Labor Demand: Technology and Inequality

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Fall, 2024

Roadmap

1. Introduction
2. Some Motivating Facts
3. Production Function and Labor Demand
4. Technology, Labor Supply, and Skill Premium
5. The Math Behind The Canonical Model *
6. More About Machine, Robot, and AI

Where Do Wages and Jobs Come From?

- In all previous lectures, we take wages (or wage functions) as something exogenously given
  - Education decision given college wage premiums
  - Major/Occupation decision given field specific wages
  - Female labor supply decision given gender wage gap
- We also assume there are infinite amount of jobs at a certain wage
  - No matter how many people choose certain education levels or jobs, they always get one certain wage (function)
- Where do wages and jobs come from? $\rightsquigarrow$ Employers!
- The missing piece here is **labor demand**: how firms decide how many workers to hire and how much wages to pay

What Affects Employers' Labor Demand?

- At a micro level, a firm decides if hiring an additional worker by comparing the benefits and costs:

$$\underbrace{M(R)P}_{\text{marginal (revenue) products}} = \underbrace{MC}_{\text{marginal costs}}$$

- If we assume perfect competition in labor market, all employers are price-takers and thus marginal costs are simply wages
  - We will discuss the deviation from perfect competition next week
- Thus wages (and hires) depend on marginal products, something clearly coming from production (function)
- So the question turns into asking what affects the production function? $\rightsquigarrow$ Two main factors from the literature:
  - **Technologies** (sometimes embodied in capital)
  - **Skill supplies** (and scarcity)

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Will AI Take Our Jobs?

Business / Tech

Elon Musk says AI will take all our jobs

By Samantha Murphy Kelly, CNN
2 minute read · Updated 7:04 PM EDT, Thu May 23, 2024

FORBES > INNOVATION > AI

Will AI Take Our Jobs?

John Werner Contributor

I am an MIT Senior Fellow, 5x-founder & VC investing in AI

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Jan 24, 2024, 04:01pm EST

A WORLD WITHOUT WORK

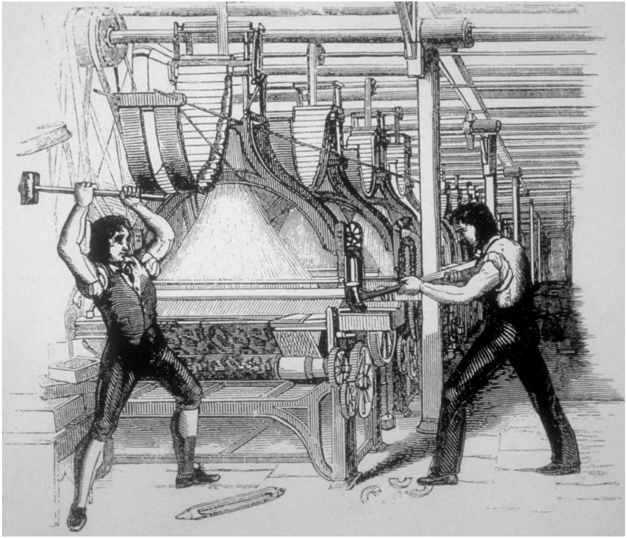
For centuries, experts have predicted that machines would make workers obsolete. That moment may finally be arriving. Could that be a good thing?

By Derek Thompson

JULY/AUGUST 2015 ISSUE

SHARE SAVE

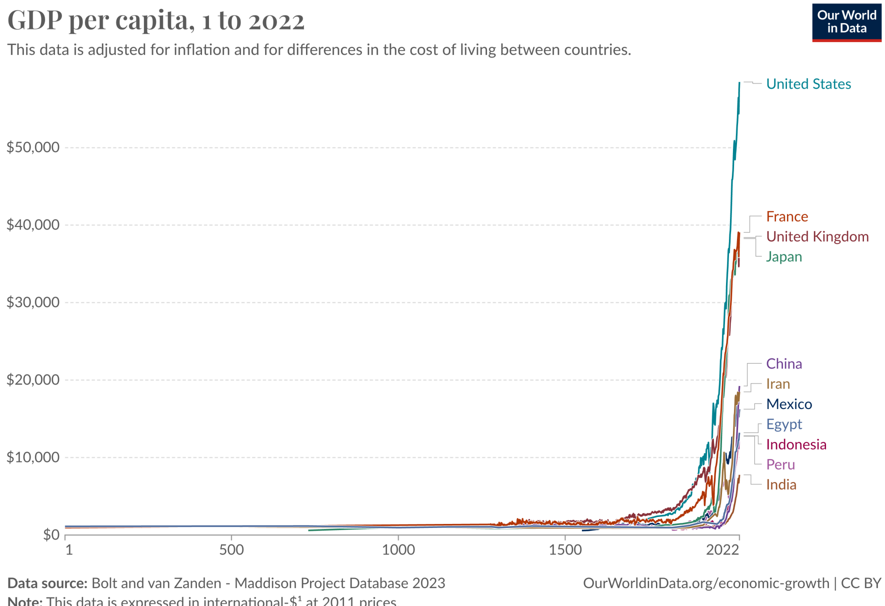
The Luddite Movement



"Why Are There Still So Many Jobs?" (Autor, 2015)

- 1st IR (1800s) $\rightarrow$ "Luddite Movement/Rebellion"
- 2nd IR (1930s) $\rightarrow$ "Technological Unemployment"
- Post WW2 $\rightarrow$ "The Automation Jobless"
- Recent AI Evolution $\rightarrow$ "Taking Over 80% of Human Jobs"
- Why firms keep hiring workers to do the jobs?
- "This time is different"? How different?

Technological Change Has Been The Best Thing Ever for Humanity



But More Recently The Impact Seems to Diverge by Education Levels (Autor, 2019)

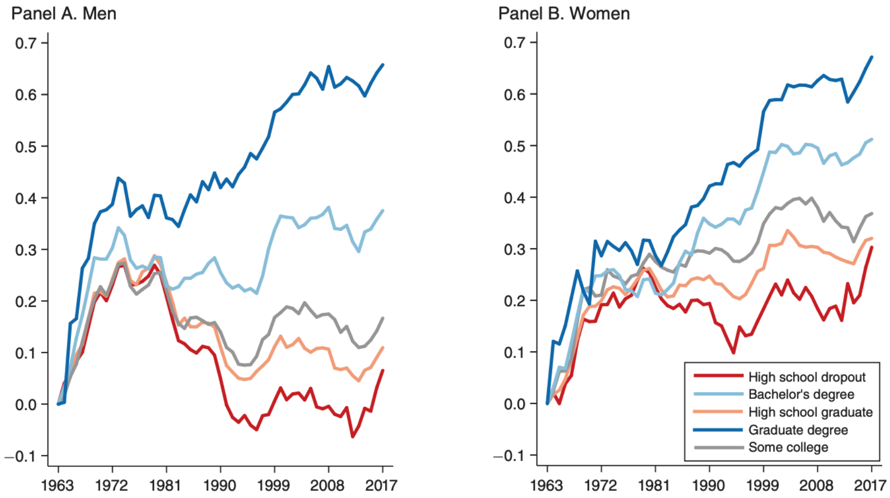
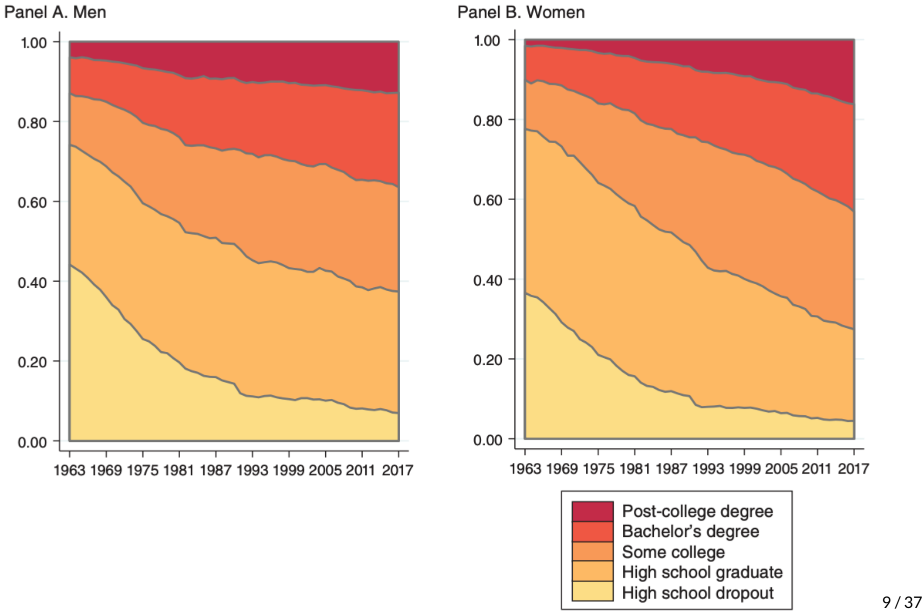


FIGURE 1. CUMULATIVE CHANGE IN REAL WEEKLY EARNINGS OF WORKING-AGE ADULTS AGES 18–64, 1963–2017

Increased Skill Premium Despite Increased Share of Higher Education Workers in US (Autor, 2019)



Recent Youth Unemployment in China

China's overqualified youth taking jobs as drivers, labourers and film extras

4 January 2025

Share Save

Stephen McDonell
China correspondent

China's Record-High College Graduates Face Economic Uncertainty

Published Nov 16, 2024 at 4:00 AM EST | Updated Nov 18, 2024 at 1:32 AM EST

Just The Facts

China's Graduate Flood

China's young generation is getting frustrated. They work very hard on a good education – and increasingly end up unemployed.

August 19, 2024

China | Degrees and difficulty

Why so many Chinese graduates cannot find work

Our number-crunching suggests that their plight could be much worse than previously thought

Roadmap

Production Function and Labor Demand

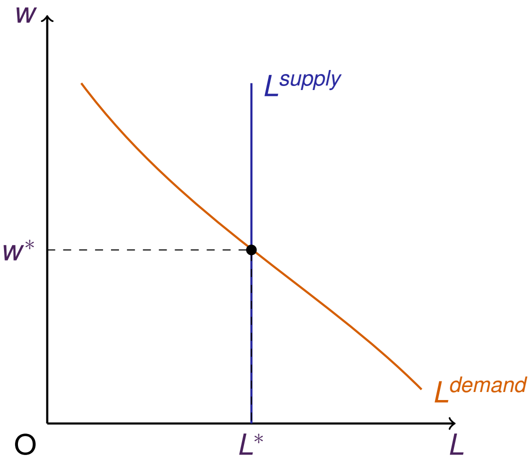
- Firm production function: $Y = F(H, L)$
  - Assume $F_K, F_L > 0$ and $F_{KK}, F_{LL} < 0$
- Assume F is constant return to scale (CRS) in K and L, i.e. $F(aK, aL) = aF(K, L)$
  - This allows us to bridge between micro level and macro level by considering a representative firm and aggregate labor demand
- Firm problem is to maximize profit: $\max_{L,K} pF(K, L) - wL - rK$
  - w is wage and r is capital rental prices; both will be determined in the equilibrium
  - Assume product market is perfect competition and product price is normalized ($p = 1$)
- **FOCs (MRP=MC)**: $F_K(K, L) = r$, $F_L(K, L) = w$
- The solutions to this system (if available) give the (input) demand functions: $K^{demand} = K(w, r)$, $L^{demand} = L(w, r)$

Equilibrium

- A competitive equilibrium requires

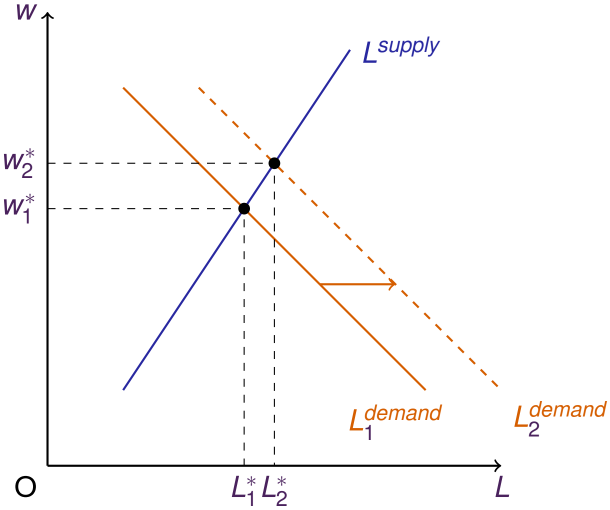
$$K^{demand}(r, w) = K^{supply}(r), L^{demand}(r, w) = L^{supply}(w)$$

, which pins down the equilibrium prices (r, w)



(This graph shows an inelastic labor supply curve and is drawn with r fixed)

An Increase in Labor Demand



(We will focus on how labor demand affect wage assuming inelastic labor supply hereafter, but remember whenever labor supply is elastic, labor demand also affect employment)

Classic Example: Cobb-Douglas

- Cobb-Douglas production function: $Y = F(K, L) = AK^{\alpha}L^{1-\alpha}$
  - A represents total factor productivity or factor-neutral technology
  - We can verify that this function is CRS
- FOCs: $\alpha AK^{\alpha-1}L^{1-\alpha} = r; (1-\alpha)AK^{\alpha}L^{-\alpha} = w$
  - Note we can also rewrite as $\alpha Y/K = r; (1-\alpha)Y/L = w$
- Marginal rate of technical substitution (MRTS): $\frac{F_K}{F_L} = \frac{\alpha L}{(1-\alpha)K} = \frac{r}{w}$
  - MRS is only a function of the factor ratio K/L, which is a property of CRS production functions
- Since this system does not have full rank, we cannot solve (K, L) given (r, w) without fixing Y; But we know that the relative use L/K must be proportional to the relative wage r/w
- So if there is an increase in A, and if both K and L are fixed, we know that r and w will raise but their ratio keeps unchanged
- Factor shares are also constrant: $\frac{rK}{Y} = \frac{F_K K}{Y} = \alpha$, $\frac{wL}{Y} = \frac{F_L L}{Y} = 1-\alpha$

Cobb-Douglas and Elasticity of Substitution

- Except being CRS, the largest reason that economists like to use CD form is: its elasticity of substitution is constant and, in fact, 1
- **Elasticity of substitution (ES)**: $\sigma \equiv -\frac{\partial \ln(K/L)}{\partial \ln(F_K/F_L)} = -\left[\frac{\partial \ln(F_K/F_L)}{\partial \ln(K/L)}\right]^{-1}$
  - Since $\frac{F_K}{F_L}$ is the slope of the isoquant, σ is the proportional change of the relative input use per percent change in the slope of the isoquant
  - Intuition: it measures how easily one input can be substituted for another
- Note that under competitive factor markets, we have $\sigma \equiv -\frac{\partial \ln(K/L)}{\partial \ln(F_K/F_L)} = -\frac{\partial \ln(K/L)}{\partial \ln r/w}$, which is perhaps more intuitive
- In the CD case, $\sigma = -\left[\frac{\partial \ln \frac{\alpha L}{(1-\alpha)K}}{\partial \ln(K/L)}\right]^{-1} = 1$
  - This is in fact why the factor shares ($\frac{rK}{Y}$, $\frac{wL}{Y}$) are fixed with CD form

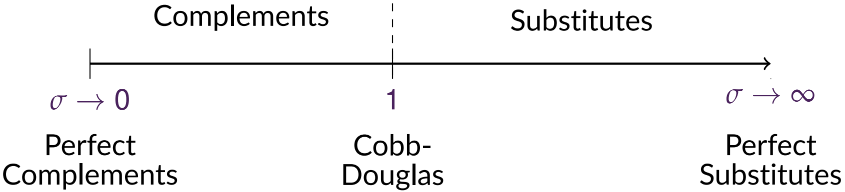
Roadmap

The Canonical Model of Skill Differential

- Now we extend a bit the simple labor demand framework that we have learned to explain evolution of skill (e.g. college) premium
  - In particular, we relax ES=1 in the CD form and allow for factor-biased technological changes
- We assume the labor supply changes of different skills are exogenous
  - I.e. not due to skill premium but due to things like demographic changes
- Input markets are perfectly competitive so that factors are paid their marginal products
- This is the ”canonical” model that have been used in the literature and regarded as quite successful considering its simplicity

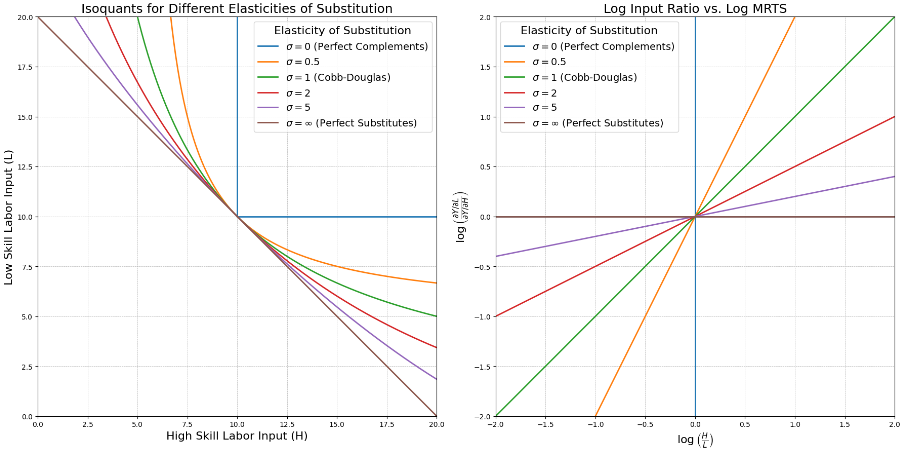
CES Aggregate Production Function

- $Y = F(H, L) = \left[(A_l L)^\rho + (A_h H)^\rho\right]^{1/\rho}$, where $\rho \leq 1$
  - L, H are two types of workers, skilled/unskilled (e.g. college/non-college)
  - A_l, A_h are factor-specific technologies, compared to the Hicks-neutral technology in CD form
- ES: $\sigma = 1/(1-\rho) \geq 0$ (hence CES)
- The value of ES will be critical to our analysis because



Isoquant Curves and Elasticity of Substitution

Recall $\sigma \equiv -\frac{\partial \ln(H/L)}{\partial \ln(F_H/F_L)} = \left[\frac{\partial \ln(F_L/F_H)}{\partial \ln(H/L)}\right]^{-1}$



Comparative Statics

- Solving the frim problem, we obtain a formula for skill premium:

$$\ln \omega \equiv \ln \frac{w_H}{w_L} = \left(\frac{\sigma - 1}{\sigma}\right) \ln \left(\frac{A_h}{A_l}\right) - \frac{1}{\sigma} \ln \left(\frac{H}{L}\right)$$

- Since $-\frac{1}{\sigma} < 0$, an increase in relative supplies ($H/L \uparrow$) reduces skill wage premium (ω) with elasticity $1/\sigma$

- Since $\frac{\sigma-1}{\sigma} \lesseqgtr 0$, the effect of an increase in $\frac{A_h}{A_l}$ depends on σ
  - If $\sigma > 1$ (substitutive), skill premiums ω increases
    (we call $\frac{A_h}{A_l}$ increase ***"Skill-Biased Technological Change"*** *in this case)*
  - If $\sigma < 1$ (complementary), skill premiums ω decreases

- These two forces—increased schooling (H/L) and technological development (A_h/A_l)—have been summarized as a **"Race Between Education and Technology"**

Bringing Model to Data

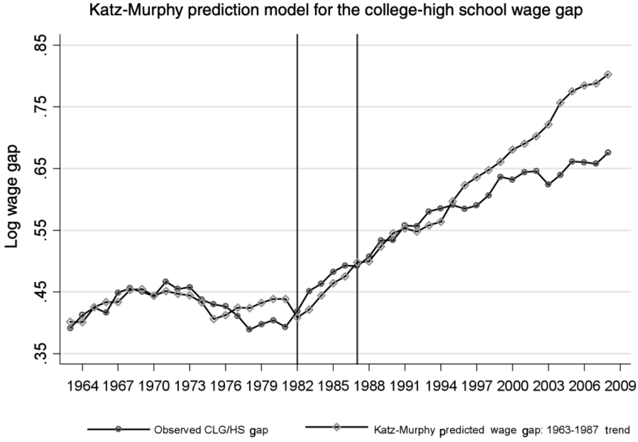
- $\ln \omega = \left(\frac{\sigma-1}{\sigma}\right) \ln \left(\frac{A_h}{A_l}\right) - \frac{1}{\sigma} \ln \left(\frac{H}{L}\right)$
- We have data on ω and H/L, and we want to estimate σ and A_h/A_L
- We assume $\left(\frac{\sigma-1}{\sigma}\right) \ln \left(A_h/A_l\right)_t = \gamma_1 t$, i.e. a linear time trend
- So we can estimate this model as:
  $\ln \omega_t = \gamma_0 + \gamma_1 t + \gamma_2 \ln(H/L) + e_t$, where $\hat{\gamma}_2$ is an estimate of $-\frac{1}{\sigma}$
- Using US data between 1963-1987, Katz and Murphy (1992) fit this model using a simple OLS regression:

$$\ln \omega = \underset{(0.01)}{0.033 \cdot t} \quad \underset{(0.15)}{-0.71 \cdot \ln \left(\frac{H}{L}\right)} + \text{constant}$$

  - There had been a (technological) trend increasing the relative skill (college) demand
  - ES between them $\widehat{\sigma} = -1/0.709 = 1.41$

Can the estimated model of KM predict future?

Acemoglu and Autor (2011) *projects the KM estimates (from 1963-1987 data) forward to 2008, showing that KM model continues to fit the aggregate data extremely well to 1995 but goes somewhat awry after that, arguably implying that demand growth from technological advance decelerates if assuming* σ *is constant*



College Premium & College-Graduate Supply in Japan

(Kawaguchi and Mori, 2016)

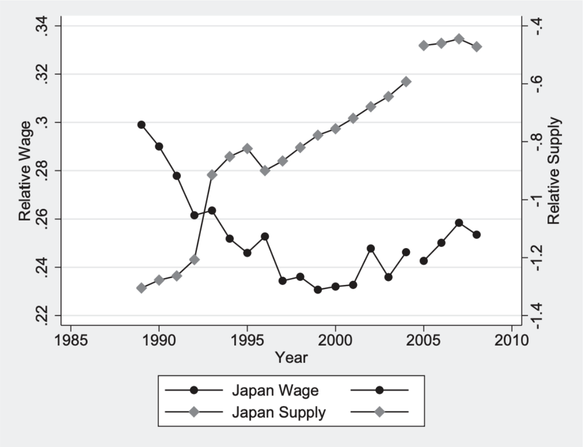


Fig. 5. Quantity of 4-year-college-graduate workers and the college wage premium, males 25–59, 1989–2006, Japan (BSWS). *Note:* Relative wages are calculated using male hourly wages. The supply measure is calculated based on male workers. The relative supply of college-educated workers to high-school-educated workers refers to the log (total hours worked by college-educated workers/total hours worked by high-school-educated workers). Hours worked by junior- or technical-college graduates are prorated to hours worked by college-educated or high-school-educated workers using the average hourly wage rates of the sample period as the weights for prorating.

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CES Function and Elasticity of Substitution

- MRS: $\frac{\partial Y/\partial L}{\partial Y/\partial H} = \frac{A_l^\rho (Y/L)^{1-\rho}}{A_h^\rho (Y/H)^{1-\rho}}$; ES: $\sigma = 1/(1-\rho) \geq 0$ (hence CES)
- If $\sigma > 1$ (or $\rho > 0$): "gross substitutes"; If $\sigma \to \infty$ (or $\rho \to 1$): "perfect substitutes" as $Y = A_l L + A_h H$ (linear)
- If $\sigma < 1$ (or $\rho < 0$): "gross complements"; If $\sigma \to 0$ (or $\rho \to -\infty$): "perfect complements" as $Y = \min\{A_l L, A_h H\}$ (Leontief)
- If $\sigma \to 1$ (or $\rho \to 0$): $Y = (A_l L)^{\frac{1}{2}} (A_h H)^{\frac{1}{2}}$ (Cobb-Douglas)
- The proofs of the last two cases are in last year's slides
- ES is critical because it determines how changes in either technology (A_l, A_h) or labor supplies (L, H) affect demand & wages

Wage Determination

- $w_L = \frac{\partial Y}{\partial L} = A_l^\rho \left[A_l^\rho + A_h^\rho (H/L)^\rho\right]^{(1-\rho)/\rho}$
  $w_H = \frac{\partial Y}{\partial H} = A_h^\rho \left[A_h^\rho + A_l^\rho (H/L)^{-\rho}\right]^{(1-\rho)/\rho}$
- $\partial w_H / \partial(H/L) \propto (\rho - 1) \leq 0$: as fraction of skilled workers in labor force increases, the wages of skilled workers should decrease (own labor demand curve is downward sloping)
- $\partial w_L / \partial(H/L) \propto (1 - \rho) \geq 0$: as fraction of skilled workers in labor force increases, the wages of unskilled workers should increase
- When $\rho \to 1$ ($\sigma \to \infty$), both derivatives are 0 as two types of workers are perfect substitutes
- When $\rho \to -\infty$ ($\sigma \to 0$), both effects are infinitely large
- Note our assumption $\rho \leq 1$ ($\sigma \geq 0$) in fact ensures "Q-complements" or "Supermodularity": a greater quantity of the one increases marginal product of the other (i.e. $\frac{\partial^2 Y}{\partial L \partial H} > 0$)

Wage Premium and Labor Supply

- $\omega \equiv \frac{w_H}{w_L} = \left(\frac{A_h}{A_l}\right)^{\rho} \left(\frac{H}{L}\right)^{-(1-\rho)} = \left(\frac{A_h}{A_l}\right)^{(\sigma-1)/\sigma} \left(\frac{H}{L}\right)^{-1/\sigma}$
- $\Rightarrow \ln \omega = \left(\frac{\sigma-1}{\sigma}\right) \ln \left(\frac{A_h}{A_l}\right) - \frac{1}{\sigma} \ln \left(\frac{H}{L}\right)$
- $\frac{\partial \ln \omega}{\partial \ln(H/L)} = -\frac{1}{\sigma} < 0$, i.e. for given skill bias A_h/A_l, an increase in relative supplies H/L lower relative wages with elasticity $1/\sigma$
  - Intuition: more tasks being allocated to L from H, decreasing marginal product of H and increasing marginal product of L
  - This effect goes to 0 when $\sigma \to \infty$: with perfect substitution, wage is purely determined by factor technology and irrelevant to relative input uses
- The estimates in the literature indicate $\sigma \in (1.4, 2)$, indicating rather finite substitutability between high and low skill workers

Wage Premium and Technological Change

- $\ln \omega = \left(\frac{\sigma-1}{\sigma}\right) \ln \left(\frac{A_h}{A_l}\right) - \frac{1}{\sigma} \ln \left(\frac{H}{L}\right)$
- $\frac{\partial \ln \omega}{\partial \ln(A_h/A_l)} = \frac{\sigma-1}{\sigma} \lesseqgtr 0$, i.e. the sign depends upon $\sigma \lesseqgtr 1$
- Why a rise in the productivity of skilled relative to unskilled (A_h/A_l) will causes the skill wage premium to fall (when $\sigma < 1$)?
    - Intuition: an increase in supply of high skilled workers effectively creates "excess supply" for a given number of unskilled workers
    - However since the broad consensus is $\sigma > 1$, this case is generally thought to be unlikely
- If $\sigma > 1$, $\frac{\partial \ln \omega}{\partial \ln(A_h/A_l)} > 0$, and we now have a reason for the increased college premium even with college expansion: an increase in A_h/A_l (i.e. "skill-biased technological change")

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The Problem of The Canonical Model

- If A_h increases and A_l holds, w_L should also increases (though w_H may increase more if $\sigma > 1$, widening inequality)
  - This is a result of Q-complements ($\sigma > 0$)
  - Thus Factor-Augmenting Technical Change always benefits everyone at absolute wage
- But recall that real wages of non-college male workers fell substantially since the 1980s in the U.S. despite being more scarce
- Our CES model cannot account for this unless we wish to argue that $A_l \downarrow$, but why would there be any technological regress?
- In fact, in our model, we cannot have new technologies—whether machines, robots, or AI—replacing any single worker!

Task-based framework and Automation

- Acemoglu and Restrepo (2018a,b, 2019) suggests that factor-augmenting technological changes does not correctly capture automation-like technological changes

- An extremely oversimplified sketch of their task-based framework features a production function like:

$$Y = AK^{\alpha}L^{\beta-\alpha}H^{1-\beta}$$

  - Note $\alpha + \beta - \alpha + 1 - \beta = 1$
  - A can incorporate factor-biased technological changes, e.g $(A_k K)^{\alpha}$
  - One key insight of their framework is that α, $\beta - \alpha$, and $1 - \beta$ can be interpreted as the ranges of tasks conducted by different inputs

- The advance in automation technologies can then be seen as an increase in α: machine can now takes the tasks of human
  - This replacement will be profitable if machine inputs are cheaper
  - Note here L simply indicates those displaced worker types, not necessarily the low skilled ones

Displacement Effect vs. Productivity Effect, Capital Deepening, and Reinstatement Effect

- Recall under CD form, $w_l = (\beta - \alpha)Y/L$, $w_h = (1 - \beta)Y/H$
- An increase in α generates a direct and negative "displacement effect" for labor type L through $(\beta - \alpha)$ (-)
- Because machine is more efficient than human, there is also a counteracting and positive "productivity effect" through Y/L (+)
- An increase in A_k ("capital deepening") increases both w_l and w_h (+)
- Creation of new tasks that only human can do ("reinstatement effect") generates the opposite effect of displacement (+)
- At short-run, displacement effect can be dominated, lowering employment and reducing w_l (but still benefiting H workers)
- At long-run, other three effects explain why we still have jobs today

New Born Occupations

YEAR	EXAMPLE OF TITLES ADDED	
1940	Automatic welding machine operator	Gambling dealer
1950	Airplane designer	Beautician
1960	Textile chemist	Pageants director
1970	Engineer computer application	Mental-health counselor
1980	Controller, remotely piloted vehicle	Hypnotherapist
1990	Certified medical technician	Conference planner
2000	Artificial intelligence specialist	Chat room host/monitor
2010	Wind turbine technician	Sommelier
2018	Pediatric vascular surgeon	Drama therapist

Table 1: Examples of new occupational titles added to the U.S. Census Bureau's Classified Index of Occupations between 1940 and 2018 Source: Autor et al. (2021b).

Who Had Been Replaced?

- The recent technological advance had been the diffusion of computer-based technologies and production robots
- Autor et al. (2003) considers two questions: *"what tasks computers do?" "what tasks human do?"*
- They argue that computers do "routine codifiable" tasks
  - *Computers "rapidly and accurately perform repetitive tasks that are deterministically specified by stored instructions (programs) that designate unambiguously what actions the machine will perform at each contingency"*
  - *Activities "that can be fully described by a set of rules and procedures, encoded in software, and carried out by nonsentient machines"*
- Thus recent technologies substitutes workers doing **"routine tasks"**:
  - I.e. repetitive and well-defined set of cognitive and manual activities
- and complements workers doing **"non-routine tasks"**:
  - I.e. creative, abstract, problem-solving, and communicating activities *(tasks are not well described by a tightly specified scripts that machines can execute)*

Routine vs. Non-Routine tasks (Autor et al., 2003)

TABLE I
PREDICTIONS OF TASK MODEL FOR THE IMPACT OF COMPUTERIZATION ON FOUR CATEGORIES OF WORKPLACE TASKS

	Routine tasks	Nonroutine tasks
	Analytic and interactive tasks	
Examples	• Record-keeping • Calculation • Repetitive customer service (e.g., bank teller)	• Forming/testing hypotheses • Medical diagnosis • Legal writing • Persuading/selling • Managing others
Computer impact	• Substantial substitution	• Strong complementarities
	Manual tasks	
Examples	• Picking or sorting • Repetitive assembly	• Janitorial services • Truck driving
Computer impact	• Substantial substitution	• Limited opportunities for substitution or complementarity

Occupations and Employment Changes (Autor, 2019)

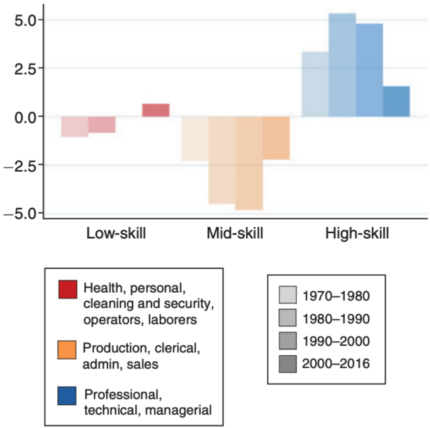


FIGURE 4. CHANGES IN OCCUPATIONAL EMPLOYMENT SHARES AMONG WORKING-AGE ADULTS, 1970–2016

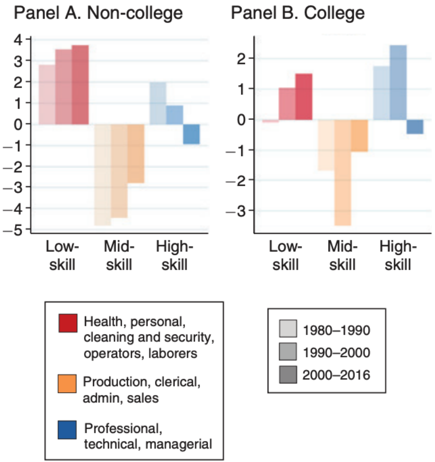


FIGURE 5. CHANGES IN OCCUPATIONAL EMPLOYMENT SHARES AMONG WORKING-AGE ADULTS, 1970–2016

Routine Exposure and Wage Changes (Acemoglu and Restrepo, 2022)

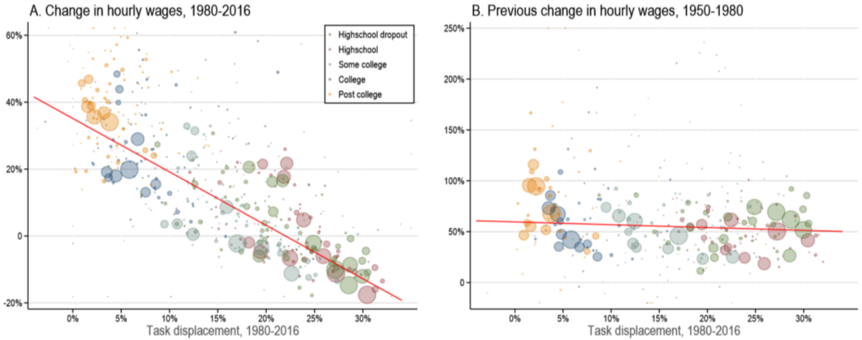


Figure 5: Exposure to task displacement and changes in real wages by demographic group, United States, 1980–2016 and 1950–1980

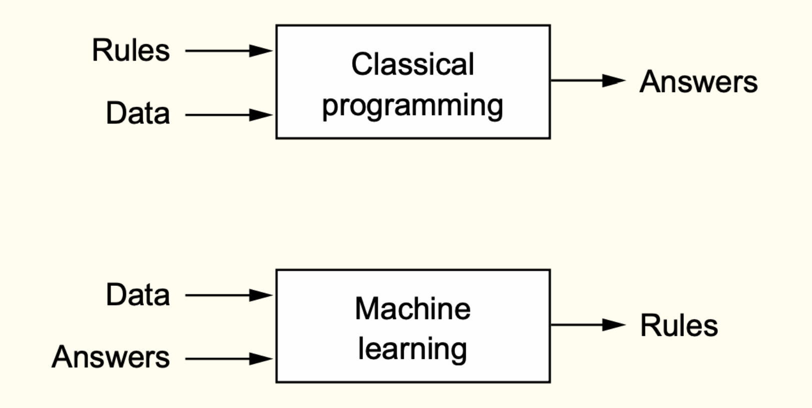
Source: Acemoglu and Restrepo (2021).

Note: Each marker corresponds to one of 500 demographic groups, defined by gender, age, education, race, and native/immigrant status. Marker sizes indicate the share of hours worked by each group and different colors indicate education levels.

Who Will Be Replaced In The Future?

- This previous dichotomy (routine vs non-routine) has been overtuned under recent (and future) AI technologies
  - Those ”non-routine” tasks had been hard to automate because, simply put, ”we don’t know the rules” (i.e. ”tacit” knowledge)
  - AI tools surmount this longstanding constraint because they can be used to infer tacit relationships that are not fully specified
- The best answer so far is perhaps **”we don’t know”** (Autor, 2022) or ”an empirical question”
  - There are some preliminary results on AI improving the productivity of both high- and low-skilled workers
  - Evidence on AI replacing human jobs is still scarce
- But task framework still provides a useful starting point to think
  - What tasks will AI be capable of accomplishing in the years (and decades) ahead?
  - What tasks will be certainly left for human to conduct?
  - What new demands of human skills will emerge at an AI-abundant world?

Machine Learning is all about "learning" (approximating) an unknown function: $y = f(\mathbf{x})$



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