Inferring Income Risk from Economic Choices:

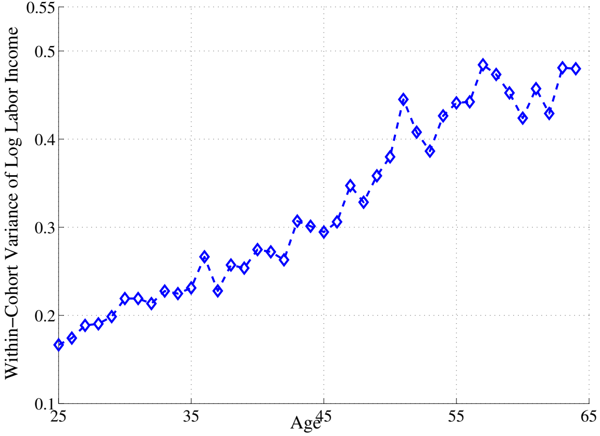
An Indirect Inference Approach

Fatih Guvenen
Minnesota and NBER

Anthony Smith
Yale University

October 23, 2010

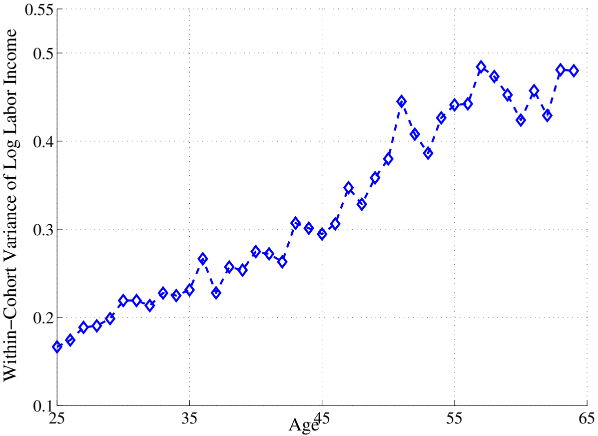
What is Risk? What is Heterogeneity?



The fanning out over time of the earnings and consumption distributions within a cohort that Deaton and Paxson (1994) document is striking evidence of a sizeable, uninsurable random walk component in earnings.

Robert Lucas (2003 AEA Presidential Address)

What is Risk? What is Heterogeneity?



The fanning out over time of the earnings and consumption distributions within a cohort that Deaton and Paxson (1994) document is striking evidence of a sizeable, uninsurable random walk component in earnings.

Robert Lucas (2003 AEA Presidential Address)

A Stochastic Process for Labor Income

y_t^i : log labor earnings of household i at age t.

$$y_t^i = \underbrace{\left[a_0 + a_1 t + a_2 t^2 + a_3 Educ + \ldots\right]}_{\text{common life-cycle component}}$$

$$+ \quad \underbrace{\left[\alpha^i + \beta^i t\right]}_{\text{profile heterogeneity}}$$

$$+ \quad \underbrace{\left[z_t^i + \varepsilon_t^i\right]}_{\text{stochastic component}}$$

where $\quad z_t^i = \rho z_{t-1}^i + \eta_t^i, \quad$ and $\quad \eta_t^i, \varepsilon_t^i \sim iid$

A Stochastic Process for Labor Income

y_t^i : log labor earnings of household i at age t.

$$y_t^i = \underbrace{\left[a_0 + a_1 t + a_2 t^2 + a_3 Educ + ...\right]}_{\text{common life-cycle component}}$$

$$+ \underbrace{\left[\alpha^i + \beta^i t\right]}_{\text{profile heterogeneity}}$$

$$+ \underbrace{\left[z_t^i + \varepsilon_t^i\right]}_{\text{stochastic component}}$$

where $z_t^i = \rho z_{t-1}^i + \eta_t^i,$ and $\eta_t^i, \varepsilon_t^i \sim iid$

A Stochastic Process for Labor Income

y_t^i : log labor earnings of household i at age t.

$$y_t^i = \underbrace{\left[a_0 + a_1 t + a_2 t^2 + a_3 Educ + ...\right]}_{\text{common life-cycle component}}$$

$$+ \underbrace{\left[\alpha^i + \beta^i t\right]}_{\text{profile heterogeneity}}$$

$$+ \underbrace{\left[z_t^i + \varepsilon_t^i\right]}_{\text{stochastic component}}$$

where $z_t^i = \rho z_{t-1}^i + \eta_t^i,$ and $\eta_t^i, \varepsilon_t^i \sim iid$

A Stochastic Process for Labor Income

y_t^i : log labor earnings of household i at age t.

$$y_t^i = \underbrace{\left[a_0 + a_1 t + a_2 t^2 + a_3 Educ + \ldots\right]}_{\text{common life-cycle component}}$$

$$+ \quad \underbrace{\left[\alpha^i + \beta^i t\right]}_{\text{profile heterogeneity}}$$

$$+ \quad \underbrace{\left[z_t^i + \varepsilon_t^i\right]}_{\text{stochastic component}}$$

where $\quad z_t^i = \rho z_{t-1}^i + \eta_t^i, \quad$ and $\quad \eta_t^i, \varepsilon_t^i \sim iid$

Three Questions about Labor Income Risk

1. How persistent and large are income shocks? i.e., what is ρ and σ_η^2 ?

2. Do individuals differ systematically in their income growth rates? i.e., is $\sigma_\beta^2 \gg 0$?

3. If indeed $\sigma_\beta^2 \gg 0$, how much do individuals know about their β^i at *different points* in their life-cycle?

Main conclusion:

Typical calibrations of incomplete markets models substantially overstate uninsurable income risk.

Three Questions about Labor Income Risk

1. How persistent and large are income shocks? i.e., what is ρ and σ_η^2 ?
2. Do individuals differ systematically in their income growth rates? i.e., is $\sigma_\beta^2 \gg 0$?
3. If indeed $\sigma_\beta^2 \gg 0$, how much do individuals know about their β^i at *different points* in their life-cycle?

Main conclusion:

Typical calibrations of incomplete markets models substantially overstate uninsurable income risk.

Three Questions about Labor Income Risk

1. How persistent and large are income shocks? i.e., what is ρ and σ_η^2 ?
2. Do individuals differ systematically in their income growth rates? i.e., is $\sigma_\beta^2 \gg 0$?
3. If indeed $\sigma_\beta^2 \gg 0$, how much do individuals know about their β^i at *different points* in their life-cycle?

Main conclusion:

Typical calibrations of incomplete markets models substantially overstate uninsurable income risk.

Three Questions about Labor Income Risk

1. How persistent and large are income shocks? i.e., what is ρ and σ_η^2 ?
2. Do individuals differ systematically in their income growth rates? i.e., is $\sigma_\beta^2 \gg 0$?
3. If indeed $\sigma_\beta^2 \gg 0$, how much do individuals know about their β^i at *different points* in their life-cycle?

Main conclusion:

Typical calibrations of incomplete markets models substantially overstate uninsurable income risk.

Existing Evidence from Labor Income Data

1. **HIP** Process ("Heterogenous Income Profiles"):
   - Early studies estimated the full model and found:

     $$\sigma_\beta^2 \gg 0 \quad \text{and} \quad 0.5 \leq \rho \leq 0.8$$

   - See Hause (1977), Lillard and Weiss (1979), Baker (1997), Haider (2001), Guvenen (2005)
2. **RIP** Process ("Restricted Income Profiles"):
   - MaCurdy (1982) suggested a test for $\beta^i \equiv 0$ and could not reject it.
   - Then he and the following literature:
     - imposed $\beta^i \equiv 0$ and estimated $0.95 < \rho < 1.0$
   - See Abowd and Card (1989), Topel (1991), Moffitt and Gottschalk (1995), Hubbard, Skinner and Zeldes (1994), Storesletten et al. (2004), etc.

Existing Evidence from Labor Income Data

1. **HIP** Process ("Heterogenous Income Profiles"):
   - Early studies estimated the full model and found:

$$\sigma_\beta^2 \gg 0 \quad \text{and} \quad 0.5 \le \rho \le 0.8$$

   - See Hause (1977), Lillard and Weiss (1979), Baker (1997), Haider (2001), Guvenen (2005)

2. **RIP** Process ("Restricted Income Profiles"):
   - MaCurdy (1982) suggested a test for $\beta^i \equiv 0$ and could not reject it.
   - Then he and the following literature:
     - imposed $\beta^i \equiv 0$ and estimated $0.95 \le \rho \le 1.0$.
   - See Abowd and Card (1989), Topel (1991), Moffitt and Gottschalk (1995), Hubbard, Skinner and Zeldes (1994), Storesletten et al. (2004), etc.

Existing Evidence from Labor Income Data

1. **HIP** Process ("Heterogenous Income Profiles"):
   - Early studies estimated the full model and found:

     $$\sigma_\beta^2 \gg 0 \quad \text{and} \quad 0.5 \le \rho \le 0.8$$

   - See Hause (1977), Lillard and Weiss (1979), Baker (1997), Haider (2001), Guvenen (2005)
2. **RIP** Process ("Restricted Income Profiles"):
   - MaCurdy (1982) suggested a test for $\beta^i \equiv 0$ and could not reject it.
   - Then he and the following literature:
     - imposed $\beta^i \equiv 0$ and estimated $0.95 \le \rho \le 1.0$.
   - See Abowd and Card (1989), Topel (1991), Moffitt and Gottschalk (1995), Hubbard, Skinner and Zeldes (1994), Storesletten et al. (2004), etc.

Existing Evidence from Labor Income Data

1. **HIP** Process ("Heterogenous Income Profiles"):
   - Early studies estimated the full model and found:

     $$\sigma_\beta^2 \gg 0 \quad \text{and} \quad 0.5 \leq \rho \leq 0.8$$

   - See Hause (1977), Lillard and Weiss (1979), Baker (1997), Haider (2001), Guvenen (2005)
2. **RIP** Process ("Restricted Income Profiles"):
   - MaCurdy (1982) suggested a test for $\beta^i \equiv \mathbf{0}$ and could not reject it.
   - Then he and the following literature:
     - imposed $\beta^i \equiv \mathbf{0}$ and estimated $\mathbf{0.95} \leq \rho \leq \mathbf{1.0}$.
   - See Abowd and Card (1989), Topel (1991), Moffitt and Gottschalk (1995), Hubbard, Skinner and Zeldes (1994), Storesletten et al. (2004), etc.

Existing Evidence from Labor Income Data

1. **HIP** Process ("Heterogenous Income Profiles"):
   - Early studies estimated the full model and found:

     $$\sigma_\beta^2 \gg 0 \quad \text{and} \quad 0.5 \leq \rho \leq 0.8$$

   - See Hause (1977), Lillard and Weiss (1979), Baker (1997), Haider (2001), Guvenen (2005)
2. **RIP** Process ("Restricted Income Profiles"):
   - MaCurdy (1982) suggested a test for $\beta^i \equiv \mathbf{0}$ and could not reject it.
   - Then he and the following literature:
     - imposed $\beta^i \equiv \mathbf{0}$ and estimated $\mathbf{0.95} \leq \rho \leq \mathbf{1.0}$.
   - See Abowd and Card (1989), Topel (1991), Moffitt and Gottschalk (1995), Hubbard, Skinner and Zeldes (1994), Storesletten et al. (2004), etc.

Existing Evidence from Labor Income Data

1. **HIP** Process ("Heterogenous Income Profiles"):
   - Early studies estimated the full model and found:

$$\sigma_\beta^2 \gg 0 \quad \text{and} \quad 0.5 \leq \rho \leq 0.8$$

   - See Hause (1977), Lillard and Weiss (1979), Baker (1997), Haider (2001), Guvenen (2005)

2. **RIP** Process ("Restricted Income Profiles"):
   - MaCurdy (1982) suggested a test for $\beta^i \equiv \mathbf{0}$ and could not reject it.
   - Then he and the following literature:
     - ★ imposed $\beta^i \equiv \mathbf{0}$ and estimated $\mathbf{0.95} \leq \rho \leq \mathbf{1.0}$.
   - See Abowd and Card (1989), Topel (1991), Moffitt and Gottschalk (1995), Hubbard, Skinner and Zeldes (1994), Storesletten et al. (2004), etc.

This Paper

Studies the joint dynamics of consumption and labor income to learn more about labor income risk.

Two Difficulties

- First, GMM requires strong assumptions.
  - "Indirect inference" circumvents many of these difficulties.
- Second, long US panel on consumption does not exist.
  - We construct a panel of imputed consumption (1968-1992) by combining CEX and PSID.

This Paper

Studies the joint dynamics of consumption and labor income to learn more about labor income risk.

Two Difficulties

- First, GMM requires strong assumptions.
  - "Indirect inference" circumvents many of these difficulties.
- Second, long US panel on consumption does not exist.
  - We construct a panel of imputed consumption (1968-1992) by combining CEX and PSID.

This Paper

Studies the joint dynamics of consumption and labor income to learn more about labor income risk.

Two Difficulties

- First, GMM requires strong assumptions.
  - "Indirect inference" circumvents many of these difficulties.
- Second, long US panel on consumption does not exist.
  - We construct a panel of imputed consumption (1968-1992) by combining CEX and PSID.

This Paper

Studies the joint dynamics of consumption and labor income to learn more about labor income risk.

Two Difficulties

- First, GMM requires strong assumptions.
  - "Indirect inference" circumvents many of these difficulties.
- Second, long US panel on consumption does not exist.
  - We construct a panel of imputed consumption (1968-1992) by combining CEX and PSID.

This Paper

Studies the joint dynamics of consumption and labor income to learn more about labor income risk.

Two Difficulties

- First, GMM requires strong assumptions.
  - "Indirect inference" circumvents many of these difficulties.
- Second, long US panel on consumption does not exist.
  - We construct a panel of imputed consumption (1968-1992) by combining CEX and PSID.

This Paper

Studies the joint dynamics of consumption and labor income to learn more about labor income risk.

Two Difficulties

- First, GMM requires strong assumptions.
  - "Indirect inference" circumvents many of these difficulties.
- Second, long US panel on consumption does not exist.
  - We construct a panel of imputed consumption (1968-1992) by combining CEX and PSID.

A Life Cycle Model

- A standard life-cycle model of consumption-savings choice (CRRA utility, borrowing constraints, retirement system).

- Information Structure. Recall: $y_t^i = \alpha^i + \beta^i t + z_t^i + \varepsilon_t^i$
  - Bayesian learning about (β^i, z_t^i) observing y_t^i and ε_t.
  - Cast learning as a Kalman filtering problem.

- Express the prior standard deviation as: $\sigma_{\beta,0} = \lambda \sigma_\beta$.
  - If $\lambda = 0 \quad \rightarrow \quad \sigma_{\beta,0} = 0$ (No prior uncertainty).
  - If $\lambda = 1 \quad \rightarrow \quad \sigma_{\beta,0} = \sigma_\beta$ (Full prior uncertainty).

- For realistic parameter values learning about β^i is very slow (Guvenen 2007).

A Life Cycle Model

- A standard life-cycle model of consumption-savings choice (CRRA utility, borrowing constraints, retirement system).
- Information Structure. Recall: $y_t^i = \alpha^i + \beta^i t + z_t^i + \varepsilon_t^i$
  - Bayesian learning about (β^i, z_t^i) observing y_t^i and ε_t.
  - Cast learning as a Kalman filtering problem.
- Express the prior standard deviation as: $\sigma_{\beta,0} = \lambda \sigma_\beta$.
  - If $\lambda = 0 \quad \rightarrow \quad \sigma_{\beta,0} = 0 \quad$ (No prior uncertainty).
  - If $\lambda = 1 \quad \rightarrow \quad \sigma_{\beta,0} = \sigma_\beta \quad$ (Full prior uncertainty).
- For realistic parameter values learning about β^i is very slow (Guvenen 2007).

A Life Cycle Model

- A standard life-cycle model of consumption-savings choice (CRRA utility, borrowing constraints, retirement system).
- Information Structure. Recall: $y_t^i = \alpha^i + \beta^i t + z_t^i + \varepsilon_t^i$
  - Bayesian learning about (β^i, z_t^i) observing y_t^i and ε_t.
  - Cast learning as a Kalman filtering problem.
- Express the prior standard deviation as: $\sigma_{\beta,0} = \lambda \sigma_\beta$.
  - If $\lambda = 0 \quad \rightarrow \quad \sigma_{\beta,0} = 0$ (No prior uncertainty).
  - If $\lambda = 1 \quad \rightarrow \quad \sigma_{\beta,0} = \sigma_\beta$ (Full prior uncertainty).
- For realistic parameter values learning about β^i is very slow (Guvenen 2007).

A Life Cycle Model

- A standard life-cycle model of consumption-savings choice (CRRA utility, borrowing constraints, retirement system).
- Information Structure. Recall: $y_t^i = \alpha^i + \beta^i t + z_t^i + \varepsilon_t^i$
  - Bayesian learning about (β^i, z_t^i) observing y_t^i and ε_t.
  - Cast learning as a Kalman filtering problem.
- Express the prior standard deviation as: $\sigma_{\beta,0} = \lambda \sigma_\beta$.
  - If $\lambda = 0 \quad \rightarrow \quad \sigma_{\beta,0} = 0$ (No prior uncertainty).
  - If $\lambda = 1 \quad \rightarrow \quad \sigma_{\beta,0} = \sigma_\beta$ (Full prior uncertainty).
- For realistic parameter values learning about β^i is very slow (Guvenen 2007).

A Life Cycle Model

- A standard life-cycle model of consumption-savings choice (CRRA utility, borrowing constraints, retirement system).

- Information Structure. Recall: $y_t^i = \alpha^i + \beta^i t + z_t^i + \varepsilon_t^i$
  - Bayesian learning about (β^i, z_t^i) observing y_t^i and ε_t.
  - Cast learning as a Kalman filtering problem.

- Express the prior standard deviation as: $\sigma_{\beta,0} = \lambda \sigma_\beta$.
  - If $\lambda = 0 \quad \rightarrow \quad \sigma_{\beta,0} = 0$ (No prior uncertainty).
  - If $\lambda = 1 \quad \rightarrow \quad \sigma_{\beta,0} = \sigma_\beta$ (Full prior uncertainty).

- For realistic parameter values learning about β^i is very slow (Guvenen 2007).

A Life Cycle Model

- A standard life-cycle model of consumption-savings choice (CRRA utility, borrowing constraints, retirement system).
- Information Structure. Recall: $y_t^i = \alpha^i + \beta^i t + z_t^i + \varepsilon_t^i$
  - Bayesian learning about (β^i, z_t^i) observing y_t^i and ε_t.
  - Cast learning as a Kalman filtering problem.
- Express the prior standard deviation as: $\sigma_{\beta,0} = \lambda \sigma_\beta$.
  - If $\lambda = 0 \quad \rightarrow \quad \sigma_{\beta,0} = 0$ (No prior uncertainty).
  - If $\lambda = 1 \quad \rightarrow \quad \sigma_{\beta,0} = \sigma_\beta$ (Full prior uncertainty).
- For realistic parameter values learning about β^i is **very slow** (Guvenen 2007).

Identification

Simplifying assumptions for intuition:

- (i) quadratic utility, (ii) no borrowing constraints, (iii) $\varepsilon_t \equiv 0$, and (iv) y_t: level of income.

1. Optimal consumption choice:

$$\text{HIP:} \qquad \Delta C_t = \Pi_t \times \underbrace{\left(y_t^i - \left(\alpha^i + \widehat{\beta}_{t-1}^i t + \rho \widehat{z}_{t-1}^i\right)\right)}_{\xi_t^i}$$

2. If $\sigma_\beta^2 \equiv 0$, learning disappears $\rightarrow$ we get (certainty equivalent) permanent income model:

$$\text{RIP:} \qquad \Delta C_t = \Psi_t \times \eta_t$$

Identification

Simplifying assumptions for intuition:

- (i) quadratic utility, (ii) no borrowing constraints, (iii) $\varepsilon_t \equiv 0$, and (iv) y_t: level of income.

1. Optimal consumption choice:

$$\text{HIP:} \qquad \Delta C_t = \Pi_t \times \underbrace{\left(y_t^i - \left(\alpha^i + \widehat{\beta}_{t-1}^i t + \rho \widehat{z}_{t-1}^i\right)\right)}_{\xi_t^i}$$

2. If $\sigma_\beta^2 \equiv 0$, learning disappears $\rightarrow$ we get (certainty equivalent) permanent income model:

$$\text{RIP:} \qquad \Delta C_t = \Psi_t \times \eta_t$$

Identification

Simplifying assumptions for intuition:

- (i) quadratic utility, (ii) no borrowing constraints, (iii) $\varepsilon_t \equiv 0$, and (iv) y_t: level of income.

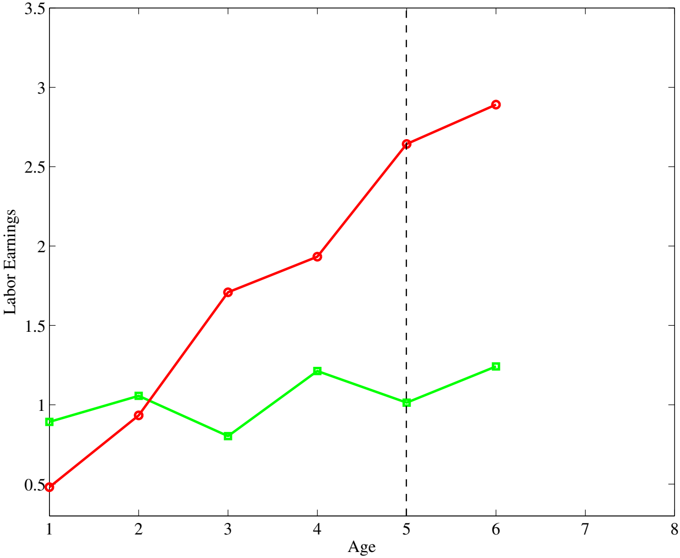
1. Optimal consumption choice:

$$\text{HIP:} \qquad \Delta C_t = \Pi_t \times \underbrace{\left(y_t^i - \left(\alpha^i + \widehat{\beta}_{t-1}^i t + \rho \widehat{z}_{t-1}^i\right)\right)}_{\xi_t^i}$$

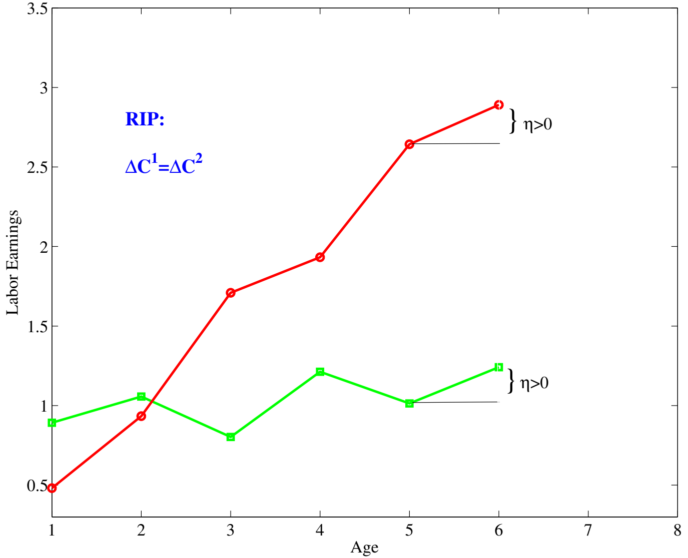
2. If $\sigma_\beta^2 \equiv 0$, learning disappears $\rightarrow$ we get (certainty equivalent) permanent income model:

$$\text{RIP:} \qquad \Delta C_t = \Psi_t \times \eta_t$$

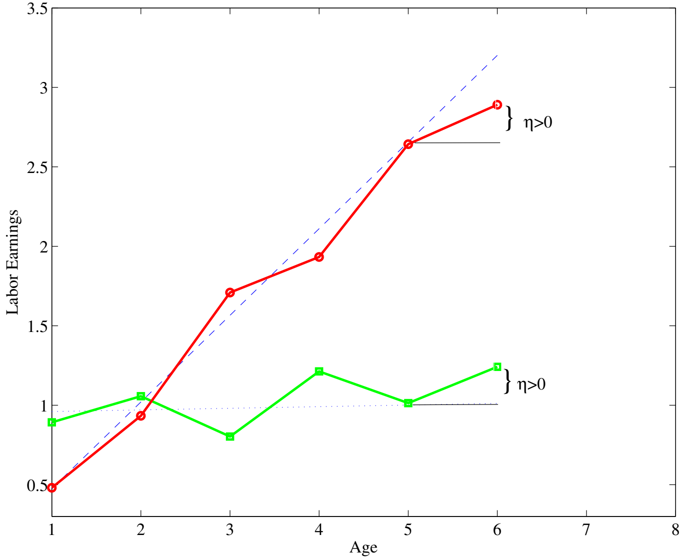
1. Identification from Consumption Changes



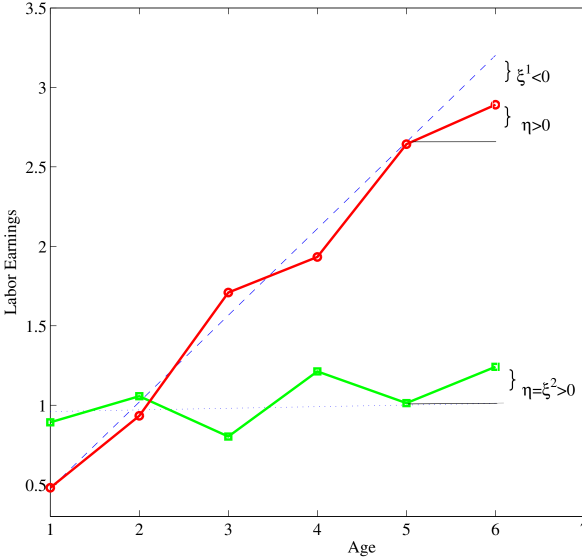
1. Identification from Consumption Changes



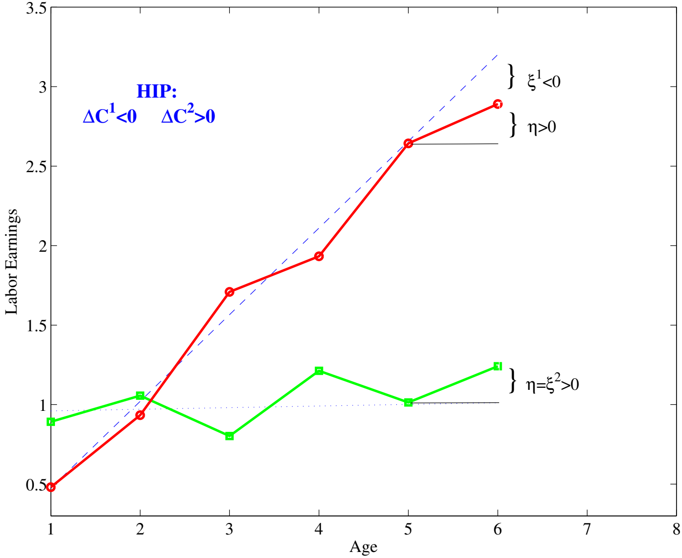
1. Identification from Consumption Changes



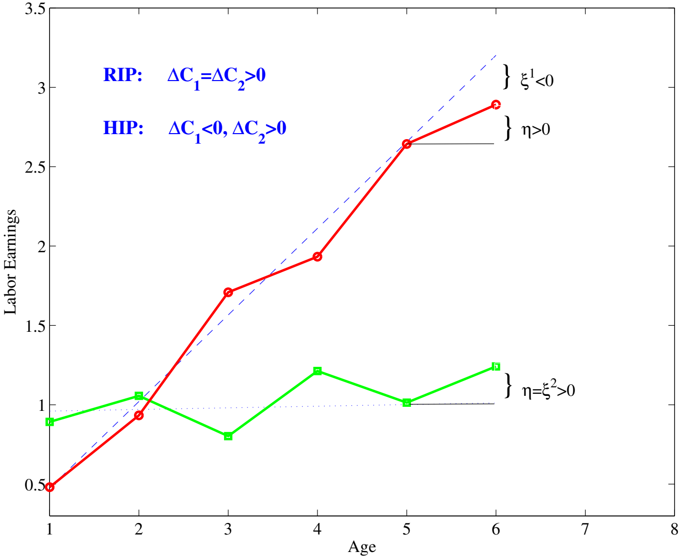
1. Identification from Consumption Changes



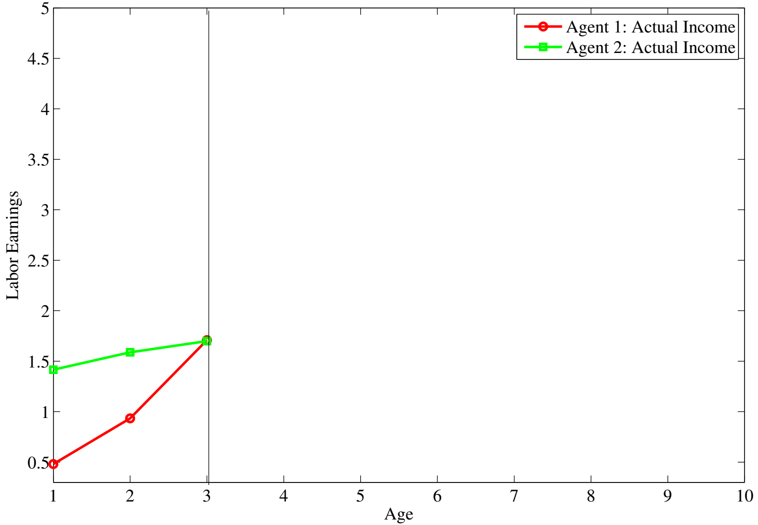
1. Identification from Consumption Changes



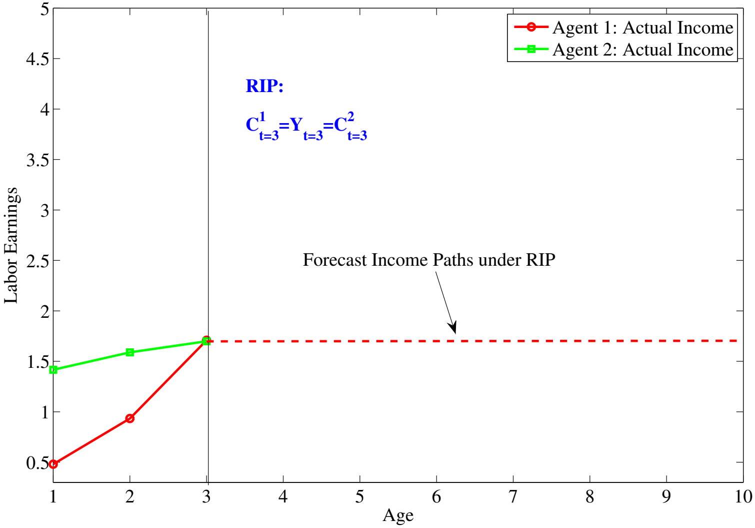
1. Identification from Consumption Changes



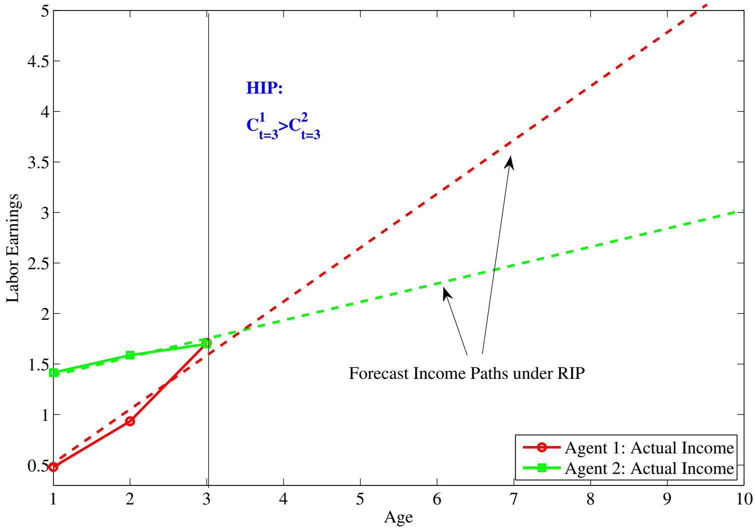
2. Identification from Consumption Levels



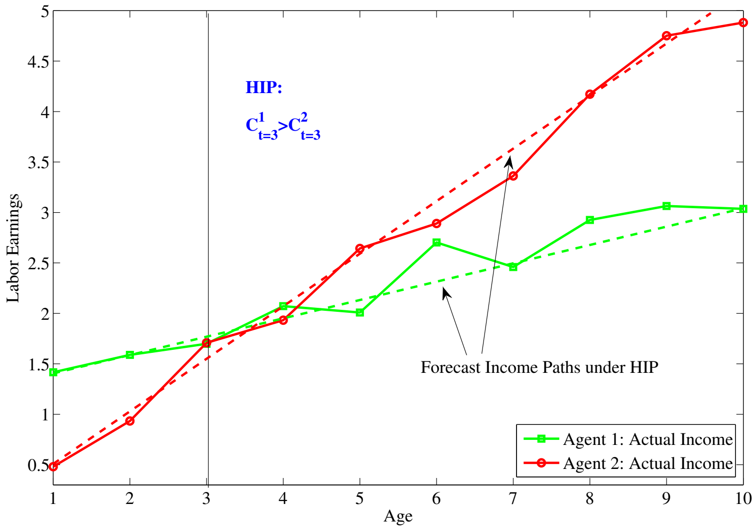
2. Identification from Consumption Levels



2. Identification from Consumption Levels



2. Identification from Consumption Levels



Indirect Inference

- We estimate the structural model using “indirect inference.”
- This approach provides a way to choose which moments to match.
- Imposes far few restrictions on the structural model than GMM.
- Monte Carlo analysis shows that the indirect inference method works very well.

Indirect Inference

- We estimate the structural model using “indirect inference.”
- This approach provides a way to choose which moments to match.
- Imposes far few restrictions on the structural model than GMM.
- Monte Carlo analysis shows that the indirect inference method works very well.

Why Indirect Inference?

The standard method since Hall and Mishkin (1982) is to derive structural equations explicitly and estimate them.

- For example, with (i) quadratic utility, (ii) no borrowing constraint, (iii) no retirement, and (iv) $Y_t = z_t + \varepsilon_t$, and $z_t = z_{t-1} + \eta_t$, we have:

$$\Delta C_t = \eta_t + \psi_t \varepsilon_t \qquad \psi_t \sim 0$$

- Persistence can be measured by $p \equiv \sigma_\eta / (\sigma_\eta + \sigma_\varepsilon)$

$$\Delta C_t = \Delta Y_t \qquad \text{if } p = 1 \quad \text{(permanent shocks)}$$
$$\Delta C_t = (\psi_t / 2) \times \Delta Y_t \qquad \text{if } p = 0 \quad \text{(i.i.d. shocks)}$$

- $\Longrightarrow$Response of consumption growth to income growth reveals persistence of income shocks.

Why Indirect Inference?

The standard method since Hall and Mishkin (1982) is to derive structural equations explicitly and estimate them.

- For example, with (i) quadratic utility, (ii) no borrowing constraint, (iii) no retirement, and (iv) $Y_t = z_t + \varepsilon_t$, and $z_t = z_{t-1} + \eta_t$, we have:

$$\Delta C_t = \eta_t + \psi_t \varepsilon_t \qquad \psi_t \sim 0$$

- Persistence can be measured by $p \equiv \sigma_\eta / (\sigma_\eta + \sigma_\varepsilon)$

$$\Delta C_t = \Delta Y_t \qquad \text{if } p = 1 \quad \text{(permanent shocks)}$$
$$\Delta C_t = (\psi_t / 2) \times \Delta Y_t \qquad \text{if } p = 0 \quad \text{(i.i.d. shocks)}$$

- $\Longrightarrow$Response of consumption growth to income growth reveals persistence of income shocks.

Why Indirect Inference?

The standard method since Hall and Mishkin (1982) is to derive structural equations explicitly and estimate them.

- For example, with (i) quadratic utility, (ii) no borrowing constraint, (iii) no retirement, and (iv) $Y_t = z_t + \varepsilon_t$, and $z_t = z_{t-1} + \eta_t$, we have:

$$\Delta C_t = \eta_t + \psi_t \varepsilon_t \qquad \psi_t \sim 0$$

- Persistence can be measured by $p \equiv \sigma_\eta / (\sigma_\eta + \sigma_\varepsilon)$

$$\Delta C_t = \Delta Y_t \qquad \text{if } p = 1 \quad \text{(permanent shocks)}$$
$$\Delta C_t = (\psi_t / 2) \times \Delta Y_t \qquad \text{if } p = 0 \quad \text{(i.i.d. shocks)}$$

- $\Longrightarrow$Response of consumption growth to income growth reveals persistence of income shocks.

Why Indirect Inference?

The standard method since Hall and Mishkin (1982) is to derive structural equations explicitly and estimate them.

- For example, with (i) quadratic utility, (ii) no borrowing constraint, (iii) no retirement, and (iv) $Y_t = z_t + \varepsilon_t$, and $z_t = z_{t-1} + \eta_t$, we have:

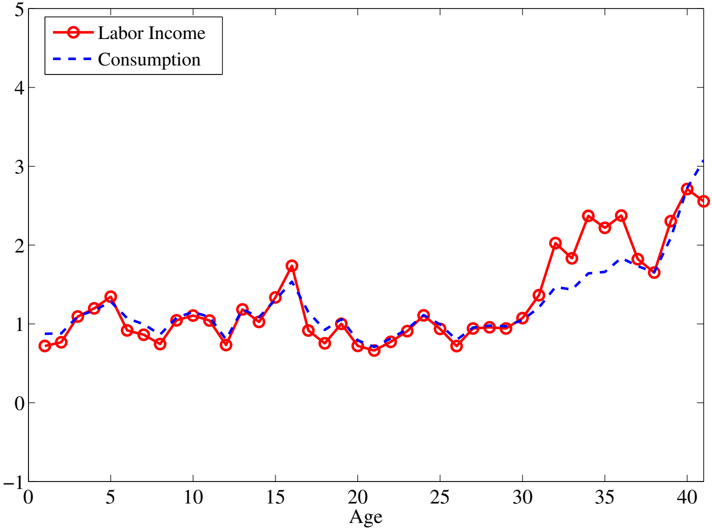
$$\Delta C_t = \eta_t + \psi_t \varepsilon_t \qquad \psi_t \sim 0$$

- Persistence can be measured by $p \equiv \sigma_\eta / (\sigma_\eta + \sigma_\varepsilon)$

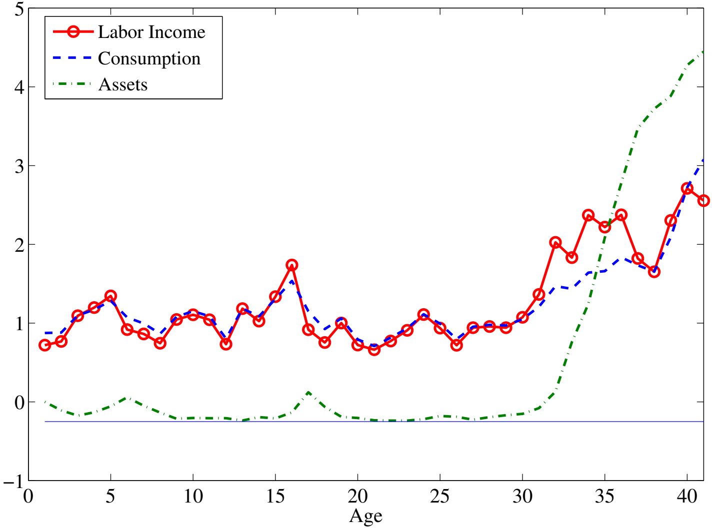
$$\Delta C_t = \Delta Y_t \qquad \text{if } p = 1 \quad \text{(permanent shocks)}$$
$$\Delta C_t = (\psi_t / 2) \times \Delta Y_t \qquad \text{if } p = 0 \quad \text{(i.i.d. shocks)}$$

- $\Longrightarrow$Response of consumption growth to income growth reveals persistence of income shocks.

An Example



An Example: Binding Constraints



A Feasible Auxiliary Model:

$$\Delta C_t = \Pi_t \times \underbrace{\left(Y_t^i - \left(\alpha + \widehat{\beta}_{t-1}^i t + \rho \widehat{z}_{t-1}^i\right)\right)}_{\widehat{\xi}_t} \tag{1}$$

- This regression is not feasible, so approximate with

$$\begin{aligned} c_t = {} & a_0 + a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t+1} + a_4 y_{t+2} \\ & + a_5 \overline{y}_{1,t-3} + a_6 \overline{y}_{t+3,T} + a_7 \overline{\Delta y}_{1,t-3} + a_8 \overline{\Delta y}_{t+3,T} \\ & + a_9 c_{t-1} + a_{10} c_{t-2} + a_{11} c_{t+1} + a_{12} c_{t+2} + error \end{aligned}$$

  where $c_t \equiv \log(C_t)$.

- Add a second regression where y_t is the dependent variable. Use the same income regressors above.

A Feasible Auxiliary Model:

$$\Delta C_t = \Pi_t \times \underbrace{\left(Y_t^i - \left(\alpha + \widehat{\beta}_{t-1}^i t + \rho \widehat{z}_{t-1}^i\right)\right)}_{\widehat{\xi}_t} \tag{1}$$

- This regression is not feasible, so approximate with

$$\begin{aligned} c_t = & \, a_0 + a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t+1} + a_4 y_{t+2} \\ & + a_5 \overline{y}_{1,t-3} + a_6 \overline{y}_{t+3,T} + a_7 \overline{\Delta y}_{1,t-3} + a_8 \overline{\Delta y}_{t+3,T} \\ & + a_9 c_{t-1} + a_{10} c_{t-2} + a_{11} c_{t+1} + a_{12} c_{t+2} + error \end{aligned}$$

  where $c_t \equiv \log(C_t)$.

- Add a second regression where y_t is the dependent variable. Use the same income regressors above.

A Feasible Auxiliary Model:

$$\Delta C_t = \Pi_t \times \underbrace{\left(Y_t^i - \left(\alpha + \widehat{\beta}_{t-1}^i t + \rho \widehat{z}_{t-1}^i\right)\right)}_{\widehat{\xi}_t} \tag{1}$$

- This regression is not feasible, so approximate with

$$\begin{aligned} c_t = {} & a_0 + a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t+1} + a_4 y_{t+2} \\ & + a_5 \overline{y}_{1,t-3} + a_6 \overline{y}_{t+3,T} + a_7 \overline{\Delta y}_{1,t-3} + a_8 \overline{\Delta y}_{t+3,T} \\ & + a_9 c_{t-1} + a_{10} c_{t-2} + a_{11} c_{t+1} + a_{12} c_{t+2} + error \end{aligned}$$

  where $c_t \equiv \log(C_t)$.

- Add a second regression where y_t is the dependent variable. Use the same income regressors above.

Monte Carlo Results

	True Value	Estim. mean	Estim. std
Income Processes Parameters:			
σ_α	0.284	0.279	0.025
σ_β	1.852	1.815	0.176
$corr_{\alpha\beta}$	–0.162	–0.146	0.148
ρ	0.754	0.758	0.025
σ_η	0.196	0.196	0.005
σ_ε	0.004	0.030	0.023
Economic Model Parameters:			
λ	0.345	0.348	0.084
δ	0.950	0.950	0.002
ψ	0.874	0.869	0.096
Measurement Errors:			
σ_y	0.147	0.142	0.007
σ_c	0.356	0.356	0.002
σ_{c_0}	0.428	0.422	0.009

Results

	Estimate	Std Error	
ρ	0.754	0.025	persistence
σ_η	0.189	0.005	std. dev. of perm. shock
σ_ε	0.004	0.021	std. dev. of transit. shock
$\sigma_\beta(\times 100)$	1.852	0.188	profile heterogeneity
λ	0.345	0.071	prior uncertainty
δ	0.950	0.001	time discount factor
ψ	0.874	0.083	borrowing constr.
σ_{u^y}	0.145	0.010	iid meas. error in income
σ_{u^c}	0.355	0.002	iid meas. error in cons.

Results

	Estimate	Std Error	
ρ	0.754	0.025	persistence
σ_η	0.189	0.005	std. dev. of perm. shock
σ_ε	0.004	0.021	std. dev. of transit. shock
$\sigma_\beta(\times 100)$	1.852	0.188	profile heterogeneity
λ	0.345	0.071	prior uncertainty
δ	0.950	0.001	time discount factor
ψ	0.874	0.083	borrowing constr.
σ_{u^y}	0.145	0.010	iid meas. error in income
σ_{u^c}	0.355	0.002	iid meas. error in cons.

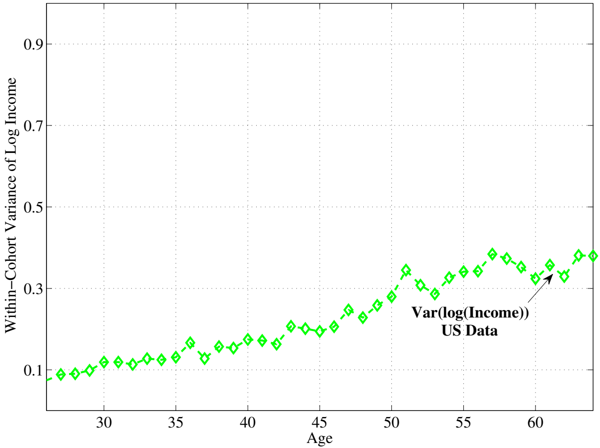
Results

	Estimate	Std Error	
ρ	0.754	0.025	persistence
σ_η	0.189	0.005	std. dev. of perm. shock
σ_ε	0.004	0.021	std. dev. of transit. shock
$\sigma_\beta(\times 100)$	1.852	0.188	profile heterogeneity
λ	0.345	0.071	prior uncertainty
δ	0.950	0.001	time discount factor
ψ	0.874	0.083	borrowing constr.
σ_{u^y}	0.145	0.010	iid meas. error in income
σ_{u^c}	0.355	0.002	iid meas. error in cons.

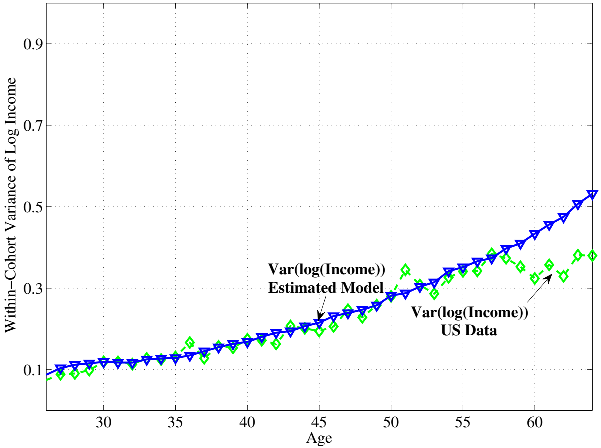
Results

	Estimate	Std Error	
ρ	0.754	0.025	persistence
σ_η	0.189	0.005	std. dev. of perm. shock
σ_ε	0.004	0.021	std. dev. of transit. shock
$\sigma_\beta(\times 100)$	1.852	0.188	profile heterogeneity
λ	0.345	0.124	prior uncertainty
δ	0.950	0.001	time discount factor
ψ	0.874	0.083	$(a_{25} = 0.33,\ a_{55} = 0.53)$
σ_{u^y}	0.145	0.010	iid meas. error in income
σ_{u^c}	0.355	0.002	iid meas. error in cons.

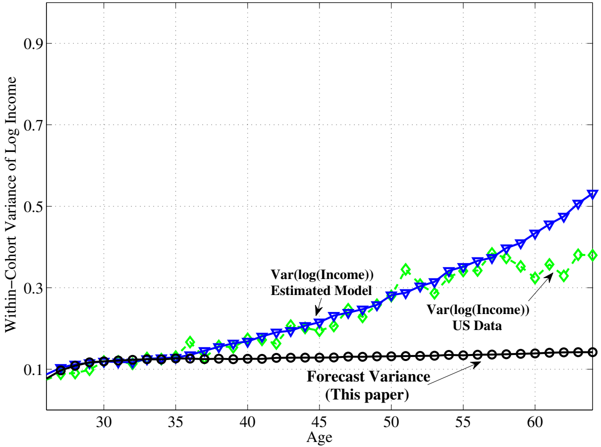
Quantifying Life Cycle Income Risk



Quantifying Life Cycle Income Risk

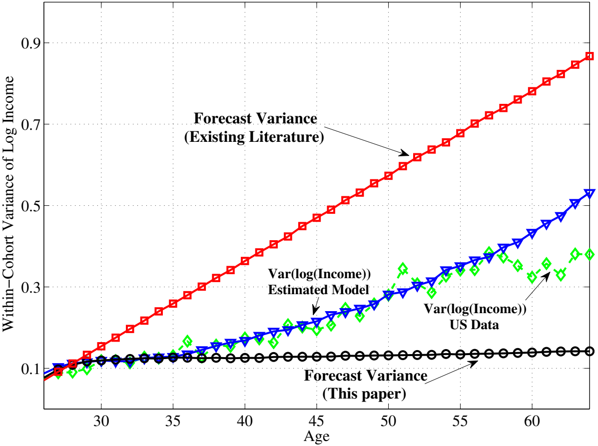


Quantifying Life Cycle Income Risk



Conclusion 1: Less than 1/3 of cross-sectional income dispersion at retirement represents risk—the rest is known heterogeneity.

Quantifying Life Cycle Income Risk



Conclusion 2: Existing estimates in the literature overstate labor income risk by a factor of 3 to 5.