Intergenerational Elasticity of Life-cycle Earnings Growth/Risk

ADITYA ALADANGADY, FEDERAL RESERVE BOARD*

[PRELIMINARY]

*The views expressed here are those of the authors and do not necessarily reflect those of the Board of Governors or the Federal Reserve System.
Motivation and Literature

How important is family background in determining a child’s earning prospects?
- Measurement error attenuates estimates. Especially tough when shocks are persistent!
  - Variation in earnings over life-cycle further complicate the matter
  - Mechanisms: Education, Neighborhoods, etc.
  - Literature tends to focus on elasticity of permanent income level between parents/children

What explains cross-sectional variance of earnings over life-cycle?
- Cross-sectional variance of earnings rises over life-cycle – heterogeneous profiles vs persistent shocks
- Timing of earnings and knowledge about earnings potential matter for spending:
  - High growth with little financial buffer → inability to smooth consumption over lifecycle
  - Lack of knowledge about future earnings growth → consumption reflects updating beliefs about earnings
- Differences in initial conditions at age 23 determine most of earnings variance (Huggett, Ventura, Yaron, 2011)
  - This view may not be robust to age-varying heteroskedasticity in shocks (Sabelhaus & Song, 2009, 2010)
Overview

Standard IGE estimates using “permanent income” are a combination of level and growth elasticities

Goal: Estimate how earnings profiles of children are related to parents.

Model/estimate a parametric empirical process of earnings
- Explicitly control for measurement error and shocks to earnings when worker is observed (standard)
- Allows for intergenerational elasticity in both level and growth of earnings profile (new)
- In progress: Expand to allow for intergenerational transfer of household-specific risk

Results suggest heterogeneity in earnings growth determined by dad’s earnings
- “True” IGE may vary over lifecycle because earnings early and late in life are driven more by parents
- Supportive evidence that some variation life-cycle earnings growth is known ex ante
An Empirical Process of Earnings

Let log real earnings for individual $i$ at age $h$, time $t$ be given by:

$$y_{ht}^i = \mu_{ht} + (a_i + b_i h) + z_{ht}^i + \epsilon_{ht}^i$$

- **Common, time-varying, age-specific profile:** $\mu_{ht}$
  - Cohort-specific life-cycle profiles allows changes in return to experience (Katz & Autor, 1999)
  - Alternative specs also allowing for changes in return to education (Katz & Murphy, 1992)

- **Ex ante heterogeneous income profiles over life-cycle:** $a_i + b_i h$,
  - $E[a_i, b_i] = [0,0]$, $Var(a_i, b_i) = [\sigma_a^2, \sigma_{a\beta}, \sigma_{a\beta\beta}, \sigma_{\beta}^2]$,
  - $a_i$ is level shift from cohort average at start of career
  - $b_i$ is how earnings moves away from cohort average as worker ages

- **AR(1) shock and IID shock:**
  - AR(1): $z_{ht}^i = \rho z_{ht-1}^i + \eta_{ht}^i$, $Var(\eta_{ht}^i) = \phi_t \sigma_{\eta}^2$
  - IID shock: $\epsilon_{ht}^i$, $Var(\epsilon_{ht}^i) = \pi_t \sigma_{\epsilon}^2$
  - $\phi_t$ and $\pi_t$ allows variance of shock to change over time
  - includes persistent/iid measurement error
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$$y^i_{ht} = \mu_{ht} + (a_i + b_i h) + z^i_{ht} + \varepsilon^i_{ht}$$

- Common, time-varying, age-specific profile: $\mu_{ht}$
- Heterogeneous income profiles over life-cycle: $a_i + b_i h$
- AR(1) shock and IID shock (including measurement error)

Individuals are related to parents via $(a_i, b_i)$

$$a_{son} = R_a a_{father} + u^a_{son}$$ $$b_{son} = R_b b_{father} + u^b_{son}$$

- Note: Other channels may be possible – ie, parents determine initial shock $z_{0t}$ which fades
What does naïve OLS yield?

Common way of estimating IGE is to regress son’s earnings on father, controlling for age/time of observation:

$$y_{ht}^{son} = Ry_{h't'}^{father} + \gamma [\mu_{ht}, \mu_{h't'}] + \nu$$

Probability limit of $\hat{R}$ is given by:

$$\hat{R} \xrightarrow{p} \frac{R_a \text{var}(\alpha) + R_b \text{var}(\beta)h^2 + \text{cov}(\alpha, \beta)(R_a + R_b)h}{\text{var}(\alpha) + \text{var}(\beta)h'^2 + 2\text{cov}(\alpha, \beta)h' + \text{var}(z_{h'}) + \text{var}(\epsilon)}$$

Estimate is attenuated by standard errors-in-variables issue (Solon, 1992 and others)
- Not simply solved by time-aggregation if errors are persistent (Mazumdar, 2001)
- Jointly estimate parameters of income process to account for bias

Even adjusting for attenuation yields weighted average of level and growth rate when $(\text{var}(\beta) > 0)$
- Human capital/learning ability transfer implies link between $(\alpha, \beta)$ for parents/children

OLS by Age
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\( \text{OLS by Age} \)
Why not run OLS age by age?
A More Structural Approach

Goal: Address biases and decompose $R$ into pieces $R_\alpha$ and $R_\beta$

- To what extend do parents transfer initial earnings level $\alpha$
- To what extent do parents transfer learning ability, education, etc in the form of $\beta$?

Doing this requires estimating variances of $\alpha_i, \beta_i, z_{ht}^i, \varepsilon_{ht}^i$ jointly


- Remove common component with age/time effects
- Minimum Distance Estimator using covariance structure of data and empirical model

Citations above focus on earning process alone

- Contribution here is estimating link to parents
PSID Data

Identification requirements:
- Parent-child match
- Long labor histories: $\beta_i$, $z_{ht}^i$, and $\epsilon_{ht}^i$ have differing effects at long lags

Panel Study of Income Dynamics
- Sampling frame explicitly related to family structure - children of respondents also followed
- Longitudinal panel from 1968 – 2015 (almost 50 years)

Would like to focus on workers with some labor force attachment
- Need long labor history to differentiate between AR1 shocks and profiles
- Not explicitly modeling labor supply decision, so focus on strong labor force attachment
Sample Selection

Sample selection criteria:
- Male household heads ages 20 to 64 from main SRC sample
- “Attached” to labor force for 10/20 years (based on hours, hourly wages, and earnings)
- Valid observations with no labor earnings are coded to $1
- Individuals without validly matched parents are retained to estimate income process

10yr attachment sample: 4,661 workers and 1,386 matched father-son pairs
20yr attachment sample: 2,230 workers and 431 matched father-son pairs
Estimating Structural Model

Let the common time-age profile be characterized by Mincer-type regression:

\[ \mu_{ht} = m_0^t + m_1^t h + m_2^t h^2 + m_3^t h^3 \]

- Allow returns to experience to vary over time (Katz & Autor, 1999)
- Returns to education absorbed by \( \beta_i \), since education groups are pooled in baseline

Estimates yield residual log real earnings given by:

\[ \tilde{y}_{ht} = y_{ht} - \mu_{ht} = (a_i + b_i h) + z_{ht} + \varepsilon_{ht} \]

- Estimation error from first stage will be absorbed into measurement error in \( z \) and \( \varepsilon \)
Model Covariance Structure

Given the parametric model for $\tilde{y}_{ht}^i$:

$$\tilde{y}_{ht}^i = (a_i + b_i h) + z_{ht}^i + \varepsilon_{ht}^i$$

The auto-covariance of log earnings is:

$$E[\tilde{y}_{ht}^i \times \tilde{y}_{h-\ell,t-\ell}^i] = \sigma_\alpha^2 + \sigma_{\alpha\beta}(2h - \ell) + \sigma_\beta^2 h(h - \ell) + \rho^\ell \text{var}(z_{h-\ell,t-\ell}^i) + 1(\ell = 0)\pi_t^2 \sigma_\varepsilon^2$$

where

$$\text{var}(z_{ht}^i) = \rho^2 \text{var}(z_{h-1,t-1}^i) + \phi_t^2 \sigma_\eta^2$$

$$\text{var}(z_{0t}^i) = \phi_0^2 \sigma_\eta^2$$

$$\text{var}(z_{h0}^i) = \phi_0^2 \sigma_\eta^2 \sum_{j=0}^{h-1} \rho^{2j}$$
Given the parametric model for $\tilde{y}^i_{ht}$:

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The auto-covariance of log earnings is:

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$$\text{var}(z^i_{h0}) = \phi^2 \sigma^2_\eta \sum_{j=0}^{h-1} \rho^{2j}$$

No AR shock inherited

Variance was stable before 1968
Model Covariance Structure

Model also implies intergenerational covariance.

Using intergenerational link:

\[ a_i = R_a a_{father(i)} + u_i^a \]
\[ b_i = R_b b_{father(i)} + u_i^b \]

Covariance of son of age \( h \) at time \( t \) with his father at age \( h' \) at time \( t' \) is:

\[ E[\tilde{y}_{ht}^i * \tilde{y}_{h',t'}^{father(i)}] = R_\alpha (\sigma_\alpha^2 + \sigma_{\alpha\beta} h') + R_\beta (\sigma_{\beta}^2 hh' + \sigma_{\alpha\beta} h) \]

Identification of \( R_\alpha \) and \( R_\beta \) relies on how intergenerational covariance depends on father and son’s ages \( h' \) and \( h \)
Minimum Distance Estimator

Sample corollaries of covariances are used to construct moments:

\[
\frac{1}{N_1} \sum_i \tilde{y}_{ht}^i \ast \tilde{y}_{h-\ell,t-\ell}^i - g_1(\theta; h, t, l) = 0
\]

\[
\frac{1}{N_2} \sum_i \tilde{y}_{ht}^i \ast \tilde{y}_{h',t}'^{father(i)} - g_2(\theta; h, h') = 0
\]

- \(g_1(\cdot)\) and \(g_2(\cdot)\) denote auto-covariance and intergenerational covariance.
- \(\theta\) is vector of \(8 + 2T\) parameters: \([\sigma_a^2, \sigma_b^2, \sigma_{ab}, \rho, \sigma_\eta^2, \sigma_\epsilon^2, \phi_t, \pi_t, R_a, R_b]\)

One-step (equally-weighted) GMM estimate of parameter vector \(\theta\)

- Sample size is likely too small for optimally-weighted GMM to perform well.
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Model Fit

20yr LF

Attachment
Age x Time x Educ
Components of variance over lifecycle
Components of variance over lifecycle
Implied IGE of Income Level by Age
What might this tell us about earnings?

OLS estimates of the IGE are in the 0.2-0.4 ballpark whereas GMM estimates are closer to 0.35-0.6.

Estimates also imply parents contribute to growth in earnings more than levels
- Possibly suggests the mechanism works through learning ability or human capital with returns later in life

What does this tell us about consumption?
- Some amount of lifetime earnings is knowable ex ante (evidence for “HIP” earnings process)
- Quantitatively matches “indirect” approach to backing out priors as in Guvenen (2007)
- Suggests covariance between consumption and income over life-cycle is more driven by constraints rather than information
Conclusions

Overall IGE can be decomposed into level and growth

Estimate structural model using the PSID
- Accounts for measurement error and transitory shocks that may lead to attenuation bias
- Uses covariance structure to separately recover level and growth components of IGE

Preliminary results suggest
- There is heterogeneity in life-cycle profiles
- Individual-specific earnings growth is tied to parent, with less link in starting level
- Implies higher standard IGE later in life