Flatter experience-wage profiles and declining labor force nonparticipation

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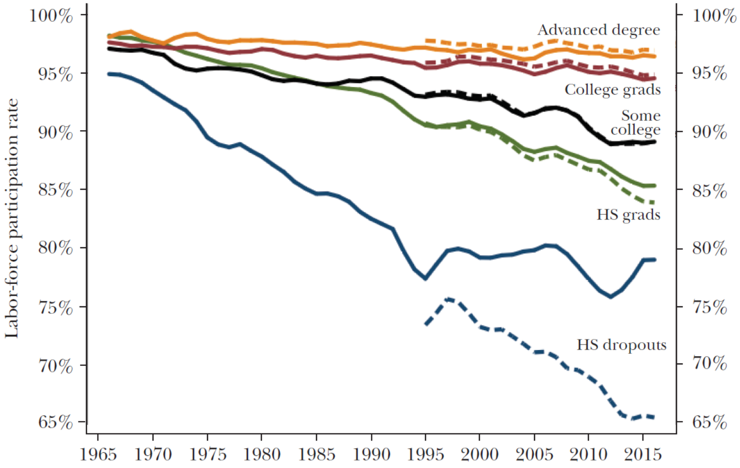
Motivation

Declining labor force participation among prime-aged low-skilled men (Binder & Bound JEP 2019)



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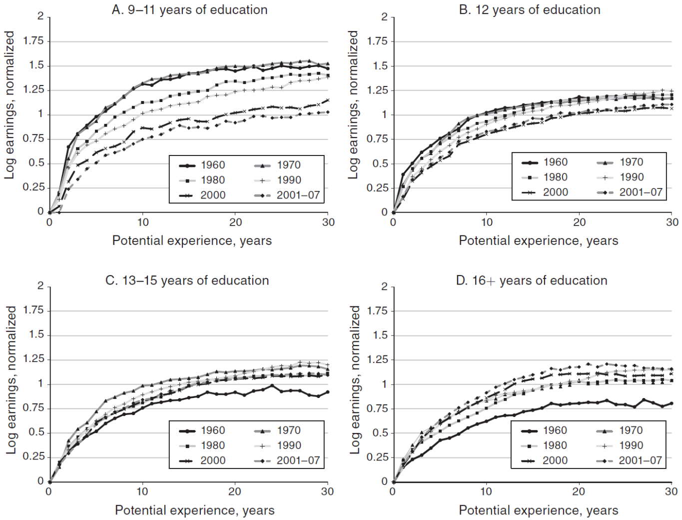
Flattening of experience-income profile of low-skilled relative to high-skilled (Elsby & Shapiro AER 2012)



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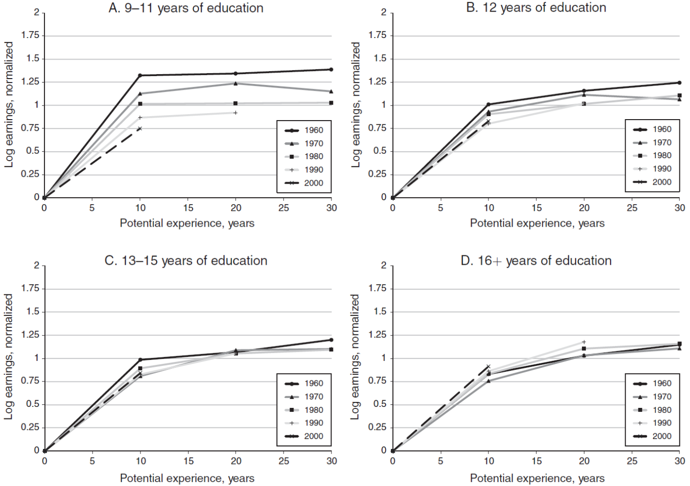

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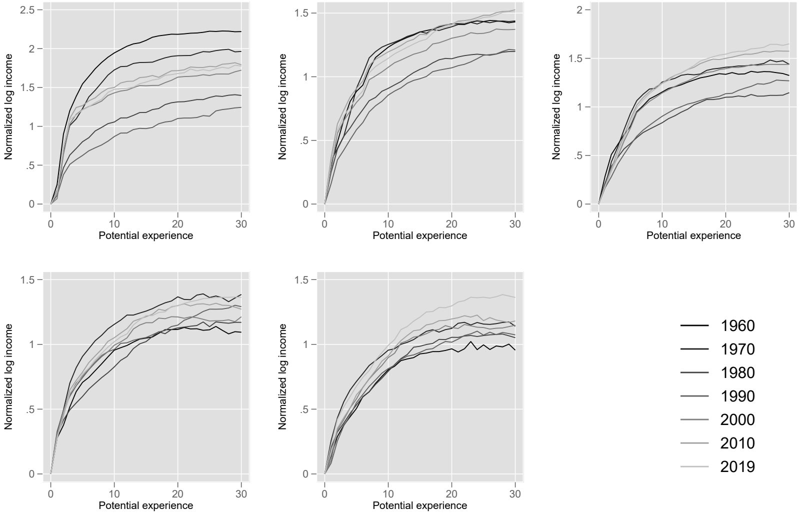
Experience-income profile of lowest-skilled has actually steepened recently!



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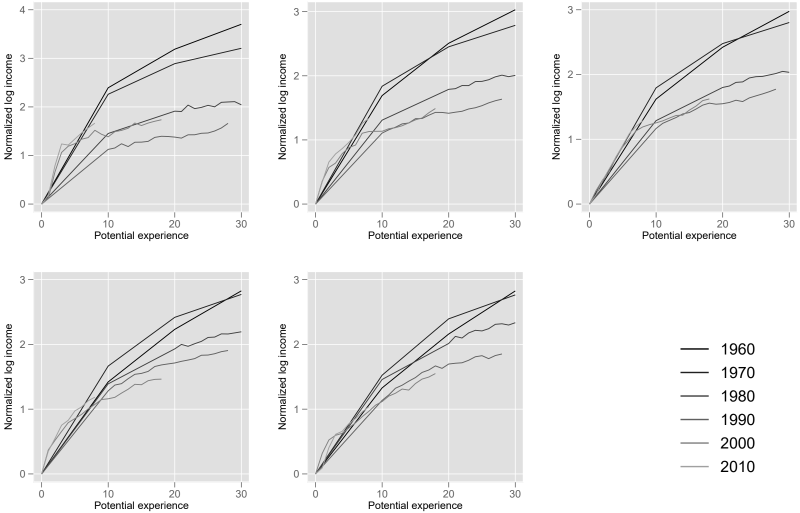
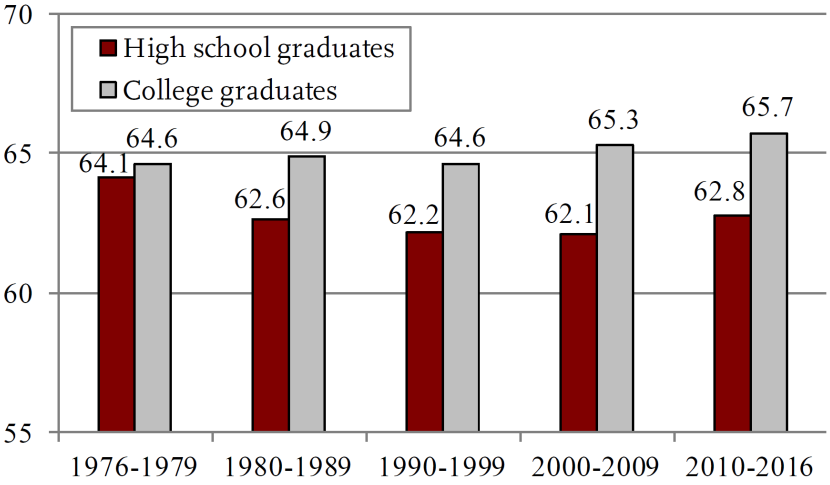


Motivation

Increase in gap of retirement age between high and low-skilled (Rutledge 2018)



Idea

Declining returns to accumulation of human capital leads to

- less human capital accumulation
- lower participation
- and earlier retirement

among low-skilled, and lower human capital level leads to

- higher sensitivity and persistence to shocks

Literature

Many explanations for declining LFP of prime-aged men:

- Skill-biased technical change (Card & Dinardo 2002, Acemoglu & Autor 2010)
- Job polarization (Foote & Ryan 2015)
- Improvements in leisure technology (Aguiar et. al. 2018)
- Disability and SSDI (Autor & Duggan QJE 2003, Krueger 2017)
- Incarceration (Binder & Bound JEP 2019)

Elements I need in my model

- Human capital accumulation
- Education
- Labor supply
- Retirement

Blinder-Weiss 1976

Agents with finite lifespan T maximize lifetime utility

$$\max_{\{c_t\}_{t=0}^{T},\{h_t\}_{t=0}^{T},\{x_t\}_{t=0}^{T}} \sum_{t=0}^{T} \beta^t u(c_t, 1-h_t) + B(A_{T+1})$$

subject to

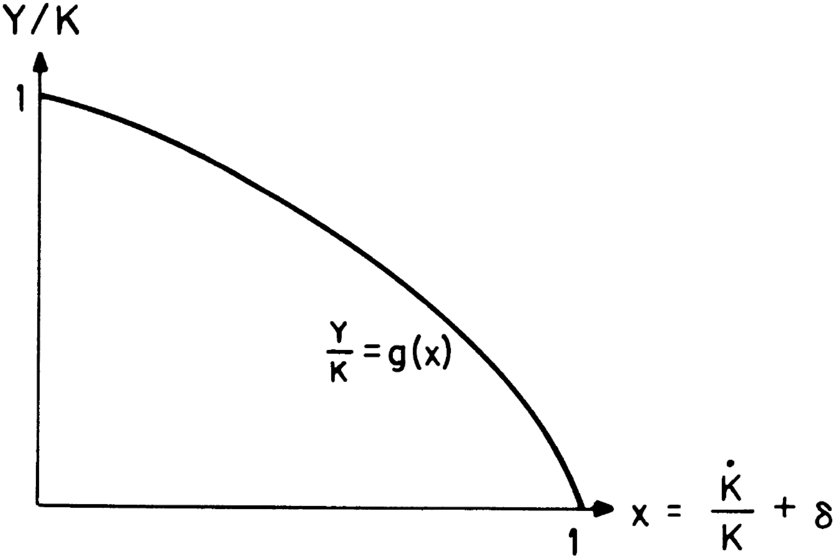
$$A_{t+1} = (1+r)A_t + h_t g(x_t) K_t - c_t,$$

$$K_{t+1} = (1-\delta)K_t + x_t h_t K_t,$$

$$x_t, h_t \in [0,1],$$

- x_t and $g(x_t)$ governs tradeoff between accumulating human capital and earnings
- B is bequest, A is assets, and K is human capital

$g(x)$

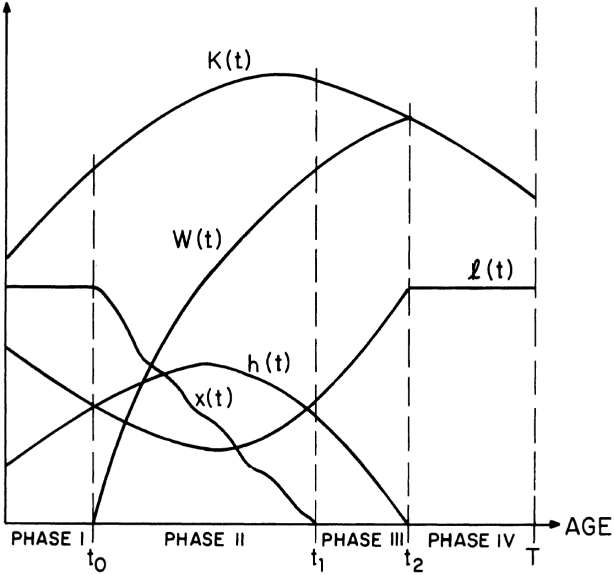


Endogenous life phases

Four phases:

- Education: $x = 1$
- Work + learning: $0 < x < 1$
- Work + no learning: $x = 0$
- Retirement: $h = 0$

Endogenous life phases



Challenges

- Both shooting method (continuous time model) and backward induction of value function (discrete time model) not working
- Possible way forward: discretize labor supply and investment decisions (Keane & Wolpin 1994)
- What is $g(x)$?
- What is causing the flattening and steepening of the experience-income profile?
  - Changes in labor markets; incorporate into the $g(x)$ function?
  - Changes in monopsony power?
  - Endogenize changes in the slope of experience-income profile

HJB

The HJB equation for the agent's problem is

$$
\begin{aligned}
\rho V(A, K, t) = \max_{c,h,x} \quad & u(c, 1-h) \\
& + \partial_A V(A, K, t)\left[rA + hg(x)K - c\right] \\
& + \partial_K V(A, K, t)\left[-\delta K + xhK\right] \\
& + \partial_t V(A, K, t)
\end{aligned}
$$

Finite difference approximation of the HJB

- nA and nK are the number of grid points for A and K
- Denote the index for A and K as i and j respectively
- Denote $V(A_i, K_j, t) = V_{ij}^t$
- Denote drift in A as μ_A, drift in K as μ_K

Forward and backward difference approximation

- Forward difference:

$$\partial_A^F V_{i,j}^t = \frac{V_{i+1,j}^t - V_{i,j}^t}{\Delta A},$$
$$\partial_K^F V_{i,j}^t = \frac{V_{i,j+1}^t - V_{i,j}^t}{\Delta A},$$

- Backward difference:

$$\partial_A^B V_{i,j}^t = \frac{V_{i,j}^t - V_{i-1,j}^t}{\Delta A},$$
$$\partial_K^B V_{i,j}^t = \frac{V_{i,j}^t - V_{i,j-1}^t}{\Delta A},$$

Choice of forward or backward difference

- Drift of state variables determined using FOCs

$$\partial_c u(c_{i,j}^t, h_{i,j}^t) = \partial_A V_{i,j}^t \tag{1}$$
$$\partial_h u(c_{i,j}^t, h_{i,j}^t) = \partial_A V_{i,j}^t \left[g(x_{i,j}^t)K\right] + \partial_K V_{i,j}^t \left[x_{i,j}^t K\right] \tag{2}$$
$$0 = \partial_A V_{i,j}^t \left[hg'(x_{i,j}^t)K\right] + \partial_K V_{i,j}^t \left[hK\right] \tag{3}$$

- Constraints:

$$0 \leq h \leq 1 \tag{4}$$
$$0 \leq x \leq 1 \tag{5}$$

- If $mu_A > 0$, use $\partial_A^F V_{i,j}^t$, if $mu_A < 0$, use $\partial_A^B V_{i,j}^t$; same for K

Choice of forward or backward difference

- Denote drift in A computed using forward difference in A and backward difference in K as μ_A^{FK}
- Choose approximation scheme that is consistent with computed drift, e.g., choose scheme FB if $\mu_A^{FB} > 0$ and $\mu_K^{FB} < 0$
- Three potential ambiguous cases: steady-state, boundary condition, tie-breaking

Steady-state

- Steady-state in one dimension, e.g., A is consistent in the forward dimension, but K is inconsistent
- $\mu_A^{FF} > 0$ and $\mu_A^{FB} > 0$, and $\mu_K^{FF} < 0$ and $\mu_K^{FB} > 0$, then set K to be steady-state
- Do so by setting $\partial_K V_{i,j}^t$ such that $\mu_K = 0$
- Steady-state in both dimension, so both A and K are inconsistent
- Do so by setting $\partial_A V_{i,j}^t$ and $\partial_K V_{i,j}^t$ such that $\mu_A = 0$ and $\mu_K = 0$

Boundary condition

- Issue: drift of state variable cannot send state outside of boundary, both computational and theoretical
- e.g., borrowing constraint $\bar{A}$
- If $\mu_A^{FF} < 0$ and $\mu_A^{FB} < 0$, then the drift sends A below $\bar{A}$
- Set $\partial_A V_{i,j}^t$ at $\bar{A}$ such that $\mu_A^{FF} = 0$ if K is forward consistent and $\mu_A^{FB} = 0$ if K is backward consistent
- Note: possible to have steady-state in K when at A boundary, and vice versa
- In the former case, K is inconsistent at A boundary

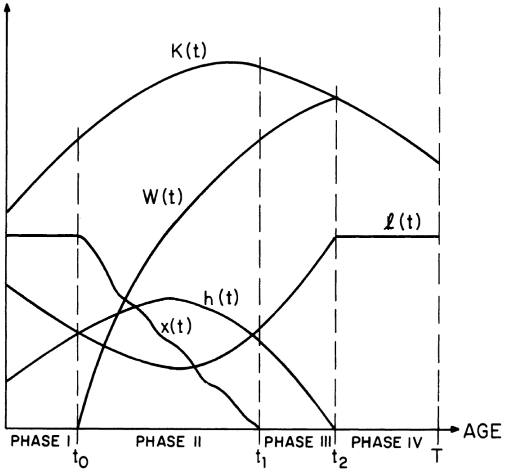
Tie-breaking

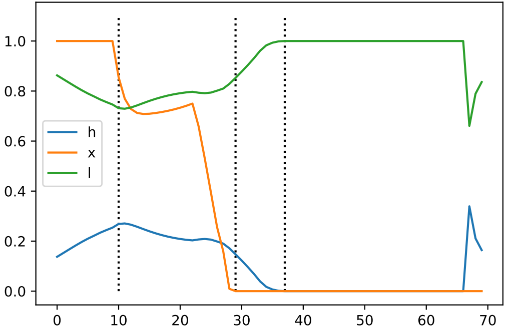
- Issue: approximation is consistent in both forwards and backwards direction
- Solution: choose approximation that leads to larger Hamiltonian value

Current computational issues

- Proving my algorithm satisfies the three conditions of Barles and Souganidis (1991) (monotonicity, consistency, stability)
- Need to check for tie-breaking issues within "boundary condition" and "steady-state"
- Speed up computation by consolidating ambiguous case checkers
- Fix terminal condition spike

Path of choice variables





Path of state variables