14.452 Economic Growth: Lecture 11, Inequality: The Canonical Approach

Daron Acemoglu

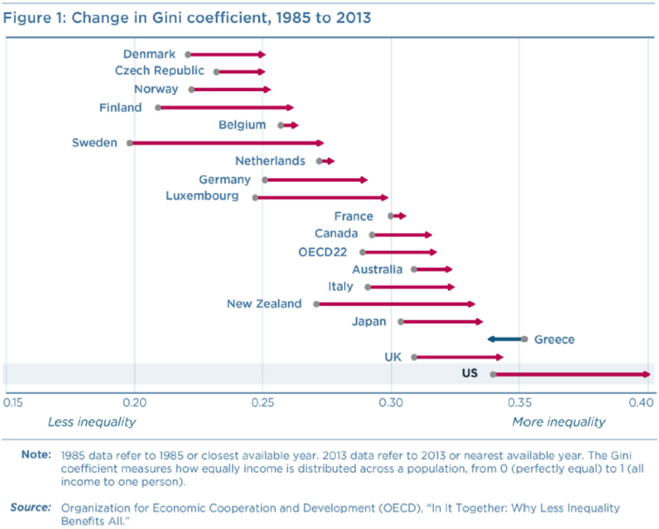
MIT

December 5, 2023

Introduction

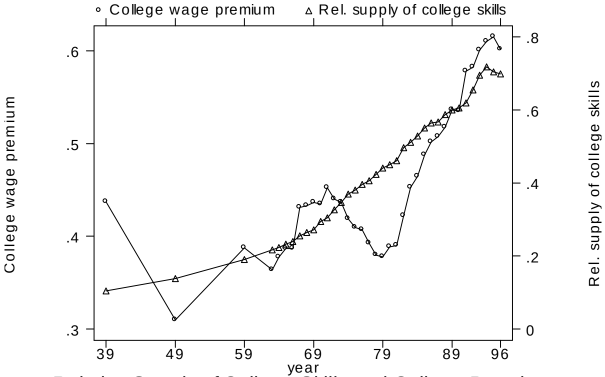
- We saw the major changes in inequality in the first lecture.
- Do basic growth models, or approaches building on them, have insightful things to say about these inequality patterns?
- Are these inequality trends driven by technology, supply and demand? What else?
- Let me briefly review some of the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

Surge in Inequality



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:



Relative Supply of College Skills and College Premium

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.
  - γ_is 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 σ.

Constant Elasticity of Substitution Production Function II

- Relative marginal product of the two factors:

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

  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 σ 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 $\sigma \to 0$ (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

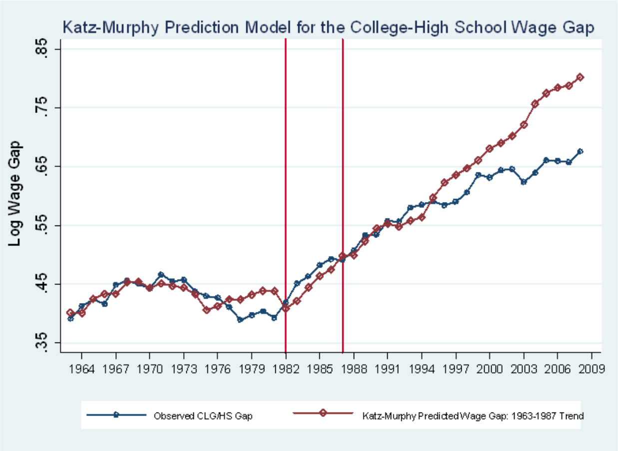
$$\begin{array}{rlll} \ln \omega_t = & \text{constant} & + \, 0.027 \times t & - \, 0.612 \cdot \ln \left(\frac{H_t}{L_t} \right) \\ & & (0.005) & (0.128) \end{array}$$

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.

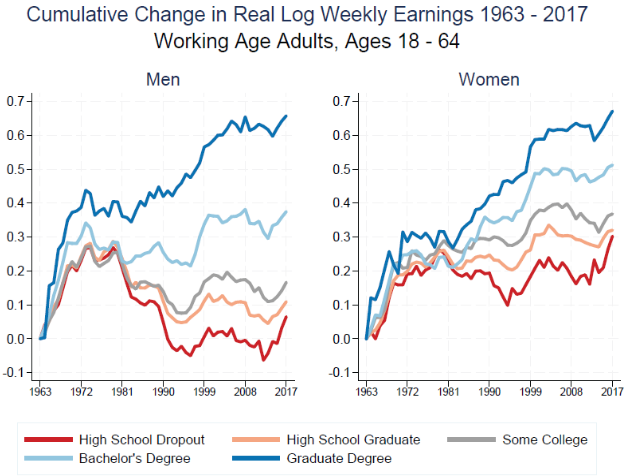
Problem 2

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



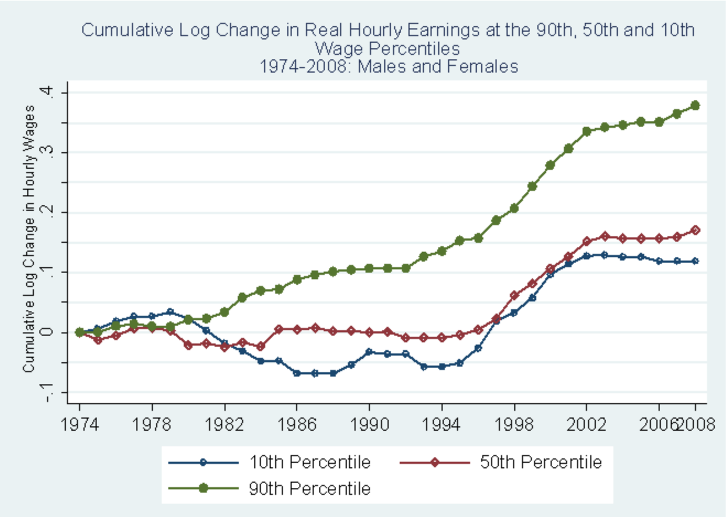
Problem 3

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



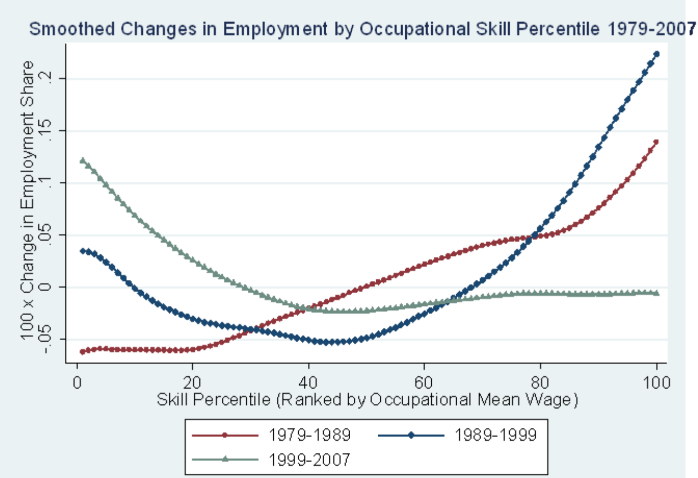
Problem 3 (continued)

- It is not composition effects:



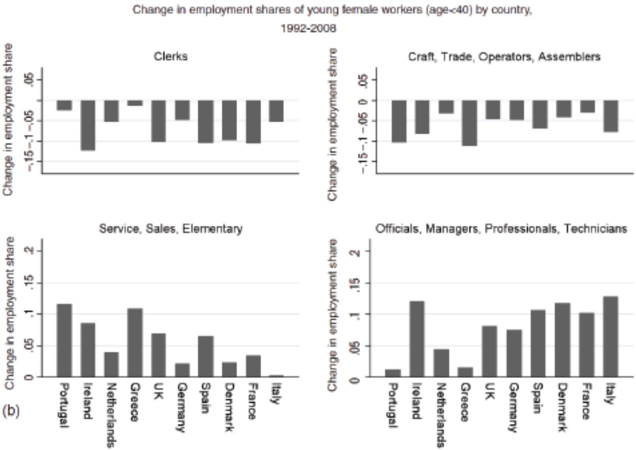
Problem 4

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



Problem 4 (continued)

- Not just confined to the US.



Task-Based Approach to Inequality

- Once again, the task-based approach provides richer perspectives.
- Original seminal paper Autor, Levy and Murnane (2003).
- Theory and empirical implementation here based on Acemoglu and Restrepo (2022).

Formal Model

- Extend the task-based model from the previous lecture to include several groups of workers (to discuss inequality).
- Also for simplicity, ignore new tasks.
- Start with a single sector model again, where output is given as:

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

- Here λ is the elasticity of substitution between tasks and $\mathcal{T}$ is the set of tasks required for this product.

Formal Model (continued)

- Task services are provided either by capital or one of G types of labor, according to production functions:

$$y(x) = A_k \cdot \psi_k(x) \cdot k(x) + \sum_{g \in \mathcal{G}} A_g \cdot \psi_g(x) \cdot \ell_g(x).$$

- Here, $\ell_g(x)$ is the amount of labor of type g allocated to task x, while $k(x)$ is the amount of task-specific capital produced for and assigned to this task.
- The A_k and A_g represent standard factor-augmenting technologies, which make factors uniformly more productive at all tasks.
- Task-specific productivity functions, $\psi_k(x)$ and $\{\psi_g(x)\}_{g \in \mathcal{G}}$, provide information on comparative advantage.
- If capital or some other factor cannot perform a task, its productivity is zero.

Formal Model (continued)

- Let us suppose that capital is produced from final good with constant marginal cost $1/q(x)$.
- Then a competitive equilibrium maximizes net output:

$$c = y - \int_{\mathcal{T}} (k(x)/q(x)) \cdot dx.$$

- Labor of all types is supplied inelastically, and we denote the total supply of labor of type g by ℓ_g.

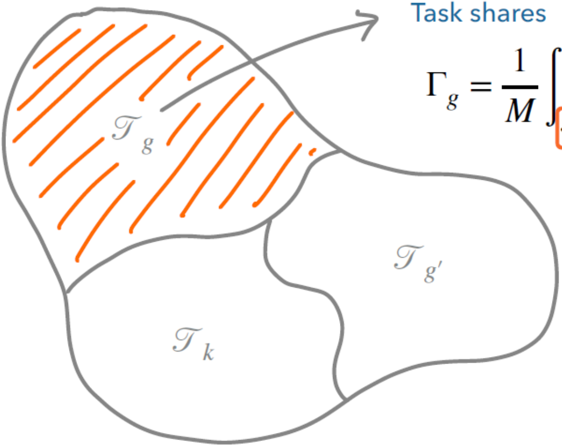
Equilibrium

- A unique equilibrium exists and in equilibrium, output is given by

$$y = \left(1 - A_k^{\lambda-1} \cdot \Gamma_k\right)^{\frac{\lambda}{1-\lambda}} \cdot \left(\sum_{g \in \mathcal{G}} \Gamma_g^{\frac{1}{\lambda}} \cdot \left(A_g \cdot \ell_g\right)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}} .$$

- Here crucially Γ_k and Γ_g's are *task shares*, which are endogenous and encapsulate the most important economic interactions.
- Because of these terms, this is not a CES production function, and despite appearances the elasticity of substitution is not λ, but an endogenous quantity $\sigma \geq \lambda$.

Tasks Shares

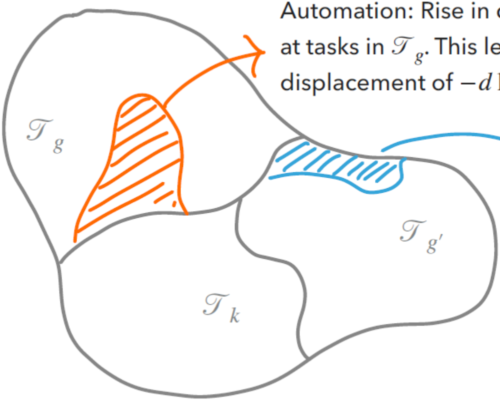


Task shares

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

Set of tasks allocated to g

Automation, Displacement and Ripple Effects



Automation: Rise in capital productivity $\psi_k(x)$ at tasks in $\mathscr{T}_g$. This leads to to (direct) task displacement of $-d \ln \Gamma_g^{auto}$

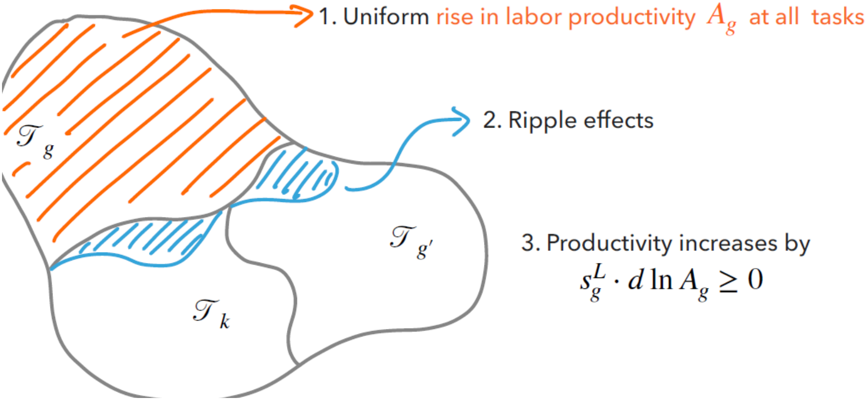
Ripple effects on g'

Productivity increases by

$$s_g^L \cdot d \ln \Gamma_g^{auto} \cdot \pi_g \geq 0$$

$\pi_g =$ cost savings

Factor-Augmenting Technology: No Displacement



3. Productivity increases by

$$s_g^L \cdot d\ln A_g \geq 0$$

Effects of Automation

- Wage and productivity effects of automation are given as

$$d\ln w_g = \frac{1}{\lambda} d\ln y + \frac{\lambda - 1}{\lambda} d\ln \tilde{A}_g - \frac{1}{\lambda} d\ln \Gamma_g^{\text{auto}} + \text{ Ripple Effects}_g,$$

$$d\ln \text{tfp} = \sum_{g\in\mathcal{G}} s_g^L \cdot d\ln \tilde{A}_g + s^K \cdot d\ln \tilde{A}_k + \sum_{g\in\mathcal{G}} s_g^L \cdot d\ln \Gamma_g^{\text{auto}} \cdot \pi_g.$$

  - The direct, task-displacement effect of automation (impacting labor type g) is given as

$$d\ln \Gamma_g^{\text{auto}} = \frac{\frac{1}{M}\int_{\mathcal{D}_g} \psi_g(x)^{\lambda-1} dx}{\frac{1}{M}\int_{\mathcal{T}_g} \psi_g(x)^{\lambda-1} dx}.$$

  - In addition, π_g is cost-savings from direct displacement (impacting labor type g). Moreover, $d\ln \tilde{A}_g = d\ln A_g + d\ln \Gamma_g^{\text{deep}}$ and $d\ln \tilde{A}_k = d\ln A_k + d\ln \Gamma_k^{\text{deep}}$ are composite terms that capture factor-augmenting technological change and productivity-deepening technological change (task-specific productivity changes that do not impact task-to-factor allocations).

Multiple Sectors

- Now extend this set up to multiple sectors, each with a similar structure to the single-sector economy above:

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

- In addition, A_i is a Hicks-neutral productivity term. $\mathcal{T}_{gi}$ denotes the set of tasks in industry i allocated to workers of type g, and $\mathcal{T}_{ki}$ denotes those allocated to capital.
- Industry-level task shares, Γ_{gi} and Γ_{ki} are now

$$\Gamma_{gi}(\mathbf{w}, \Psi) = \frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} \cdot dx; \; \Gamma_{ki}(\mathbf{w}, \Psi) = \frac{1}{M_i} \int_{\mathcal{T}_{ki}} (\psi_k(x) \cdot q(x))^{\lambda}$$

- Finally, household budgets are allocated across sectors with expenditure shares $s_i^Y(\mathbf{p})$, where $\mathbf{p} = (p_1, p_2, \dots, p_I)$ is the vector of industry prices.

Equilibrium

- A unique competitive equilibrium exists again and has a similar characterization. In particular, wage effects of technology are given as:

$$
\begin{aligned}
d \ln w_g \quad = \quad & \frac{1}{\lambda} d \ln y + \frac{1}{\lambda} \sum_{i \in \mathcal{I}} \omega_g^i \cdot d \ln \zeta_i + \frac{\lambda - 1}{\lambda} d \ln \tilde{A}_g \\
& - \frac{1}{\lambda} \sum_{i \in \mathcal{I}} \omega_g^i \cdot d \ln \Gamma_{gi}^{\text{auto}} + \text{ Ripple Effects}_g .
\end{aligned}
$$

- The new term is $\frac{1}{\lambda} \sum_{i \in \mathcal{I}} \omega_g^i \cdot d \ln \zeta_i$, which represents the consequences of sectoral reallocation following from technology changes (ω_g^i is the share of labor income of group g earned in industry i, capturing the importance of the sector for the labor demand for group g.
- In addition, the direct task displacement effect now combines displacements across sectors.

Measurement: Additional Assumptions

- Let us simplify measurement by imposing the following two assumptions:

Assumption

(no ripple effects) *Workers can only produce non-overlapping sets of tasks (i.e., $\psi_g(x) > 0$ only if $\psi_{g'}(x) = 0$ for all $g' \neq g$).*

Assumption

(parallel automation) *Only routine tasks can be automated and, within an industry, different groups of workers are displaced from their routine tasks at a common rate.*

Measurement: Task Displacement

- Under these assumptions, (direct) task displacement can be measured as

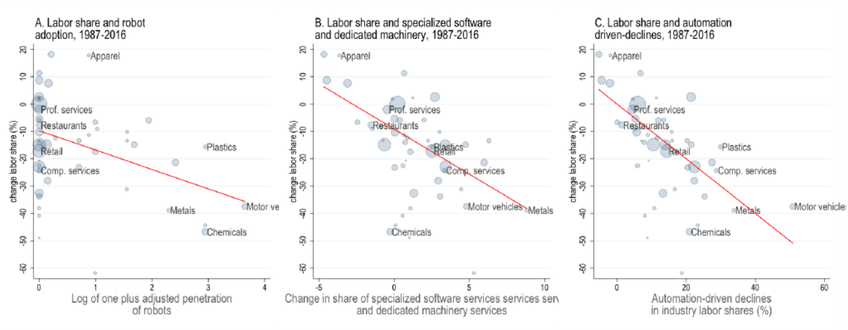
$$\text{Task displacement}_g^{\text{direct}} = \sum_{i \in \mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \left(-d \ln s_i^{L,\text{auto}} \right).$$

- Note everything is filtered through industry labor share changes (induced by automation), denoted by $d \ln s_i^{L,\text{auto}}$, and the term $\omega_{gi}^R / \omega_i^R$ represents the specialization of group g in industry i (formally, share of labor income in routine tasks in this industry going to demographic group g).
- This task displacement measure can be interpreted as fraction of tasks in which a group has a comparative advantage that are then lost automation.

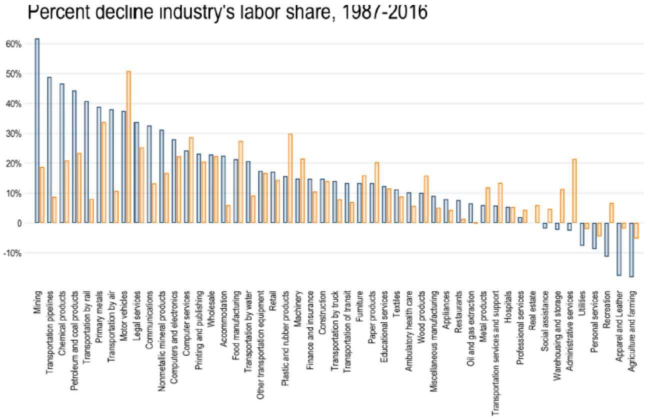
Measurement: Practical Issues

- Now task displacement at group level can be measured using standard Census/ACS type data sets, which include information on demographics, employment, wages, industry and occupation, combined with estimates of $d \ln s_i^{L,\text{auto}}$, which can be obtained by regressing industry-level labor share changes on proxies for the adoption of automation technologies.
- In practice, use advances in industry-level robotics technology; measures of specialized software investment at the industry level; and measures of specialized equipment at the industry level.

Industry Labor Share Changes

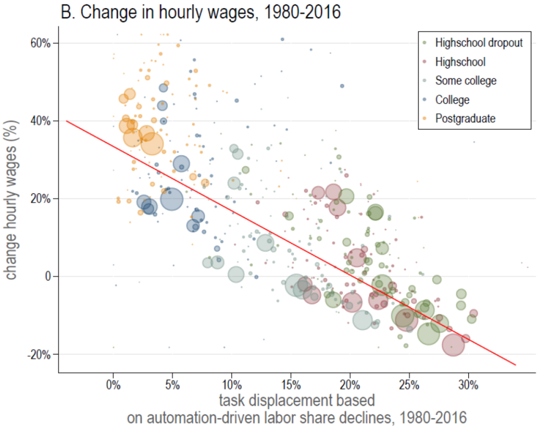


Overall and Automation-Induced Industry Labor Share Declines



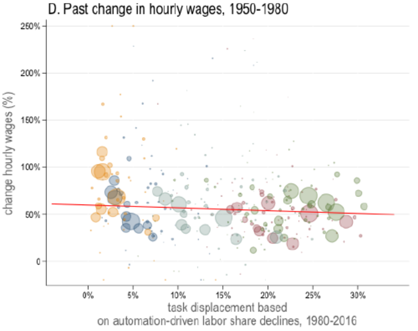
- Blue: labor share decline. Orange: automation-driven decline ($R^2 = 50\,\%$)

Main Result


B. Change in hourly wages, 1980-2016
change hourly wages (%)
60%
40%
20%
0
-20%
0%
5%
10%
15%
20%
25%
30%
task displacement based
on automation-driven labor share declines, 1980-2016
Highschool dropout
Highschool
Some college
College
Postgraduate

Quantitative Magnitudes and Pre-Trends

- Task displacement (due to automation and offshoring) explains between 50% and 70% of all between-group wage inequality changes in the US since 1980.
- Most of this (about 90%) due to automation.
- No similar trends before 1980, before the onset of digital and robotics and automation technologies.



Robustness

- Very robust across various specifications. For example, to flexibly controlling for
  - other types of skill-biased technological change (which appear unimportant).
  - other types of capital deepening and technological change (not themselves important and no similar effects).
  - import competition from China (turns out to be much less important than automation for inequality)
  - various labor market institutional features (some effects, but less important)
  - product market concentration and markups (no similar effects, though some impacts through compositional changes).
- Similar patterns across regions.

What is Left Out?

- General equilibrium effects — in particular ripple effects and induced composition effects — also need to be estimated.
- The extent of productivity effects need to be estimated separately.
- For a general methodology for doing so, see paper.
- When these are incorporated, quantitative magnitudes are similar, but in a more nuanced way.
  - Direct effects become somewhat less important but ripple effects are present and quantitatively significant.
  - Ripple effects "democratize" wage losses, as the direct effects of automation are spread to indirectly-affected groups.
  - There are positive productivity effects from automation, but not large enough to eliminate wage losses for many demographic groups.
  - Thus, large distributional effects from automation coupled with small productivity gains.
- Why all of this since 1980? Related to discussion in the previous lecture: potentially much more automation today and less new tasks and other worker-friendly technologies.

Conclusion

- Task-based models to aggregate production and growth thus also useful for studying inequality.
- Much to be done both theoretically and empirically.