

# **Earnings and Consumption Dynamics: A Nonlinear Panel Data Framework - By Arellano, Blundell and Bonhomme**

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# Motivation

- New framework for estimating nonlinear earning dynamics  
     $\implies$  Implications for consumption (variation)
- New method for studying persistence of shocks to income

# Motivation

- New framework for estimating nonlinear earning dynamics  
⇒ Implications for consumption (variation)
- New method for studying persistence of shocks to income

## Why should we care

- Policy Relevance
  - a) Persistence affects income inequality
  - b) Insurance and taxation
- Methodology Contribution

# Overview

Canonical Model

The Model

Identification

Estimation

Results

Conclusion

# Canonical Model

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# Canonical Model

Earnings:  $y_{it} = \eta_{it} + \epsilon_{it}$

- $\eta_{it}$  - persistent component,  $\eta_{it} = \eta_{i,t-1} + \nu_{it}$
- $\eta_{it}$  - indep. of conditional quantile  $\tau$
- $\epsilon_{it}$  - transitory component, i.i.d.
- $\nu_{it}$  - independent of  $\eta_{i,t-1}$

$\implies$  Random walk and independent shock

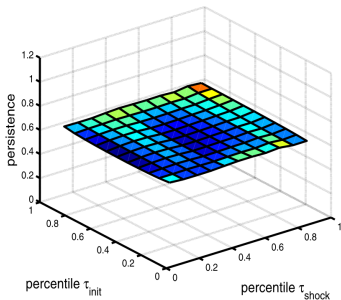
$$\implies \frac{\partial \eta_{it}}{\partial \eta_{i,t-1}} = \rho_t(\eta_{i,t-1}) = 1$$

Simulate Life Cycle Model: Given policy functions, get assets and consumption

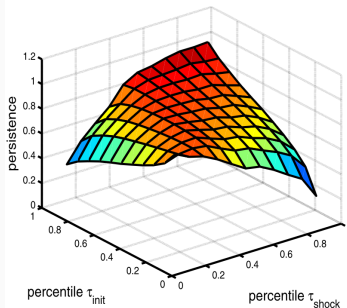
$\implies$  DONE

# Canonical Model

(c) Earnings, canonical model



(a) Earnings, PSID data



Are linear models appropriate? Precautionary savings, borrowing constraints?

# The Model

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# Earnings

Earnings:  $y_{it} = \eta_{it} + \epsilon_{it}$

Think in Quantiles: Given  $\eta_{i,t-1}$  every quantile has different persistence (Nonlinear)

- $\eta_{it}$  - persistent component,  $\eta_{it} = Q_t(\eta_{i,t-1}, u_{it})$ ,  
where  $Q_t(\eta_{i,t-1}, \tau) = \tau$ -th quantile of  $\eta_{it} | \eta_{i,t-1} \forall \tau \in (0, 1)$
- $(u_{it} | \eta_{i,t-1}) \sim U(0, 1)$
- $\epsilon_{it}$  - transitory component, i.i.d.

$$\implies \frac{\partial Q_t(\eta_{i,t-1}, \tau)}{\partial \eta} = \rho_t(\eta_{i,t-1}, \tau), \text{ depends on size and sign of } u_{it}$$

$$\text{On average: } \rho_t(\tau) = \mathbb{E}\left[\frac{\partial Q_t(\eta_{i,t-1}, \tau)}{\partial \eta}\right]$$

Intuitive:  $\rho$ 's measure *persistence of earnings history*

# Consumption

Distributions known, today's realizations known

(1) Assets:  $A_{it} = (1 + r)A_{i,t-1} + Y_{i,t-1} - C_{i,t-1}$

(2) Log earnings:  $\ln Y_{it} = \kappa_t + \eta_{it} + \epsilon_{it}$

(3)  $V_t(A_{it}, \eta_{it}, \epsilon_{it}) =$   
 $\max_{C_{it}} u(C_{it}) + \beta \mathbb{E}_t[V_{t+1}(A_{i,t+1}, \eta_{i,t+1}, \epsilon_{i,t+1})]$

Important now: Conditional distribution of  $\eta_{i,t+1}$  given  $\eta_{i,t}$

Solving for  $C_{it}$  using (1), (2) and (3)

$$\implies C_{it} = G_t(A_{it}, \eta_{it}, \epsilon_{it})$$

But how to get there? Get it directly from the data!

## Bringing it to the data

- Log consumption:  $g_t(a_{it}, \eta_{it}, \epsilon_{it}, \nu_{it})$ , with  $\nu_{it}$  being unobservables
- Net assets:  $a_{it} = h_t(a_{i,t-1}, c_{i,t-1}, y_{i,t-1}, \eta_{i,t-1}, \nu_{it})$ , with  $\nu_{it}$  i.i.d. and independent
- Average Consumption:  $\mathbb{E}[g_t(a, \eta, \epsilon, \nu_{i,t})]$ , given earnings, assets
- Derivative at the average:  $\phi_t(a, \eta, \epsilon) = \mathbb{E} \frac{\partial g_t(a, \eta, \epsilon, \nu_{i,t})}{\partial \eta}$

# Identification

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Not the central point of the paper, but...

- Nonlinear Model with latent variable  $(\eta_{it}, \epsilon_{it})$
- Goal: Identify joint distributions of  $\eta_i$ 's,  $\epsilon_i$ 's from earnings data
- Crucial assumption: The distributions of  $(y_{it}|y_{i,t-1})$  and  $(\eta_{it}|y_{i,t-1})$  both need to satisfy **completeness**
- Intuition: If we only use  $y_{i,t-1}$  to estimate  $h(y_{it})$ ,  $\mathbb{E}[h(y_{it})|y_{i,t-1}] = 0$  the only instance where this is optimal is if  $h = 0$ . Otherwise, we gain information by adding a non-noise variable, i.e.  $\eta_{i,t-1}$

$\implies \eta_{i,t}$  serially correlated

Identification strategy:

- Note:  $f(a_1|y) = \int f(a_1|\eta_1)f(\eta_1|y)d\eta_1$
- Start with first period. Get initial conditional distribution  $f(a_1|y) = \mathbb{E}[f(a_1|\eta_{i1})|y_i = y]$  as  $\epsilon_{it}$  and  $u_{it}$  independent.
- Next,  $f(c_1|a_1, y) = \mathbb{E}[f(c_1|a_{i1}, \eta_{i1}, y_{i1})|a_{i1} = a_1, y_i = y]$ , as  $\nu_{it}$  independent
- Next, do the same with  $t = 2$  and apply Bayesian updating

# Estimation

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(1) Use Quantile regression to jointly estimate

- $Q_t(\cdot, \cdot), \epsilon_{it}, \eta_1$
- $Q_t(\eta_{i,t-1}, \tau) = \sum_{k=0}^K a_k^Q(\tau) \phi_k(\eta_{i,t-1}, age_{it})$
- $Q_t(age_{it}, \tau) = \sum_{k=0}^K a_k^A(\tau) \phi_k(age_{it})$
- In practice: Use Hermite Polynomials (low order)

(2) Given these, estimate c and a

- $g_t(a_{it}, \eta_{it}, \epsilon_{it}, \tau) = \sum_{k=1}^K b_k^g \tilde{\phi}_k(a_{it}, \eta_{it}, \epsilon_{it}, age_{it}) + b_0^g(\tau)$
- $Q_t(\eta_{i,1}, age_{i1}, \tau) = \sum_{k=0}^K b_k^a(\tau) \tilde{\phi}_k(\eta_{i,1}, age_{i1})$
- $h_t(a_{i,t-1}, c_{i,t-1}, y_{i,t-1}, \eta_{i,t-1}, \tau) = \sum_{k=1}^K b_k^h \tilde{\phi}_k(a_{i,t-1}, c_{i,t-1}, y_{i,t-1}, \eta_{i,t-1}, age_{it}) + b_0^h(\tau)$

Note: All estimates will depend on age and quantile

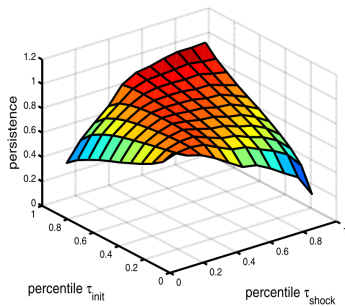


# Results

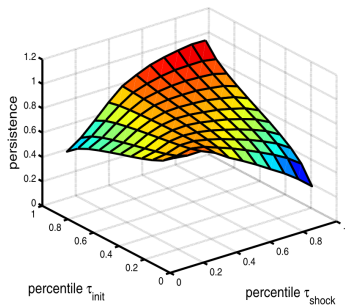
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# Persistence of Earnings

(a) Earnings, PSID data

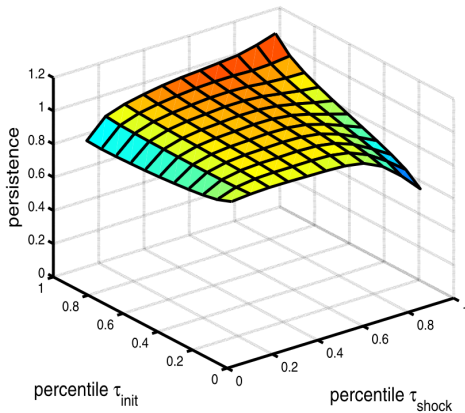


(b) Earnings, nonlinear model



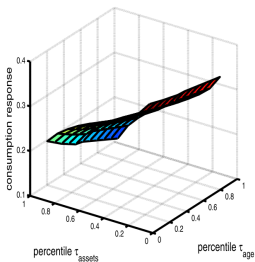
## Persistence of $\eta$ - Simulated Data

(d) Persistent component  $\eta_{it}$ , nonlinear model

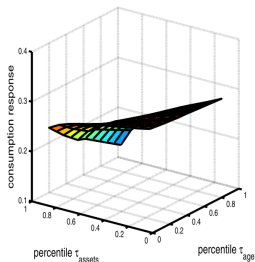


# Consumption Responses

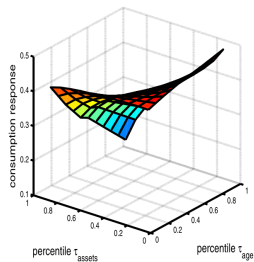
(a) Response to earnings  
PSID data



(b) Response to earnings  
Nonlinear model



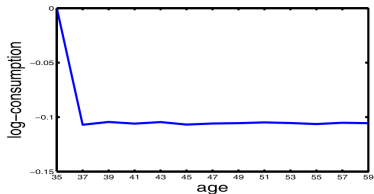
(c) Response to  $\eta_{it}$   
Nonlinear model



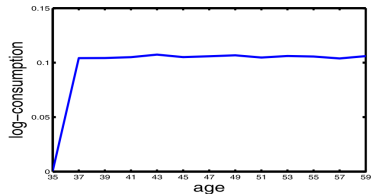
# Impulse Response Function - Canonical Model

Canonical model

(g)  $\tau_{shock} = .1$



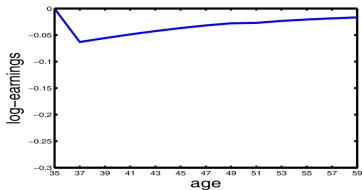
(h)  $\tau_{shock} = .9$



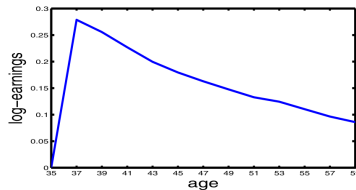
# Impulse Response Function - Nonlinear Model

$$\tau_{init} = .1$$

(a)  $\tau_{shock} = .1$

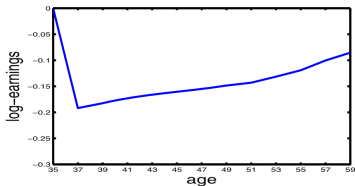


(b)  $\tau_{shock} = .9$

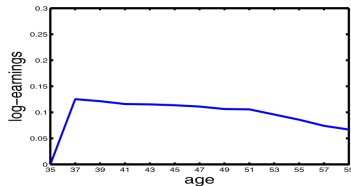


$$\tau_{init} = .9$$

(e)  $\tau_{shock} = .1$



(f)  $\tau_{shock} = .9$



## Conclusion

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1. We can now model nonlinear persistence
2. Simulation-based quantile regression method and conditions for Nonparametric identification
3. Consumption responses vary
4. Asymmetric persistence pattern, more unusual less persistent