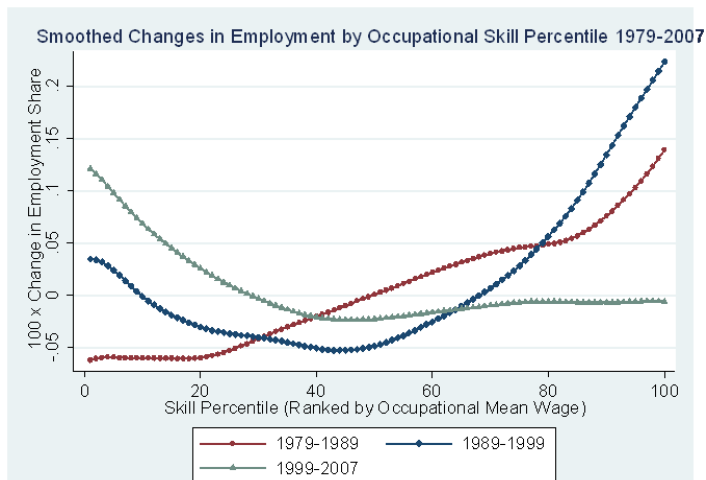
## Problem 3 (continued)

- It is not composition effects:



## Problem 4

- No occupational evidence for skill-biased change since the 1990s (Acemoglu and Autor, 2011).



# Problem 4 (continued)

- Not just confined to the US.

Change in employment shares of young female workers (age <40) by country,  
1992-2008

