"Inferring Labor Income Risk From Economic Choices: An Indirect Inference Approach"

by Fatih Guvenen and Anthony Smith

October 27, 2010

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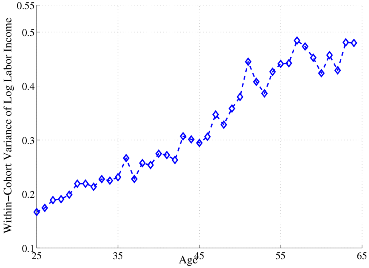
- It is well documented that within-cohort dispersion of labor earnings rises substantially over the life cycle.



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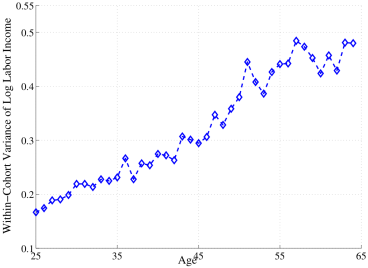

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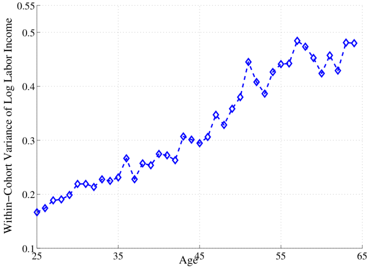

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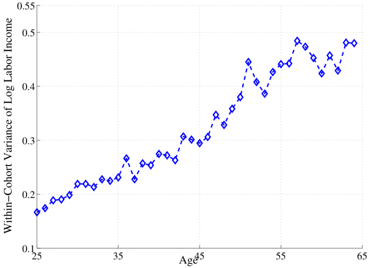
- There are different interpretations of this pattern, with different policy and welfare implications
- One is that the rise in inequality stems from the accumulation of persistent idiosyncratic shocks.
- The alternative is a systematic fanning out of earnings over time, which can represent uncertainty if individuals have to learn their growth rate.



Overview

- This paper will assume that individuals face the following income process

$$y_t^i = \underbrace{g(t, \text{observables}, \ldots)}_{\text{common life cycle component}} + \underbrace{\alpha^i + \beta^i t}_{\text{profile heterogeneity}} + \underbrace{z_t^i + \epsilon_t^i}_{\text{stochastic component}} \quad (1)$$

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- They will estimate this model using indirect inference on the PSID data set with non-durable consumption data imputed from the CEX.
- The auxiliary model will be motivated by the model above under quadratic utility and no borrowing constraints

The Learning Problem

- The assume that $\beta^i = \beta^i_k + \beta^i_u$ where β^i_k is observed and $\sigma^2_\beta = \sigma^2_{\beta_k} + \sigma^2_{\beta_u}$. Let $\lambda \equiv \frac{\sigma^2_{\beta_\mu}}{\sigma^2_\beta}$.

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- Learning β^i can then be written as a Kalman Filter problem with state equation

$$\begin{bmatrix} \beta^i \\ z^i_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \rho \end{bmatrix} \begin{bmatrix} \beta^i \\ z^i_t \end{bmatrix} + \begin{bmatrix} 0 \\ \eta^i_{t+1} \end{bmatrix}$$

With a second observation equation

$$\tilde{y}^i_t \equiv y^i_t - \alpha^i - \epsilon^i_t = \begin{bmatrix} t & 1 \end{bmatrix} \begin{bmatrix} \beta^i \\ z^i_t \end{bmatrix}$$

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- For future reference we will define $\hat{\xi}^i_t = \tilde{y}^i_t - \mathbb{E}_{t-1}(\tilde{y}^i_t)$

The Linear-Quadratic Framework

- The consumption-savings problem in the quadratic utility frame work can be written as

$$V_t^i(a_t^i, \hat{\beta}_t^i, \hat{z}_t^i) = \max_{C_t^i, a_{t+1}^i} \left\{ -(C_t - C^*)^2 + \frac{1}{1+r} \mathbb{E}_t \left[V_{t+1}^i(a_{t+1}^i, \hat{\beta}_{t+1}^i, \hat{z}_{t+1}^i) \right] \right\}$$

subject to

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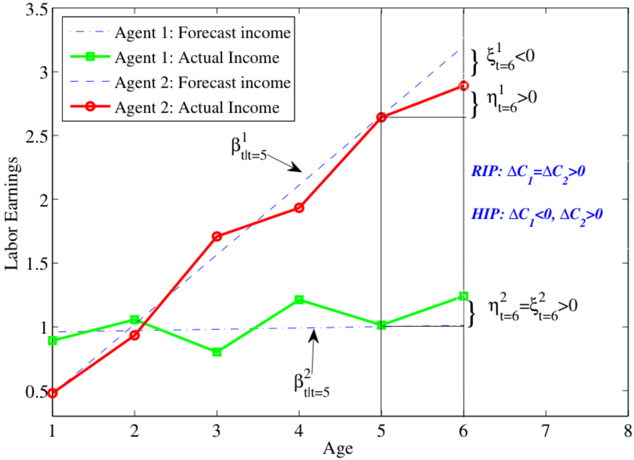
- All new information comes from $\hat{\xi}_t^i$, thus one can obtain $\Delta C_t = \Pi_t \times \hat{\xi}_t^i$ and derive the level of optimal consumption

$$C_t^i = \varphi_t w_t^i + \frac{1}{1+r} \Phi_{t+1} \hat{\beta}_t^i + \frac{1}{1+r} \rho \Psi_{t+1} \hat{z}_t^i$$

Some Examples

From this framework one can see that individuals with different beliefs about their growth rate β will respond differently to the save earnings innovation. This will help determine beliefs in the estimation



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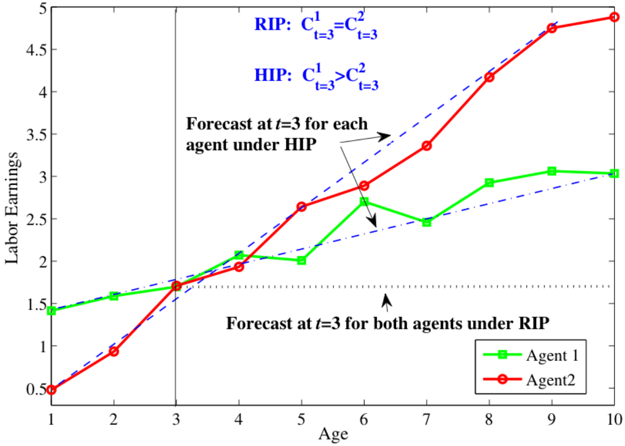
Proposition

Controlling for and individuals income and assets, the consumption level is an increasing function of the individuals beliefs $\hat{\beta}^i_t$.



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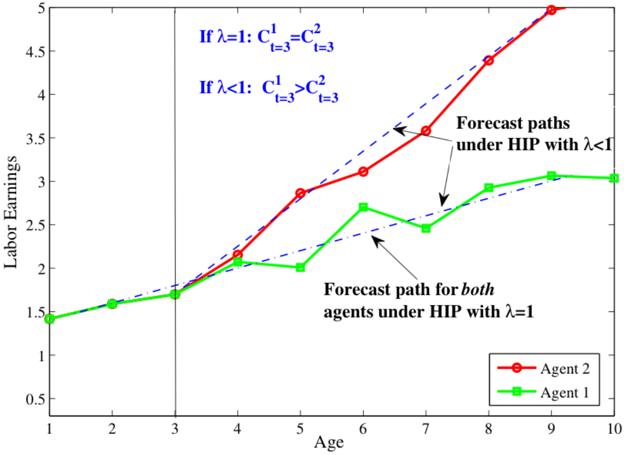
Consumption decisions can also be informative about the degree of private information, λ.



Full Consumption Savings Model

- Agents live T periods and retire at date $R < T$. The Dynamic Program for the full consumption savings model is

$$V_t^i(w_t^i, \hat{\beta}_t^i, \hat{z}_t^i; \alpha^i) = \max_{C_t^i, a_{t+1}^i} \left\{ \frac{(C_t^i)^{1-\phi}}{1-\phi} + \delta \mathbb{E}_t \left[V_{t+1}^i(w_{t+1}^i, \hat{\beta}_{t+1}^i, \hat{z}_{t+1}^i; \alpha^i) \right] \right\}$$

subject to

$$\begin{aligned} C_t^i + a_{t+1}^i &= w_t^i \\ w_t^i &= (1+r)a_t^i + Y_t^i \\ Y_t^i &= \underline{Y} + \exp(\overline{y}_t + \alpha^i + \beta^i t + z_t^i + \epsilon_t^i) \\ a_{t+1}^i &\geq \underline{a}_t, \text{ and Kalman Recursions} \end{aligned}$$

$\overline{y}_t$ is the population average of log income at age t.

- For retirement we have, where $Y^i = \Phi(Y_R^i, \overline{Y})$

$$V_t^i(w_t^i; Y_R^i) = \max_{C_t^i, a_{t+1}^i} \left[\frac{(C_t^i)^{1-\phi}}{1-\phi} + \delta V_{t+1}^i(w_{t+1}^i; Y_R^i) \right]$$

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- The basic approach involves estimating a demand system for food consumption as a function of non-durable expenditures, demographic variables, and relative prices
- They also extend the method to cover the period from 1968 to 1992 (instead of 1980 - 1992).
- They convert the Data to Per-Adult Equivalent Units by regressing each variable on family size, a race dummy a region dummy, a dummy indicating whether the head is employed, a dummy indicating residence in a large city, and a set of cohort dummies. Use the residuals in the analysis below.

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and

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- They also divide the population into 2 groups: between 25 and 38, and between 39 and 55. Allow the coefficients to vary across these two groups.

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- Fill in missing data using a reasonable procedure to match percentiles. Will still be consistent if same procedure is applied to real and simulated data.
- They compute the Wealth to income ratio in 1984 and 1989, average and add the additional moment

$$10 \times (WY_{PSID} - WY_{Model})^2$$

  to the objective function.

Estimation

- Used the following objective function for the data

$$\mathcal{L} = |\Sigma|^{-J/2} \exp\left(-\frac{1}{2} \sum_i \sum_t \epsilon_t^{i,Data} \Sigma^{-1} (\epsilon_t^{i,Data})' \right)$$

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$$\hat{\theta} = \text{argmin}_\theta \left[\mathcal{L}(\hat{\mathbf{a}}, \hat{\mathbf{b}}, \hat{\Sigma}, PSID) - \mathcal{L}(\tilde{\mathbf{a}}(\theta), \tilde{\mathbf{b}}(\theta), \tilde{\Sigma}(\theta), PSID)\right]$$

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- Use Monte-Carlo to study small sample bias and identification. Find strong evidence for local identification.

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- Note that lambda is estimated to be around 0.345 which means that $\frac{\sigma^2_{\beta_k}}{\sigma^2_{\beta}} = 1 - \lambda^2 = .880$.

	Baseline
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σ_β	1.852
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$corr_{\alpha\beta}$	–0.162
	(0.151)
ρ	0.754
	(0.025)
σ_η	0.196
	(0.005)
σ_ε	0.004
	(0.021)
λ	0.345
	(0.074)
δ	0.950
	(0.001)
ψ	0.874
	(0.083)
σ_y	0.147
	(0.007)
σ_c	0.356
	(0.002)
σ_{c_0}	0.428
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.. at age	30
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- Also estimated discount factor to some precision. This, however, is condition on the fixed value of ϕ. δ is quite sensitive to the preset value of risk aversion.
- They also did some analysis on the goodness of fit of the model. Over 100 repetitions of the objective function the test statistic has a mean of 2.29 and a maximum value of 4.03. The PSID data yielded a value of 26.37.

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σ_η	0.196
	(0.005)
σ_ε	0.004
	(0.021)
λ	0.345
	(0.074)
δ	0.950
	(0.001)
ψ	0.874
	(0.083)
σ_y	0.147
	(0.007)
σ_c	0.356
	(0.002)
σ_{c_0}	0.428
	(0.009)
max % constrained..	12.7%
.. at age	30
$\underline{a}_0$ / mean income	0.33
$\underline{a}_{55}$ / mean income	0.53

Estimation results

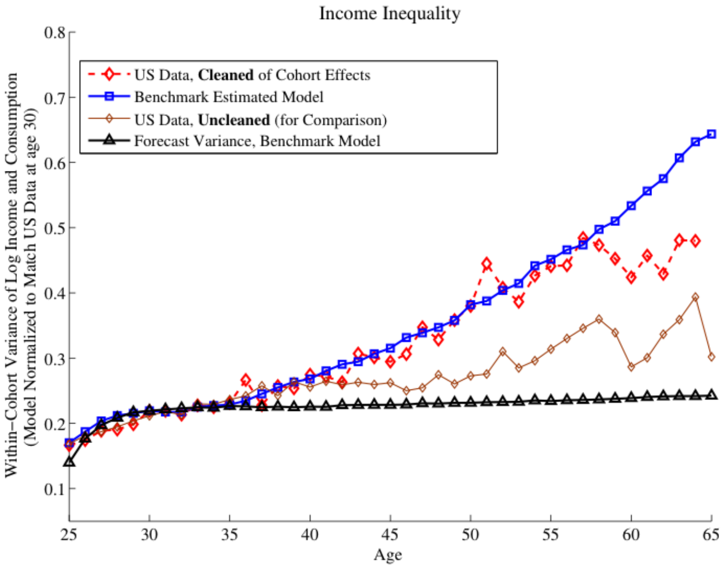
- Note that lambda is estimated to be around 0.345 which means that $\frac{\sigma^2_{\beta_k}}{\sigma^2_\beta} = 1 - \lambda^2 = .880$.
- Also estimated discount factor to some precision. This, however, is condition on the fixed value of ϕ. δ is quite sensitive to the preset value of risk aversion.
- They also did some analysis on the goodness of fit of the model. Over 100 repetitions of the objective function the test statistic has a mean of 2.29 and a maximum value of 4.03. The PSID data yielded a value of 26.37.
- This is because the model falls short in matching the auxiliary consumption model.

	Baseline
	(1)
σ_α	0.284
	(0.027)
σ_β	1.852
	(0.188)
$corr_{\alpha\beta}$	–0.162
	(0.151)
ρ	0.754
	(0.025)
σ_η	0.196
	(0.005)
σ_ε	0.004
	(0.021)
λ	0.345
	(0.074)
δ	0.950
	(0.001)
ψ	0.874
	(0.083)
σ_y	0.147
	(0.007)
σ_c	0.356
	(0.002)
σ_{c_0}	0.428
	(0.009)
max % constrained..	12.7%
.. at age	30
$\underline{a}_0$ / mean income	0.33
$\underline{a}_{55}$ / mean income	0.53

Goodness of Fit

		constant	y_{t-1}	y_{t-2}	y_{t+1}	y_{t+2}	$\overline{y}_{1,t-3}$	$\overline{y}_{t+3,T}$	$\Delta y_{1,t-3}$	$\Delta y_{t+3,T}$	c_{t-1}	c_{t-2}	c_{t+1}	c_{t+2}
PANEL A: INCOME EQUATION														
Young Group:														
(1)	Data	**−0.036**^{a}	**0.346**	**0.360**	**0.077**	**0.097**	**−0.098**	**0.150**	0.037	-0.022				
(2)	Model	−0.026$^{\dagger\dagger b}$	0.337	0.357	0.093	0.102	−0.081	0.124	-0.016††	-0.021				
Middle-Age Group:														
(3)	Data	0.006**	**0.418**	**0.358**	**0.111**	**0.093**	−0.027	0.043**	0.031	0.028				
(4)	Model	−0.001††	0.401	0.375	0.122	0.105	−0.038	0.022	0.012	0.045				
PANEL B: CONSUMPTION EQUATION														
Young Group:														
(5)	Data	−0.007	**0.108**	0.042*	−0.023	−0.005	−0.045*	-0.017	0.030	−0.002	**0.248**	**0.262**	**0.178**	**0.175**
(6)	Model	−0.021††	0.105	0.079†	−0.022	−0.039	−0.079	0.025	0.001	0.013	0.208††	0.205†††	0.248†††	0.229†††
Middle-Age Group:														
(7)	Data	−0.004	**0.136**	0.046**	−0.014	−0.040*	−0.082**	0.012	0.030	0.028	**0.270**	**0.260**	**0.177**	**0.187**
(8)	Model	0.007††	0.103	0.041	0.009	−0.044	0.050†††	-0.042††	0.027	0.041	0.197†††	0.211††	0.224††	0.257†††

Implications



Risk Aversion and Time Preference

- Cannot separately identify δ and ϕ, using Monte Carlo and 200 observations find a correlation of the parameters to be -0.88. Suggests only a combination is identified.
- They do some sensitivity analysis and find that one can either fix δ or ϕ, but fixing both will create sever biases. Finally they find that the main role of the Wealth to Income moment is to pin down δ.