Technology Usage and Life-Cycle Earnings

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Introduction	Empirical Findings	Model	Quantitative Analysis	Conclusion
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Motivation				

Human capital theory is a standard framework to explain life-cycle earnings.

Missing element: people of different ages use different technologies.

- technologies differ by productivity
- skill-technology complementarity
- technology choice is endogenous

Research question:

How does technology usage affect life-cycle earnings and through what channels?

Goldin and Katz 1998

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What I do			

Investigate technology usage patterns:

- construct an index to measure technology usage using occupations as a proxy.
- document empirical relationships between technology uasge and labor earnings.

Develop a life-cycle model with endogenous technology choice and human capital investments
account for technology usage patterns over the life-cycle and across education.
quantify the contribution of technology usage to life-cycle earnings.

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Main findings				

- Technology usage plays a key role in life-cycle earnings. It contributes
 - $\bullet~25\%$ growth in mean earnings between age 23 and 60.
 - 46% growth in life-cycle inequality (variance of log earnings).
- Earnings growth and inequality are amplified by the interaction of technology and human capital through a reinforcement mechanism.
- Oplicy implications: the distortionary effect of a progressive tax on earnings growth would be underestimated in a model *without* technology usage.

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Measurement of technology usage

Utilize O*NET data set to measure technology using **occupations** as proxy.

Construct an index based on how intensively workers use information technology.

• draw information from the importance of programming skills, etc.

Distance to the frontier: a **time-invariant** index $n_i \in [-1, 0]$ Examples of occupation:



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Empirical Findings	Quantitative Analysis	
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Technology usage matters a lot at the occupational level

Control for occupation fixed effects in a two-step regression

$$\ln w_{i,t} = \beta_0 + \sum_j \lambda_j OCC_j + \sum_t \beta_{2,t} \text{year}_t + \beta_3 \text{age}_{i,t} + \beta_4 \text{age}_{i,t}^2 + X'_{i,t}\gamma + \epsilon_{i,t}$$
(1)
$$\hat{\lambda}_j = \beta_{0'} + \beta_1 n_j + \epsilon_j$$
(2)

To what extent the variation across occupations $(\hat{\lambda}_j)$ can be explained by technology?

- β_1 is estimated to be 0.78 (standard error 0.063).
- $R^2 = 0.473$ in the second step \rightarrow the technology dimension explains **almost half** of the variations across occupations.

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More college workers in advanced technologies



Overview of the life-cycle model

Key features:

- A college decision before the working stage
- Endogenous technology switching: choose $n \in [-1, 0]$
- Human capital accumulation at the working stage
- Rich interactions between these two terms
- Incomplete markets: idiosyncratic shocks

Details

Trade-offs of technology usage

Benefit:

- Earnings function is the product of technology level and human capital
 - \rightarrow technology-skill complementarity (direct channel)

Costs:

- Workers have to pay a catch-up cost (disutility) to work with any type of technology in each period
 - The cost decreases with the level of human capital (catch-up channel)
- Workers suffer human capital loss if switching to a better technology (switching channel)

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Empirical Findings	Model	Quantitative Analysis	
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a: asseth: HCn: techz: shockj: ageValue fSiyu Shi (EUI)Technology and Life-cycle EarningsAug 2023

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 $a: \mathsf{asset} \quad h: \mathsf{HC} \quad n: \mathsf{tech} \quad z: \mathsf{shock} \quad j: \mathsf{age}$ $\underbrace{\mathsf{Value f}}_{\mathsf{Siyu Shi} \ (\mathsf{EUI})} \quad \mathsf{Technology and Life-cycle Earnings} \quad \mathsf{Aug 2023}$

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V(a,h,n,z,j)

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Parameterization

Targeted moments:

- Life-cycle technology usage profiles: mean distance
- Life-cycle earnings profiles: mean and dispersion (variance of log earnings)
- College attainment rate

8 parameters chosen externally: demographic and technology-related

24 parameters chosen internally

- catch-up cost: technology gap across education
- human capital and shocks: earnings profiles

Empirical Findings	Quantitative Analysis	
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Model fit: earnings growth profiles



Empirical Findings	Quantitative Analysis	
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Model fit: earnings inequality profiles



Empirical Findings	Quantitative Analysis	
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Model fit: technology usage profiles



Quantifying the role of technology usage

Remove technology usage from the model

- Everyone is assigned to the same technology over the life-cycle
- No catch-up cost (no disutility term associated with technology usage)
- \rightarrow boils down to a risky human capital investments model

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	% of college workers	Mean earnings growth (log)	Δ in life-cycle inequality (log)
Benchmark	29.8	59.4	12.3
Remove technology usage	18.2	44.6	6.6

Mechanism

Implication on non-linear taxation

Recalibrate the model without technology usage and compare policy implications of a progressive tax with the benchmark model

	% of college workers	Mean earnings growth (log)	Δ in life-cycle inequality (log)
Benchmark (proportional tax)	29.8	59.4	12.3
Without technology With technology	19.8 18.9	50.2 45.9	10.4 10.2

- Progressive taxes distorts HC investments and hence lowers earnings growth.
- This distortionary effect is larger when considering technology usage.

	Quantitative Analysis 000000	Conclusion

- Technology usage contributes almost half of the growth in life-cycle inequality and one-third of the growth in mean earnings through the interaction with human capital.
- Technology usage also provides additional incentives for college education.
- Important implications of non-linear taxation on labor earnings.

Main takeaways

Relative positions are stable between 2003 and 2021 [Back]



Relative positions are also stable between 1977 and 2003



Construct a similar index in 1977 using 4th edition of the Dictionary of Occupational Titles

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Technology and Life-cycle Earnings

Tradeoffs: college education (back)

Individuals are heterogeneous in initial human capital h_0 and psychic cost q

Benefits:

 \bullet Additional human capital accumulation in college by choosing x

$$h_c(h_0, x) = (h_0 \cdot x)^{\alpha_h} + h_0$$

- Faster HC accumulation at the working stage.
- Initial advantage: better access to advanced technologies after graduation. Costs:
 - Time cost: four years of earnings
 - Psychic cost of college education (disutility): $c_h(x,q) = q(x + \mathbb{1}\{x > 0\})$

Timing of the working stage **back**

The value function of a worker of education s at age j:

$$V_s(a,h,n,z,j) = \int \max\{V_s^{stay}(a,h,n,z,j), V_s^{move}(a,h,n,\mathbf{Z},j)\}dF(\mathbf{Z})$$

(1) Workers first draw a vector of shocks **Z** over the technology distribution.

- Shocks for each technology are independently drawn from the same lognormal distribution.
- V is evaluated before drawing \mathbf{Z} .
- ② Decide to stay with the current technology or switch to new technologies?
- If switch, how far to switch?
- Ollect earnings, make HC investment and smooth consumption.

Value of staying with the same technology

$$\begin{split} V_s^{stay}(a,h,n,z,j) &= \max_{c,a',e} \quad \log(c) - \underbrace{\zeta e^2}_{\mathsf{HC investment}} - \underbrace{\phi_s(n,h,j)}_{\mathsf{catch-up cost}} \\ &+ \beta \int \sum_{h_{min}}^{h_{max}} V_s(a',h',n,z',j+1) P_s(h'|h,e,j) dF_s(z'|z) \\ &\text{s.t.} \quad a'+c = (1+r)a + w(h,n,z,j) - T(w,a) \end{split}$$
j: age a: asset h: HC n: technology z: shock $s \in \{C, NC\}$ T(·): linear tax

Value of switching (productivity shocks \mathbf{Z} known)

Choose the new technology n' and go back to the "stay" scenario

$$V_s^{move}(a, h, n, \mathbf{Z}, j) = \max_{n' \in [-1, 0]} \quad V_s^{stay}(a, \underbrace{\tilde{h}(n', n, h)}_{\text{HC after switching}}, n', z_{n'}, j)$$

Z: vector of productivity shocks over the technology distribution $n' \in [-1, 0]$

- Workers still need to pay the catch-up if they choose to switch.
- One might switch to a worse technology if he draws a really good shock z.

Joint distribution of technology and education (untargeted) **Deck**



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Age profiles of switching probabilities (untargeted) (Deck)

~ 6 Fraction of stayers .7 .8 9 S 25 30 35 50 55 60 40 45 Aae Data Model

Probability of staying



Probability of upgrading

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- Catch-up channel: zero catch-up cost of technology usage
- Direct channel: technology has no effects on earnings

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	% of college workers	Mean earnings growth	Δ in life-cycle inequality (log)	
Benchmark	29.8	1.84	12.3	
Shut down catch-up channel	17.1	2.11	1.5	
Shut down direct channel	13.2	1.56	5.6	

- Catch-up channel: zero catch-up cost of technology usage
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	% of college workers	Mean earnings growth	Δ in life-cycle inequality (log)	corr(tech,HC) at age 55
Benchmark	29.8	1.84	12.3	0.37
Shut down catch-up channel	17.1	2.11	1.5	-0.38
Shut down direct channel	13.2	1.56	5.6	

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Shut down catch-up channel	17.1	2.11	1.5	-0.38
Shut down direct channel	13.2	1.56	5.6	
Remove technology usage	18.2	1.58	6.6	

Taxation on labor earnings (back)

Tax on labor earnings \boldsymbol{w}

Benabou 2002

$$T(w) = \tau(w) \cdot w$$

where the average tax rate is

$$\tau(w) = 1 - \lambda (w/\bar{w})^{-\tau_p}$$

- λ governs the level of tax rate
- τ_p governs the progressivity.
- \bar{w} is the mean labor earnings in the economy
- $\tau_p = 0 \rightarrow \text{proportional tax with flat rate } 1 \lambda.$