Human Capital and Growth: The Roles of Skills and Heath

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A. Introduction

The labor market is essential for economic development (*Deming 2022*).

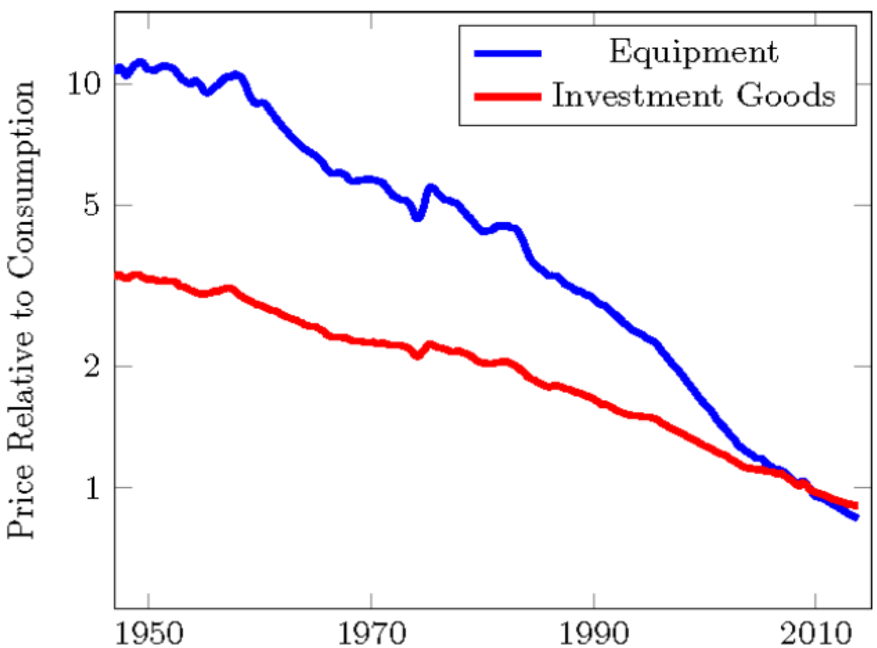
- **Teachers & mentors: *Tamura (2001)*, Fudenberg-Rayo (2019)**
- **Educational choice: Lucas (1988), *Laing-Palivos-Wang (1995)*, Fender-Wang (2003), *Grossman-Helpman-Oberfield-Sampson* (2016)**
- **Occupational choice: Banerjee-Newman (1993), *Grossman (2004)***
- **On-the-job learning: Lucas (1993), Laing-Palivos-Wang (*1995*, 2004)**
- **Human capital mobility & stratification: Benabu (1996), Chen-Peng-Wang (2009), Lee-Seshadri (2019), Zimmerman (2019)**
- **Entrepreneurship: Bernhardt&Lloyd-Ellis (2000), Jiang-Wang-Wu (2009)**
- **Globally declined trend in the labor share: Karabarbounis-Neiman (2014), Grossman-Helpman-Oberfield-Sampson (2018), *Acemoglu-Restrepo (2019)***
- **Health capital: *Acemoglu-Johnson (2007)*, *Wang-Wang (2016, 2020)*, *Bloom-Canning-Kotschy-Prettner-Schünemann (2019)*, *Eichenbaum-Rebelo-Trabandt (2020)***
- **Locational human capital mobility: Lucas (2004), Bond-Riezman-Wang (2016), Liao-Wang-Wang-Yip (2020, 2021)**
- **Automation, technology change, jobs and earnings: *Acemoglu-Restrepo (2019)*, *Braxton-Taska (2023)***

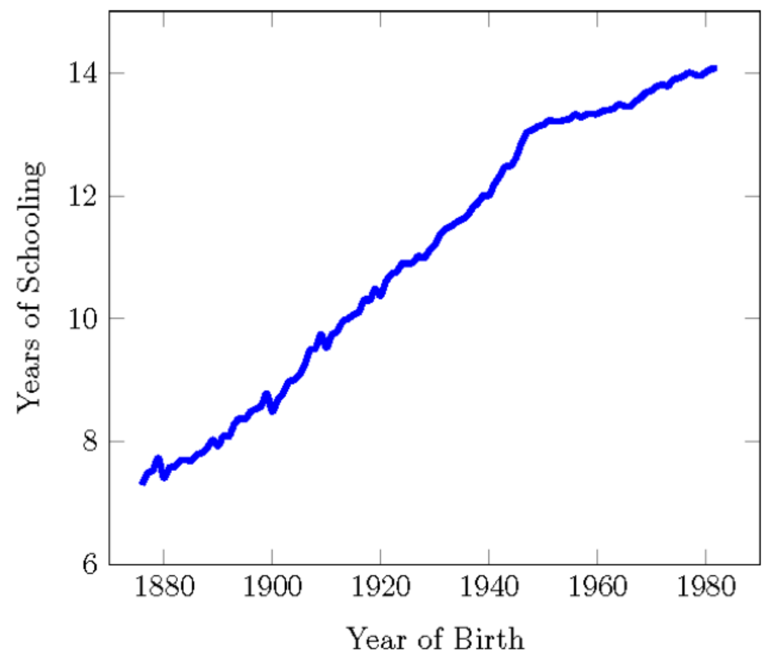
B. Measurement of Human Capital

- Conventional studies use crude measures of human capital, such as:
  - literacy rate
  - primary (P)/secondary (S)/higher (H) education enrollment
  - P/S/H education attainment
  - years of schooling
- It is more appropriate to use refined measures:
  - Bils and Klenow (2000) use weighted enrollment rate: E=6*P+6*S+5*H
  - Tallman and Wang (1994):
    - use weighted attainment rates to compute aggregate effective educastion: E=1*P+1.4*S+2*H, or, 1*P+2*S+4*H
    - then, setting $H = E^{\nu}$ and log-differentiating the aggregate production function, $\frac{\dot{y}}{y} = \frac{\dot{A}}{A} + \alpha\left(\frac{\dot{K}}{K} - n\right) + (1-\alpha)\nu\frac{\dot{E}}{E}$, one obtains the estimates ν
    - straightforward growth-accounting shows that human capital accounted for 45%, 20% and 28% of output growth in Taiwan, Korea and Thailand, respectively

C. Skill-Capital Complementarity: Grossman-Helpman-Oberfield-Sampson (2016)

- **Observation in the U.S.: on BGP despite falling investment good price and a less-than-one elasticity of substitution between capital and labor (Chirinko et al. 2011; Oberfield-Raval 2014)**
- **Uzawa revisited**





1. The Puzzle

- **Production:** $Y_t = F\left(A_t K_t, B_t L_t, s_t\right)$
  - **disembodied technologies: A, B**
  - **years of schooling: s**
- **Investment specific technological change via q (embodied):** $Y_t = C_t + I_t/q_t$
- **Capital evolution:** $\dot{K}_t = I_t - \delta K_t$
- **Disembodied technological change via A:** γ_A
- **Total capital-augmenting technological change:** $\gamma_K \equiv g_A + g_q$
- **Elasticity of substitution between capital and labor:** $\sigma_{KL} \equiv \left(F_L F_K\right) / \left(F_{LK} F\right)$
- **If a BGP exists with constant capital and labor income shares, then**

  $$\left(1 - \sigma_{KL}\right) \gamma_K = \sigma_{KL} \frac{F_L}{F_K} \frac{\partial \left(F_s / F_L\right)}{\partial K} \dot{s}$$

  - **Uzawa: s is constant, then BGP with constant capital and labor income shares requires** $\sigma_{KL} = 1 \ or \ \gamma_K = 0$
  - **Aggregate human capital H(BL, s): so** $F_s / F_L = H_s / H_L$ **independent of K and hence BGP with constant capital and labor income shares again requires** $\sigma_{KL} = 1 \ or \ \gamma_K = 0$

2. The Basic Model

- **Dynastic utility of a family with N members alive (growing at an exogenous rate n):** $u(t_0) = \int_{t_0}^{\infty} N_t e^{-\rho(t-t_0)} \frac{c_t^{1-\eta} - 1}{1-\eta} dt$
- **Labor:** $L_t = D(s_t) N_t$**, with D decreasing in s to capture the time foregone as a result of schooling**
- **Output per effective labor (BL):** $f(k_t, s_t) \equiv F(k_t, 1, s_t)$ **with** $k_t = A_t K_t / B_t L_t$
  - **(A1)** $f(k, s) = D(s)^{-\mu\beta} h[kD(s)^{\mu}]$**, with** $\mu > 0$
    - **h strictly increasing and strictly concave**
    - **f strictly log supermodular in k and s**
    - **under A1,** $\sigma_{KL} < 1$ **and** $\partial(F_s/F_L)/\partial K > 0$
  - **(A2)** $(i)\ \beta \geq d_{\max};\ (ii)\ \frac{\mu\beta-1}{\mu-1} \in (d_{\min}, d_{\max})$**, where** $\mathcal{E}_h(z) \equiv zh'(z)/h(z)$**,** $d_{\min} \equiv \lim_{z\to\infty} \mathcal{E}_h(z)$ **and** $d_{\max} \equiv \lim_{z\to 0} \mathcal{E}_h(z)$
    - **(i) ensures MPs nonnegative**
    - **(ii) ensures interior schooling choice**
  - **example:** $F(AK, BL, s) = (BL)^{1-\beta}\left\{(AK)^{-\alpha} + [D(s)^{-\mu} BL]^{-\alpha}\right\}^{-\beta/\alpha}$ **and** $h(z) = (1+z^{-\alpha})^{-\beta/\alpha}$

- **Social planner's problem:**

$$\max_{\{c_t, s_t\}} \int_{t_0}^{\infty} N_t e^{-\rho(t-t_0)} \frac{c_t^{1-\eta}-1}{1-\eta} dt$$

s.t.

$$Y_t \leq B_t L_t D(s_t)^{-\mu\beta} h\left[\frac{A_t K_t}{B_t L_t} D(s_t)^{\mu}\right] ;$$

$$L_t = D(s_t) N_t ;$$

$$\dot{K}_t = q_t (Y_t - N_t c_t) - \delta K_t .$$

- **Bounded growth: (A3)** $\rho > n + (1-\eta)\left[\gamma_L + \frac{\mu\beta-1}{(1-\beta)\mu}\gamma_K\right]$
- **Along a BGP,** $g_Y = g_K - g_q$ **and** $g_D = -\gamma_K/\mu(1-\beta)$**, so** $g_Y = n + \gamma_L + \gamma_K(\mu\beta-1)/\mu(1-\beta)$
  - **per capita output growth (g_Y - n) is rising with labor augmenting technical progress and total capital-augmenting technological change**
  - **capital income share is constant given by** $\theta_K = \frac{\mu\beta-1}{\mu-1}$
  - **no puzzle**
- **Key: labor quantity (L) and quality (s) do not enter production symmetrically**

3. Decentralized Economy with Time-in-School

- **Time in school:** $D(s) = 1 - s$
- **Production efficiency => factor demand**
  - $f_k(k_t, s_t) = r_t$
  - $f(k_t, s_t) - r_t k_t = w_t(s_t)$
- **Then, BGP features standard KR equation with:**
  - $\mathcal{E}_h\left[\kappa(s_t, r_t)(1 - s_t)^{\mu}\right] = \dfrac{\mu\beta - 1}{\mu - 1}$
  - $\dot{s}_t = (1 - s_t)\dfrac{\gamma_K}{\mu(1 - \beta)}$**: schooling grows at a declining rate**
  - **capital share constant as in the social planner problem**
  - **so, no puzzle**
- **Results can be generalized to models with manager-worker team work, directed technological change, and continuous-time OLG with survival rates a la Yaari (1965) and Blanchard (1985)**

D. The Role of Teachers: Tamura (2001)

- **Empirical facts of Schooling across U.S. States: 1901-90**
  - **enrollment rate (73.3 to 92.1%): ↑by 6% over 1901-60; 12% over 1960-90**
  - **class size (36.9 to 16.9 students/teacher): ↓by 12 1901-60 & 8 over 1960-90**
  - **relative teacher salary (from 1.53 to 2.35 to 1.76 teacher to average income ratio): ↑by 0.8 over 1901-60 and ↓0.6 over 1960-90**

1. The Model

- **Two-period lived overlapping generations with constant population**
- **Altruistic Preferences: U =** $\frac{c_t^\sigma}{\sigma} + \beta \frac{h_{t+1}^\sigma}{\sigma}$**, 0< β < 1 and σ < 1**
- **School Quality and Human Capital Evolution:**
  - **teacher quality (teacher-parents human capital ratio):**

$$Q_{it} = \frac{\text{average human capital of school district } i \text{ teachers}}{\text{average human capital of school district } i \text{ parents}} = \frac{E\{h_{it}^T\}}{E\{h_{it}\}}$$

- **class size (student-teacher ratio):**

$$C_{it} = \frac{\text{number of students in school district } i}{\text{number of teachers in school district } i} = \frac{N_{it}}{N_{it}^T}$$

- **Human capital accumulation (HC):** $h_{it+1} = Ah_{it}(C_{it}^{-\epsilon}Q_{it}^{1-\epsilon})^{\nu}$, $1 > \epsilon > 0,\ 1 \geq \nu > 0$
- **Individual Budget Constraints (BC):** $c_{it} = h_{it}(1 - \tau_{it})$
- **Local Governments' Budget Constraints (GBC):**
  - **poor school districts ($N_{Pt} = \alpha$):** $\alpha\tau_P h_P = N_P^T E\{h_P^T\}$
  - **rich school districts ($N_{Rt} = 1\text{-}\alpha$):** $(1-\alpha)\tau_R h_R = N_R^T E\{h_R^T\}$

2. Equilibrium and Results

- **Substituting (GBC's) into (HC) yields the human capital evolution equations:**
  - **poor districts:** $h_{Pt+1} = Ah_{Pt}\left(\frac{\alpha\tau_P h_{Pt}}{\alpha E\{h_{Pt}^T\}}\right)^{\epsilon\nu}\left(\frac{E\{h_{Pt}^T\}}{h_{Pt}}\right)^{(1-\epsilon)\nu} = Ah_{Pt}\tau_{Pt}^{\epsilon\nu}Q_{Pt}^{(1-2\epsilon)\nu}$
  - **rich districts:** $h_{Rt+1} = Ah_{Rt}\left[\frac{(1-\alpha)\tau_R h_{Rt}}{(1-\alpha)E\{h_{Rt}^T\}}\right]^{\epsilon\nu}\left(\frac{E\{h_{Rt}^T\}}{h_{Rt}}\right)^{(1-\epsilon)\nu} = Ah_{Rt}\tau_{Rt}^{\epsilon\nu}Q_{Rt}^{(1-2\epsilon)\nu}$

- **Main results:**
  - $\dfrac{h_{i,t+1}}{h_{i,t}} = A\tau_{i,t}^{\varepsilon\nu} Q_{i,t}^{(1-2\varepsilon)\nu}$, **increasing in Q_i iff $\varepsilon < 1/2$**
  - $\dfrac{h_{R,t+1}/h_{R,t}}{h_{P,t+1}/h_{P,t}} = A\left(\dfrac{\tau_{R,t}}{\tau_{P,t}}\right)^{\varepsilon\nu}\left(\dfrac{Q_{R,t}}{Q_{P,t}}\right)^{(1-2\varepsilon)\nu}$ **=> convergence with $\varepsilon < 1/2$**

3. Empirical Analysis:

- **C reduces real per capita income growth, while Q enhances it**
- **Over the entire sample (1882-1990),**
  - **enhancement in Q accounts for 60% of real growth**
  - **reduction in C accounts for 40%**
- **In the past 4 decades (1950-1990),**
  - **enhancement in Q accounts for 13% of real growth**
  - **reduction in C accounts for 85%**
- **Remark: The role of faculty in college students' success and intergenerational mobility has also been verified by Chetty-Friedman-Saez-Turner-Yagan (2017)**

E. Occupational Choice and Allocation of Talents: Grossman (2004)

- **Composition of labor can be by race, gender, skills (vertical/horizontal), or, by occupation (workers/managers/entrepreneurs) - the focus of this paper**
- **Empirical evidence: Murphy-Shleifer-Vishny (1991)**

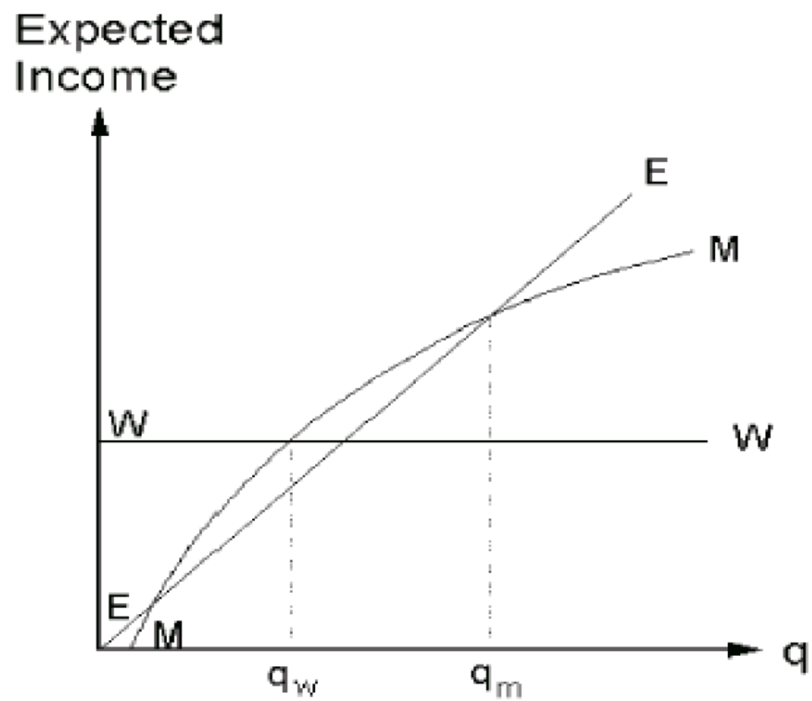
1. The Model

- **Two sectors:**
  - **auto (team work): workers productivity cannot be easily measured or monitored (incomplete contract)**
  - **software (individual work): workers productivity can be readily measured and monitored**
- **Production (a = auto, s = software):**
  - **auto: 2 tasks with skills q_j of the team member of the j^{th} task ($j = 1,2$) and with output = $F(q_1, q_2)$, where $F_j > 0$, $F_{jj} < 0$, $F_{12} > 0$ (complementarity), CRS, with $2fq$ measuring the potential output of auto by a pair of talents of q and $f = F(1,1)/2$**
  - **software: Ricardian technology, with $G(q) = \lambda q$, where $\lambda > 0$ is the inverse of the unit labor requirement**

- **Distribution of talents: uniform distribution over compact support [q_{min} , q_{max}]**
- **Preferences: $U(c_a , c_s)$, $U_1 > 0$, $U_2 > 0$, $U_{11} < 0$, $U_{22} < 0$, $U_{12} > 0$, risk neutral, homogeneous of degree one**

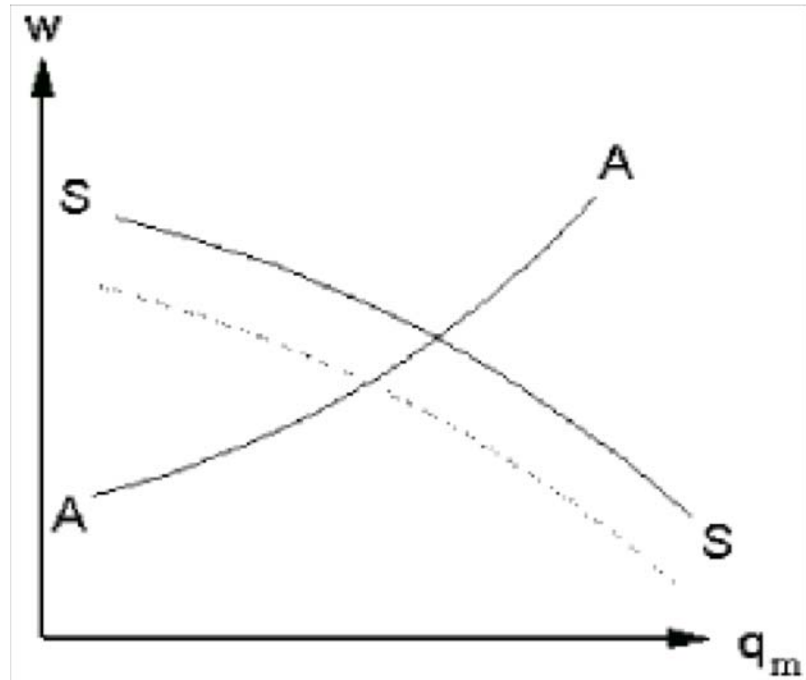
2. Equilibrium

- **Walrasian equilibrium with relative price $p = P_s/P_a$ and incomplete labor contract**
- **Labor market clearing: $L_a + L_s = L$, where 1/2 of L_a are managers and 1/2 workers with L_s as entrepreneurs**
- **Expected income: W = w, M = F(.) - w, E = λpq**
- **Occupational choice:**
  - **low q: workers**
  - **intermediate q: managers**
  - **high q: entrepreneurs**



workers managers entrepreneurs

3. Results



- **Equilibrium wage determination**
  - **q_m↑ => L_s↓ => $(L-L_s)/2$↑ => w↓**
    => SS downward-sloping
  - **q_m↑ => F_j, as a result of talent complementarity => w↑**
    => AA downward-sloping
- **Comparative statics**
  - **trade effect to s-exporting country:**
    p ↑ => s^s ↑ and for given w, q_m↓ (SS shifts down)
    => w↓, q_m↓ and inequality ↑
  - **mean-preserving spread (with q_m sufficiently low):**
    => for given w, q_m↓ (SS shifts down)
    for given q_m, F_j lower, so w↓ (AA down)
    => w↓, q_m↓, *s*↑ and inequality ↑

4. Further issues: entrepreneurship (Jiang-Wang-Wang 2010) and venture capitalism (Lu-Wang 2012, Alter-Lee-Wang 2014)

F. Learning, Matching, Unemployment and Growth: Laing-Palivos-Wang (1995)

- **Main idea:**
  - **the extent of labor-market frictions affects the return to education**
  - **education raies both initial productivity and rate of on the job learning**

1. The Model

- **Constant birth $\boldsymbol{\beta}$, permanent exit after matching**
- **Education: schooling *s***
  - **costs $\boldsymbol{c}(\boldsymbol{s})$ $(\boldsymbol{c}'>0,\boldsymbol{c}''>0)$**
  - **generates human capital $\boldsymbol{k}=\boldsymbol{\phi}(\boldsymbol{s})\boldsymbol{K_o}$** $(\phi'>0,\phi''<0,\phi(0)>0,\phi(\infty)<1)$ **(Stokey 1991)**
- **Production:**
  - **CRS with OJL at rate $\boldsymbol{\gamma}(\boldsymbol{s})$ $(\boldsymbol{\gamma}'>0,\boldsymbol{\gamma}''<0,\boldsymbol{\gamma}(\infty)<\boldsymbol{\delta})$**
  - **value of production ($\boldsymbol{a_s}>0$):** $a(s)=\int_0^\infty \phi(s)K_0 e^{\gamma(s)\tau_E}e^{-\delta\tau_E}\,d\tau_E \quad =\dfrac{\phi(s)K_o}{\delta-\gamma(s)}$
  - **Assumptions:** $\boldsymbol{a_{ss}}<0;\ \boldsymbol{a}(0)>\boldsymbol{v}_0$

- **Value Functions (setting $\dot{J}_i = 0,\ \dot{\Pi}_i = 0$):**

$$\delta J_E = \delta w + 0 \cdot (J_u - J_E)$$

$$\delta J_u = 0 + \mu (J_E - J_u)$$

$$\delta \Pi_F = \delta (a - w) + 0 \cdot (\Pi_v - \Pi_F)$$

$$\delta \Pi_V = 0 + \eta (\Pi_F - \Pi_V)$$

$$\Rightarrow J_u = \frac{\mu}{\mu + \delta} w,\ \ \Pi_v = \frac{\eta}{\eta + \delta}(a - w)$$ **(firms take outside option Π_v as given)**

- **Equilibrium Conditions:**
  - **Equilibrium Entry:** $\Pi_v = v_0$
  - **Steady- State Matching:** $\mu U = \eta V = m_o M(U, V)$
    - **M is strictly increasing and strictly concave in each argument, satisfying CRS, Inada and boundary conditions (Diamond 1982)**
  - **Steady-State Population:** $\mu U = \beta$

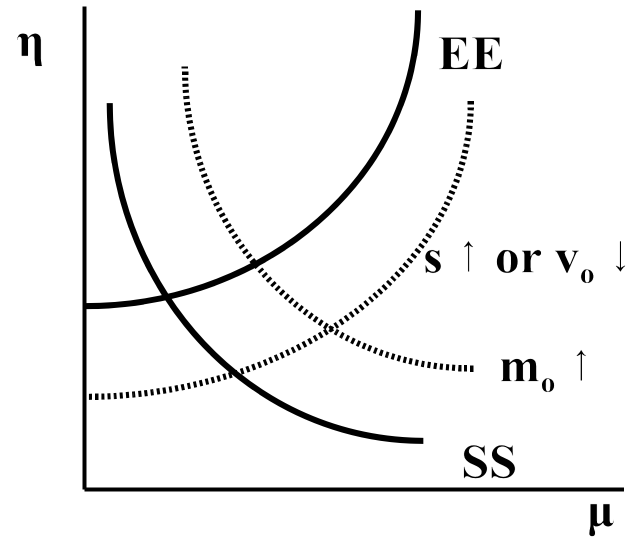
- **Solution Method (backward to ensure subgame perfection):**
  - **Stage 3: Nash bargain upon successful match to determine the wage offer w(s,μ) cooperatively by maximizing** $(J_E - J_U)^{1/2}(\Pi_F - \Pi_V)^{1/2}$
  - **Stage 2: equilibrium entry and steady-state matching to determine flow contact rates (μ,η) given s**
  - **Stage 1: maximizing worker expected value at entry (J_U) net of schooling cost (c(s)) to pin down s**

2. Equilibrium

- **Wage offer:** $w = \dfrac{\mu + \delta}{\mu + 2\delta}(a - \Pi_v) = w(\underset{+}{\mu}, \underset{+}{s}, \underset{+}{K_0}, \underset{-}{\Pi_v})$

- **Equilibrium entry, matching and schooling:**
  - **(EE)** $\dfrac{\eta}{\eta + \delta}(a - w(\mu, \bullet)) = v_o$
  - **(SS)** $\boldsymbol{\eta} = \boldsymbol{m_0 M(\frac{U}{V}, 1) = m_0 M(\frac{\eta}{\mu}, 1)}$
  - **FOC(s)** $\dfrac{\mu}{\mu + 2\delta} a_s = c_s \Rightarrow s = s(\mu),\ s_\mu > 0$

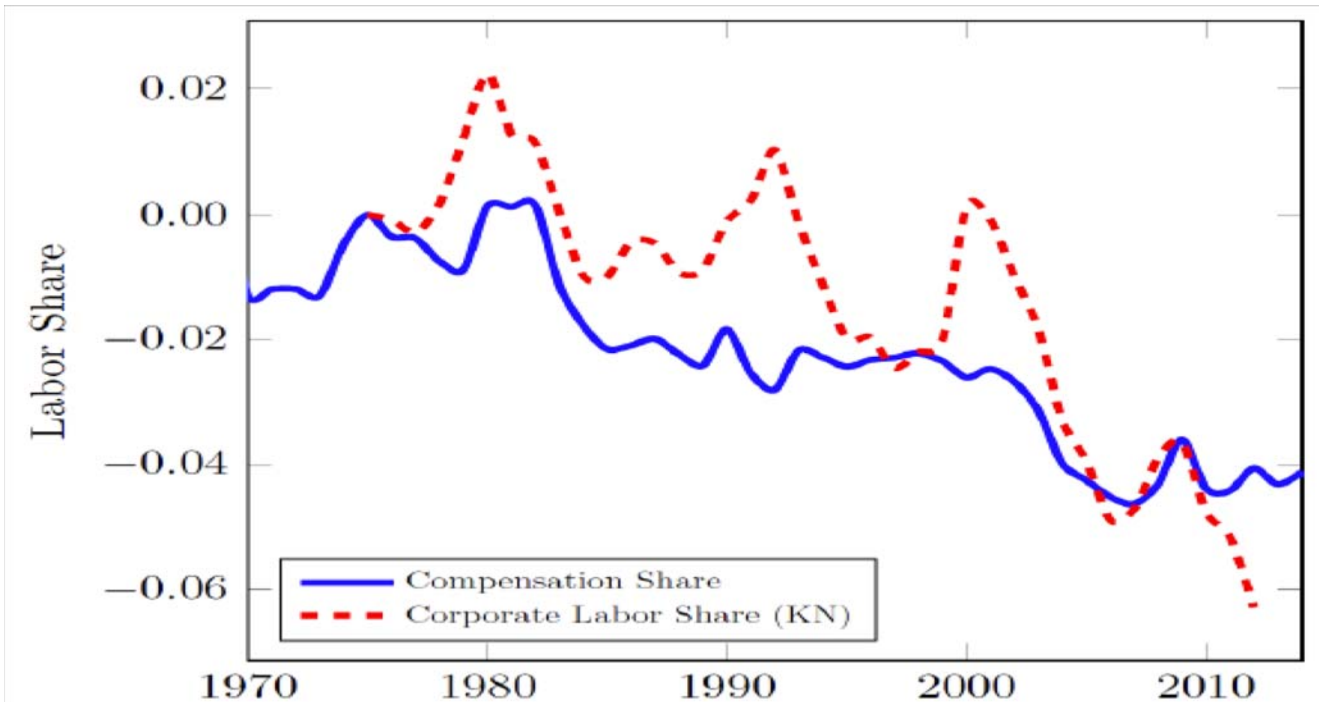
- **Comparative Statics:**
  - **Benchmark Case: the effect of μ on wage is stronger than on productivity (ensuring EE upward-sloping)**
  - **Growth: $\theta = \gamma(s(\mu))$**
    - **increasing in K_0, m_0**
    - **decreasing in v_0**
  - **Unemployment: $U = \beta/\mu$**
    - **decreasing in K_0, m_0**
    - **increasing in v_0**
  - **negative θ-U relationship (Okun's law)**



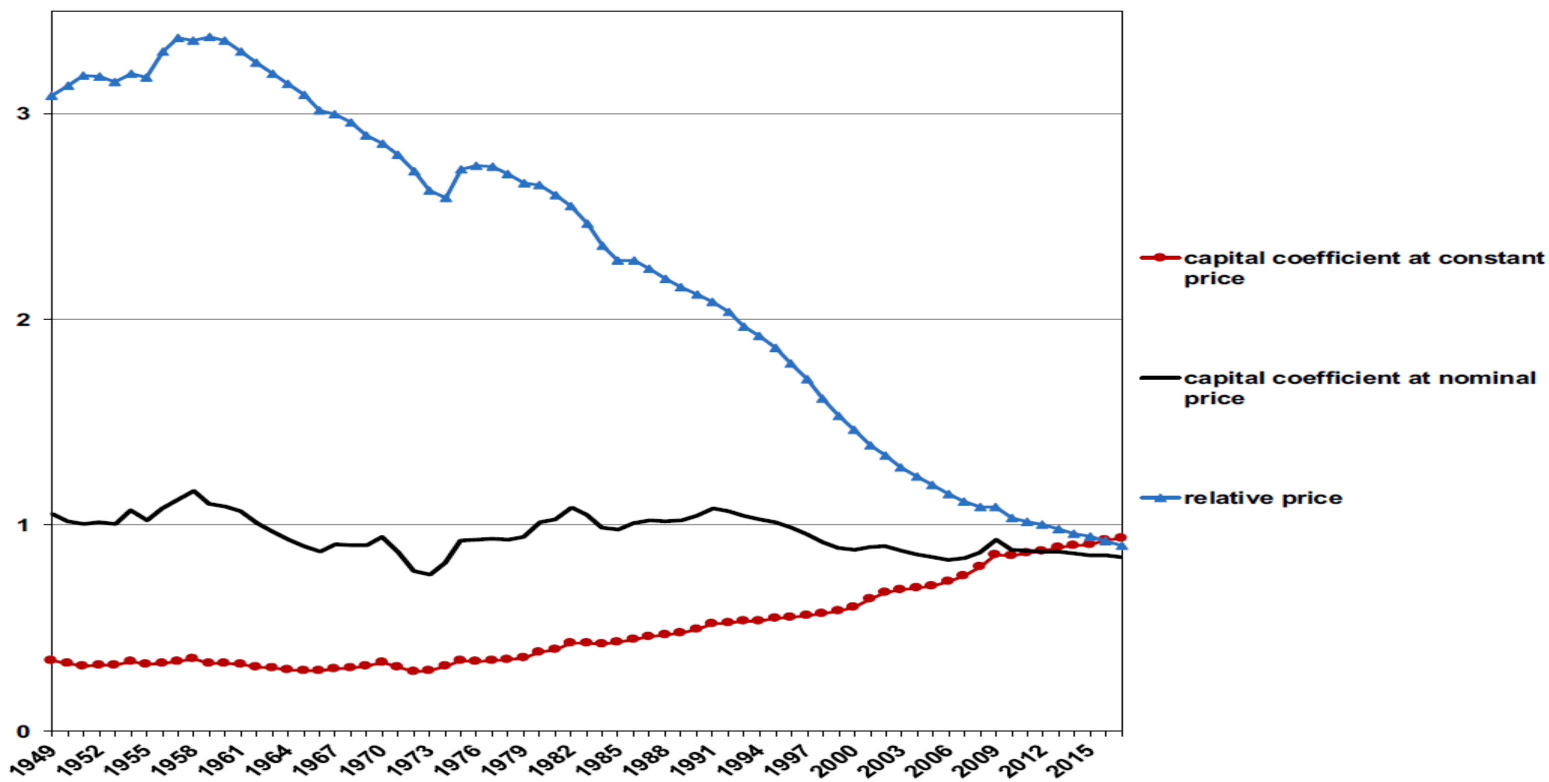
- **What if the effect of μ on wage is weaker than on productivity (EE downward-sloping)**
  - **possibility of multiple equilibria with co-existence of**
    - **thick labor-market, high education, high growth equilibrium**
    - **thin labor-market, low education, low growth equilibrium**
  - **small improvements in labor matching efficacy or entry friction can shift an economy from low to high growth equilibrium (no need for big push)**

G. Automation and the Labor Share: Acemoglu-Restrepo (2019)

- **Globally declined trend in the labor share: Karabarbounis-Neiman (2014), Grossman-Helpman-Oberfield-Sampson (2018)**



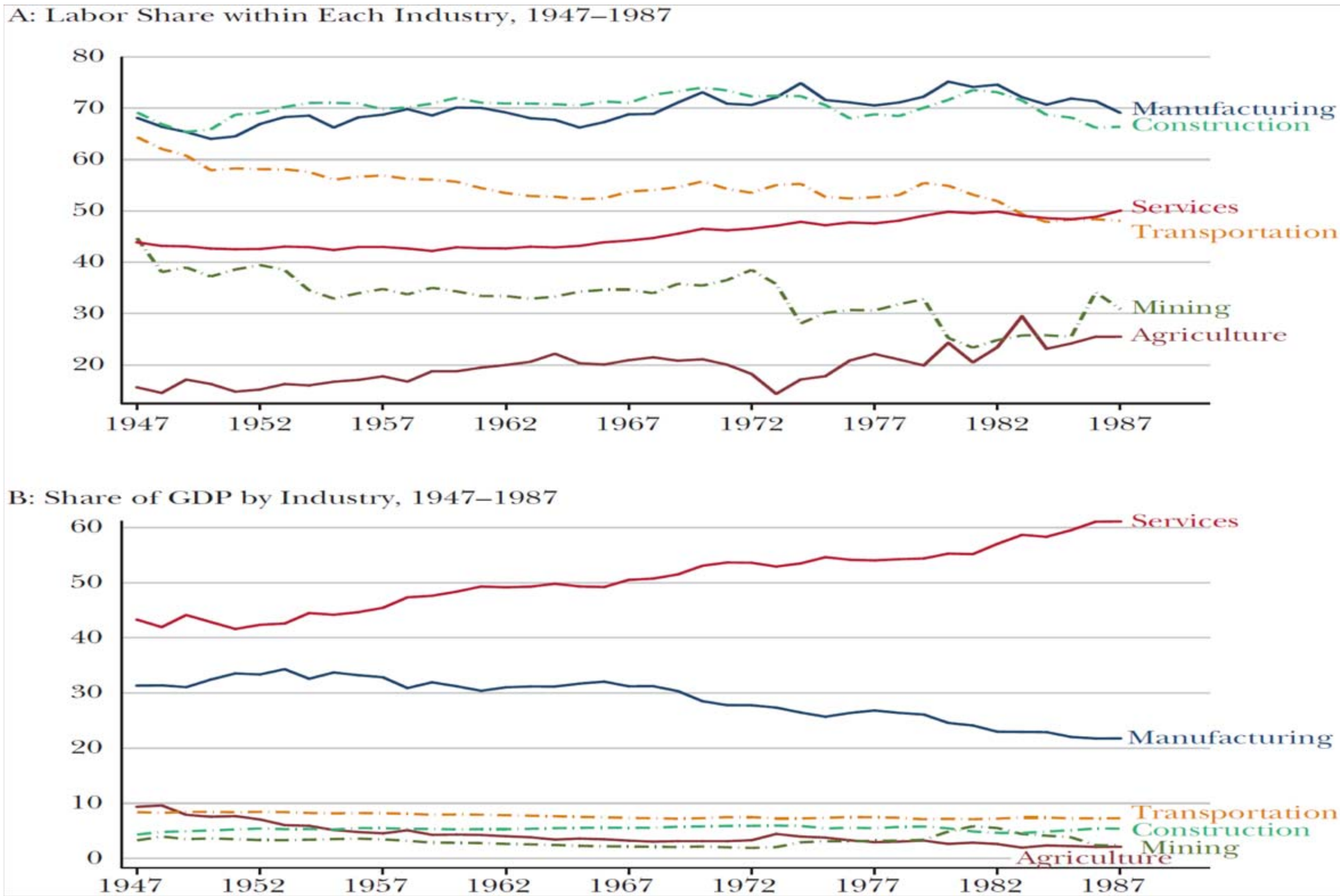
- **Rising capital coefficient and declining relative price of capital: Karabarbounis-Neiman (2014), Cheng (2017), Cette-Koehl-Philippon (2019)**

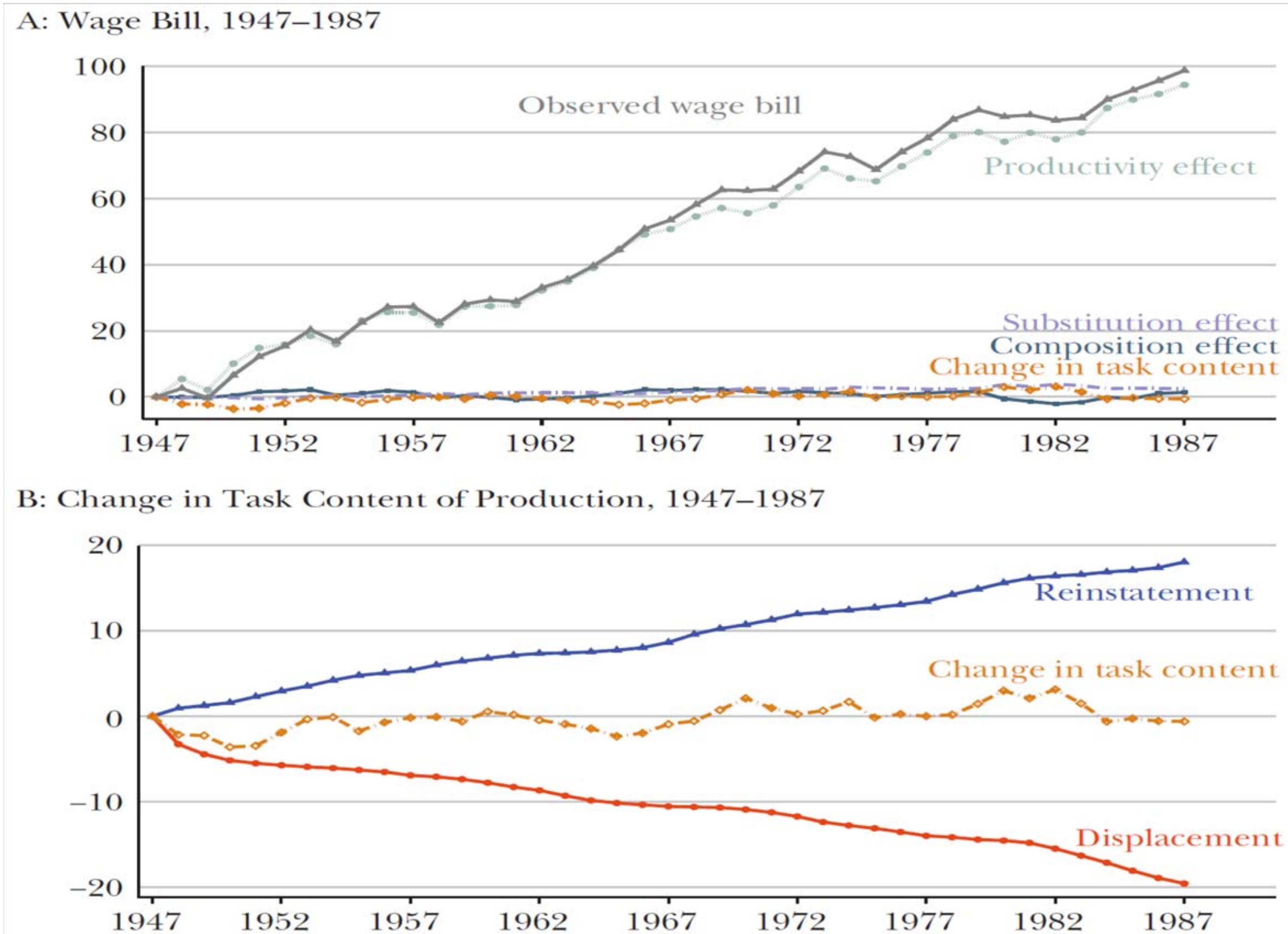


- **The task-based model of automation: Acemoglu-Restrepo (2018, 2019)**
  - **displacement effect: capital displaces labor**
  - **productivity effect: automation raises productivity**
  - **reinstatement effect: new tasks reinstate labor into broader range of tasks, thus changing the *task content* in favor of labor**
  - **task substitution effect: substitution across tasks**
- **Production:** $$Y = \Pi(I,N)\left(\Gamma(I,N)^{\frac{1}{\sigma}}(A^L L)^{\frac{\sigma-1}{\sigma}} + (1-\Gamma(I,N))^{\frac{1}{\sigma}}(A^K K)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$
  - **Π(I,N) = TFP, depending on degree of automation I and task level N**
  - **Γ(I,N) = labor-favoring task content parameter, decreasing in I but increasing in N (when σ = 1, Γ(I,N) = n = N - I)**
  - **labor share:** $$s^L = \frac{1}{1 + \frac{1-\Gamma(I,N)}{\Gamma(I,N)}\left(\frac{R/A^K}{W/A^L}\right)^{1-\sigma}}$$
    - **increasing in Γ(I,N)**
    - **increasing in $(W/A^L)/(R/A^K)$ if tasks are complements (σ < 1), but decreasing in it if tasks are substitutes (σ > 1): empirical estimates show σ < 1 but closer to one (0.8)**
  - **wage bill = value-added * labor share**

- **One sector model:**
  - **Effect of automation on labor demand = productivity effect (+) + displacement effect (-) => it is not the "brilliant" automation technologies that threaten employment and wages, but "so-so technologies" that generate small productivity improvements**
  - **Effect of new tasks on labor demand = Productivity effect (+) + Reinstatement effect (+) => reinforcing positive effect > productivity effect**
  - **Effect of factor-augmenting technologies on labor demand = Productivity effect (+) + Substitution effect (-) => positive if $\sigma > 1 - s^L$ (true empirically)**
- **Multisectoral model (sectoral index = i):**
  - **Wage bill = GDP * Σ_i (Labor share in i * Share of value added in i)**
  - **Effect of automation in i on aggregate labor demand = Productivity effect (+) + Displacement effect (-) + Composition effect (?)**
  - **Effect of new tasks in i on aggregate labor demand = Productivity effect (+) + Reinstatement effect (+) + Composition effect (?)**
  - **Under $\sigma < 1$, Change in aggregate wage bill = Productivity effect (+) + Composition effect (?) + Substitution effect (?) + Change in task content (- if I ↑, + if N↑)**
  - **Change in task content in i = Percent change in labor share in i - Substitution effect in i**

- **Early episode 1947-1987: labor/value-added shares & decomposition analysis**




A: Wage Bill, 1947–1987
Observed wage bill
Productivity effect
Substitution effect
Composition effect
Change in task content
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B: Change in Task Content of Production, 1947–1987
Reinstatement
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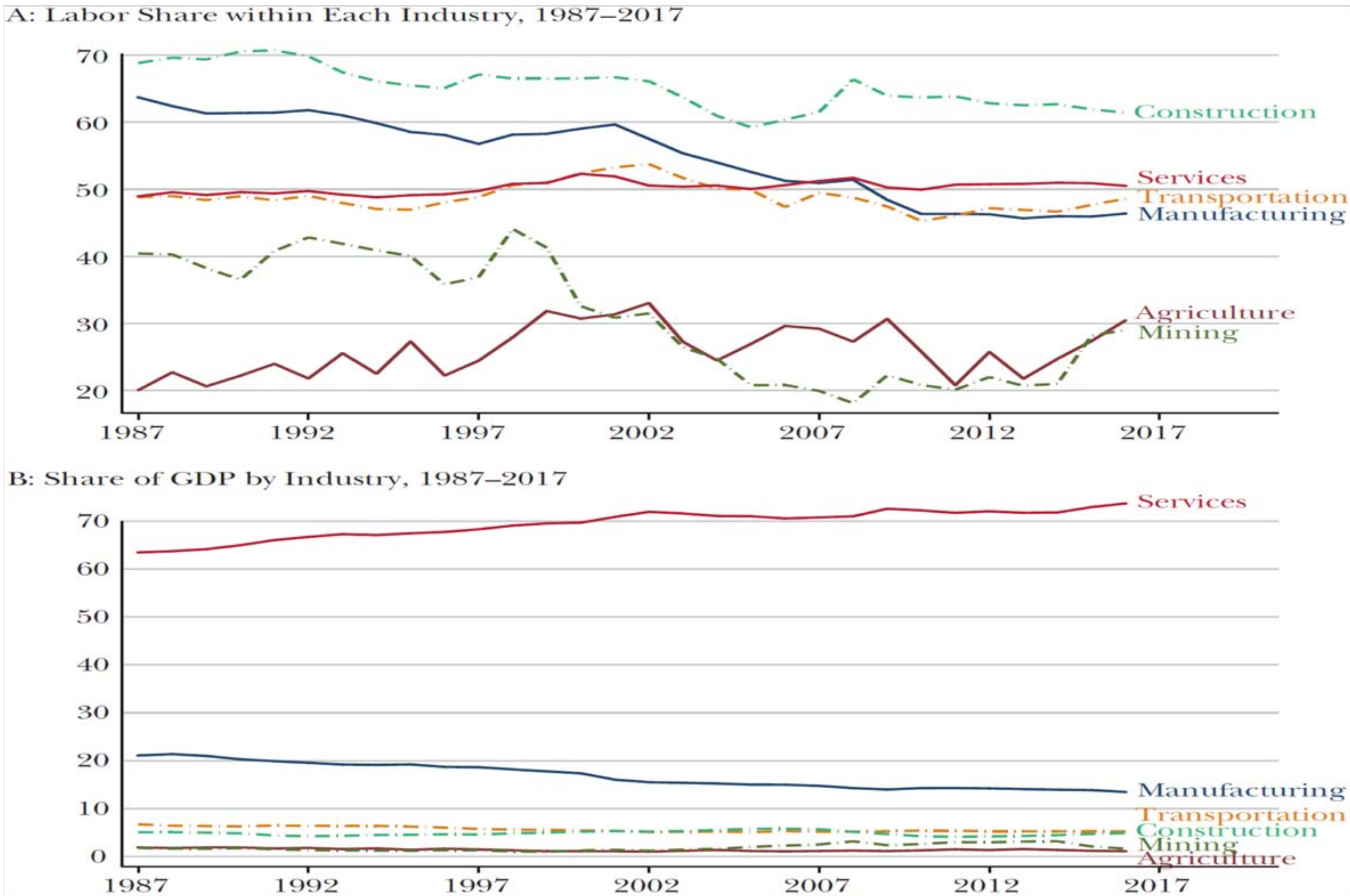
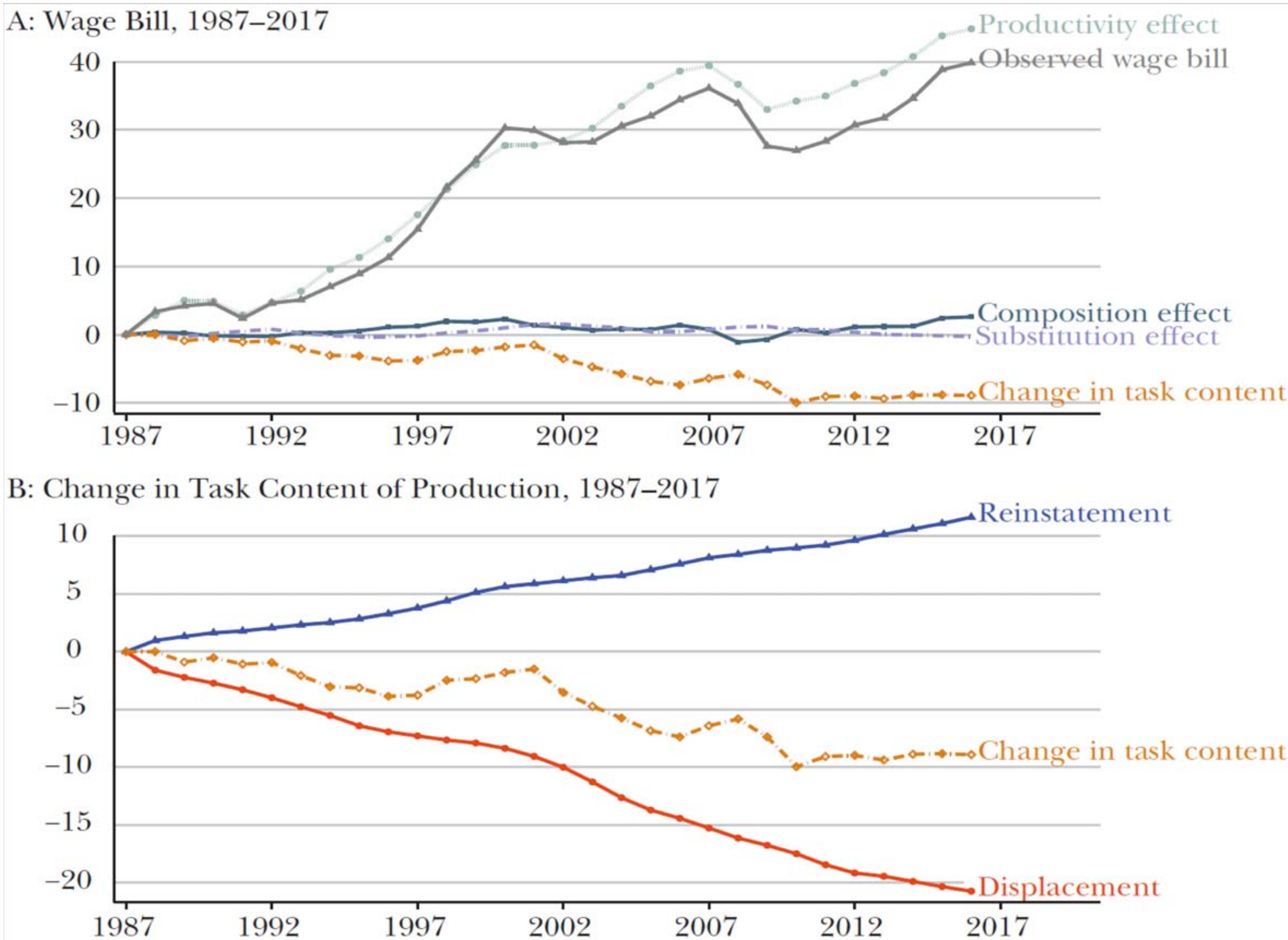
- **Recent episode 1987-2017: labor/value-added shares & decomposition analysis**




A: Wage Bill, 1987–2017
Productivity effect
Observed wage bill
Composition effect
Substitution effect
Change in task content
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B: Change in Task Content of Production, 1987–2017
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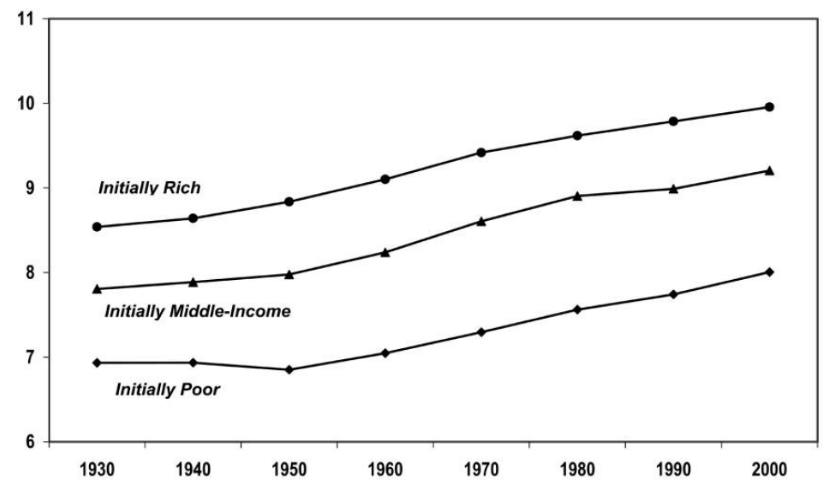
H. Health Capital: Acemoglu-Johnson (2007)

- **Sub-Saharan Africa and South Asia have suffered high disease and intense poverty.**
- **Poor health environments may be important for explaining why geography matters for growth, especially for those countries in sub-Saharan Africa and South Asia long falling in the low-growth trap.**
- **Basic idea:**
  - **Increased life expectancy raises population and lowers capital-labor and land-labor ratios, leading to lower per capita output**
  - **Lengthened life expectancy encourages labor-market participation and saving, resulting in more capital accumulation and higher per capita output**
  - **This non-monotone effects can be best seen from experiences facing initially poor countries**



1. The Model

- **Country i's aggregate output:** $Y_{it} = (A_{it}H_{it})^{\alpha}K_{it}^{\beta}L_{it}^{1-\alpha-\beta}$
- **Land:** $L_{it} = L_i = 1$
- **Effective labor:** $H_{it} = h_{it}N_{it}$
- **Life expectancy X_{it}, affecting:**
  - **Population and technology:** $N_{it} = \bar{N}_i X_{it}^{\lambda}$ **and** $A_{it} = \bar{A}_i X_{it}^{\gamma}$
  - **Individual human capital:** $h_{it} = \bar{h}_i X_{it}^{\eta}$
- **Capital accumulation with an exogenous saving rate s:** $K_{it+1} = s_i Y_{it}$ **+ (1 - δ)**K_{it}

2. The Estimation

- **Regression:**

$$y_{it} = \frac{\alpha}{1-\beta}\log\bar{A}_i + \frac{\alpha}{1-\beta}\log\bar{h}_i + \frac{\beta}{1-\beta}\log s_i - \frac{\beta}{1-\beta}\log\delta - \frac{1-\alpha-\beta}{1-\beta}\log\bar{N}_i + \frac{1}{1-\beta}[\alpha(\gamma+\eta) - (1-\alpha-\beta)\lambda]x_{it}$$

depending on life expectancy and an array of other variables

3. Data

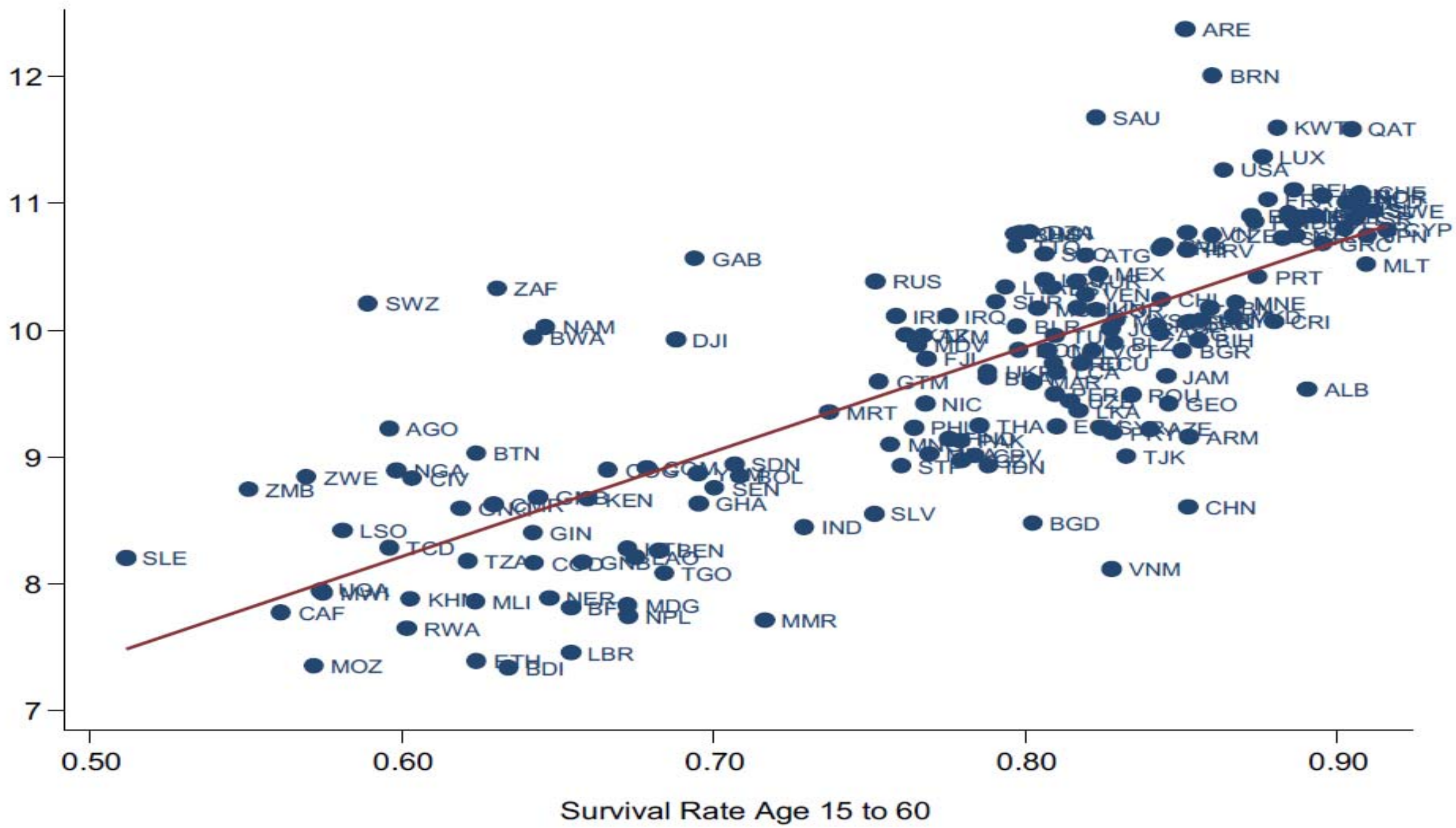
Life Expectancy	Initially Poor	Initially Middle-Income	Initially Rich
At Birth in 1900	28.77	36.92	49.36
At Birth in 1940	40.63	50.93	65.13
At Birth in 1980	61.92	69.66	74.30
At Age 20 in 1940	56.96	64.51	70.41
At Age 20 in 1980	70.27	73.59	75.73

4. Main Findings

- **Predicted mortality has a large effect on changes in life expectancy since 1940, but not before**
- **1% increase in life expectancy raises population by 1.7-2%**
- **The effect of life expectancy on per capita real GDP is negligible**

I. Health and Development: Bloom-Canning-Kotschy-Prettner-Schünemann (2019) and Wang-Wang (2016, 2020)

I-A. Bloom-Canning-Kotschy-Prettner-Schünemann (2019)



- **Production:** $Y_t = A_t K_t^{\alpha} H_t^{1-\alpha}$
- **Aggregate human capital:** $H_t = \sum_j^{J} \nu_{j,t}$
- **Individual human capital (generalized Mincerian equation):**

  $$\nu_{j,t} = \exp\left(\phi_h h_{j,t} + \phi_s s_{j,t} + \phi_{a,1} a_{j,t} + \phi_{a,2} a_{j,t}^2\right)$$

  - **add health h to the equation**
  - **use wage data to backout the coefficients**
- **Under log normality, aggregate human capital per worker in log:**

  $$\ln\left(\frac{H_t}{L_t}\right) = \ln\left(\frac{\sum_j^{J} \nu_{j,t}}{L_t}\right) = \frac{\left[\sum_j^{J} \ln\left(\nu_{j,t}\right)\right]}{L_t} + \frac{\sigma_t^2}{2}$$

  $$= \frac{\sum_j^{J} \phi_h h_{j,t} + \phi_s s_{j,t} + \phi_{a,1} a_{j,t} + \phi_{a,2} a_{j,t}^2}{L_t} + \frac{\sigma_t^2}{2}$$

- **Per capita output:**

  $$\ln(y_{i,t}) = \ln(A_{i,t}) + \alpha \ln(k_{i,t}) + (1-\alpha)\left(\phi_h h_{i,t} + \phi_s s_{i,t} + \phi_{a,1} a_{i,t} + \phi_{a,2} a_{i,t}^2 + \frac{\sigma_{i,t}^2}{2}\right)$$

- **Rate of TPF growth based on technology diffusion at rate λ, schooling, lagged y and country-specific factor x (Baumol 1986):**

  $$\Delta \ln(A_{it}) = \lambda\left[\mu_t + x_{i,t}{}'\Theta + \rho s_{i,t-1} - \ln(y_{i,t-1})\right] + \varepsilon_{i,t}$$

- **Growth regression:**

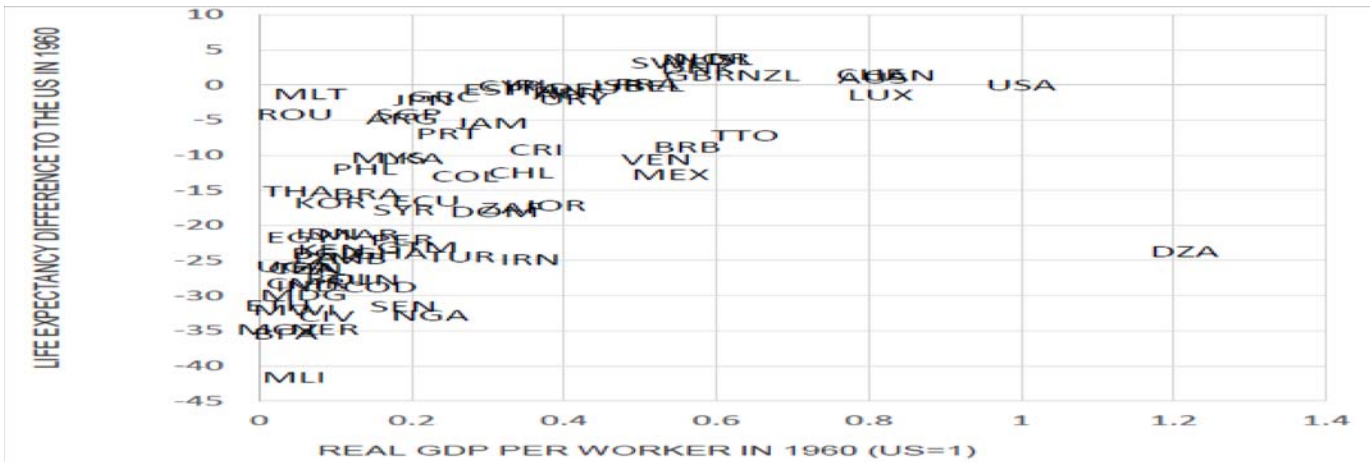
$$\Delta\ln(y_{i,t}) = \lambda[\mu_t + x'_{i,t}\Theta + \rho s_{i,t-1} - \ln(y_{i,t-1})] + \alpha\Delta\ln(k_{i,t})$$
$$+ (1-\alpha)\left(\phi_h\Delta(h_{i,t}) + \phi_s\Delta(s_{i,t}) + \phi_{a,1}\Delta(a_{i,t}) + \phi_{a,2}\Delta(a_{i,t}^2) + \frac{\Delta(\sigma_{i,t}^2)}{2}\right) + \varepsilon_{i,t}$$

- **Main results (OLS): γ = unrestricted coefficient on lagged dependent y_{-1}**

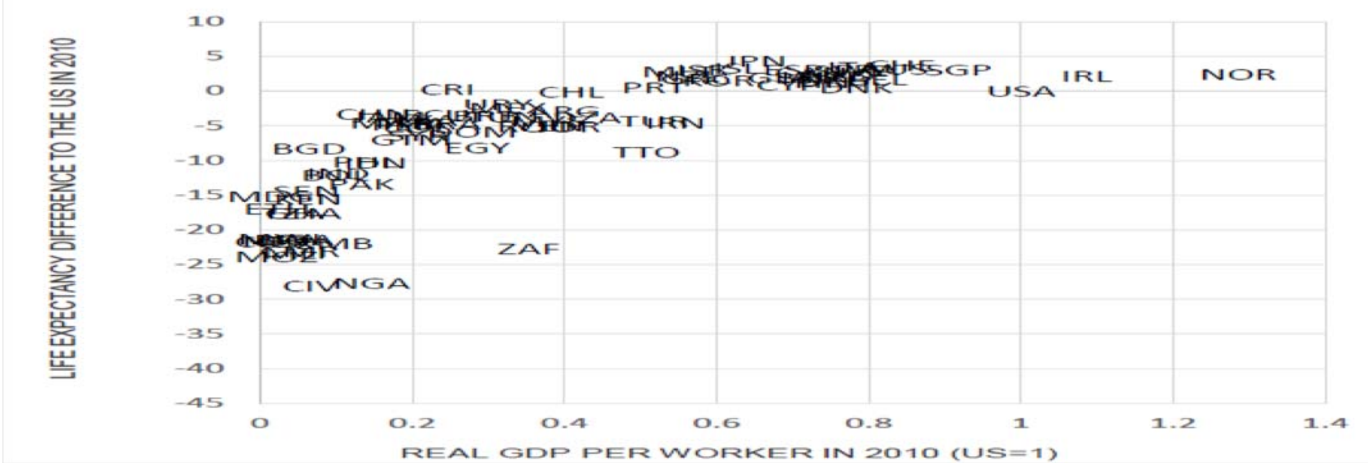
γ	< 0
α	0.35
ϕ_h	9.1%
ϕ_s	11.4%
$\phi_{a,1}$	> 0
$\phi_{a,2}$	< 0

  - **growth effect of health is almost as large as that of schooling**
  - **human capital dispersion (Gini) has negative effect on growth (but statistically not significant at 5% level)**
  - **technology diffusion λ about 0.4**

I-B. Health and Value of Life: Wang-Wang (2020)



(a) Life expectancy difference and relative income in 1960



- **Difference in life expectancy at birth (from the US benchmark):**

	(a) Classification by initial development stage				(b) Classification by development speed			
Year	Low	Middle-low	Middle-high	High	Low	Stable	High	Rapid
1960	-25.409	-19.426	-10.062	-2.136	-19.804	-15.472	-8.522	-10.121
1970	-21.386	-16.355	-6.861	-1.336	-17.122	-12.322	-6.037	-5.981
1980	-19.704	-14.461	-5.928	-1.450	-15.402	-11.72	-5.351	-4.786
1990	-18.609	-12.296	-4.258	-0.673	-13.942	-10.828	-3.805	-2.955
2000	-17.816	-11.099	-3.426	0.057	-13.743	-9.819	-2.420	-1.967
2010	-14.106	-9.035	-2.863	0.434	-11.432	-7.697	-1.668	-0.806

- **Value of life (1,000 2011 US$):**

	(a) Classification by initial development stage				(b) Classification by development speed			
Year	Low	Middle-low	Middle-high	High	Low	Stable	High	Rapid
1960	83.309	228.380	494.682	1136.661	482.053	584.591	520.038	206.387
1970	134.468	346.274	805.317	1530.893	619.524	801.374	840.278	431.553
1980	213.126	455.670	1077.642	1873.848	684.960	999.900	1143.189	802.844
1990	273.836	505.487	1227.043	2034.931	625.341	1094.681	1375.646	1099.705
2000	401.778	710.074	1630.365	2586.140	680.036	1368.325	1940.069	1680.754
2010	571.276	982.961	2049.406	2975.411	848.182	1597.444	2379.360	2290.207

- **Relative value of life (US = 1):**

Year	(a) Classification by initial development stage				(b) Classification by development speed			
	Low	Middle-low	Middle-high	High	Low	Stable	High	Rapid
1960	0.049	0.133	0.288	0.663	0.281	0.341	0.303	0.120
1970	0.061	0.158	0.368	0.699	0.283	0.366	0.384	0.197
1980	0.085	0.181	0.429	0.746	0.273	0.398	0.455	0.320
1990	0.094	0.174	0.423	0.702	0.216	0.377	0.474	0.379
2000	0.110	0.193	0.445	0.705	0.185	0.373	0.529	0.458
2010	0.134	0.230	0.480	0.696	0.198	0.374	0.557	0.536

- **Gain from additional life year (1,000 2011 US$):**

Year	(a) Classification by initial development stage				(b) Classification by development speed			
	Low	Middle-low	Middle-high	High	Low	Stable	High	Rapid
1960	1.157	2.618	4.263	8.157	4.694	4.539	3.869	1.604
1970	1.465	3.312	6.014	10.210	5.250	5.726	5.814	2.955
1980	1.837	3.577	7.132	11.534	5.176	6.539	7.115	4.966
1990	2.086	3.495	7.285	11.567	4.179	6.551	8.002	6.332
2000	2.716	4.432	9.076	13.824	4.236	7.719	10.582	9.143
2010	3.516	5.675	10.947	15.049	5.066	8.650	12.277	11.638

J. Pandemic and the Macroeconomy: Eichenbaum-Rebelo-Trabandt (2020)

- The 1918 Flu, 2002 SARS, 2013-16 Ebola and 2019-2021 COVID-19 are acute viral infections interfering with proper functioning of innate immune system.
- Their high transmission and death rates have created miserable public health problems accompanied by macroeconomic downturns.
- Thus, while the issues were initially under study by medical and public health scholars, the latest world-wide pandemic has induced high numbers of macroeconomic research.
- The challenge is how to incorporate canonical epidemiology frameworks into dynamic macro models.

1. Epidemiology: The Classic SIR Model (Kermack-McKendrick 1927) and the Herd Immunity

- Individuals are divided into 4 groups:
  - S: susceptible (those who have not yet been exposed to the disease)
  - I: infected (those who contracted the disease),
  - R: recovered (those who survived the disease and acquired immunity)
  - D: deceased (those who died from the disease)

- **Population evolution:**
  - **At a point in time t, a fraction of susceptible individual is newly infected: $T_t = \pi_i S_t$**
  - **Those newly infected (T) exit from the susceptible state: $S_{t+1} = S_t - T_t$**
  - **Those newly infected enter the infected state whereas those recovered ($\pi_r I_t$) or died ($\pi_d I_t$) exit from the state: $I_{t+1} = I_t + T_t - R_t - D_t$**
  - **Similarly, the population of the recovered and deceased states evolves according to: $R_{t+1} = R_t + \pi_r I_t$ and $D_{t+1} = D_t + \pi_d I_t$**
  - **Normalizing initial population $Pop_0 = 1$ and ignoring birth/immigration: $Pop_{t+1} = Pop_t - \pi_d I_t$**
  - **Initial condition: $I_0 = \varepsilon$ and $S_0 = 1-\varepsilon$**
- **Reproduction via disease transmission at a given point in time (notation duplication owing to following the epidemiology literature):**
  - **R = the average number of persons infected by a case**
  - **R_0 = the reproduction number in the absence of control measures in a fully susceptible population**
  - **Fundamental reproduction equation: $R = (1-p_C)(1-p_I)R_0$**
    - **p_C = reduction in transmission due to non-pharmaceutical intervention**
    - **p_I = proportion of immune individuals due to recovery and vaccines**

- **Herd Immunity: $R < 1$**
  - **That is, the condition requires: $p_I > 1- 1/[(1-p_C) R_0]$**
  - **COVID-19: $R_0 = 2.5$ to 4 (the new string from UK is above 10)**
  - **In the absence of any intervention ($p_C = 0$), $R_0 = 10/3$ implies $p_I > 70\%$**
  - **If intervention (selected lockdown, mask and social distance) reduce transmission by 40%, then the condition is $p_I > 50\%$**
  - **In the above intervention case, if vaccine is only 80% effective, then the condition becomes $p_I > 5/8 = 62.5\%$**
- **General issues:**
  - **the structure is mechanical, lacking behavioral responses**
  - **the probabilities are likely time and group varying**

2. The SIR-Macro Model

- **Infection rates via:**
  - **consumption (C): $\pi_1(S_tC_t^S)(I_tC_t^I)$ due to interaction between S and I types**
  - **work hours (N): $\pi_2(S_tN_t^S)(I_tN_t^I)$**
  - **social contact: $\pi_3S_tI_t$**
  - **thus, $T_t = \pi_1(S_tC_t^S)(I_tC_t^I) + \pi_2(S_tN_t^S)(I_tN_t^I) + \pi_3S_tI_t$**

- **Budget for type-i (i = s, i, r):** $(1+\mu_t)c_t^j = w_t\phi^j n_t^j + \Gamma_t$
  - **productivity φ lower for infected (<1 for i and = 1 for s and r)**
  - **μ = consumption tax, reflecting containment policy making c more costly**
  - **Γ = government lump-sum transfer**
- **Lifetime utility:**
  - **susceptible:** $U_t^s = u(c_t^s, n_t^s) + \beta\left[(1-\tau_t)U_{t+1}^s + \tau_t U_{t+1}^i\right]$**, where** $\tau_t = \pi_1 c_t^s\left(I_t C_t^I\right) + \pi_2 n_t^s\left(I_t N_t^I\right) + \pi_3 I_t$
  - **infected:** $U_t^i = u(c_t^i, n_t^i) + \beta\left[(1-\pi_r-\pi_d)U_{t+1}^i + \pi_r U_{t+1}^r\right]$
  - **recovered:** $U_t^r = u(c_t^r, n_t^r) + \beta U_{t+1}^r$
- **Government budget constraint:** $\mu_t\left(S_t c_t^s + I_t c_t^i + R_t c_t^r\right) = \Gamma_t\left(S_t + I_t + R_t\right)$
- **Goods and labor market clearing:**

$$S_t C_t^s + I_t C_t^i + R_t C_t^r = AN_t,$$

$$S_t N_t^s + I_t N_t^i \phi^i + R_t N_t^r = N_t$$

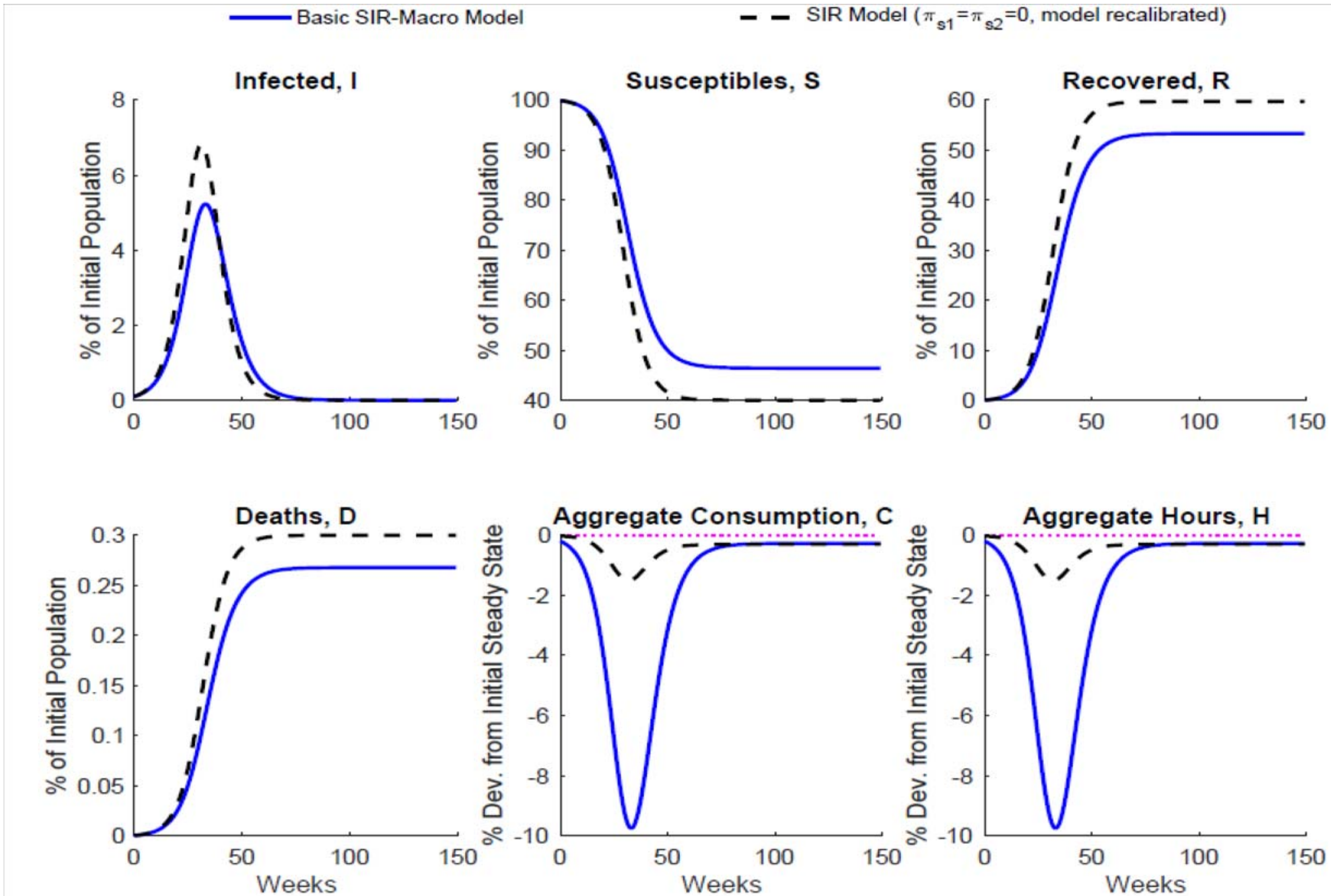
- **Potential issues:**
  - **asset accumulation and incidental bequest**
  - **health investment and health insurance**
  - **age-dependent infection rates**

3. Quantitative Analysis

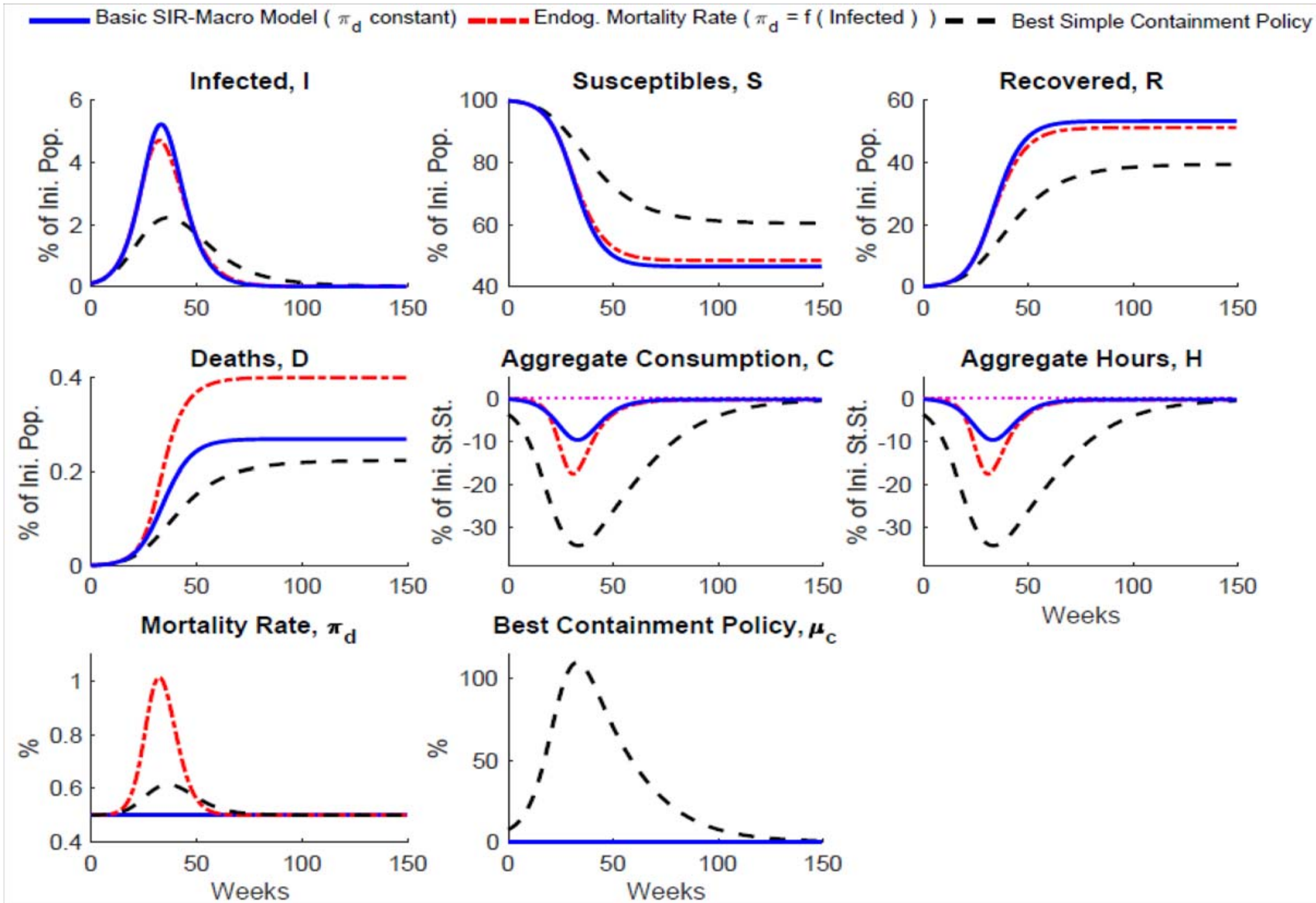
- **Basic parametrization:**

	Consumption %[b]	Infection Rate %[c]	Death Rate %[d]	U.S. Deaths Millions[e]
Percent of population eventually infected in canonical SIR model				
50	−3.42	3.20	0.21	0.72
60 (baseline)	−4.66	5.23	0.26	0.88
70	−5.21	8.15	0.31	1.05
Productivity of infected people, ϕ^i				
0.7	−4.61	4.85	0.26	0.85
0.8 (baseline)	−4.66	5.23	0.27	0.88
Share of initial infections due to consumption, work and general contacts				
$1/12, 1/12, 5/6$	−2.77	6.15	0.287	0.94
$1/6, 1/6, 2/3$ (baseline)	−4.66	5.23	0.267	0.88
$1/3, 1/3, 1/3$	−7.24	3.25	0.218	0.72
Mortality rate, π_d				
$0.005 \times 7/18$ (baseline)	−4.66	5.23	0.26	0.88
$0.01 \times 7/18$	−8.25	4.74	0.51	1.69

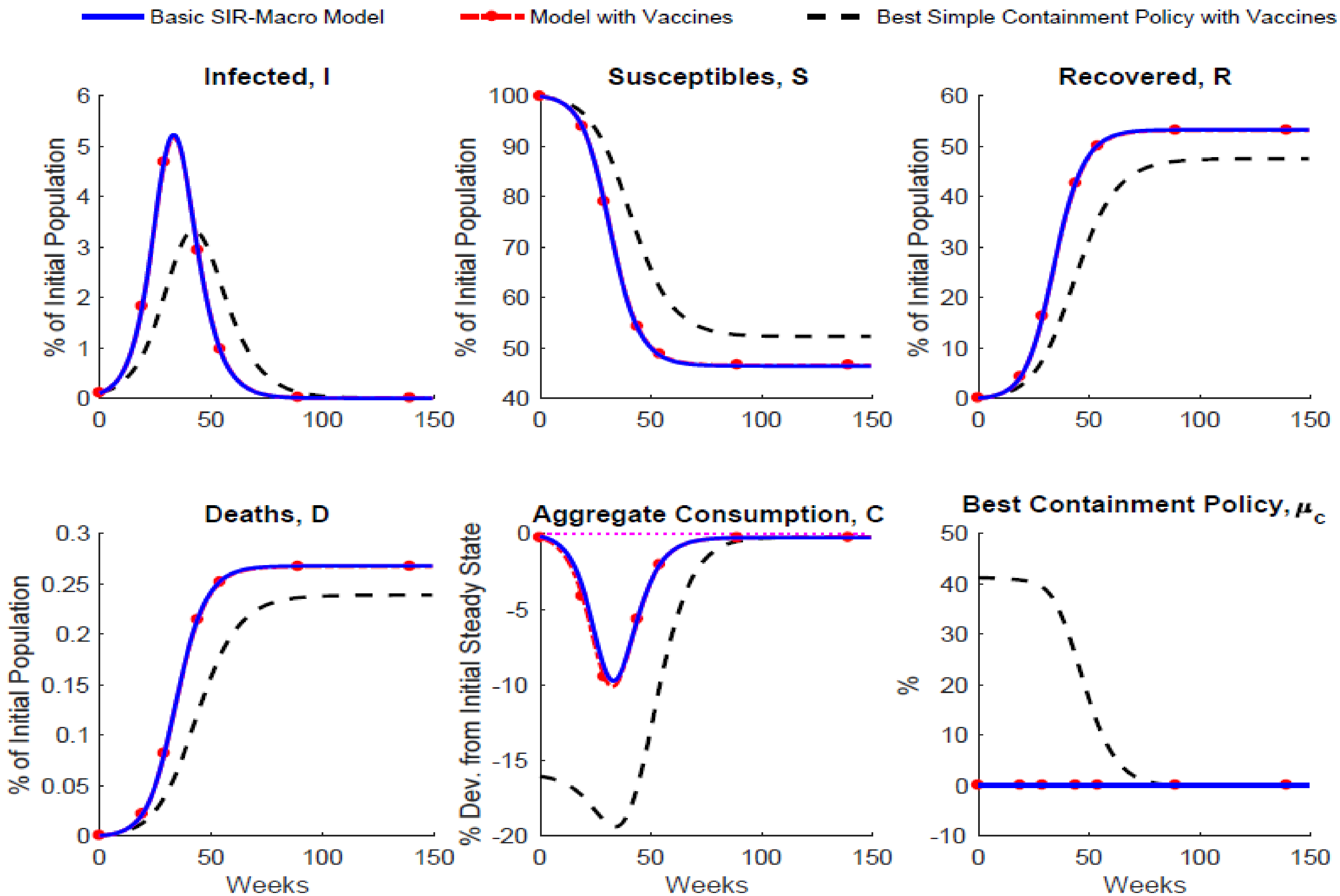
- **SIR-Macro vs. SIR**



- **Optimal containment policy (via μ)**

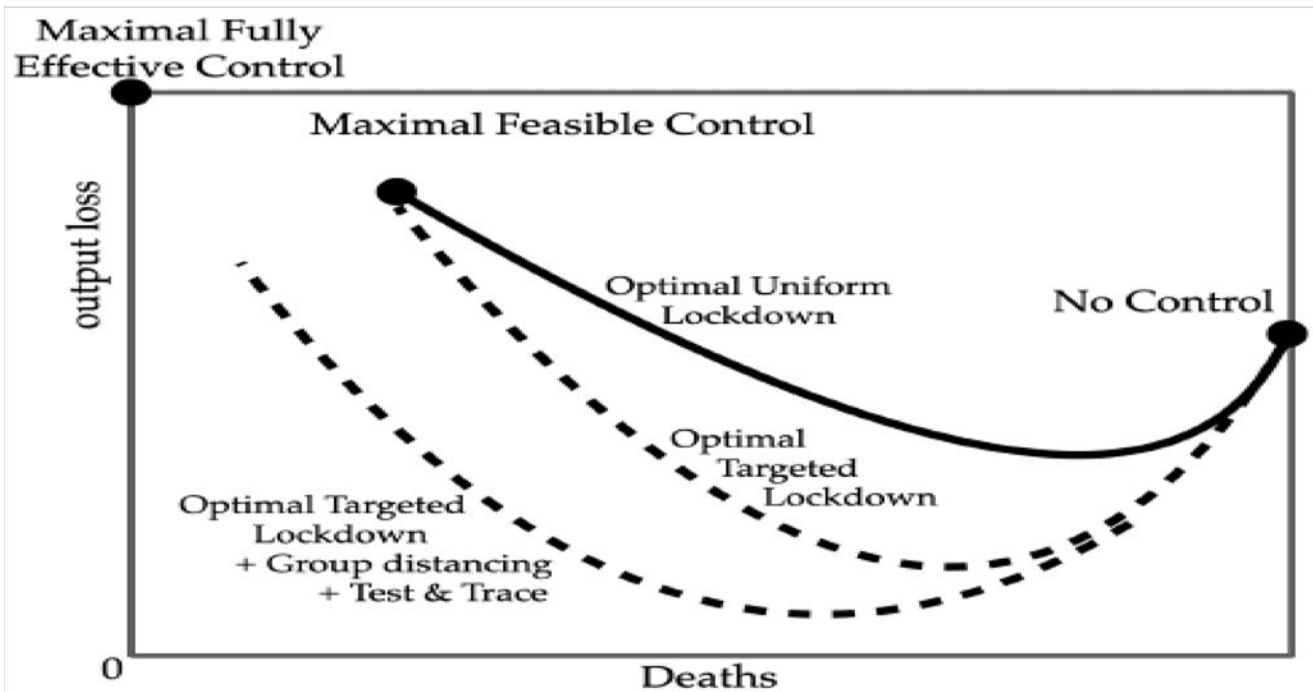


- **Containment and vaccine:**

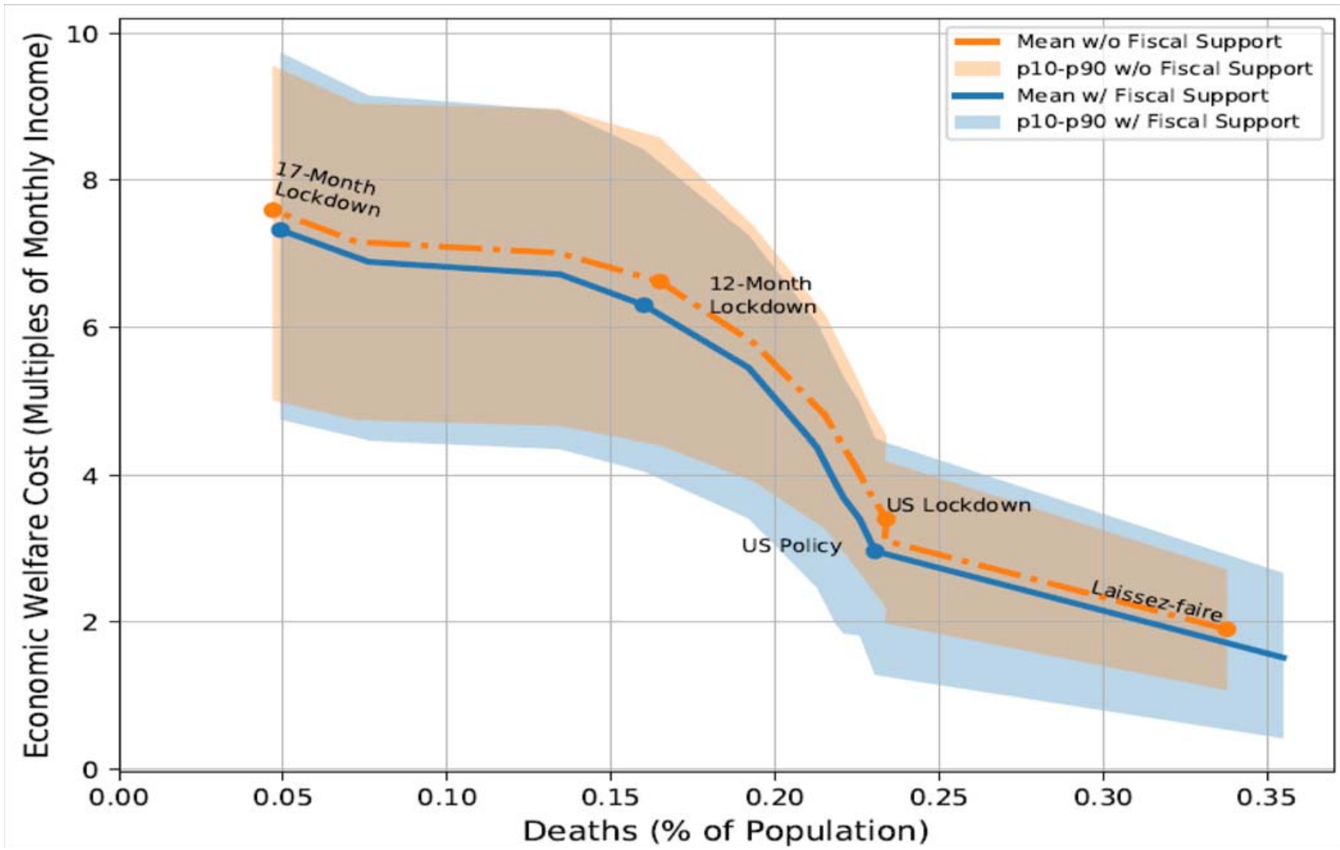


4. Development of the literature

- **Acemoglu-Chernozhukov-Werning-Whinston (2020): multi-risk SIR**
  - **individuals are potentially heterogeneity in age, occupation, productivity, labor supply**
  - **they thus have different vulnerability and different response**
  - **targeted policies treating people in different age group differentially can be much more effective**



- **Kaplan-Moll-Violante (2020): economic welfare costs of the pandemic**
  - **uneven economic losses across the population => heterogeneous welfare costs**
  - **such heterogeneities matter for effective policy design**



- **Wang-Yao (2023): dynamic lifecycle framework**
  - **individuals are heterogenous in (age, gender, education, occupation, sociability)**
  - **intervention policy induces heterogeneous responses in consumption-saving, work and social activities, and health investment over the life course**
  - **with multi-dimensional externalities at work, marketplace and home, the effectiveness of intervention policy and the net gain vary drastically**

- **The state of new normal**
  - **more online shopping**
  - **more flexible workplaces/hours**
  - **more toward virtual activities**
  - **rising adoption of automation**

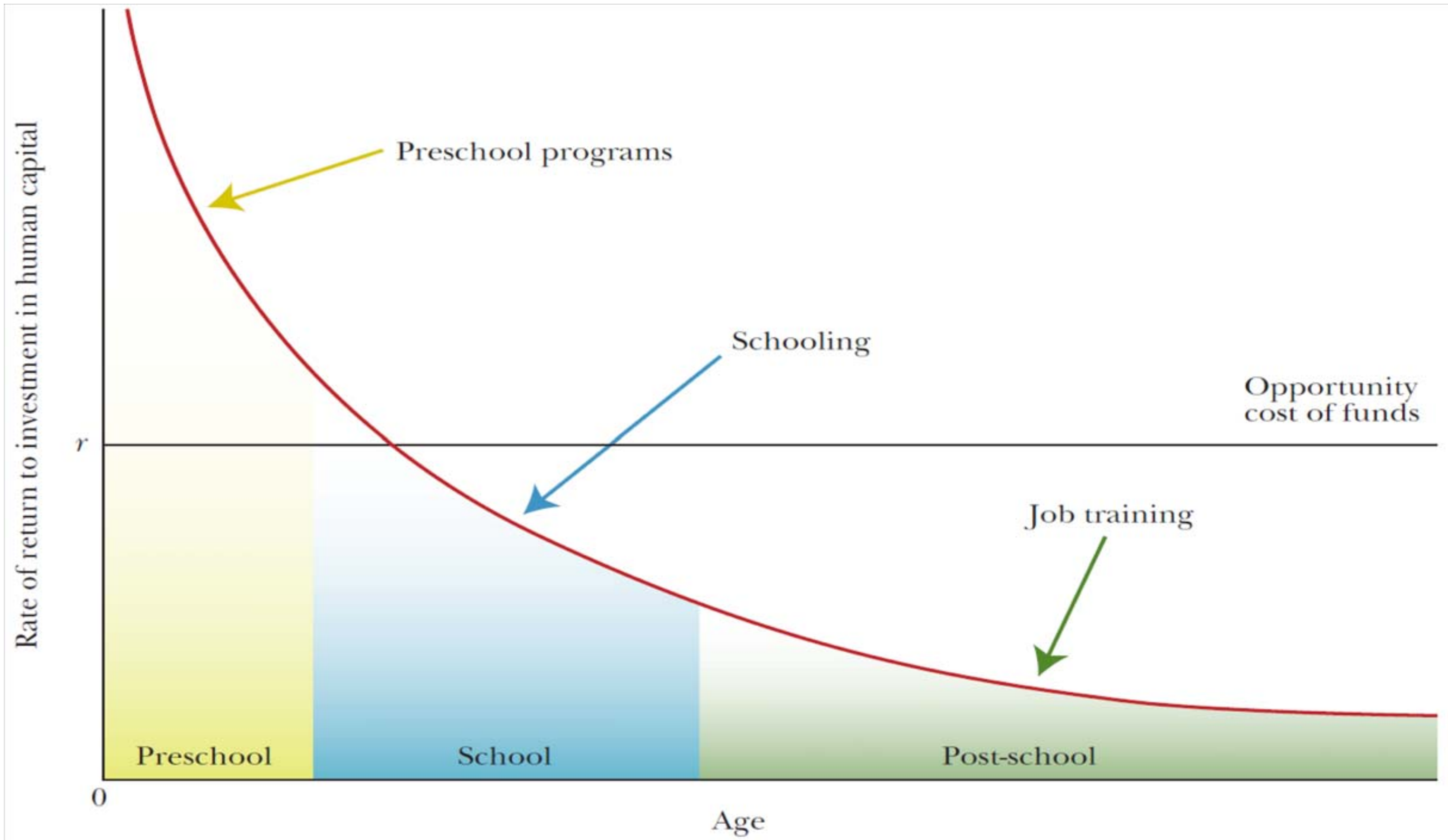
K. Microfounded Human Capital Theory

- **To better understand the macroeconomic consequences of human capital accumulation, we have to source to better micro evidence and such data-based microfoundation**

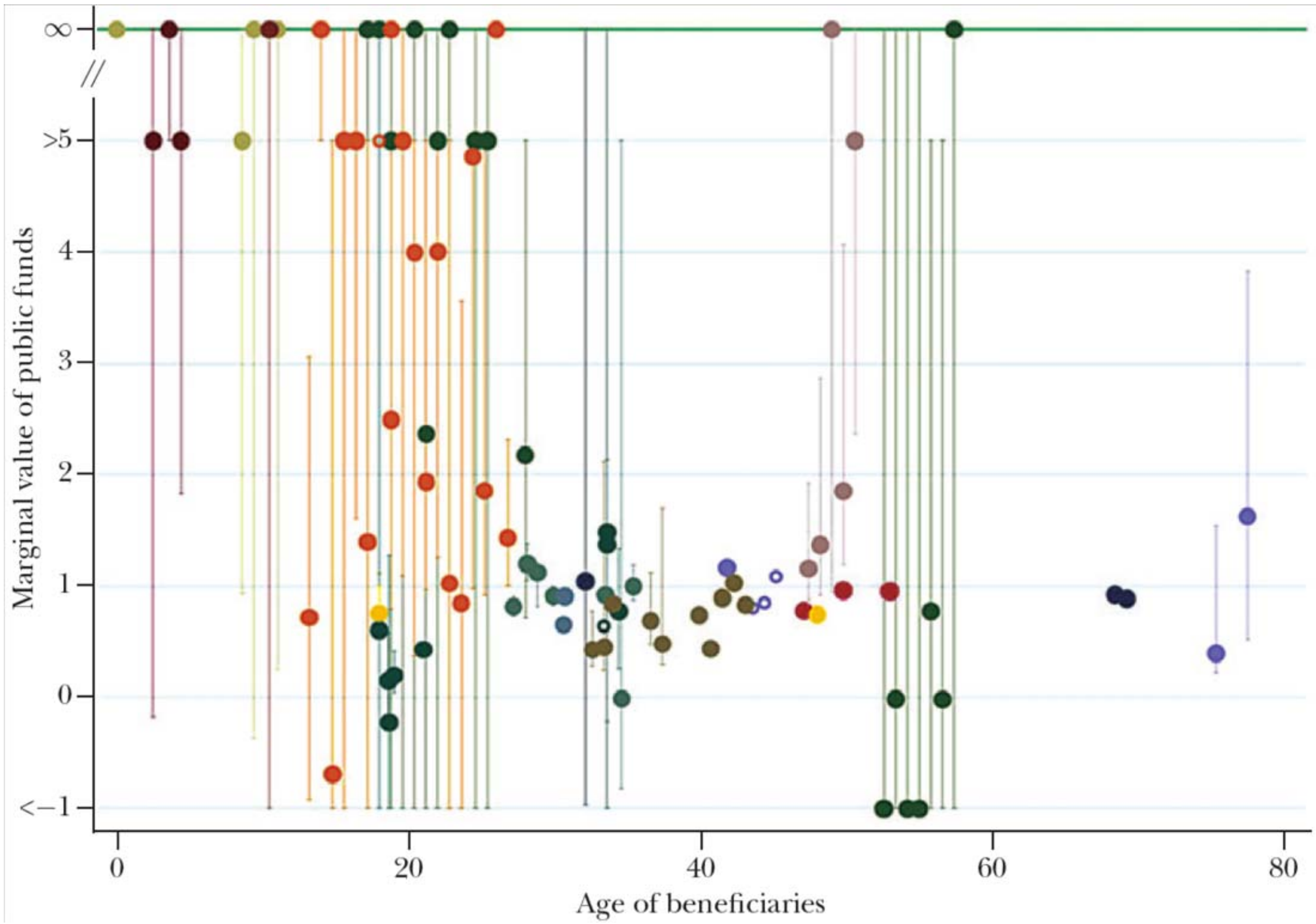
1. Micro evidence: Four facts about human capital, Deming (2022)

- **Fact 1: Human Capital Explains a Substantial Share of the Variation in Labor Earnings within and across Countries**
    - **Mincerian regression: year of schooling critical even upon controlling experiences and others**
    - **Hendricks and Schoellman (2018): by using pre- and post-migration wages of US migrants from the New Immigrant Survey, it is suggested that 62% of the wage gain is explained by human capital**
    - **using migrants' wage gain data, Hendricks, Herrington, and Schoellman (2021) calibrate a development accounting model and find human capital to explain 50-75% of cross-country income differences**

- **Fact 2: Human Capital Investments Have High Economic Returns Throughout Childhood and Young Adulthood**
  - **Heckman (2006):**



- Hendren & Sprung-Keyser (2020) from 133 human capital interventions:

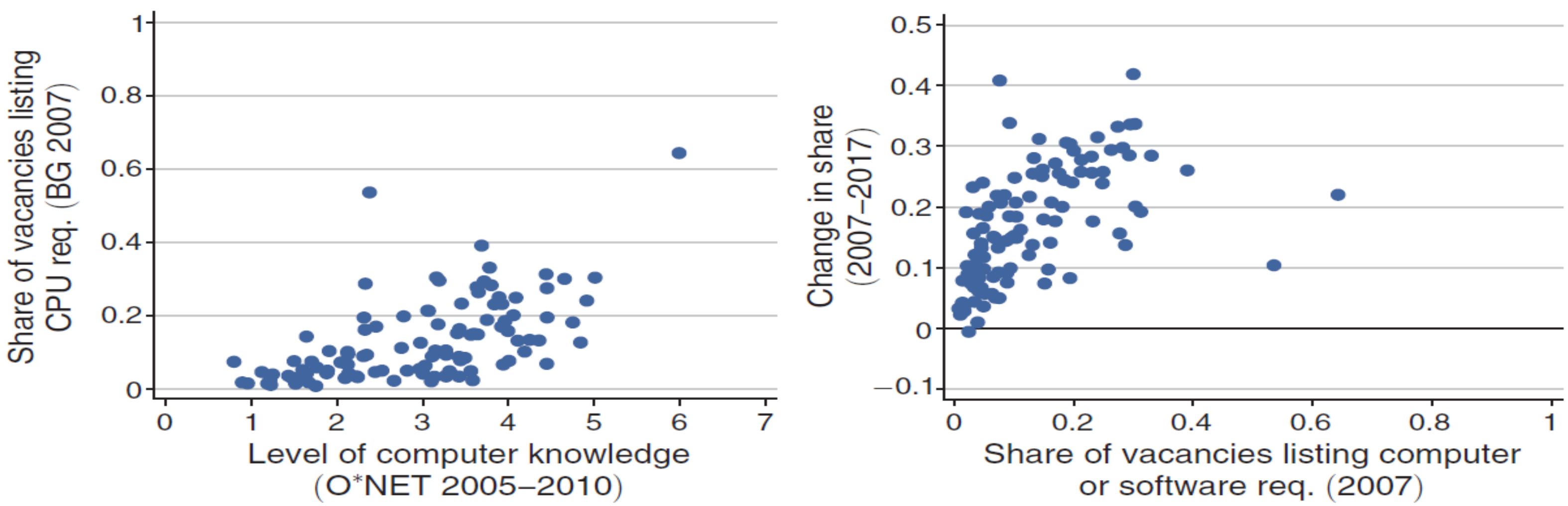


- **Fact 3: The Technology for Producing Foundational Skills Such as Numeracy and Literacy Is Well Understood, and Resources Are the Main Constraint**
  - **Hanushek (2003): education investments such as reducing class size or raising teacher salary do not work because schools do not use resources efficiently**
  - **but newer quasi-experimental evidence shows additional resources do improve education outcomes (cf. literature review by Jackson 2020)**
- **Fact 4: Higher-Order Skills Such as Problem-solving and Teamwork Are Increasingly Economically Valuable, and the Technology for Producing Them Is Not Well Understood**
  - **experimental studies such as Hoffman and Tadelis (2021) find people management skills reduce attrition among similar workers**
  - **Weidmann and Deming (2021) identifies individual contribution to group performance and find it correlated to skills such as measurement by test scores from "reading the mind in the eyes"**

2. Technology-induced job loss: Braxton-Taska (2023)

- **Technology change requires workers to update skills to perform new tasks**
- **Those lacking the required updated skills get displaced, moving to occupations at which their current skills are still employable and receiving lower pay**
- **Consider a simple two-period model where at the end of the first period a share of δ workers get displaced**
- **Two occupations with technology $z_L < z_H$: $z_L = (1-\eta)z_H$, η is technology gap**
- **Workers are risk-neutral, heterogeneous in human capital (skills) h ~ F(h)**
- **Upon a successful match, production is based on an up-to-the-task function a la Albrecht-Vroman (2002):** $f(h,z) = \begin{cases} z, & \text{if } h \geq z; \\ 0, & \text{otherwise} \end{cases}$**, where z is the minimum skill requirement for the task in an occupation with technology z**
- **At the beginning of the second period, a new technology z_H' is introduced to the high-technology occupation: $z_H' = (1+\gamma)z_H$, γ > 0 measures the size of technology change embodied in matches**
- **Share of workers in high occupation in period 1 failing to be in high occupation in period 2:** $\pi = \dfrac{F(z_H') - F(z_H)}{1 - F(z_H)}$

- **Main findings:**
  - **Workers displaced from occupation with new technology are more likely to switch occupations following the displacement**
  - **If $\pi > \gamma/(\eta + \gamma)$, workers displaced from occupation with new technology suffer larger earning losses than those from occupation without experiencing technology change**
  - **The large earning losses for workers displaced from occupation with new technology are concentrated among occupation switchers**
- **Data: technology changes by occupations**

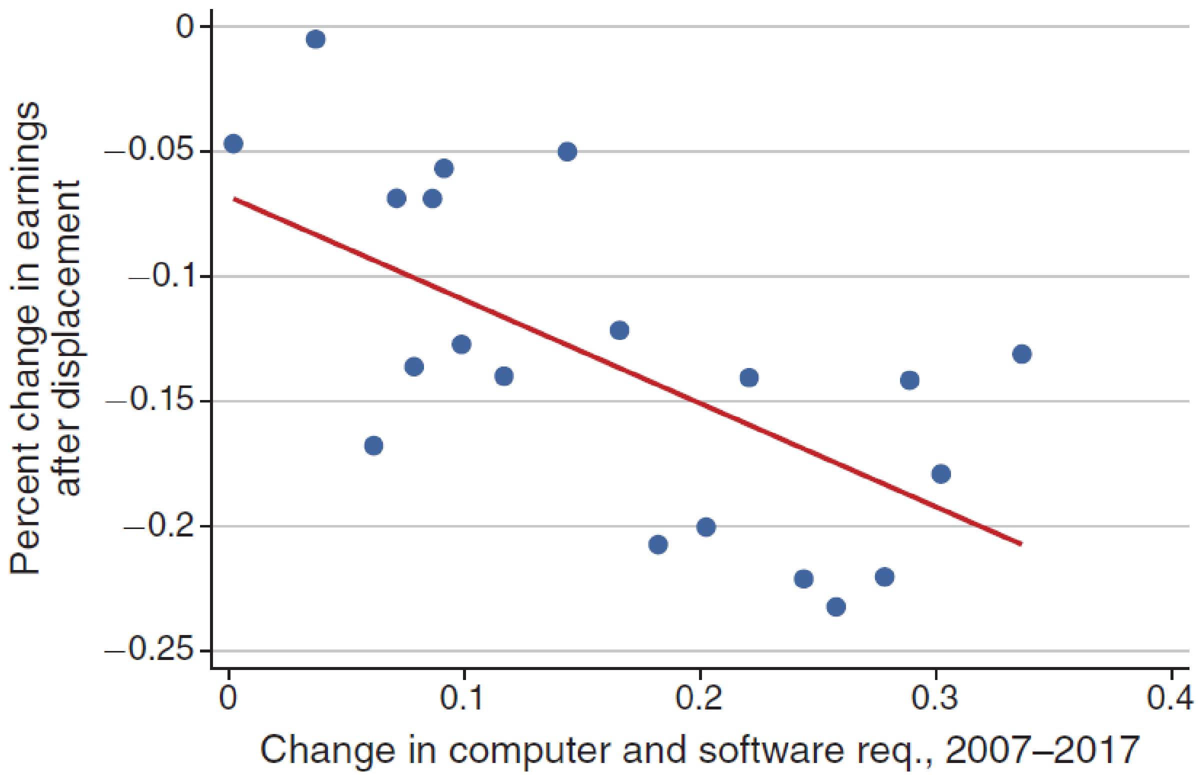


Rank	SOC-4	Occupation	Chg. computer req. (2007–2017) (1)	Nonroutine cognitive (2)	Routine cognitive (3)	Nonroutine manual (4)	Routine manual (5)
Panel A. Occupations with largest increase in computer and software requirements							
1	1710	Architects	0.419	1.603	0.657	−0.187	−0.285
2	3310	Supervisors of protective service workers	0.408	1.036	0.160	1.845	−0.250
3	3390	Protective service workers	0.338	−0.656	1.160	−0.966	−1.036
4	1720	Engineers—aerospace/biomedical/computer	0.337	0.323	−0.468	−1.587	−0.868
5	4330	Financial clerks	0.336	−0.705	1.878	−0.633	−0.311
6	1721	Engineers—industrial/mechanical/nuclear	0.332	0.644	−0.084	−2.095	−0.558
7	1520	Mathematical science occupations	0.315	0.888	−0.789	−2.455	−1.355
8	4750	Oil, gas, and mining extraction workers	0.312	−0.290	0.340	0.635	2.158
9	1120	Advertising, marketing, and sales managers	0.306	1.815	−1.540	0.419	−1.506
10	2740	Media and communication equipment workers	0.304	0.097	0.605	−0.235	1.112
Panel B: Occupations with smallest increase in computer and software requirements							
1	3990	Personal care and service workers	0.044	−0.641	−2.490	0.894	−1.245
2	3730	Grounds maintenance workers	0.042	−1.010	−2.386	0.091	2.112
3	5130	Food processing workers	0.041	−0.832	0.150	−0.736	1.281
4	3720	Cleaners	0.039	−1.992	−1.330	−1.225	0.647
5	3920	Animal trainers and caretakers	0.036	−0.234	−1.760	1.154	−0.706
6	3520	Cooks and food preparation workers	0.033	−1.209	−0.585	−0.059	1.085
7	3590	Restaurant attendants, dishwashers, hosts	0.029	−1.758	−1.242	−0.041	0.762
8	4730	Helpers, construction trades	0.022	−0.624	−0.228	−0.214	1.099
9	3530	Food and drink servers	0.010	−1.040	−0.394	0.210	0.214
10	5330	Drivers—ambulance/bus/tractor trailer/taxi	−0.005	−1.207	0.476	2.487	1.323

- **Impacts of technology change on displacement outcomes**

	Displaced (1)	CPS nondisplaced (2)
Change in computer requirements	0.161	0.159
Weekly real earnings (displaced job)	$849.42	—
Weekly real earnings (current job)	$759.62	$889.64
Years since displacement	2.02	—
Weeks unemployed after displacement	15.34	—
Switch occupation (d)	0.631	—
Age	41.64	43.10
Years of education	13.95	14.14
Observations	6,742	44,994

- **Technology change and earning loss**



- **On average, technology change accounts for 45% of earning declines from job loss**