Summary of
"Technological transitions with skill heterogeneity across generations"
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Overview

Research question

Why are some technological transitions particularly unequal and slow to play out? (What is the role of life-cycle and skill-specificity?)

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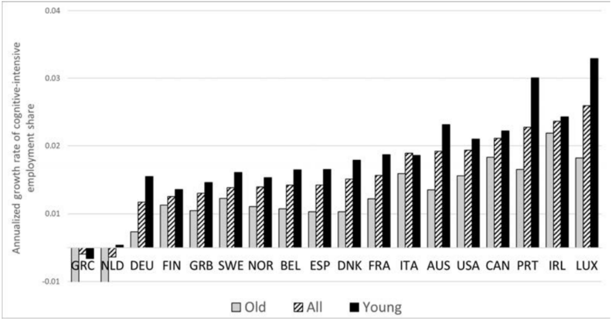
Primary contribution

A tractable model relating the speed of technological transitions to skill-specificity and skill investment cost

1. q-skill model of technology transitions
2. Empirical evidence
3. Calibrated model results

Motivation



- Microdata shows differential effects between generations
- Claim this is evidence of high cognitive skill specificity and high skill supply elasticity at longer horizons (low elasticity at short horizons)
- LeChatelier principle: the elasticity of relative output supply increases over time due to changes in the skill distribution across generations

Model environment

- Consumption good is CES aggregator of high- and low-tech intermediate inputs:

$$Y_t = \left[(A_t X_{Ht})^{\frac{\theta-1}{\theta}} + (X_{Lt})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}$$

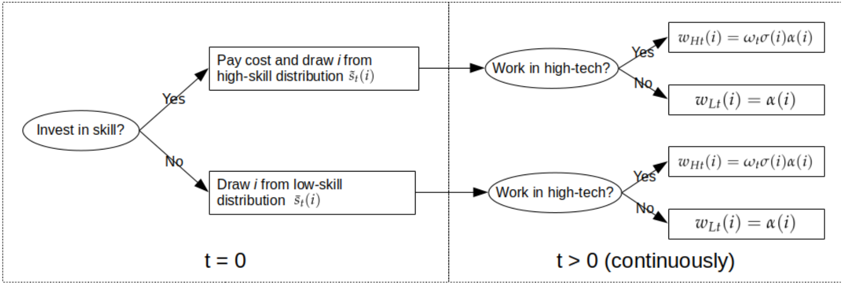
- Heterogeneity in worker skill type with differential productivity:

$$X_{Lt} = \int_0^1 \alpha(i) s_{Lt}(i) di, \; X_{Ht} = \int_0^1 \alpha(i)\sigma(i) s_{Ht}(i) di$$

where $\sigma(i)$ denotes the gains from high-skilled labor

Skill investment

- OLG with stochastic lifetimes
- Worker choice over costly and risky skill investment



Two key parameters

- **Technology-skill specificity** is inversely related to the short-run skill supply elasticity η, in turn depends on the slope of $\sigma\left(l_t\right)$:

$$\eta \equiv \left|\frac{\partial \log l_t\left(\omega_t\right)}{\partial \log \omega_t}\right| = \left(\frac{\partial \log \sigma\left(l_t\right)}{\partial \log i}\right)^{-1}$$

- Higher $1/\eta$ implies degree of technology-skill specificity is higher because short-run worker reallocation following relative wage changes is smaller

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- **Cost of skill investment** is $1/\psi$. Cost of high-skill lottery is second term in skill investment problem:

$$\max_{\tilde{s}_t(\cdot):\int_0^1 \tilde{s}_t(i)di=1} \int_0^1 V_t(i)\tilde{s}_t(i)di - \frac{1}{\psi}\int_0^1 \log\left(\frac{\tilde{s}_t(i)}{\bar{s}_t(i)}\right)\tilde{s}_t(i)di$$

where $V_t(i)$ is present discount value of consumption

- Lower cost (higher ψ) implies higher sensitivity of long-run supply of high-i types to changes in relative wage

Dynamics

- Transform complex infinite-dimensional fixed-point problem to system of differential equations with log-linear expansion around equilibrium
- Assignment threshold l_t is the type that is indifferent between working with any of the two technologies such that:

$$\omega_t \sigma \left(l_t \right) = 1$$

- q is the present discounted value of the log-relative wage ≡ "relative lifetime wage":

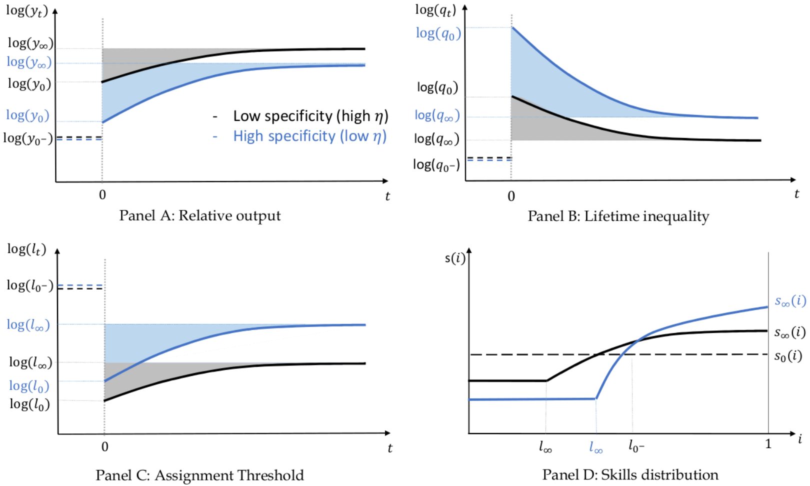
$$\log \left(q_t \right) \equiv \int_t^{\infty} e^{-(\rho+\delta)(s-t)} \log \left(\omega_s \right) ds$$

- Impulse responses:

$$\begin{bmatrix} \Delta \log \left(l_t \right) \\ \Delta \log \left(q_t \right) \\ \Delta \log \left(y_t \right) \end{bmatrix} \propto \underbrace{\begin{bmatrix} -\eta \\ \frac{1}{\rho+\lambda} \\ 1+\kappa\eta \end{bmatrix}}_{\text{Short-run}} + \underbrace{\frac{\psi}{\chi} \begin{bmatrix} \eta \\ \frac{-1}{\rho+\delta+\lambda} \\ \theta-1 \end{bmatrix} \left(1-e^{-\lambda t}\right)}_{\text{Short-to long-run transition}}$$

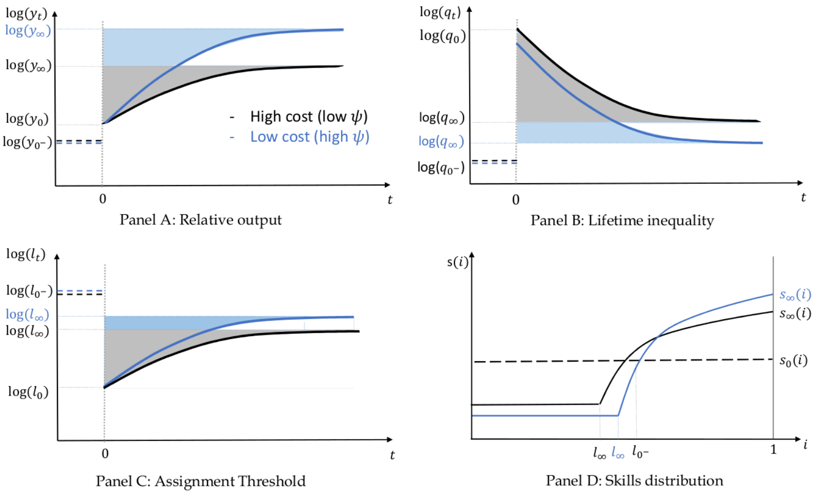
Dynamic response to skill biased tech shock ($\theta > 1$)

Figure 2: Comparative statics with respect to η



Dynamic response to skill biased tech shock ($\theta > 1$)

Figure 3: Comparative statics with respect to ψ



Bringing the model to the data

- Can only credibly measure short-term effects
- Use model to infer dynamics from snapshots of:
  1. within-generation change in employment of the "old" generation born before the shock:

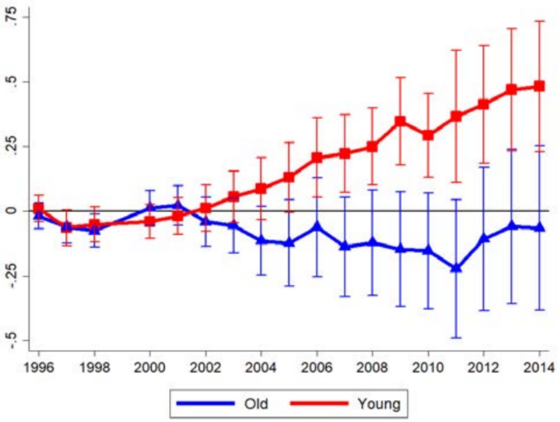
$$\frac{\partial\left|\varepsilon_0^{\text{twithin}}\right|}{\partial \eta} > 0, \quad \frac{\partial\left|\varepsilon_0^{\text{within}}\right|}{\partial \psi} = 0$$

  2. between-generation difference in employment of "young" generations entering at the time of the shock and "old" generations born before the shock

$$\frac{\partial\left|\varepsilon_0^{\text{between}}\right|}{\partial \eta} < 0, \quad \frac{\partial\left|\varepsilon_0^{\text{between}}\right|}{\partial \psi} > 0$$

Cognitive intensity and growth estimate

$$\textit{employment growth} = \sum_c \left(\alpha_t^c + \beta_t^c * \text{cognitive intensity}_o\right) 1_{[g=c]} DSL_i + \delta_{o,t} + \zeta_{g,t} + X_{io,t}^g \gamma_t^g + \epsilon_{io,t}^g$$



(a) Relative employment response for each generation

Calibrated model simulation

- High-tech productivity shock that increases the employment share in the cognitive-intensive technology from 20% to 50% (convergence of "developed" countries)

Table 3: Changes in Average Welfare and Lifetime Welfare Inequality

	Baseline ($\eta \approx 0, \psi = 0.35$)		Low specificity ($\eta = 0.75, \psi = 0.35$)	
	$\Delta\bar{U}$	$\Delta\bar{\Omega}$	$\Delta\bar{U}$	$\Delta\bar{\Omega}$
True	46%	39%	44%	29%
Short-run	31%	76%	40%	45%
Long-run	55%	30%	47%	24%
$DCIR(q)$	0.9		0.4	

Conclusion

- Tractable model maps short-run observables to transition dynamics based on "frictions" from life-cycle and skill-technology specificity
- Some empirical evidence to support the motivation and calibrate the model
- Evidence that the "frictions" result in economically significant welfare impacts