

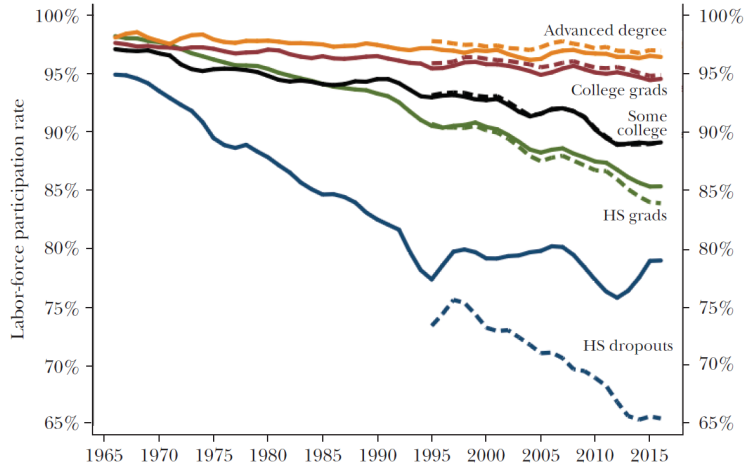
Flatter experience-wage profiles and declining labor force nonparticipation

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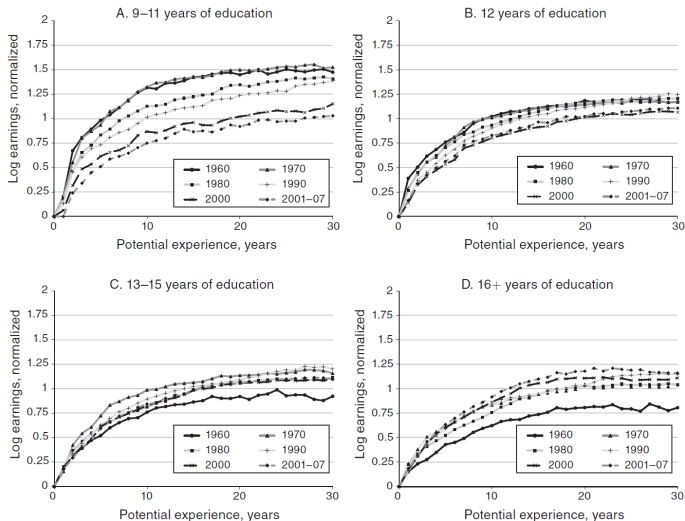
Motivation

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



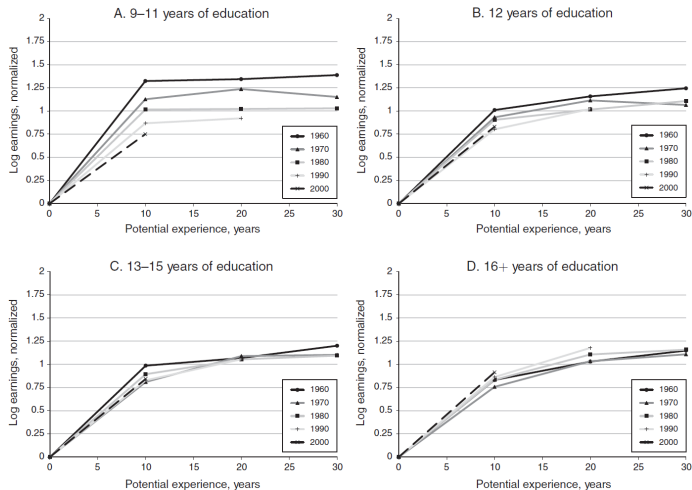
Motivation

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



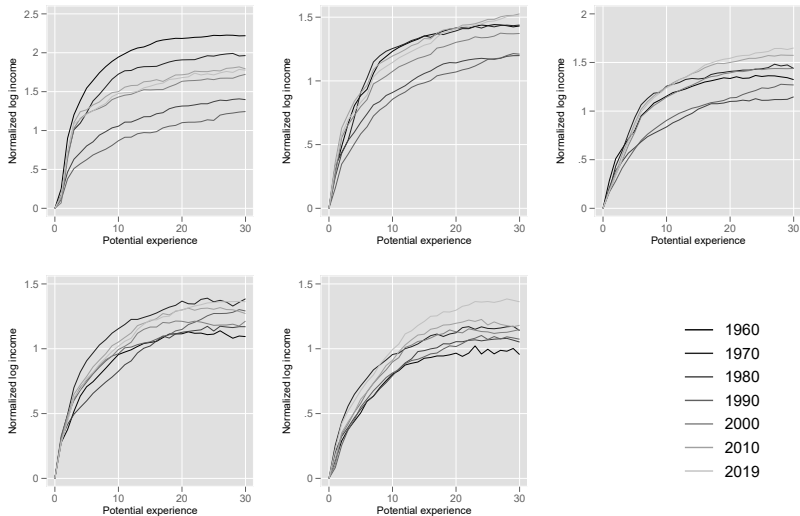
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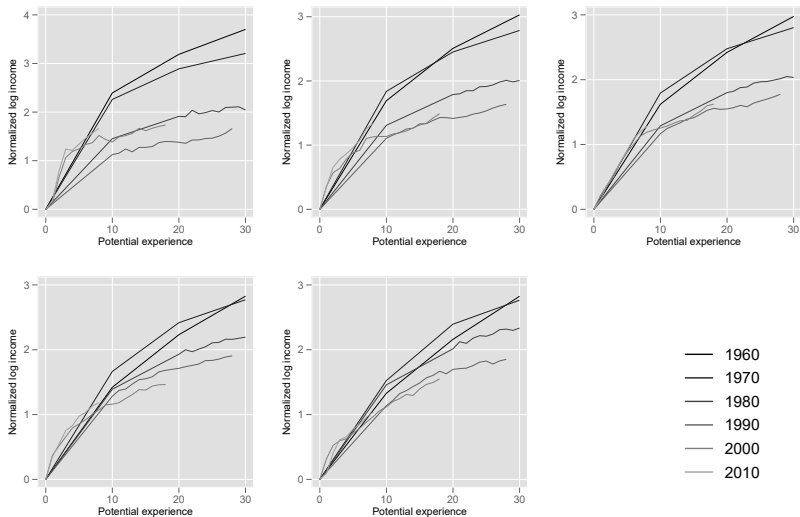
Motivation

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



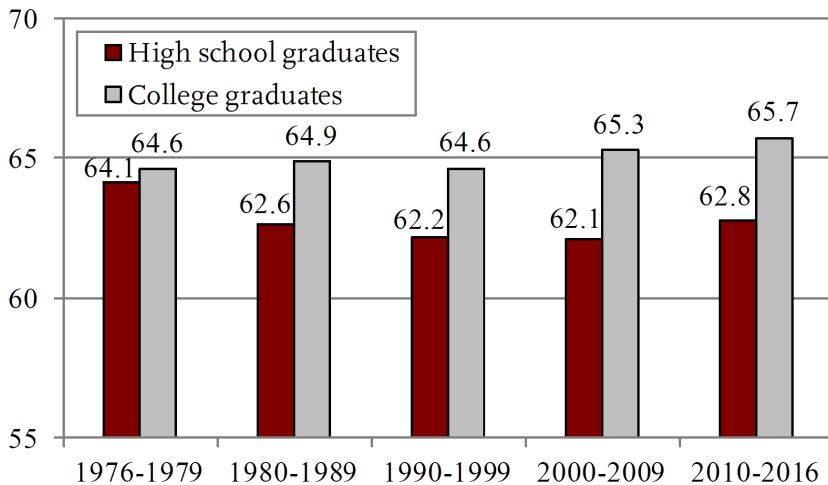
Motivation

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



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

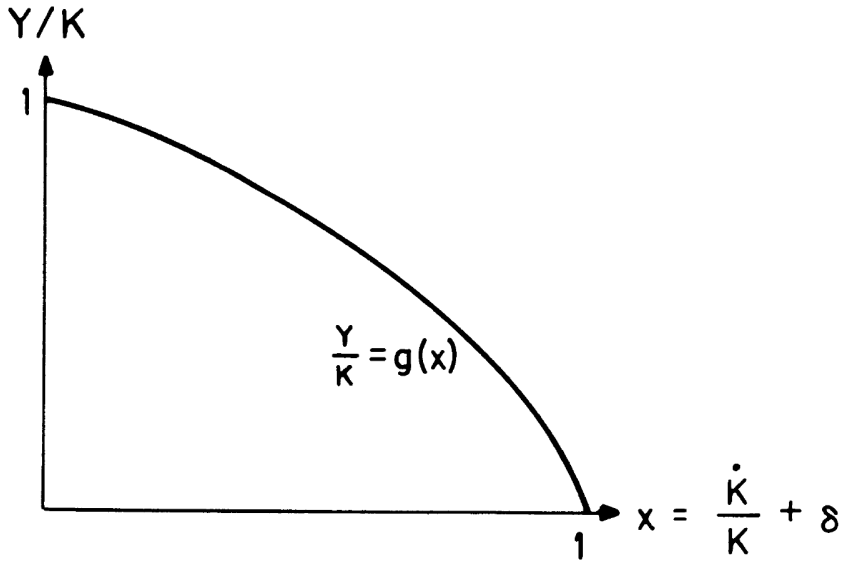
$$A_{t+1} = (1 + r)A_t + h_t g(x_t) K_t - c_t,$$

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

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

- ▶ 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

$$g(x)$$

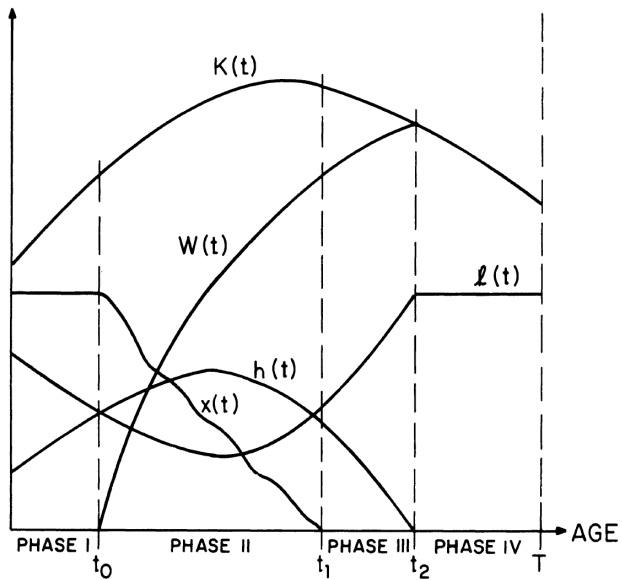


Endogenous life phases

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

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

Finite difference approximation of the HJB

- ▶ n_A and n_K 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:

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

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

- ▶ Backward difference:

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

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

Choice of forward or backward difference

- At any grid point i, j at time t , solve for c, h, x :

$$\partial_c u(c_{i,j}^t, h_{i,j}^t) = \partial_A V_{i,j}^t \quad (1)$$

$$\partial_h u(c_{i,j}^t, h_{i,j}^t) = \partial_A V_{i,j}^t [g(x_{i,j}^t)K_j] + \partial_K V_{i,j}^t [x_{i,j}^t K_j] \quad \text{if } 0 < h < 1 \quad (2)$$

$$\partial_h u(c_{i,j}^t, h_{i,j}^t) \geq \partial_A V_{i,j}^t [g(x_{i,j}^t)K_j] + \partial_K V_{i,j}^t [x_{i,j}^t K_j] \quad \text{if } h = 0 \quad (3)$$

$$\partial_K V_{i,j}^t [hK_j] = -\partial_A V_{i,j}^t [hg'(x_{i,j}^t)K_j] \quad \text{if } 0 < x < 1 \quad (4)$$

$$\partial_K V_{i,j}^t [hK_j] \geq -\partial_A V_{i,j}^t [hg'(x_{i,j}^t)K_j] \quad \text{if } x = 1 \quad (5)$$

$$\partial_K V_{i,j}^t [hK_j] \leq -\partial_A V_{i,j}^t [hg'(x_{i,j}^t)K_j] \quad \text{if } x = 0 \quad (6)$$

- Problem: Do we use ∂_A^F or ∂_A^B , and ∂_K^F or ∂_K^B ?

Choice of forward or backward difference

- ▶ Backwards in A , forwards in K : $\partial_A^B + \partial_K^F \Rightarrow \mu_A^{BF}, \mu_K^{BF}$
- ▶ Choose approximation scheme that is consistent with computed drift
- ▶ e.g., $\partial_A^B + \partial_K^F$ requires $\mu_A^{BF} < 0, \mu_K^{BF} > 0$
- ▶ Consistent scheme may not always exist:
 - ▶ Boundaries
 - ▶ Steady-states
- ▶ May have more than 1 consistent scheme due to non-concavity of V

Discretizing HJB

- ▶ Stack all $V_{i,j}^{t+1}$ into V^{t+1} , a vector of length $nA * nK$
- ▶ V^{t+1} has associated optimal c^t, h^t, x^t , flow utility $U(V^{t+1})$, and drifts μ^t
- ▶ At each i, j , there is an associated upwind direction for ∂V
- ▶ Matrix $A(V^{t+1})$ encodes these directions and drifts μ^{t+1} , so $A(V^{t+1}) * V^{t+1} = \partial V^{t+1} * \mu^{t+1}$

Discretizing HJB

Recall HJB:

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

Discretized and stacked version:

$$\rho V^t = U(V^{t+1}) + A(V^{t+1}) * V^t + \frac{V^{t+1} - V^t}{\Delta t} \quad (7)$$

- Solve backwards from terminal bequest motive: $V^T = B(A^T)$

Boundaries

- ▶ What do we do at A_{min} , A_{max} , K_{min} , and K_{max} ?
- ▶ Problem: need $\mu_A \geq 0$ at A_{min} and $\mu_A \leq 0$ at A_{max}
- ▶ Possible solution: make A_{max} very large so that $\mu_A^{BF}, \mu_A^{BB} < 0$ naturally at A_{max}
- ▶ Choose BF or BB according to consistency with μ_K
- ▶ Cannot make A_{min} very small, e.g., borrowing constraint $\bar{A} = A_{min}$
- ▶ If $\mu_A^{FF}, \mu_A^{FB} < 0$ at A_{min} , then set ∂_A at A_{min} so that $\mu_A^{FF}, \mu_A^{FB} = 0$
- ▶ Note: possible to have steady-state in K when at A boundary, and vice versa

Steady-state in one dimension

- ▶ What do we do when one of the state variables is never consistent?
- ▶ e.g., $\mu_A^{FF}, \mu_A^{FB} > 0$, so A is consistent in the F direction
- ▶ but $\mu_K^{FF} < 0$ and $\mu_K^{FB} > 0$
- ▶ I set K to be at steady-state
- ▶ Do so by setting ∂_K so that $\mu_K = 0$
- ▶ We will get $\partial_A^F, \partial_K \Rightarrow \mu_A > 0, \mu_K = 0$

Steady-state in both dimensions

- ▶ Steady-state in both dimension, so both A and K are inconsistent
- ▶ We don't have a consistent $\mu_A^{FF}, \mu_A^{FB} > 0$, or $\mu_A^{BF}, \mu_A^{BB} < 0$
- ▶ Neither do we have a consistent $\mu_K^{FF}, \mu_K^{BF} > 0$, or $\mu_K^{FB}, \mu_K^{BB} < 0$
- ▶ Then set ∂_A and ∂_K such that $\mu_A = 0$ and $\mu_K = 0$

Non-concavity of V

- ▶ With concave V , $\partial_A^F < \partial_A^B$
- ▶ $\Rightarrow \mu_A^{FF} < \mu_A^{BF}$
- ▶ We will not have A consistent in both F and B :
 - ▶ $\mu_A^{BF} < 0 < \mu_A^{FF}$ contradicts $\mu_A^{FF} < \mu_A^{BF}$
- ▶ However, this may happen with non-concave V
- ▶ Solution: choose approximation that leads to larger Hamiltonian value

Progress since last meeting

- ▶ Improved algorithm explanation slides
- ▶ Met with Johannes:
 - ▶ He suggested I fix terminal condition spike by increasing bequest motive (completed, seems to work, not sure if best solution, will try others)
 - ▶ He thinks my modified algorithm to impose boundary/steady state/boundary + steady state conditions seem reasonable
 - ▶ He suggested a modification for rare cases where boundary/steady state coincide with non-concavity ambiguity: add tie-breaking (will need to wrap boundary/steady state condition checkers inside functions; 40% done)
 - ▶ Create 1-slide explainer (what does Titan think?)
- ▶ Not completed: Look at data and calibrate (will do after algorithm is faster)

One-slide explainer

- ▶ Discretize HJB over grids of A, K indexed by i, j :
- ▶ Approximate derivatives of V using finite difference
- ▶ Forward difference:

$$\partial_A V(A_i, K_j, t) = \frac{V(A_{i+1}, K_j, t) - V(A_i, K_j, t)}{\Delta A} \quad (8)$$

- ▶ Backward difference:

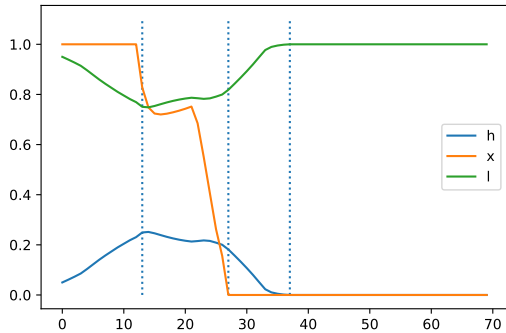
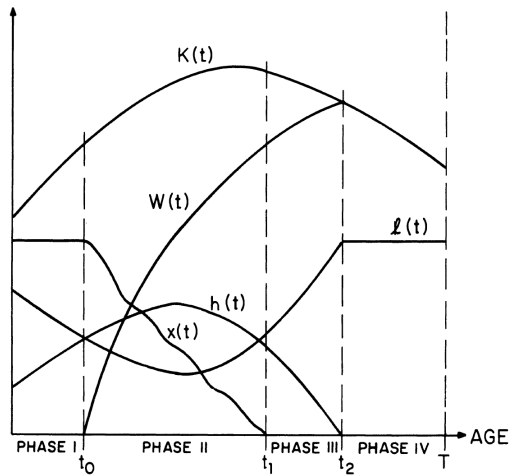
$$\partial_A V(A_i, K_j, t) = \frac{V(A_i, K_j, t) - V(A_{i-1}, K_j, t)}{\Delta A} \quad (9)$$

- ▶ Choose direction and optimal choice via “upwind scheme”: direction is consistent with drift of state variable implied by optimal choice
- ▶ Once we know V^{t+1} , only unknown in discretized HJB is V^t
- ▶ Solve backwards from terminal V^T

Current computational issues

- ▶ Proving my algorithm satisfies the three conditions of Barles and Souganidis (1991) (monotonicity, consistency, stability)
- ▶ Speed up computation by consolidating ambiguous case checkers within a single function (goes hand-in-hand with Johannes' suggestion)
- ▶ Length of time in schooling depends on initial wealth due to credit constraint
 - ▶ With too much assets, agents end up not accumulating much human capital or assets
 - ▶ With too little assets, $x = 1$ period is very short
 - ▶ May need to allow for debt? Will require modified bequest motive

Path of choice variables



Path of state variables

