Generational inertia in skill adoption

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Motivation

- Technological advancements transform the nature of work: some old skills become obsolete and new skills emerge
- Reallocation of older incumbent workers and entry of younger generations, e.g. ICT transition (Adão et al. 2021)

⇒ Do old workers play another role?

- Older workers are involved in the skill acquisition of younger generations (i.e. mentoring)

⇒ What are the implications during technological transitions?

This paper

- I develop a (static) model that shows how older generations (of workers) can impede the skill adoption of younger generations in technological transitions
  - Older workers serve as mentors to young workers and lower the cost of skills they know
  - This gives incentives to workers to adopt outdated skills
  - The effect is stronger at the bottom of the distribution

- Preview of the results:
  1. Increasing the quality of mentors *may* raise productive labor and output, and reduce wage inequality
  2. Technological change raises productivity, hence productive labor and output, but the effect on wages is unclear
  3. Emergence of new skills generates wage polarization (top versus the rest)

Related literature

- **Technological transitions.** Chari and Hopenhayn (1991), Caselli (1999), Violante (2002), MacDonald and Weisbach (2004), Deming and Noray (2020), Adão et al. (2021), Buera et al. (2021)
  - ⇒ New perspective on the role of older workers in technological transitions
  - ⇒ Generational inertia explains speed of technological transitions
- **Human capital accumulation in technological transitions.** Caselli (1999), MacDonald and Weisbach (2004), Deming and Noray (2020)
  - ⇒ Improving the skill acquisition of younger generations while mitigating the negative effects of technological transitions on wage inequality
- **Skill-biased technological change (SBTC) and wage inequality.** Katz and Murphy (1992), Murphy and Welch (1992), Acemoglu (2002), Aghion et al. (2002), Card and DiNardo (2002), Shi (2002), Hornstein et al. (2005), Acemoglu and Autor (2011), Loebbing (2022)
  - ⇒ SBTC through endogenizing the skill acquisition process of younger generations under Hicks-Neutral technological change

Production with several skilled labor types

- Population is normalized to one
- Output-per-capita: $Y = AL^{\beta}$, with $A > 0$ and $\beta \in (0, 1)$
- There exist several levels of skilled labor L^s which are perfect substitutes to produce the output and only differ in their inherent productivity μ^s.
- Let $\mathcal{S} = \{0, 1, \dots, s, \dots, S\}$ be the set of skills, with $\mu^0 < \mu^1 < \cdots < \mu^s < \cdots < \mu^S$
- Labor is the sum of all efficient units of skilled labor:

$$L = \sum_{s \in \mathcal{S}} \mu^s L^s$$

Labor demand

- Wage gap between two workers with skills s and s' only reflects the inherent productivity gap, i.e. $w^s/w^{s'} = \mu^s/\mu^{s'}$
- The elasticity of the inverse labor demand is:

$$\varepsilon \equiv \frac{\partial w^s}{\partial L}\frac{L}{w^s} = \beta - 1 < 0, \ \forall s \in S.$$

- Since all types of labor are perfect substitutes for producing the output: workers are hired from the most-productive skill to the least-productive skill

What skill to learn?

- To decide which skill to learn, agents solve:

$$\max_{s \in \mathcal{S}} U_i^s = w^s - c_i^s,$$

where w^s is the (expected) wage and $c_i^s \equiv c\left(M^s, \phi_i\right)$ is the cost to learn s

- Learning ability ϕ_i. Each agent has a learning ability $\phi_i \in [0,1] \sim \Phi'$ which reduces the cost of learning
- Mentors M^s. $\forall s$, there is a share of mentors $M^s \in [0,1]$ facilitating the learning of that skill and any other skill that is less productive

$\Rightarrow$ Assumptions on the learning cost function are central to the paper!

Learning cost function

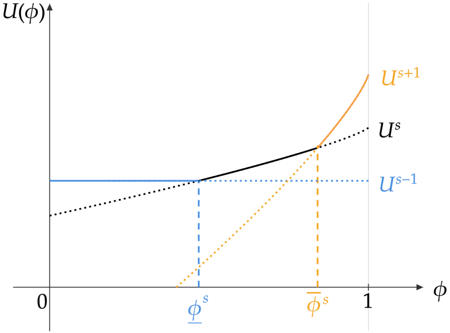
- Cost function for an agent i to learn a skill s is

$$c_i^s \equiv c\left(M^s, \phi_i\right),$$

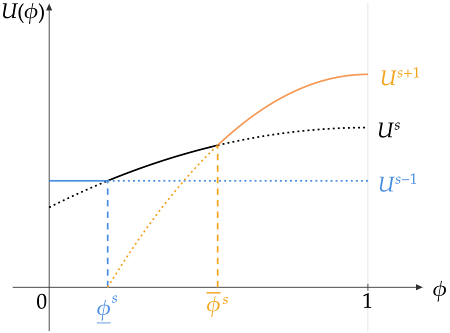
where $\phi_i \in [0,1]$ is the learning ability and $M^s \in [0,1]$ the share of mentors

1. c is twice differentiable
2. First-order derivatives are both negative
3. $c(1, \phi_i) = c(M^s, 1) = 0$
4. Low learning ability agents have greater returns to mentoring, i.e. $\frac{\partial^2 c_i^s}{\partial \phi_i \partial M^s} = \frac{\partial^2 c_i^s}{\partial M^s \partial \phi_i} < 0$

Proposition 1. Learning ability thresholds



(a) with increasing marginal returns to ϕ



(b) with decreasing marginal returns to ϕ

Labor supply and labor market equilibrium

- Labor supply with skill s is:

$$L^s \equiv \int_{\phi^s}^{\phi^{s+1}} \Phi'(x)dx = \Phi(\phi^{s+1}) - \Phi(\phi^s),$$

where (ϕ^s, ϕ^{s+1}) are the learning ability thresholds

- Labor market allocation:

$$L^s = \begin{cases} 1 - \Phi(\phi^S) & \text{if } s = S, \\ \Phi(\phi^{s+1}) - \Phi(\phi^s) & \text{if } \underline{s} \leq s < S, \\ 0 & \text{otherwise,} \end{cases}$$

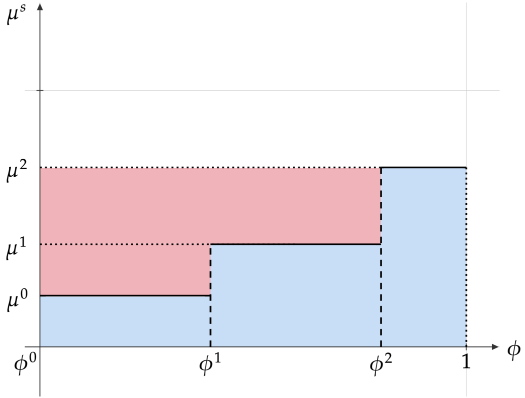
Effective, potential and missing productive labor

- Productive labor can be written as:

$$\underbrace{L}_{\text{Effective}} = \underbrace{\mu^S}_{\text{Potential}} \underbrace{- \sum_{s \in \mathcal{S}} \Delta\mu^s \Phi(\phi^s)}_{\text{Missing}},$$

where $\Delta\mu^s \equiv \mu^s - \mu^{s-1}$ and
$\phi^s = \phi^s(w^s, w^{s-1}, M^s, M^{s-1})$

$\Rightarrow$ How can we shrink the missing potential productive labor?



How to raise productive labor?

1. Better mentors dM^s. $dL > 0$, $dY > 0$ and $dw^s < 0\ \forall s$
   - if marginal returns to M are increasing
   - AND if the quality of mentors increases for most productive skills
2. Technological change dA. $dL > 0$ and $dY > 0$
   - Effect on wages: $dw^s > 0$ if RTS in production are large enough, i.e. $\beta > 1 - \left(\frac{\partial L}{\partial A}\frac{A}{L}\right)^{-1}$
3. New skill $d(S+1)$. $dL > 0$ and $dY > 0$
   - Effect on wages: $dw^s < 0$ (except at the top) $\implies$ wage polarization

Conclusion

- I develop a theory to explain how the distribution of skills evolves from one generation of workers to another in a given occupation and industry

1. The labor demand is constrained by the skill distribution of the labor supply that depends on the learning ability distribution and the distribution of mentors
2. Productive labor can be raised with *i)* "better" mentors, *ii)* technological change and *iii)* emergence of new skills
   - Productivity–inequality trade-off along the distribution

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