Interaction between Automation and Human Capital: Labor Share and Inequality

Rong Fan

Indiana University

November 11, 2022

Motivation: Automation

Automation

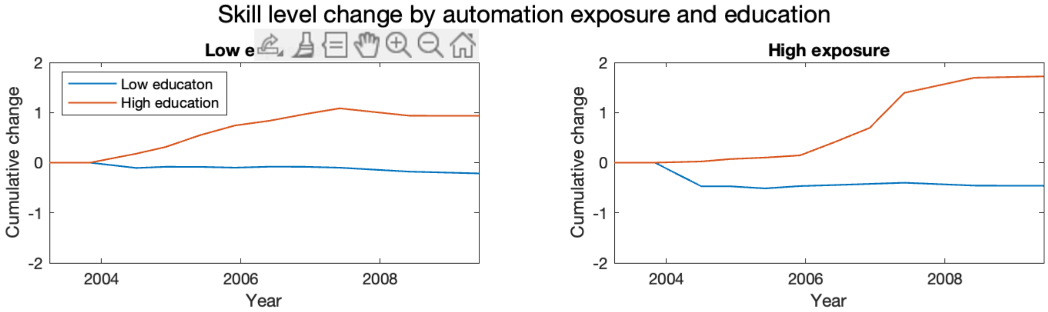
- Productivity effect

Motivation: Automation

Automation

- Productivity effect
- Displacement effect
  - Labor share and employment
  - Wage premium and inequality

Motivation: Human Capital



- O*NET occupational skill level: by automation exposure and education level
- Different skill level change at low and high automation exposure
- Different responses of skilled and unskilled workers

Motivation: Automation and Human Capital

Automation Automation

- Productivity effect
- Displacement effect
  - Labor share and employment
  - Wage premium and inequality

Human capital

- Labor share and employment: race between human capital and automation
- Wage premium and inequality: heterogeneous human capital responses

Research Question

Research questions

- Interaction between automation and human capital?
- Heterogeneous responses of skilled and unskilled workers?
- Labor share, wage premium, and inequality change in the era of automation?

Research Question

Research questions

- Interaction between automation and human capital?
- Heterogeneous responses of skilled and unskilled workers?
- Labor share, wage premium, and inequality change in the era of automation?

Methodology

- Task model with endogenous automation and human capital
- Calibrate to match the data 1980-2005
- Two scenarios: with and without endogenous human capital
- Empirical evidence

Related Literature

- **Automation:**
  - Acemoglu and Restrepo (2018); Aghion et al. (2021); Acemoglu and Autor (2011)

Related Literature

- **Automation:**
  - Acemoglu and Restrepo (2018); Aghion et al. (2021); Acemoglu and Autor (2011)
  - Endogenous human capital

Related Literature

- **Automation:**
  - Acemoglu and Restrepo (2018); Aghion et al. (2021); Acemoglu and Autor (2011)
  - Endogenous human capital

- **Automation and human capital:**
  - Sachs and Kotlikoff (2012); Athreya and Eberly (2015)

Related Literature

- **Automation:**
  - Acemoglu and Restrepo (2018); Aghion et al. (2021); Acemoglu and Autor (2011)
  - Endogenous human capital
- **Automation and human capital:**
  - Sachs and Kotlikoff (2012); Athreya and Eberly (2015)
  - After-school human capital accumulation
  - Heterogeneous workers

Related Literature

- **Automation:**
  - Acemoglu and Restrepo (2018); Aghion et al. (2021); Acemoglu and Autor (2011)
  - Endogenous human capital
- **Automation and human capital:**
  - Sachs and Kotlikoff (2012); Athreya and Eberly (2015)
  - After-school human capital accumulation
  - Heterogeneous workers
- **Interaction between technology and human capital:**
  - Stokey (2014); Stokey (2020); Beaudry et al. (2006)

Related Literature

- **Automation:**
  - Acemoglu and Restrepo (2018); Aghion et al. (2021); Acemoglu and Autor (2011)
  - Endogenous human capital
- **Automation and human capital:**
  - Sachs and Kotlikoff (2012); Athreya and Eberly (2015)
  - After-school human capital accumulation
  - Heterogeneous workers
- **Interaction between technology and human capital:**
  - Stokey (2014); Stokey (2020); Beaudry et al. (2006)
  - Two types of R&D: automation and innovation

Task Model

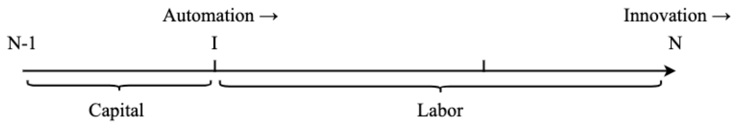
- Household: skilled and unskilled
  - Consumption/Saving
  - Working/Training

Task Model

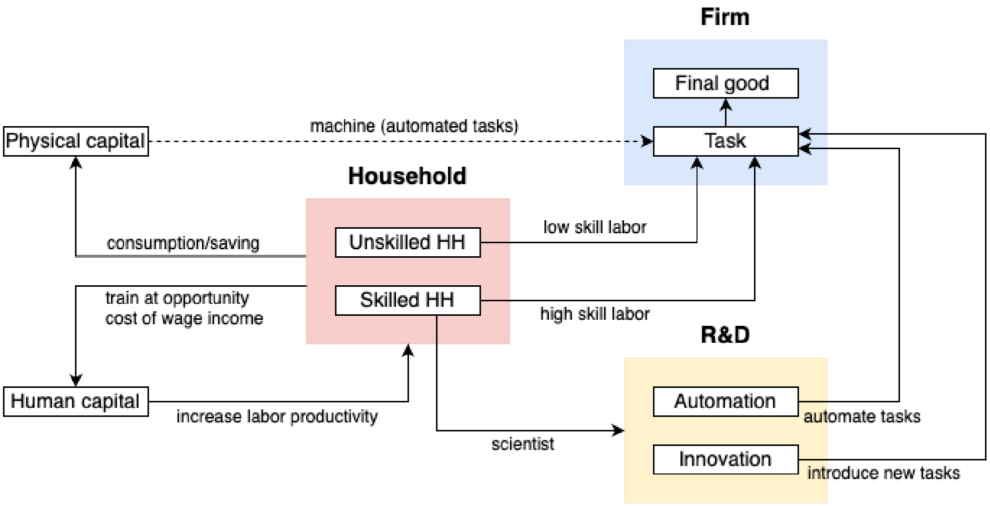
- Household: skilled and unskilled
  - Consumption/Saving
  - Working/Training
- Production: task and final good producer
  - Tasks $\in [N-1, N]$, constant measure 1
  - Automation $\in [N-1, I]$
  - Tasks $\to$ Final good

Task Model

- Household: skilled and unskilled
  - Consumption/Saving
  - Working/Training
- Production: task and final good producer
  - Tasks $\in [N-1, N]$, constant measure 1
  - Automation $\in [N-1, I]$
  - Tasks $\rightarrow$ Final good
- R&D: automation and innovation
  - Automation: $I \rightarrow$
  - Innovation: $N \rightarrow$



Model Flowchart



Task Producer Problem

Tasks are produced by combining:

- Patent intermediates
- Production factors

Task Producer Problem

Tasks are produced by combining:

Patent intermediates

$$\text{Production factors} \quad \begin{cases} \text{capital} \\ \text{low-skill labor} \\ \text{high-skill labor} \end{cases}$$

Task Producer Problem

Tasks are produced by combining:

		Input	Price
Patent intermediates		$q(i)$	ψ
Production factors	capital	$k(i)$	R
	low-skill labor	$l(i)$	W_L
	high-skill labor	$h(i)$	W_H

Task Producer Problem

Tasks are produced by combining:

		Input	Price	Productivity
Patent intermediates		$q(i)$	ψ	
Production factors	capital	$k(i)$	R	$\gamma_K = 1$
	low-skill labor	$l(i)$	W_L	$\gamma_L(i, h_L) = e^{B(N-1)+B_L(i-(N-1))}e^{bh_H}$
	high-skill labor	$h(i)$	W_H	$\gamma_H(i, h_H) = e^{B(N-1)+B(i-(N-1))}e^{bh_L}$

The task producers solve the following problem:

$$\max \quad p(i)y(i) - \psi q(i) - Rk(i) - W_L l(i) - W_H h(i)$$

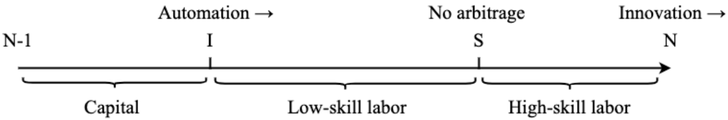
$$\underset{\text{Task index}}{\underset{\downarrow}{y(i)}} = \begin{cases} q(i)^\eta \Big(\gamma_K k(i) + \gamma_L(i, h_L)l(i) + \gamma_H(i, h_H)h(i)\Big)^{1-\eta} & \text{, automated} \\ q(i)^\eta \Big(\gamma_L(i, h_L)l(i) + \gamma_H(i, h_H)h(i)\Big)^{1-\eta} & \text{, not automated} \end{cases}$$

Task Price and Factor Allocation

$$\underbrace{p(i)}_{\substack{\downarrow \\ \text{perfectly} \\ \text{competitive}}} = \begin{cases} \Psi \min\{R^{1-\eta}, \left(\frac{W_L}{\gamma_L(i,h_L)}\right)^{1-\eta}, \underbrace{\left(\frac{W_H}{\gamma_L(i,h_H)}\right)^{1-\eta}}_{\substack{\downarrow \\ \text{effective cost}}}\} & \text{, automated} \\ \Psi \min\{\left(\frac{W_L}{\gamma_L(i,h_L)}\right)^{1-\eta}, \left(\frac{W_H}{\gamma_L(i,h_H)}\right)^{1-\eta}\} & \text{, not automated} \end{cases}$$

Task Price and Factor Allocation

$$\underset{\substack{\downarrow \\ \text{perfectly} \\ \text{competitive}}}{p(i)} = \begin{cases} \Psi \min\{R^{1-\eta}, \left(\frac{W_L}{\gamma_L(i,h_L)}\right)^{1-\eta}, \underset{\substack{\downarrow \\ \text{effective cost}}}{\left(\frac{W_H}{\gamma_L(i,h_H)}\right)^{1-\eta}}\} & \text{, automated} \\ \Psi \min\{\left(\frac{W_L}{\gamma_L(i,h_L)}\right)^{1-\eta}, \left(\frac{W_H}{\gamma_L(i,h_H)}\right)^{1-\eta}\} & \text{, not automated} \end{cases}$$



- Technology frontier N and automation I are determined by R&D sector
- S is determined by no arbitrage condition

Final Good Producer

The final good producers solve the following problem:

$$\max \quad Y - \int_{N-1}^{N} p(i)y(i)di$$

$$\underbrace{Y}_{\text{final goods}} = \tilde{A}\left(\int_{N-1}^{N} \underbrace{y(i)}_{\text{tasks}}^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}$$

Final Good Producer

The final good producers solve the following problem:

$$\max \quad Y - \int_{N-1}^{N} p(i)y(i)di$$

$$\underset{\substack{\downarrow \\ \text{final goods}}}{Y} = \tilde{A}\Big(\int_{N-1}^{N} \underset{\substack{\downarrow \\ \text{tasks}}}{y(i)}^{\frac{\sigma-1}{\sigma}} di\Big)^{\frac{\sigma}{\sigma-1}}$$

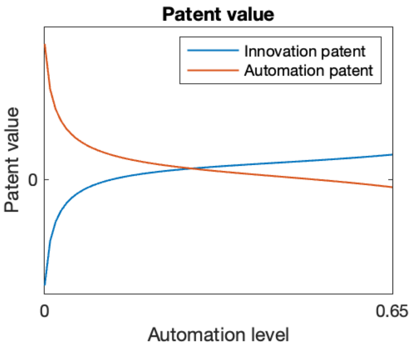
Task demand function:

$$y(i) = \tilde{A}^{\sigma-1} Y p(i)^{-\sigma}.$$

Research and Development Sector

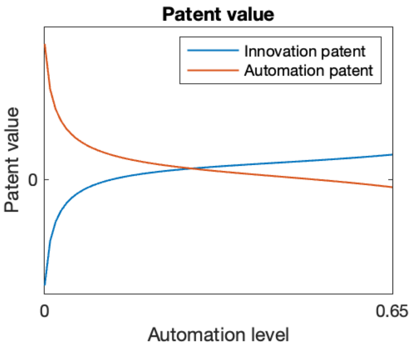
- Patent value: $P = \eta p(i) y(i)$

Research and Development Sector



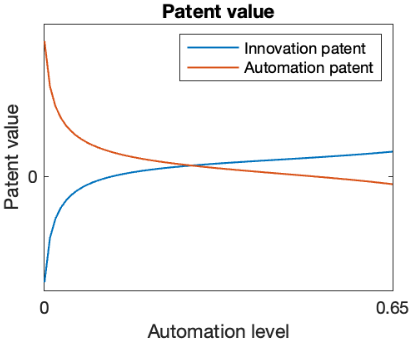
- Patent value: $P = \eta p(i) y(i)$

Research and Development Sector



- Patent value: $P = \eta p(i) y(i)$
- Automation $\uparrow$, R $\uparrow$, W $\downarrow$
- Innovation patent $\uparrow$, Automation patent $\downarrow$

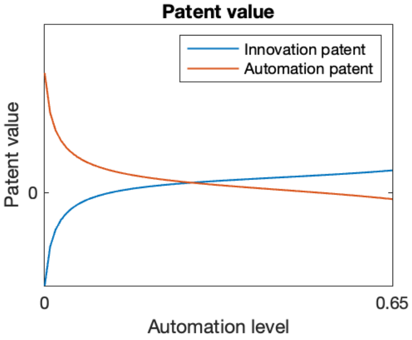
Research and Development Sector

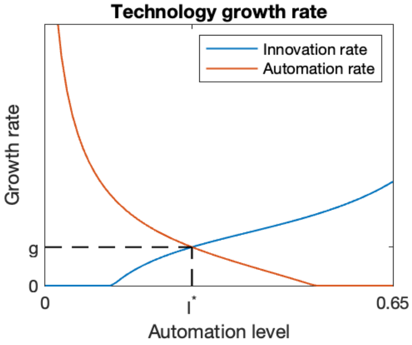


- Patent value: $P = \eta p(i) y(i)$
- Automation $\uparrow$, R $\uparrow$, W $\downarrow$
- Innovation patent $\uparrow$, Automation patent $\downarrow$

- $\underset{\text{Rate}}{\underset{\downarrow}{\kappa(\epsilon)}} = \underset{\text{Scientist}}{\underset{\downarrow}{\epsilon}}^{\lambda} / \mu$

Research and Development Sector

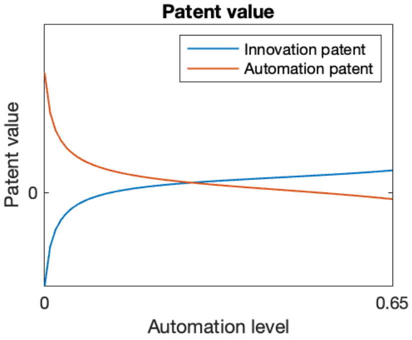


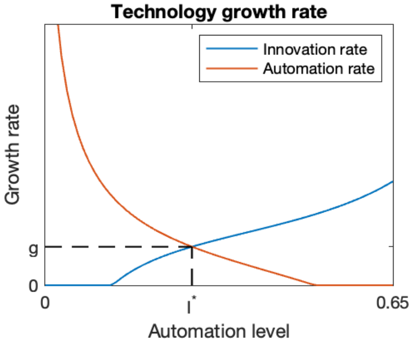


- Patent value: $P = \eta p(i) y(i)$
- Automation $\uparrow$, R $\uparrow$, W $\downarrow$
- Innovation patent $\uparrow$, Automation patent $\downarrow$

- $\underset{\text{Rate}}{\underset{\downarrow}{\kappa(\epsilon)}} = \underset{\text{Scientist}}{\underset{\downarrow}{\epsilon}}^{\lambda}/\mu$

Research and Development Sector





- Patent value: $P = \eta p(i) y(i)$
- Automation $\uparrow$, R $\uparrow$, W $\downarrow$
- Innovation patent $\uparrow$, Automation patent $\downarrow$

- $\underbrace{\kappa(\epsilon)}_{\text{Rate}} = \underbrace{\epsilon}_{\text{Scientist}}^{\lambda}/\mu$
- No arbitrage: $\kappa'(\epsilon)P = W_H$

Households: Skilled and Unskilled

Households maximize their lifetime utility by making:

- Consumption and saving decision
- Working and training decision

$$\rho V_j(K_j, h_j) = \max_{C_j, l_j} \quad \frac{C_j^{1-\theta}}{1-\theta} + V_{jK}(K_j, h_j)\dot{K}_j + V_{jh}(K_j, h_j)\dot{h}_j, \quad \underbrace{j = \{H, L\}}_{\text{skilled or unskilled}}$$

subject to the laws of motion:

$$\text{Physical capital: } \dot{K}_j = rK_j + W_j l_j + \Pi_j - C_j$$

$$\Pi_j\text{: skilled workers receive patent profits}$$

$$\text{Human capital: } \dot{h}_j = \frac{(1-l_j)^{\alpha_j}}{\mu_{hj}}$$

Human Capital Investment

Law of motion:

$$\underbrace{\dot{h}_j}_{\text{change in human capital}} = \frac{\overbrace{(1 - l_j)^{\alpha_j}}^{\text{training time}}}{\underbrace{\mu_{hj}}_{\text{training cost}}}, \quad \underbrace{j = \{H, L\}}_{\text{skilled or unskilled}}$$

Human Capital Investment

Law of motion:

$$\underbrace{\dot{h}_j}_{\text{change in human capital}} = \frac{\overbrace{(1 - l_j)}^{\text{training time}}{}^{\alpha_j}}{\underbrace{\mu_{hj}}_{\text{training cost}}}, \quad \underbrace{j = \{H, L\}}_{\text{skilled or unskilled}}$$

Grossman et al. (2021)
Stantcheva (2015)

- $\alpha_j \to 1$, learning or doing
- $\alpha_j \to 0$, learning by doing
- $\alpha_H > \alpha_L$, different learning ability

Human Capital Investment

Law of motion:

$$\underbrace{\dot{h}_j}_{\substack{\text{change in}\\ \text{human capital}}} = \frac{\overbrace{(1-l_j)^{\alpha_j}}^{\text{training time}}}{\underbrace{\mu_{hj}}_{\text{training cost}}}, \quad \underbrace{j = \{H, L\}}_{\text{skilled or unskilled}}$$

Grossman et al. (2021)
Stantcheva (2015)

- $\alpha_j \to 1$, learning or doing
- $\alpha_j \to 0$, learning by doing
- $\alpha_H > \alpha_L$, different learning ability

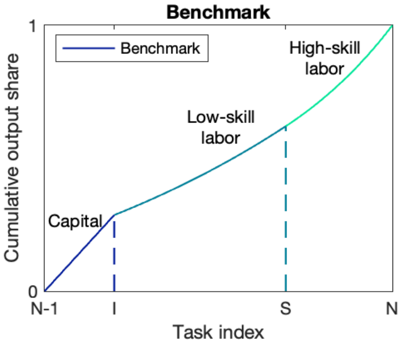
Euler:
Trade off between physical and human capital

$$\underbrace{\frac{\delta \log W_j(h_j) l_j}{\delta h_j} \frac{\delta \dot{h}_j}{\delta(1-l_j)}}_{\text{Direct wage gain}} + \underbrace{\frac{\delta \log W_j(h_j)}{\delta h_j}\dot{h}_j + \frac{\delta \log W_j(h_j)}{\delta t}}_{\text{Return to human capital}} = \underbrace{r}_{\text{Return to physical capital}}$$

Balanced Growth Path

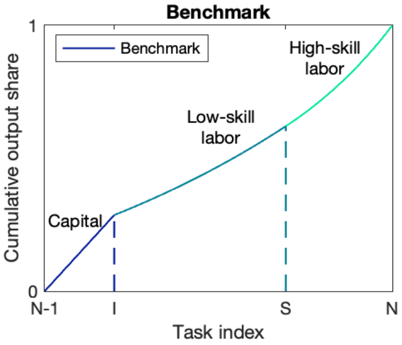
- Normalized variables $x = Xe^{-\int_0^t g(\tau)d\tau}$ are constant on BGP
  - Growth rates $\{g_N, g_I, g_{hH}, g_{hL}\}$
  - Automation level and the labor allocation $\{\tilde{I}, \tilde{S}\}$
  - Factor shares $\{s_K, s_L, s_H\}$, the rental rate of capital $\{r\}$, labor supply $\{L_H, L_L\}$
  - Normalized capital, output and consumption $\{k, y, c_H, c_L\}$, labor wages $\{\omega_H, \omega_L\}$
- Optimization problem
- Market clear

Automation and Human Capital



Equation

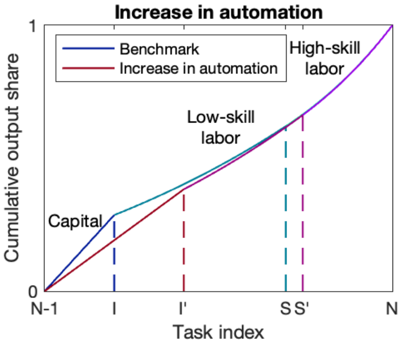
Automation and Human Capital



- Automation $\uparrow$

Equation

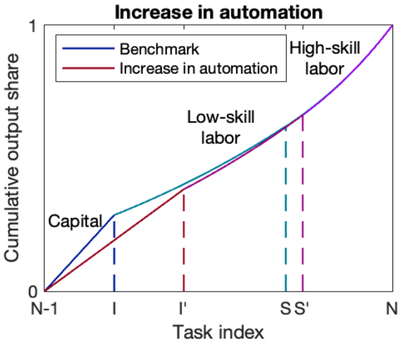
Automation and Human Capital

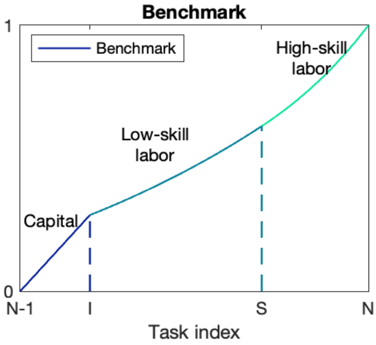


- Automation $\uparrow$
- Labor share $\downarrow$: displacement effect
- Wage premium $\uparrow$: relocation effect

Equation

Automation and Human Capital



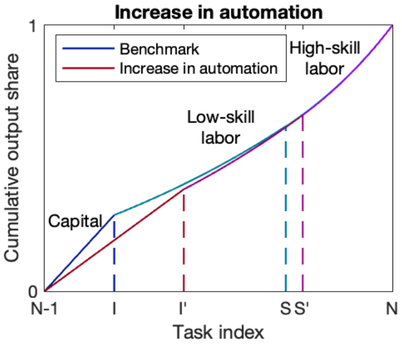


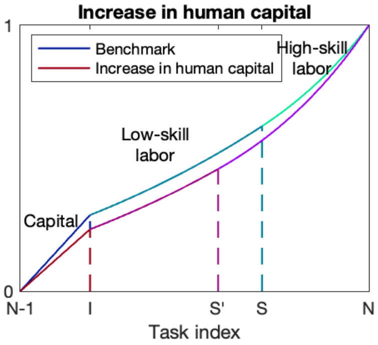
- Automation ↑
- Labor share ↓: displacement effect
- Wage premium ↑: relocation effect

- Human capital of skilled workers ↑

Equation

Automation and Human Capital



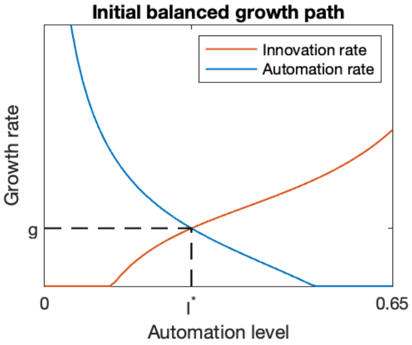


- Automation ↑
- Labor share ↓: displacement effect
- Wage premium ↑: relocation effect

- Human capital of skilled workers ↑
- Labor share ↑: labor supply
- Wage premium ↑: productivity

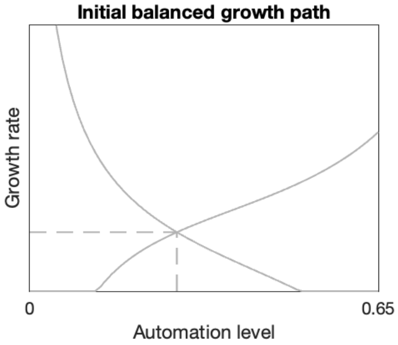
Equation

Technological Revolution



Equation

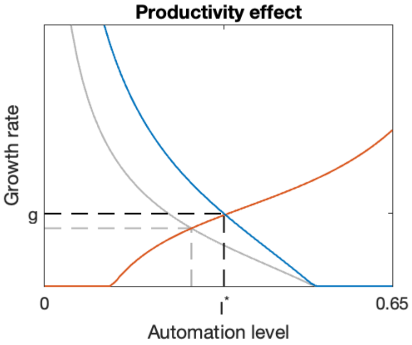
Technological Revolution



Automation cost $\downarrow$

Equation

Technological Revolution

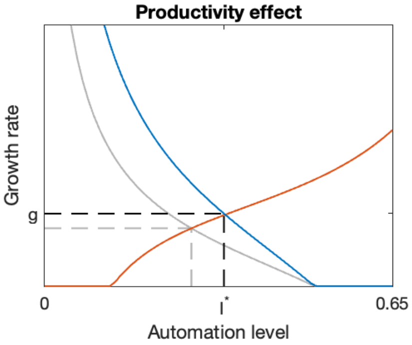


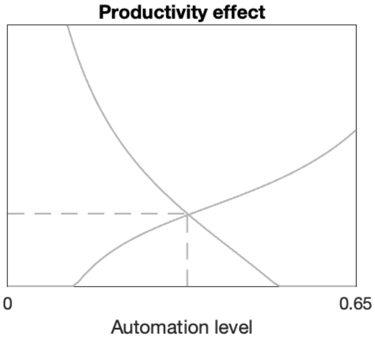
Automation cost ↓

- Automation curve ↑
- Automation ↑

Equation

Technological Revolution





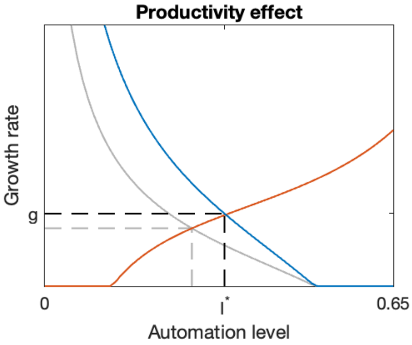
Automation cost $\downarrow$

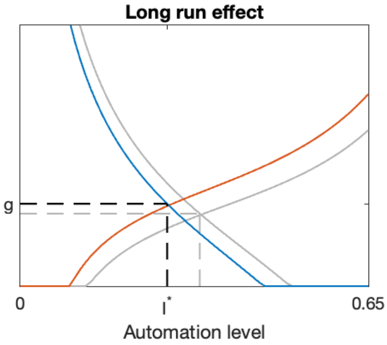
- Automation curve $\uparrow$
- Automation $\uparrow$

Long run effect

Equation

Technological Revolution





Automation cost ↓

- Automation curve ↑
- Automation ↑

Long run effect

- Long run k ↓
- Innovation patent ↑
- Automation patent ↓

Equation

Return to Human Capital

$$\text{Return to human capital} = \underbrace{\frac{\delta \log W_j(h_j)}{\delta h_j}\dot{h}_j}_{\text{direct retrun}} + \underbrace{\frac{\delta \log W_j(h_j)}{\delta t}}_{\text{technological environment}}$$

Return to Human Capital

$$\text{Return to human capital} = \underbrace{\frac{\delta \log W_j(h_j)}{\delta h_j}\dot{h}_j}_{\text{direct retrun}} + \underbrace{\frac{\delta \log W_j(h_j)}{\delta t}}_{\text{technological environment}}$$

$$\text{Skilled: } \frac{dW_H(h_H, t)}{dt} = g_{WN} + g_{WI} + \frac{s_L}{s_H + s_L} g_{WS}$$

$$\text{Unskilled: } \frac{dW_L(h_L, t)}{dt} = \underset{\substack{\downarrow \\ \text{productivity}}}{g_{WN}} + \underset{\substack{\downarrow \\ \text{displacement}}}{g_{WI}} - \frac{s_H}{s_H + s_L} \underset{\substack{\downarrow \\ \text{rellocation}}}{g_{WS}}$$

Return to Human Capital

$$\text{Return to human capital} = \underbrace{\frac{\delta \log W_j(h_j)}{\delta h_j}\dot{h}_j}_{\text{direct retrun}} + \underbrace{\frac{\delta \log W_j(h_j)}{\delta t}}_{\text{technological environment}}$$

$$\text{Skilled: } \frac{dW_H(h_H, t)}{dt} = g_{WN} + g_{WI} + \frac{s_L}{s_H + s_L} g_{WS}$$

$$\text{Unskilled: } \frac{dW_L(h_L, t)}{dt} = \underbrace{g_{WN}}_{\text{productivity}} + \underbrace{g_{WI}}_{\text{displacement}} - \frac{s_H}{s_H + s_L} \underbrace{g_{WS}}_{\text{rellocation}}$$

Technological revolution

Equation

Return to Human Capital

$$\text{Return to human capital} = \underbrace{\frac{\delta \log W_j(h_j)}{\delta h_j}\dot{h}_j}_{\text{direct retrun}} + \underbrace{\frac{\delta \log W_j(h_j)}{\delta t}}_{\text{technological environment}}$$

$$\text{Skilled: } \frac{dW_H(h_H,t)}{dt} = g_{WN} + g_{WI} + \frac{s_L}{s_H + s_L} g_{WS}$$

$$\text{Unskilled: } \frac{dW_L(h_L,t)}{dt} = \underbrace{g_{WN}}_{\text{productivity}} + \underbrace{g_{WI}}_{\text{displacement}} - \frac{s_H}{s_H + s_L} \underbrace{g_{WS}}_{\text{rellocation}}$$

Technological revolution

- Productivity effect: better allocation and higher innovation rate $g_{WN} \uparrow$

Equation

Return to Human Capital

$$\text{Return to human capital} = \underbrace{\frac{\delta \log W_j(h_j)}{\delta h_j}\dot{h}_j}_{\text{direct retrun}} + \underbrace{\frac{\delta \log W_j(h_j)}{\delta t}}_{\text{technological environment}}$$

$$\text{Skilled: } \frac{dW_H(h_H, t)}{dt} = g_{WN} + g_{WI} + \frac{s_L}{s_H + s_L} g_{WS}$$

$$\text{Unskilled: } \frac{dW_L(h_L, t)}{dt} = \underset{\text{productivity}}{\underset{\downarrow}{g_{WN}}} + \underset{\text{displacement}}{\underset{\downarrow}{g_{WI}}} - \frac{s_H}{s_H + s_L} \underset{\text{rellocation}}{\underset{\downarrow}{g_{WS}}}$$

Technological revolution

- Productivity effect: better allocation and higher innovation rate $g_{WN} \uparrow$
- Displacement effect: automation replaces labor $g_{WI} \downarrow$

Equation

Return to Human Capital

$$\text{Return to human capital} = \underbrace{\frac{\delta \log W_j(h_j)}{\delta h_j}\dot{h}_j}_{\text{direct retrun}} + \underbrace{\frac{\delta \log W_j(h_j)}{\delta t}}_{\text{technological environment}}$$

$$\text{Skilled: } \frac{dW_H(h_H, t)}{dt} = g_{WN} + g_{WI} + \frac{s_L}{s_H + s_L} g_{WS}$$

$$\text{Unskilled: } \frac{dW_L(h_L, t)}{dt} = \underset{\substack{\downarrow \\ \text{productivity}}}{g_{WN}} + \underset{\substack{\downarrow \\ \text{displacement}}}{g_{WI}} - \frac{s_H}{s_H + s_L} \underset{\substack{\downarrow \\ \text{rellocation}}}{g_{WS}}$$

Technological revolution

- Productivity effect: better allocation and higher innovation rate $g_{WN} \uparrow$
- Displacement effect: automation replaces labor $g_{WI} \downarrow$
- Relocation effect: unskilled workers relocate to higher index tasks $g_{WS} \uparrow$

Equation

Internal Calibration

Parameter	Description	Value	Targeted moment	Value
ρ	Discount rate	0.0121	Long run interest rate	4.0%
η	Patent share	0.1125	RD and GDP ratio	2.8%
A	Capital productivity	0.1190	Short run interest rate	4.0%
B_H	Skill comparative advantage	2.2651	Wage premium (1980)	1.4
μ_N	Cost of innovation	2.3619	RD growth rate	2.8%
μ_I	Cost of automation	9.0135	Labor share (1980)	0.625
μ_h	Cost of h_L accumulation	193.5608	Human capital growth rate	0.3%
α_H	h_H accumulation function	0.9026	Change of training time (H)	0.141
α_L	h_L accumulation function	0.2797	Change of training time (L)	0.160
λ	RD Decreasing return	0.7675	Wage premium (2005)	1.6
z	Technological revolution	0.7853	Labor share (2005)	0.605

Balanced Growth Path

Moment	1980	2005	
		Fixed human capital	Endogenous human capital
Automation level	0.6818	0.7796	0.7623
Labor share	0.6174	0.5906	0.5939
Skilled labor share	0.2814	0.2758	0.2840
Unskilled labor share	0.3360	0.3148	0.3099
Wage premium	1.4012	1.4454	1.5897
Technology growth rate	4.2036%	5.5177%	5.2122%
Human capital growth rate	0.2612%	0.2612%	0.2743%
Welfare inequality	1.0087	1.0902	1.1859

Balanced Growth Path

Moment	1980	2005 Fixed human capital	2005 Endogenous human capital
Automation level	0.6818	0.7796	0.7623
Labor share	0.6174	0.5906	0.5939
Skilled labor share	0.2814	0.2758	0.2840
Unskilled labor share	0.3360	0.3148	0.3099
Wage premium	1.4012	1.4454	1.5897
Technology growth rate	4.2036%	5.5177%	5.2122%
Human capital growth rate	0.2612%	0.2612%	0.2743%
Welfare inequality	1.0087	1.0902	1.1859

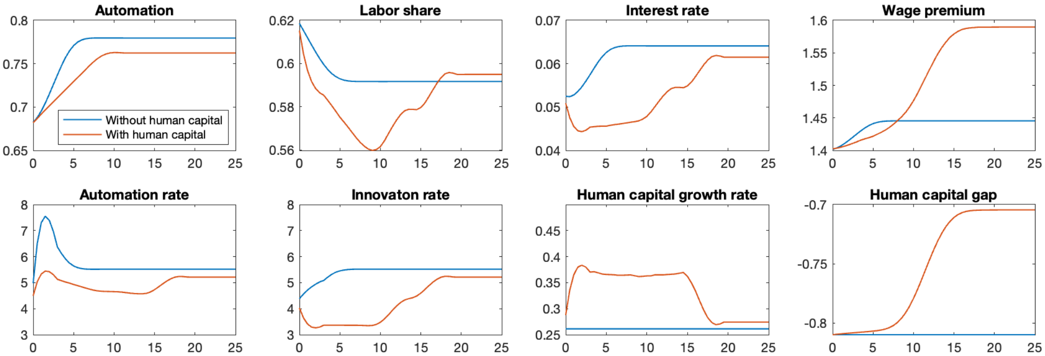
- Endogenous human capital increases labor share

Balanced Growth Path

Moment	1980	2005	
		Fixed human capital	Endogenous human capital
Automation level	0.6818	0.7796	0.7623
Labor share	0.6174	0.5906	0.5939
Skilled labor share	0.2814	0.2758	0.2840
Unskilled labor share	0.3360	0.3148	0.3099
Wage premium	1.4012	1.4454	1.5897
Technology growth rate	4.2036%	5.5177%	5.2122%
Human capital growth rate	0.2612%	0.2612%	0.2743%
Welfare inequality	1.0087	1.0902	1.1859

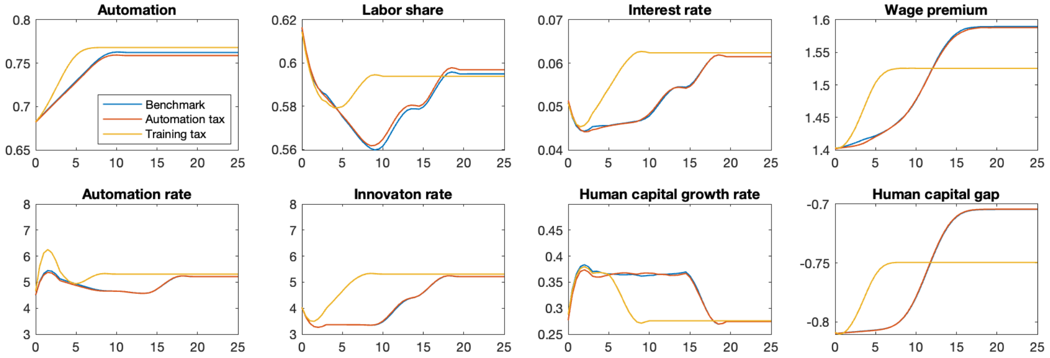
- Endogenous human capital increases labor share
- Uneven responses increase the inequality

Transition



- Endogenous human capital amplifies the effect of automation
- Labor share drops more in the short run: human capital adjustment
- It takes longer for innovation rate to catch up

Policy implications



- Automation tax: increase labor share
- Training tax on skilled workers: decrease inequality

SPP

Empirical Evidence: O*NET

$$\underbrace{\text{Skill}_{ijt}}_{\substack{\text{Occupational level}\\ \text{O*NET}}} = \underbrace{T_t}_{\text{Time dummies}} + T_t \times \underbrace{\text{Automation}_i}_{\substack{\text{Exposure}\\ \text{Webb (2019)}}} + \underbrace{\Gamma_{it}}_{\text{Control variables}} + \epsilon_{ijt}$$

Empirical Evidence: O*NET

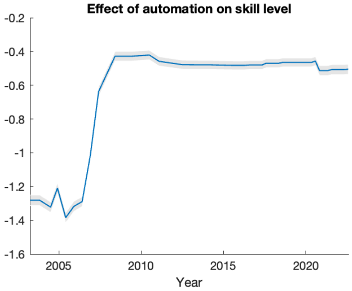
$$\text{Skill}_{ijt} = T_t + T_t \times \text{Automation}_i + \Gamma_{it} + \epsilon_{ijt}$$

Skill$_{ijt}$ → Occupational level O*NET

T_t → Time dummies

Automation$_i$ → Exposure Webb (2019)

Γ_{it} → Control variables



Automation

- Automation ↑ Occupational skill ↑
- Productivity effect: improve allocation
- Complement human capital: adaptation

Different Responses

$$\text{Skill}_{ijt} = T_t + T_t \times \text{Automation}_i + T_t \times \text{Education}_{it} + T_t \times \text{Automation}_i \times \text{Education}_{it} + \Gamma_{it} + \epsilon_{ijt}$$

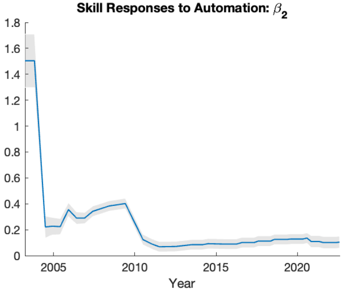
Occupational level
O*NET

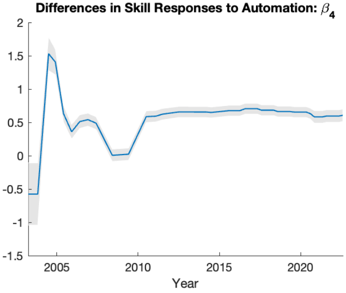
Time dummies

Exposure
Webb (2019)

Share of college graduates
O*NET

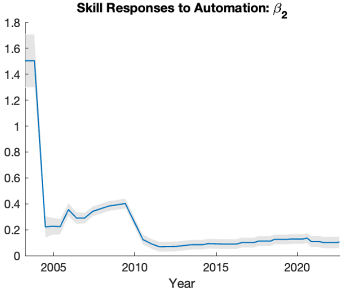
Control variables

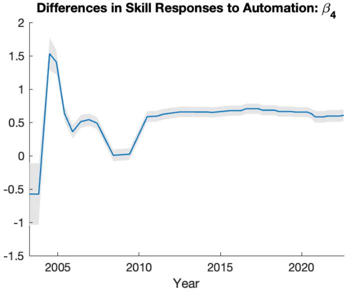




Different Responses

$$\underbrace{\text{Skill}_{ijt}}_{\substack{\text{Occupational level}\\ \text{O*NET}}} = \underbrace{T_t}_{\text{Time dummies}} + T_t \times \underbrace{\text{Automation}_i}_{\substack{\text{Exposure}\\ \text{Webb (2019)}}} + T_t \times \underbrace{\text{Education}_{it}}_{\substack{\text{Share of college graduates}\\ \text{O*NET}}} + T_t \times \text{Automation}_i \times \text{Education}_{it} + \underbrace{\Gamma_{it}}_{\text{Control variables}} + \epsilon_{ijt}$$





- After control for education, automation decreases skill growth
- Skilled workers increase skill level more

Conclusion

Main takeaways

- A reduction in automation costs increases productivity

Conclusion

Main takeaways

- A reduction in automation costs increases productivity
- Human capital investment complements innovation but substitutes automation

Conclusion

Main takeaways

- A reduction in automation costs increases productivity
- Human capital investment complements innovation but substitutes automation
- Endogenous human capital amplifies the effect of the technological revolution

Conclusion

Main takeaways

- A reduction in automation costs increases productivity
- Human capital investment complements innovation but substitutes automation
- Endogenous human capital amplifies the effect of the technological revolution
- An automation tax decreases automation and increases labor share. A training tax on skilled workers is more efficient in reducing inequality and accelerating the recovery.

Comparative Statistics 1

The change in labor share is given by the following equation:

$$d\ln(s_L+s_H) = \frac{\hat{\sigma}-1}{\hat{\sigma}}\frac{s_K}{1-\eta}\underbrace{\left(\frac{s_L}{s_L+s_H}\frac{d\ln\tilde{\Gamma}_L}{d\tilde{I}} - \frac{d\ln H}{d\tilde{I}}\right)d\tilde{I}}_{\text{Automation}}$$
$$-\frac{\hat{\sigma}-1}{\hat{\sigma}}\frac{s_K}{1-\eta}\underbrace{(d\ln K - BdN - bdh - d\ln L)}_{\text{Capital deepening}}$$

where the average change of human capital and labor supply is defined as:

$$d\ln h = \frac{s_H}{s_H+s_L}d\ln h_H + \frac{s_L}{s_H+s_L}d\ln h_L$$
$$d\ln L = \frac{s_H}{s_H+s_L}d\ln L_L + \frac{s_L}{s_H+s_L}d\ln L_L$$

back

Comparative Statistics 2

The change of allocation $\tilde{S}$ can be written as:

$$\underbrace{d\tilde{S}}_{\text{Allocation}} = \frac{1}{\epsilon(\tilde{S})}\Big(\underbrace{\frac{1}{\hat{\sigma}}(d\ln L_L - d\ln L_H - bdh_{HL})}_{\text{Labor supply}} - \underbrace{\frac{\hat{\sigma}-1}{\hat{\sigma}}\frac{d\ln\tilde{\Gamma}_L}{d\tilde{I}}d\tilde{I}}_{\text{Automaton}}\Big)$$

where $\epsilon(\tilde{S})$ is the inverse of allocation elasticity taking the form:

$$\epsilon(\tilde{S}) = \underbrace{\frac{\hat{\sigma}-1}{\hat{\sigma}}(\frac{d\ln\tilde{\Gamma}_L}{d\tilde{S}} - \frac{d\ln\tilde{\Gamma}_H}{d\tilde{S}})}_{\text{Wage elasticity}} + \underbrace{(B - B_L)}_{\text{Comparative advantage}}$$

back

Comparative Statistics 3

The change of wages can be written as:

$$d\ln W_L = \underbrace{d\ln Y}_{\text{Productivity}} + \underbrace{\frac{\hat{\sigma}-1}{\hat{\sigma}}\frac{d\ln\tilde{\Gamma}_L}{d\tilde{I}}d\tilde{I}}_{\textit{Displacement}} + \underbrace{\frac{\hat{\sigma}-1}{\hat{\sigma}}\frac{d\ln\tilde{\Gamma}_L}{d\tilde{S}}d\tilde{S}}_{\text{Relocate}}$$

$$d\ln W_H = \underbrace{d\ln Y}_{\text{Productivity}} + \underbrace{\frac{\hat{\sigma}-1}{\hat{\sigma}}\frac{d\ln\tilde{\Gamma}_H}{d\tilde{S}}d\tilde{S}}_{\text{Relocate}}$$

$$d\ln\omega = (B - B_L)d\tilde{S} + bdh_{HL}$$

back

R&D Problem 1

Patent Value

$$\text{Innovation: } P_N(t) = V_N(N(t), t) - V_I(N(t) - 1, t)$$
$$\text{Automation: } P_I(t) = V_I(I(t), t) - V_N(I(t), t)$$

Present discounted value of future profit

$$\text{Task N using labor: } V_N(N, t) = \int_t^\infty e^{-\int_t^\tau r(s)ds} \pi(N, \tau) d\tau$$
$$\text{Task I using machine: } V_I(I, t) = \int_t^\infty e^{-\int_t^\tau r(s)ds} \pi(I, \tau) d\tau$$

back

R&D Problem 2

Scientist productivity

$$\dot{N} = \frac{1}{\mu_N}\epsilon_N^{\lambda} \qquad \dot{I} = \frac{1}{\mu_I}\epsilon_I^{\lambda}$$

No arbitrage condition

$$\frac{\lambda \epsilon_I(t)^{\lambda-1}}{\mu_I}P_I(t) = \frac{\lambda \epsilon_N(t)^{\lambda-1}}{\mu_N}P_N(t) = W_H(t).$$

Technology growth rate

$$g_N = \frac{1}{\mu_N}\left(\frac{\mu_N W_H}{\lambda P_N}\right)^{\frac{\lambda}{\lambda-1}} \qquad g_I = \frac{1}{\mu_I}\left(\frac{\mu_I W_H}{\lambda P_I}\right)^{\frac{\lambda}{\lambda-1}}$$

back

Wage Growth

$$g_{WN} = \underbrace{Bg_N}_{\text{Productivity}} + \underbrace{a(\tilde{I})(g_K - g_L - Bg_N - bg_h)}_{\text{Capital deepening}}$$

$$g_{WI} = \underbrace{a(\tilde{I})\frac{d\ln H}{d\tilde{I}}(g_I - g_N)}_{\text{Productivity}} + \underbrace{\frac{s_L}{s_H + s_L}(1 - a(\tilde{I}))\frac{d\ln\tilde{\Gamma}_L}{d\tilde{I}}(g_I - g_N)}_{\text{Displacement}}$$

$$g_{WS} = \frac{B - B_L}{\epsilon(\tilde{S})}\underbrace{(\frac{1}{\hat{\sigma}}(g_{LL} - g_{LH} + b(g_{hL} - g_{hH}))}_{\text{Labor supply}} - \underbrace{\frac{\hat{\sigma} - 1}{\hat{\sigma}}\frac{d\ln\tilde{\Gamma}_L}{d\tilde{I}}(g_I - g_N))}_{\text{Relocation}}$$

back

External Calibration

Parameter	Description	Value	Reference
θ	Intertemporal elasticity of substitution	0.9	Beaudry and Van Wincoop (1996)
σ	Factor elasticity of substitution	2	
δ	Depreciation rate	0.1	BEA Depreciation Estimates
B_L	Comparative advantage of unskilled workers	1	
b	Return to human capital	1	
ϵ_H	high-skill workers share	0.3	FRED
ϵ_L	Low skill workers share	0.7	FRED
λ	R&D production function	0.5	Prettner and Strulik (2020)

Table: External Calibration

back

Social Planner's Problem

Innovation patent

$$\text{SPP: } \frac{\lambda \epsilon_N^{\lambda-1}}{\mu_N} \frac{(1-\eta) P_N^{SPP}}{Y} = \frac{W_H}{Y}$$

$$\text{CE: } \frac{\lambda \epsilon_N^{\lambda-1}}{\mu_N} \frac{P_N}{Y} = \frac{W_H}{Y}$$

Training for skilled workers

$$\text{SPP: } \frac{L_H}{\epsilon_H} \frac{b\delta \dot{h}_H}{\delta(1-l_H)} + g_{WH} = \frac{R}{1-\eta} - \delta$$

$$\text{CE: } l_H \frac{b\delta \dot{h}_H}{\delta(1-l_H)} + g_{WH} = r(1+\tau_{hH})$$

back

Empirical Evidence: ATES

VARIABLES	(1) Training hours	(2) Training hours
High school × AOE	-4.544***	-7.138***
	(0.0672)	(0.0671)
Associate × AOE	7.670***	4.465***
	(0.0863)	(0.0862)
Bachelor or higher × AOE	5.722***	3.765***
	(0.0794)	(0.0793)
AOE	-2.314***	-2.857***
	(0.0604)	(0.0606)
High school	2.959***	2.438***
	(0.0325)	(0.0324)
Associate	4.718***	4.356***
	(0.0386)	(0.0386)
Bachelor or higher	10.36***	10.16***
	(0.0342)	(0.0342)
Constant	18.28***	36.38***
	(0.0299)	(0.0344)
Observations	495,266,531	495,266,531
R-squared	0.018	0.022
Time dummies	Yes	Yes
Control variable	No	Yes

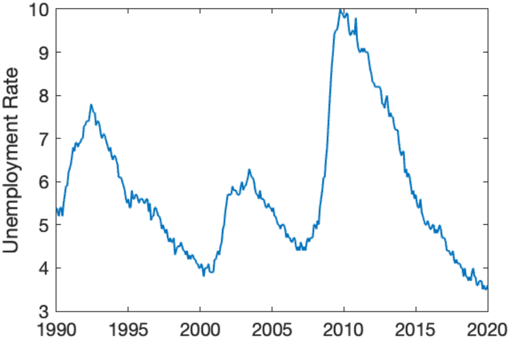
Skill Mismatch and Jobless Recovery

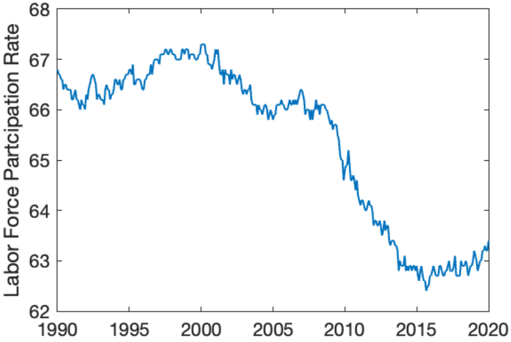
Rong Fan

Indiana University

November 10, 2022

Motivation





- Unemployment Rate (UR): excessive response and slow recovery
- Unemployment Rate (UR): 3.5% in February 2020
- Labor Force Participation Rate (LFPR): 66% $\rightarrow$ 63.3%

Research Question

Research questions

- Excessive response of unemployment rate and labor force participation rate?
- Decline trend of labor force participation rate?
- Skill mismatch and labor market structural change?

Research Question

Research questions

- Excessive response of unemployment rate and labor force participation rate?
- Decline trend of labor force participation rate?
- Skill mismatch and labor market structural change?

Methodology

- Search-and-matching model with heterogeneous skill and technology
- Sequential auction: on- and off- the job search
- Benchmark: calibrate to match the data 1987-1993
- Structural change in 2007-2013: three scenarios
- Empirical evidence

Skill Mismatch

Match output $f(z, a, b)$

- a: skill
- b: technology

$$f(z, a, b) = z \underbrace{(\kappa a + (1 - \kappa)b)}_{\text{productivity}} - \underbrace{\{a < b\}\alpha_u \frac{(b-a)^2}{b}}_{\text{Underqualification penalty}}$$

Skill Mismatch

Match output $f(z, a, b)$

- a: skill
- b: technology

$$f(z, a, b) = z \underbrace{(\kappa a + (1-\kappa) b)}_{\text{productivity}} - \underbrace{\{a < b\}\alpha_u \frac{(b-a)^2}{b}}_{\text{Underqualification penalty}}$$

Overqualification disutility $d(z, a, b)$

$$d(a, b) = 1\{a > b\}\alpha_o \frac{(b-a)^2}{a}$$

Labor Market Dynamics: Sequential Auction

$$\underset{\substack{\downarrow \\ \text{unemployment}}}{V_u} + \underbrace{D(a,b)}_{\text{disutility}} \xrightarrow[\text{Wage bargaining}]{\text{On the job search}} \underset{\substack{\downarrow \\ \text{outside option}}}{V_e(z,a,b',b)} \xrightarrow{\text{Climb job ladder}} \dots$$

$$\xrightarrow{\text{Climb job ladder}} V_e(z,a,b'',b) \xrightarrow[\text{exogenous separation}]{\text{endogenous separation}} V_u + D(a,b)$$

Extension

Home productivity shock

$$\epsilon_n \sim Pareto(\epsilon_{min}, \lambda_n)$$

Endogenous skill and technology

$$\bar{S}(z, a, b) = \max_{a^*, b^*} \quad S(z, a^*, b^*) - \phi_a \frac{(a^* - a)^2}{a} - \phi_b \frac{(b^* - b)^2}{b}.$$

Calibration

	Benchmark (1987-1993)	Scenario 1	Scenario 2 (2007-2013)	Scenario 3
Structural change		Technology level	Skill dispersion	Higher training cost
Matching moment		Labor share	Skill variance	Training/GDP
Unemployment rate	0.0541	0.0554	0.0668	0.0512
Labor for participation rate	0.6637	0.6313	0.6175	0.6488
Mismatch	0.2643	0.3080	0.3144	0.3013
Unemployment volatility	0.0756	0.0942	0.0835	0.0940

Calibration

	Benchmark (1987-1993)	Scenario 1	Scenario 2 (2007-2013)	Scenario 3
Structural change		Technology level	Skill dispersion	Higher training cost
Matching moment		Labor share	Skill variance	Training/GDP
Unemployment rate	0.0541	0.0554	0.0668	0.0512
Labor for participation rate	0.6637	0.6313	0.6175	0.6488
Mismatch	0.2643	0.3080	0.3144	0.3013
Unemployment volatility	0.0756	0.0942	0.0835	0.0940

- Mismatch $\uparrow$, U volatility $\uparrow$, LFPR $\downarrow$

Calibration

	Benchmark (1987-1993)	Scenario 1	Scenario 2 (2007-2013)	Scenario 3
Structural change		Technology level	Skill dispersion	Higher training cost
Matching moment		Labor share	Skill variance	Training/GDP
Unemployment rate	0.0541	0.0554	0.0668	0.0512
Labor for participation rate	0.6637	0.6313	0.6175	0.6488
Mismatch	0.2643	0.3080	0.3144	0.3013
Unemployment volatility	0.0756	0.0942	0.0835	0.0940

- Mismatch ↑, U volatility ↑, LFPR ↓
- Training cost ↑, U ↓, LFPR ↑

Conclusion

- Skill mismatch increases unemployment rate and volatility

Conclusion

- Skill mismatch increases unemployment rate and volatility
- Endogenous skill and technology amplifies volatility

Conclusion

- Skill mismatch increases unemployment rate and volatility
- Endogenous skill and technology amplifies volatility
- Mismatch can be a result of
  - Higher technology level
  - Higher skill heterogeneity
  - Higher training cost

Central Bank Digital Currency in Small Open Economies

Rong Fan, Todd Walker, Wayne Robinson and Allan Wright

Indiana University

November 11, 2022

Motivation

- 17.9% of Bahamians are unbanked. (Central Bank of the Bahamas)
- Electronic payment: only Nassau and Freeport
- Over 90% of Bahamians have used internet in last three months. (World Bank)

Motivation

- 17.9% of Bahamians are unbanked. (Central Bank of the Bahamas)
- Electronic payment:
  only Nassau and Freeport
- Over 90% of Bahamians have used internet in last three months. (World Bank)

Sand Dollar

- Transaction efficiency
- Financial inclusion
- Regulated payment
- Dollarization

Research Question

Research questions

- CBDC and transaction frictions?
- CBDC and social welfare?
- CBDC and fiscal and monetary policy efficiency?

Research Question

Research questions

- CBDC and transaction frictions?
- CBDC and social welfare?
- CBDC and fiscal and monetary policy efficiency?

Methodology

- TANK model with constrained and unconstrained households
- Households are facing liquidity constraints
- CBDC as a more efficient and safer asset than cash
- Dollarization: deposit and cash can be indexed by domestic or foreign currency

Unconstrained Household

$$\max_{c_{1t},h_{1t},s_{1t},l_{1t},d_{1t}(j),b_{1Ht},b_{1Ft}} E_0 \sum_0^\infty \beta^t \left(\frac{c_{1t}^{1-\sigma}}{1-\sigma} - \chi \frac{h_{1t}^{1+\phi}}{1+\phi}\right),$$

subject to the budget and liquidity constraints:

$$\text{BC: } (1+s_{1t}+\tau_c)c_{1t} + \int_0^1 (d_{1t}(j) - \frac{r^d_{t-1}(j)}{\pi_t} d_{1t-1}(j))dj + (b_{1Ht} - \frac{r_{t-1}}{\pi_t} b_{1Ht-1})$$
$$+ s_t(b_{1Ft} - r^*_{t-1} b_{1Ft-1}) \leq w_t h_{1t} + t_{1t} + \Gamma_{1t} - \frac{\kappa_B}{2} s_t((1-\lambda)b_{1Ft} - \bar{b}_F)^2$$

$$\text{Liquidity: } l_{1t} = \int_0^1 (d_{1t}(j)^{\frac{\epsilon_b-1}{\epsilon_b}} dj)^{\frac{\epsilon_b}{\epsilon_b-1}}$$

$$\text{Transaction cost: } s_{1t} = z_t A \frac{c_{1t}}{l_{1t}} + B \frac{l_{1t}}{c_{1t}} - 2\sqrt{AB}$$

Constrained Households

$$\max_{c_{2t},h_{2t},l_{2t},s_{2t},m_{2t},CBDC_{2t}} E_0 \sum_0^{\infty} \beta^t \left(\frac{c_{2t}^{1-\sigma}}{1-\sigma} - \chi \frac{h_{2t}^{1+\phi}}{1+\phi}\right)$$

subject to the budget and liquidity constraints:

$$\text{BC: } (1 + s_{2t} + \underbrace{\tau_c \frac{CBDC_{2t}}{l_{2t}}}_{\text{consumption tax}})c_{2t} + (m_{2t} - \underbrace{\frac{1-\delta_m}{\pi_t}}_{\text{cost of cash}} m_{2t-1}) + (CBDC_{2t} - \frac{1}{\pi_t} CBDC_{2t-1})$$

$$\leq w_t h_{2t} + t_{2t}$$

$$\text{Liquidity: } l_{2t} = ((m_{2t})^{\frac{\epsilon_m - 1}{\epsilon_m}} + (CBDC_{2t})^{\frac{\epsilon_m - 1}{\epsilon_m}})^{\frac{\epsilon_m}{\epsilon_m - 1}}$$

$$\text{Transaction cost: } s_{2t} = z_t A \frac{c_{2t}}{l_{2t}} + B \frac{l_{2t}}{c_{2t}} - 2\sqrt{AB}$$

Dollarization

Unconstrained households

$$l_{1t} = \int_0^1 (d_{1Ht}(j)^{\frac{\epsilon_b - 1}{\epsilon_b}} dj)^{\frac{\epsilon_b}{\epsilon_b - 1}} + s_t \int_0^1 (d_{1Ft}(j)^{\frac{\epsilon_b - 1}{\epsilon_b}} dj)^{\frac{\epsilon_b}{\epsilon_b - 1}}$$

Dollarization

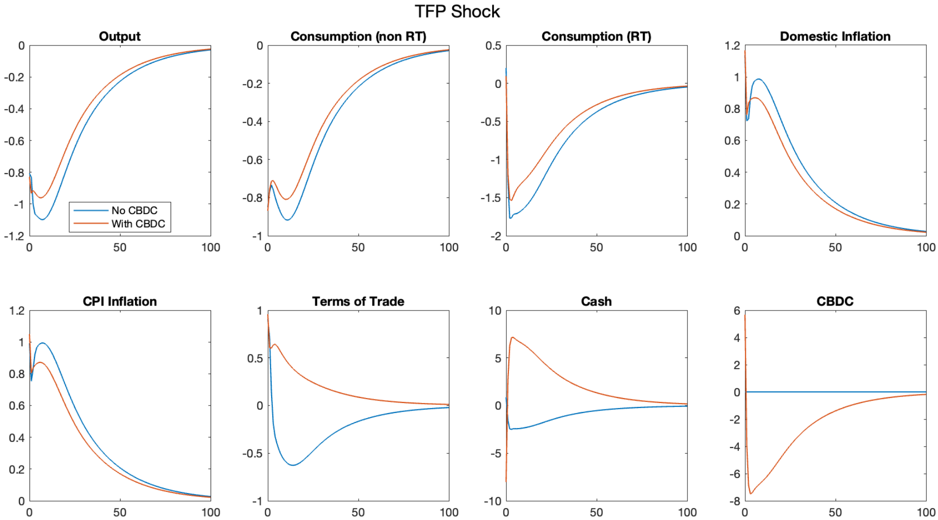
Unconstrained households

$$l_{1t} = \int_0^1 (d_{1Ht}(j)^{\frac{\epsilon_b - 1}{\epsilon_b}} dj)^{\frac{\epsilon_b}{\epsilon_b - 1}} + s_t \int_0^1 (d_{1Ft}(j)^{\frac{\epsilon_b - 1}{\epsilon_b}} dj)^{\frac{\epsilon_b}{\epsilon_b - 1}}$$

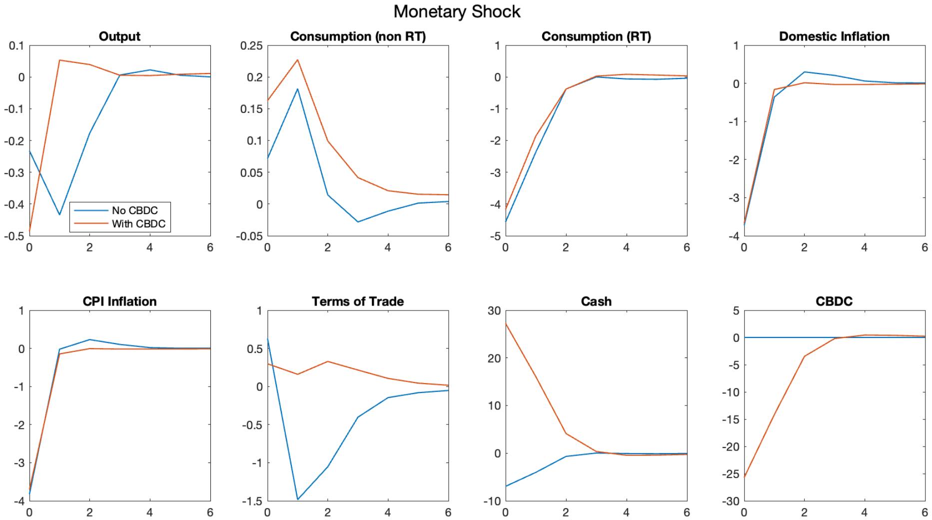
Constrained households

$$l_{2t} = ((m_{2Ht})^{\frac{\epsilon_m - 1}{\epsilon_m}} + (s_t m_{2Ft})^{\frac{\epsilon_m - 1}{\epsilon_m}} + (CBDC_{2t})^{\frac{\epsilon_m - 1}{\epsilon_m}})^{\frac{\epsilon_m}{\epsilon_m - 1}}$$

Impulse Response: TFP



Impulse Response: Monetary



Preliminary Results

Main takeaways:

- CBDC increases the welfare of constrained households by 2.73%
  - Transaction friction
  - Financial inclusion

Preliminary Results

Main takeaways:

- CBDC increases the welfare of constrained households by 2.73%
  - Transaction friction
  - Financial inclusion
- CBDC increases the tax revenue

Preliminary Results

Main takeaways:

- CBDC increases the welfare of constrained households by 2.73%
  - Transaction friction
  - Financial inclusion
- CBDC increases the tax revenue
- CDBC increases the monetary policy efficiency when the SOE is dollarized