

WHAT DO DATA ON MILLIONS OF U.S. WORKERS SAY ABOUT LIFE CYCLE INCOME RISK?¹

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Workshop on the Estimation of Economic Models of Earnings Dynamics
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¹The findings and conclusions expressed are solely those of the authors and do not represent the views of Federal Reserve Board, Federal Reserve Bank of New York or SSA.

EARNINGS DYNAMICS: OPEN QUESTIONS

1. How **big** are earnings shocks?
2. How **persistent** are they?
 - Do positive and negative shocks have similar persistence?
3. How do the properties of shocks vary **over the life cycle**?
 - e.g., standard deviation, skewness, kurtosis, etc.
4. Are shocks **log normally** distributed? How about higher order moments?

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1. Small survey-based data sets, e.g., the PSID
 - between 500 to 2000 individuals per year
2. Employ covariance matrix estimation (CME), developed for a data-constrained environment

This paper:

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 - as many as 5,000,000 individuals per year.
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- **Representative sample of US males covering 34 years: 1978 to 2011**
- Salary and wage workers (from W2 forms)
- Individuals **aged 25–60**
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 - **Very large sample size** (200+ million observations)
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- CME method was developed for a severely data-constrained environment.
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Uses a unique, confidential, and very large administrative dataset to:

1. **Document** new empirical facts on life cycle earnings dynamics
2. **Estimate** lifecycle labor income risk
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NEW EMPIRICAL FACTS

FOUR SETS OF EMPIRICAL FACTS

1. Average income growth over the life cycle
2. Cross-sectional moments of earnings growth
3. Short- and long-run dynamics of income growth
4. Scarring Effects of Long-Term Unemployment
5. Distribution of Lifetime Income (skip today)

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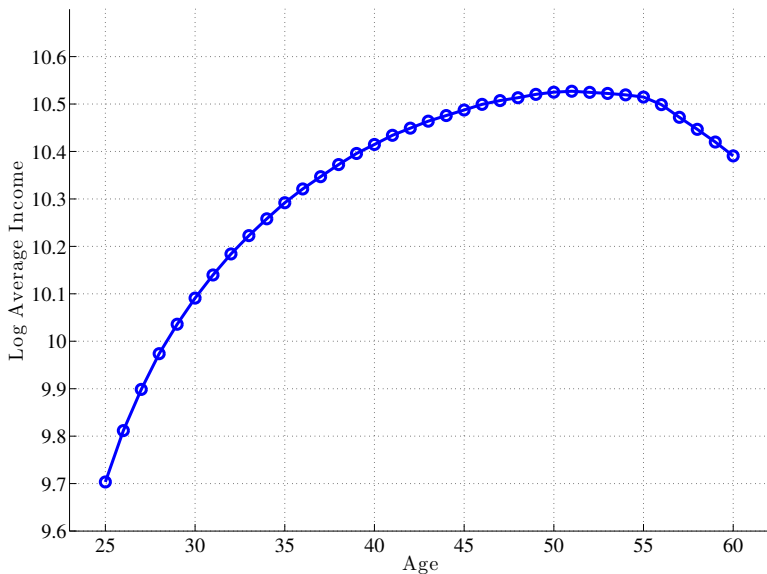
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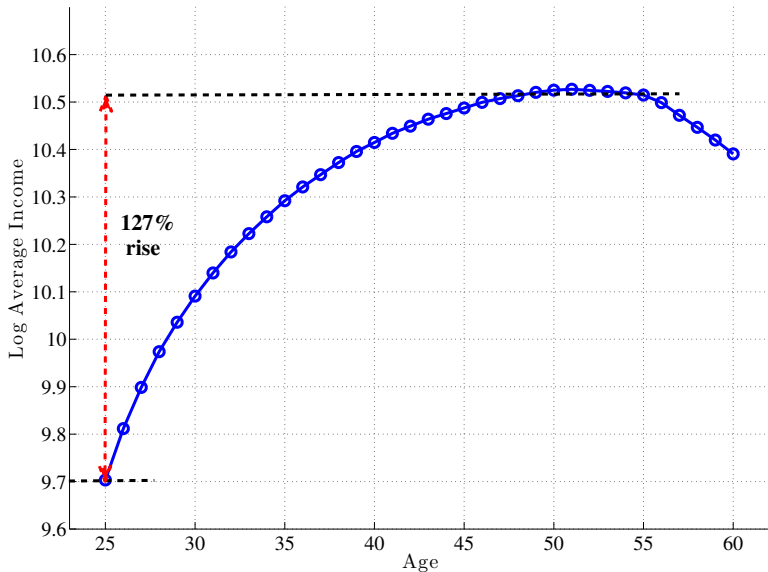
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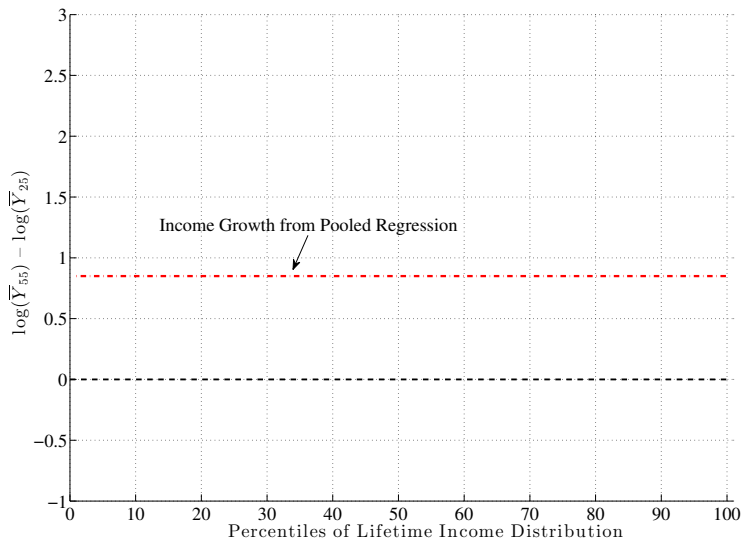
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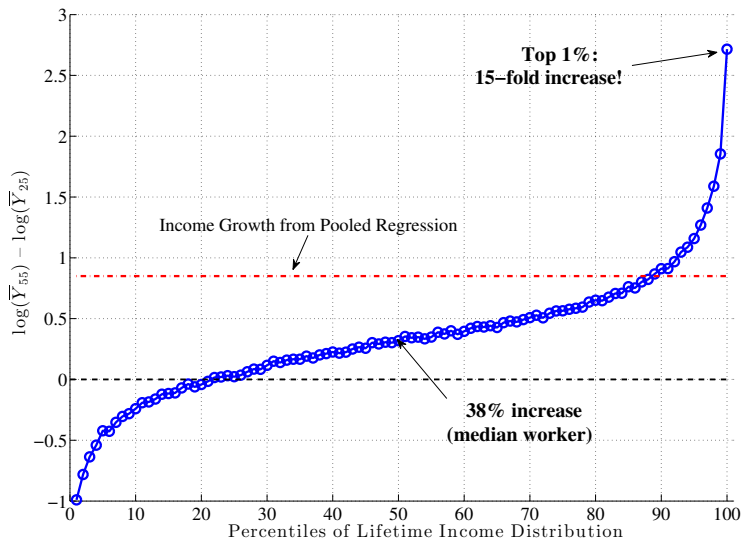
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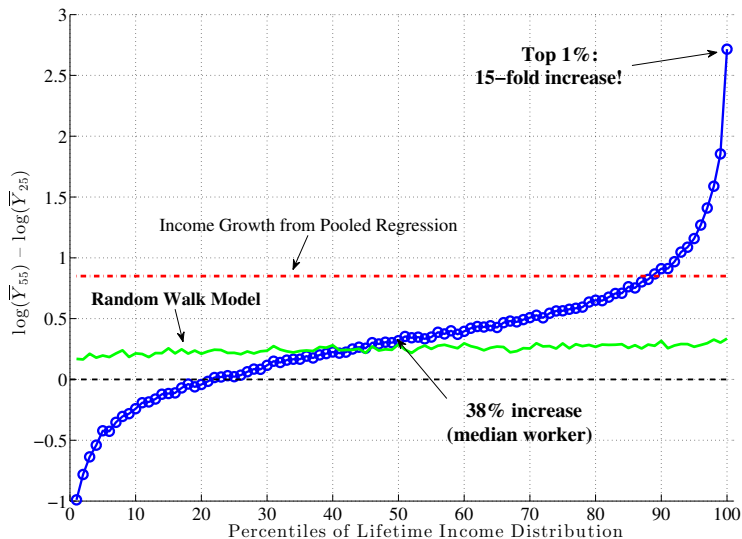
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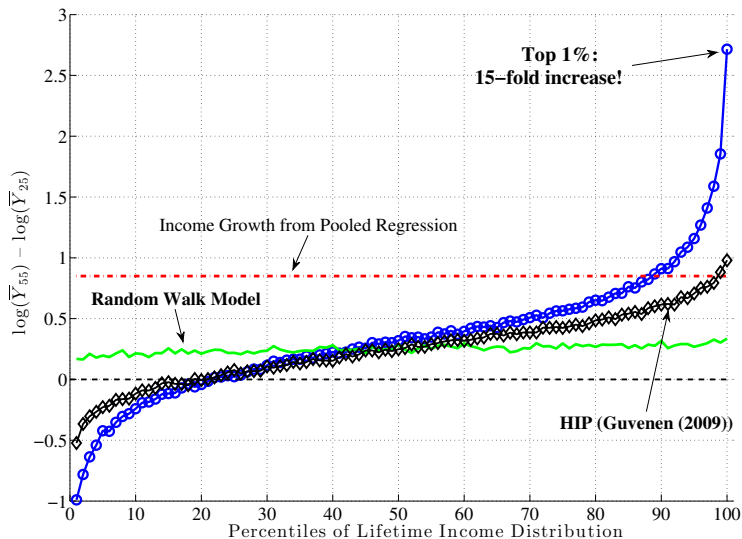
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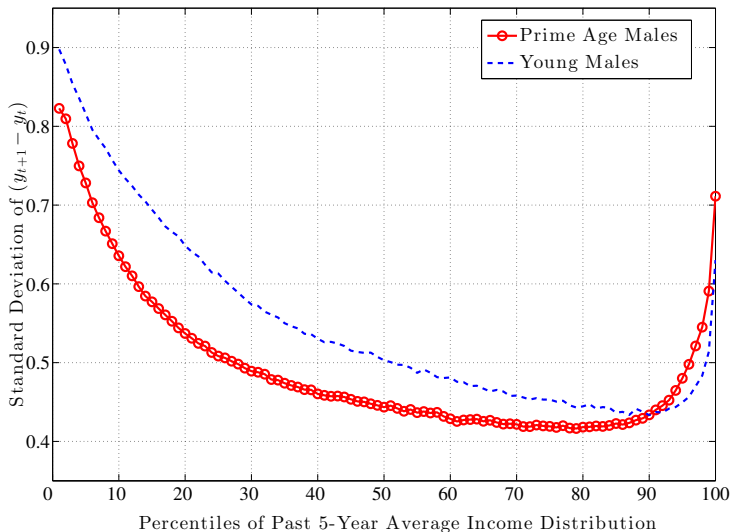
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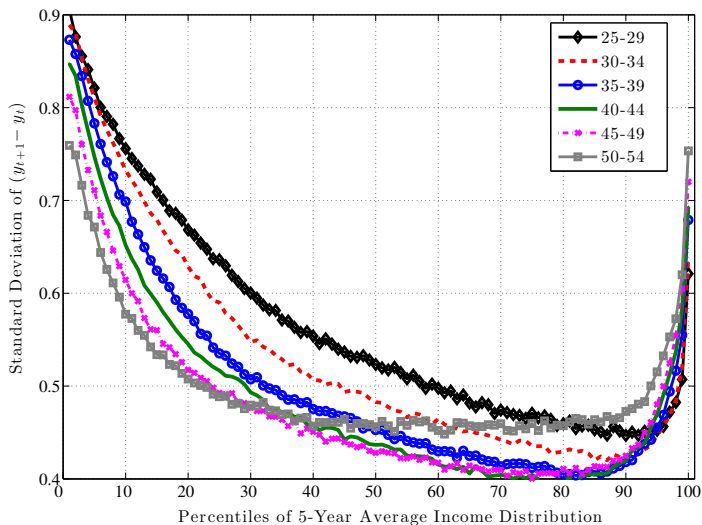
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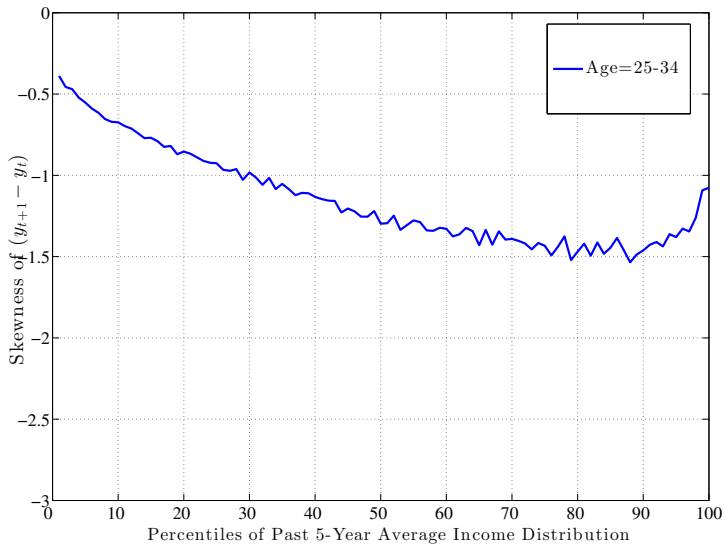
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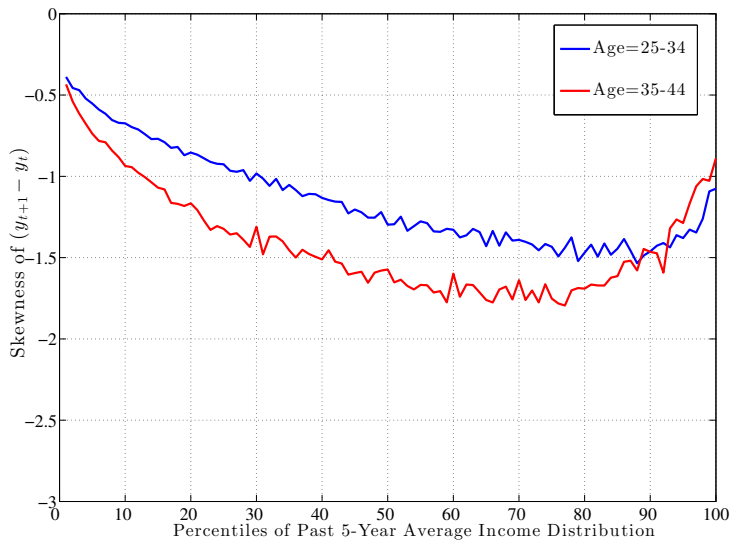


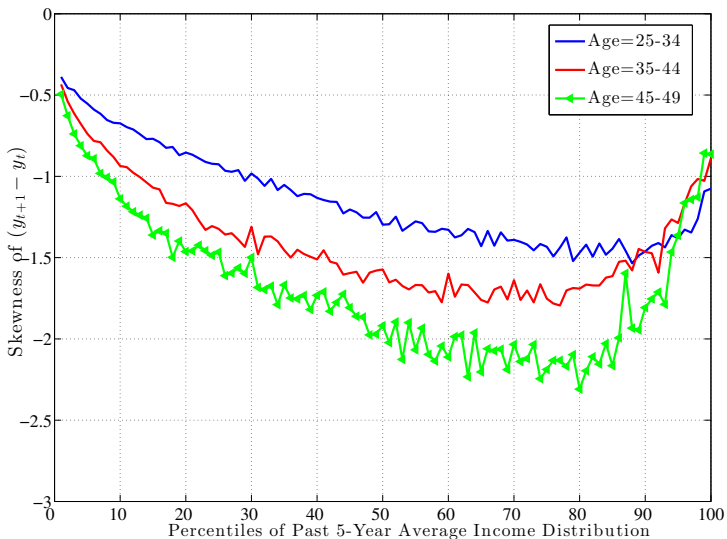
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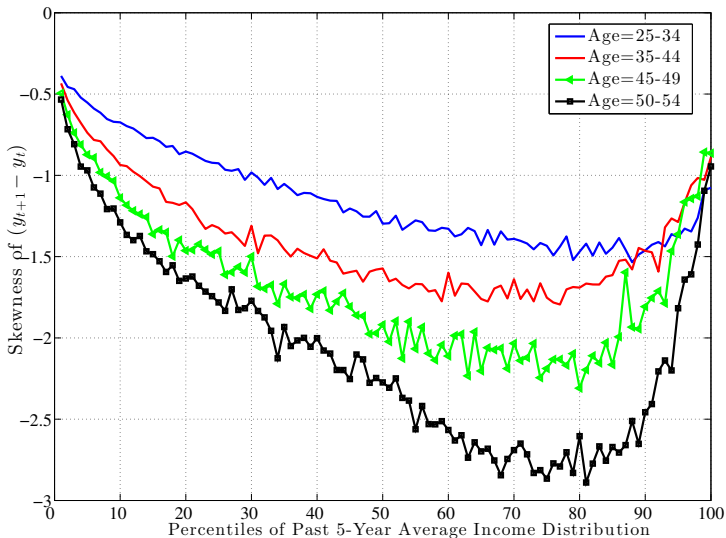
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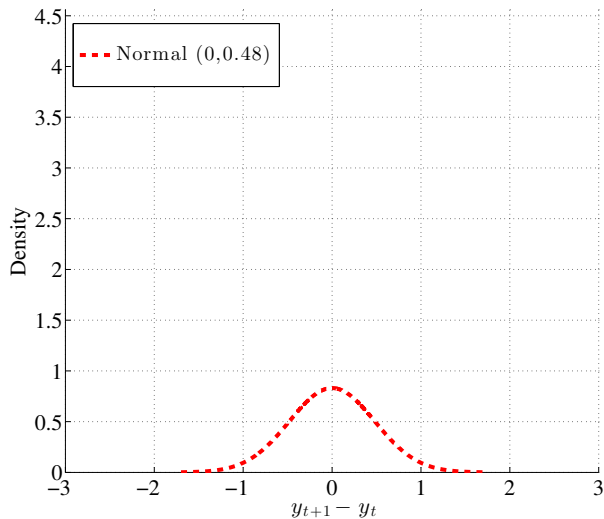
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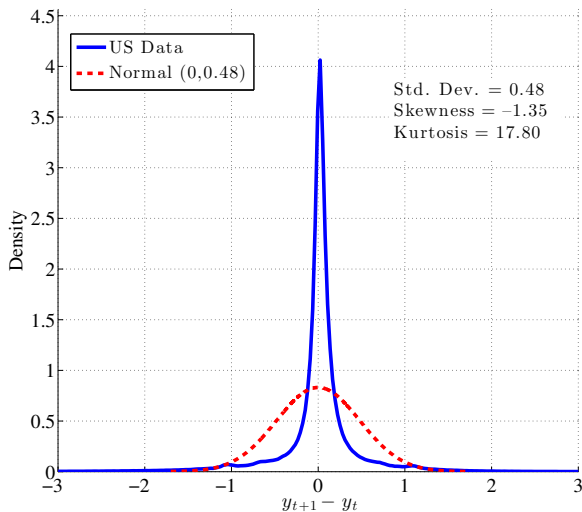


Kurtosis

II.C HISTOGRAM OF $y_{t+1} - y_t$



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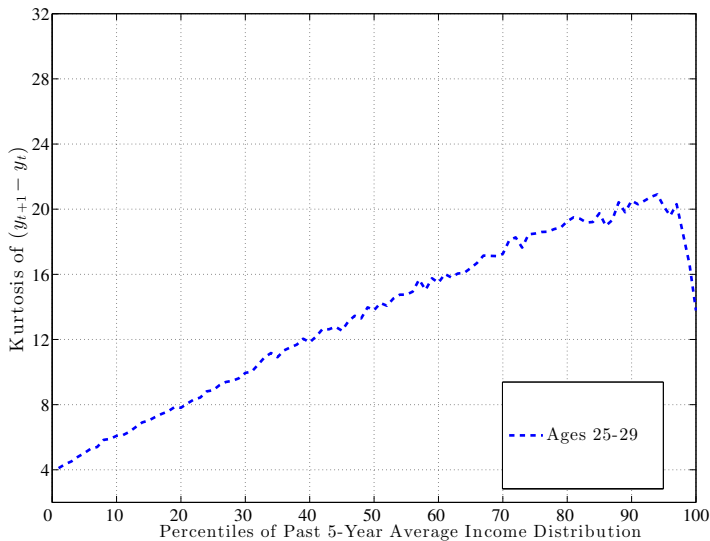


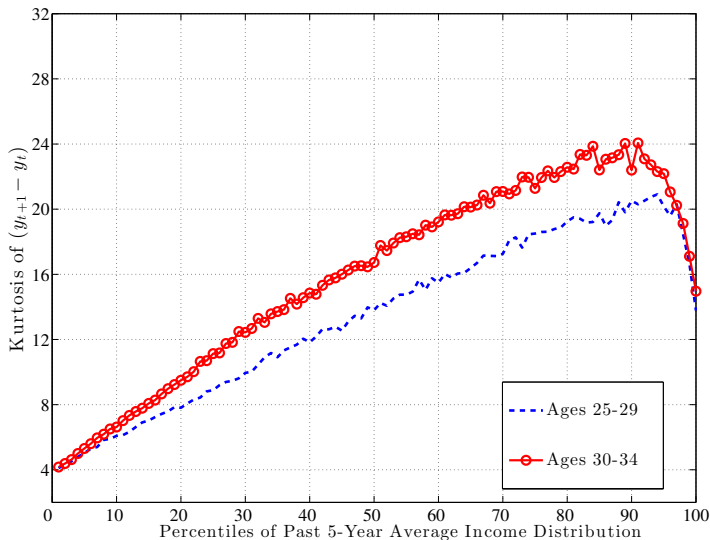
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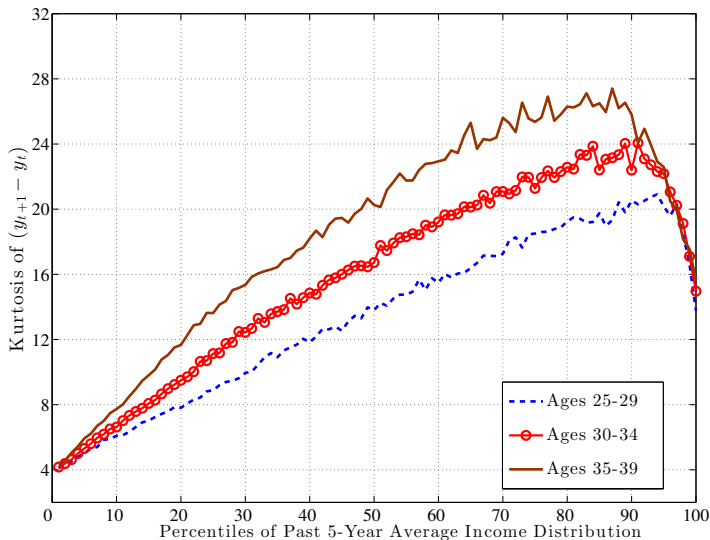
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0.05	0.42	0.10
0.10	0.63	0.20
0.20	0.79	0.39
0.50	0.90	0.80
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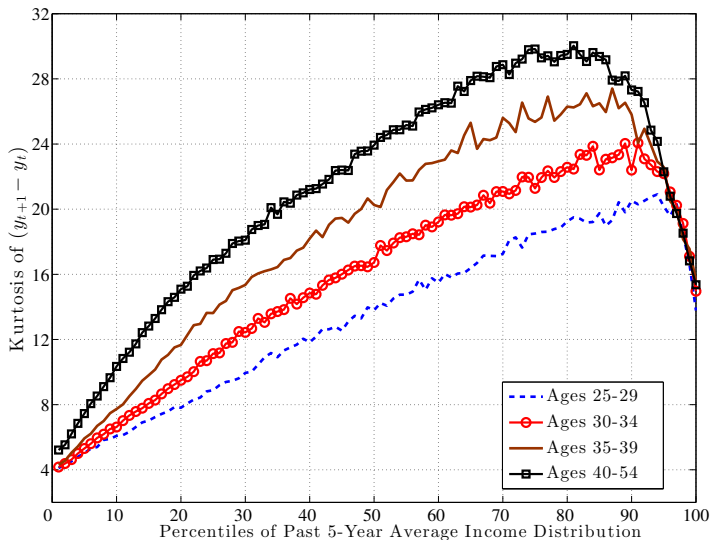
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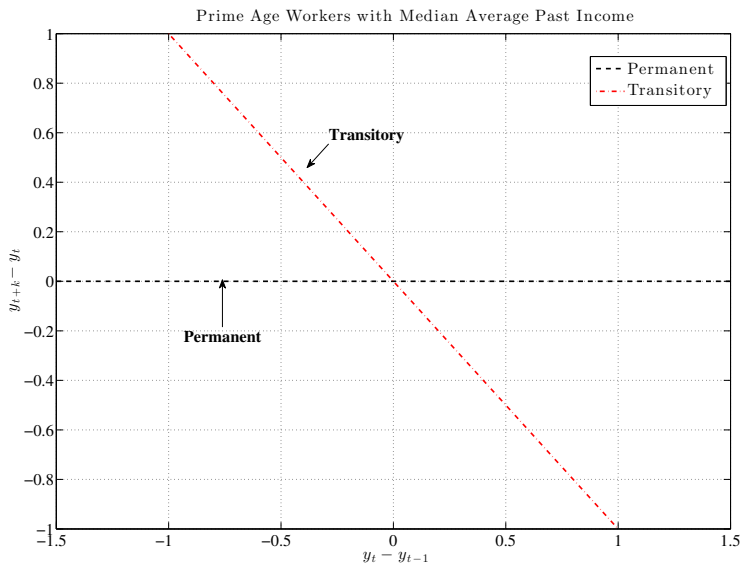
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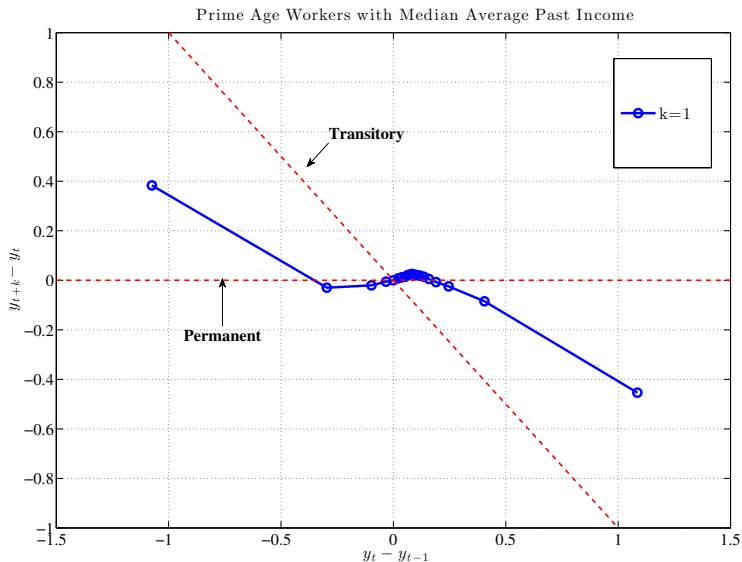
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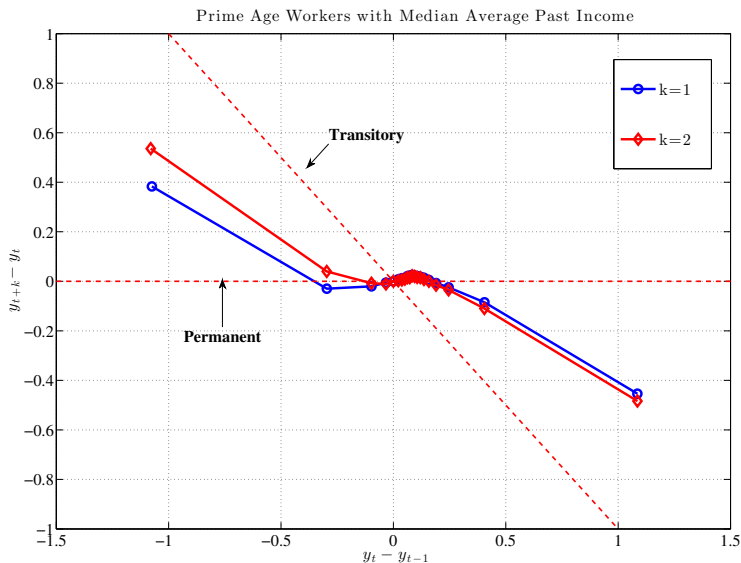
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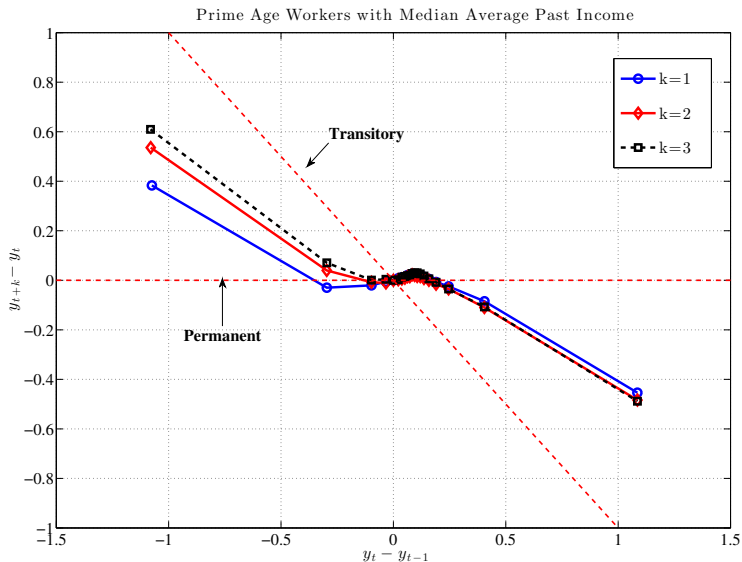
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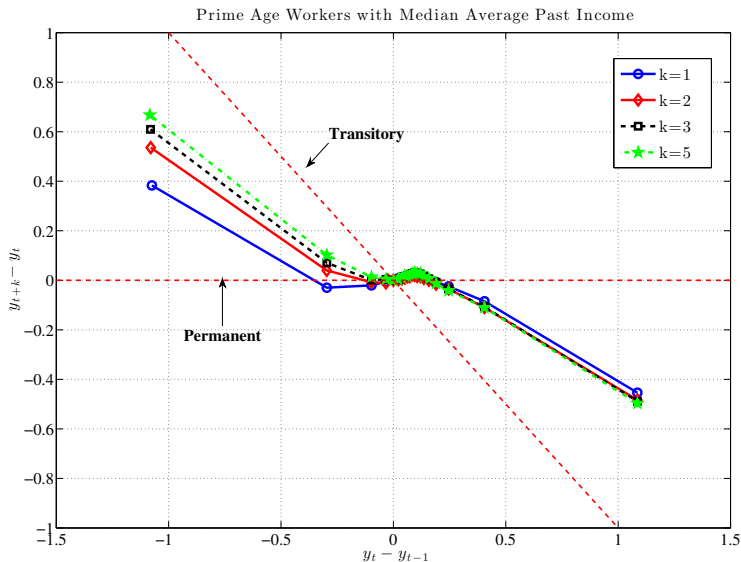
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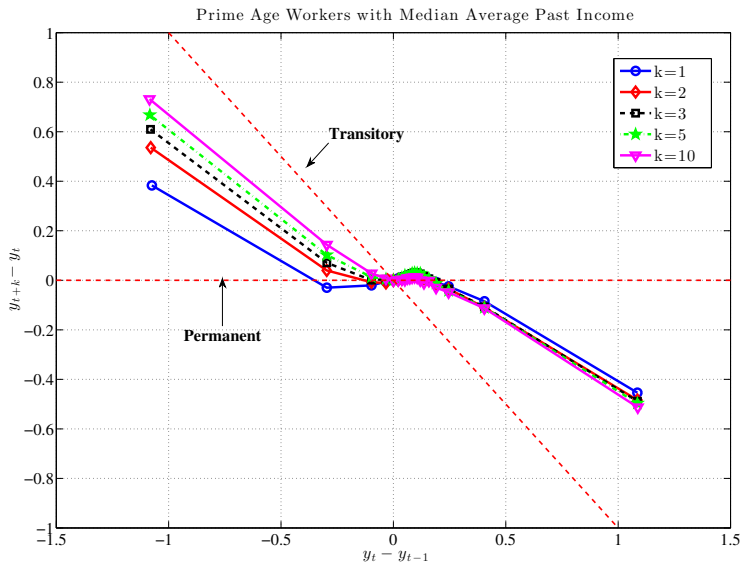
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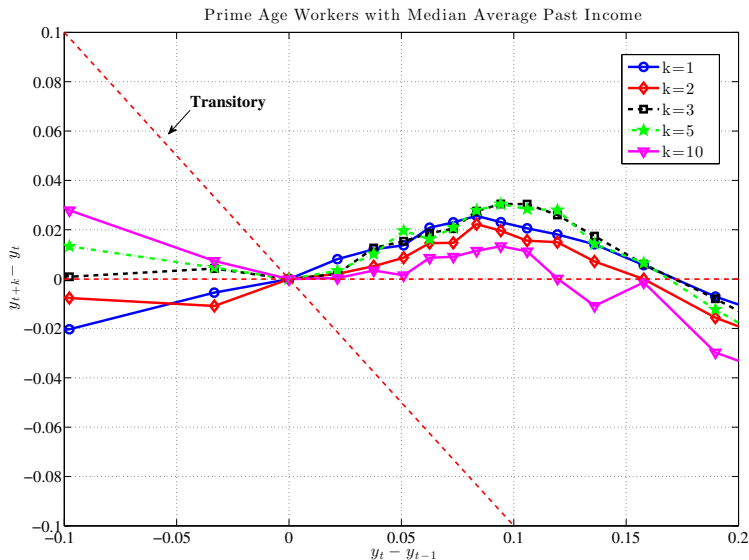
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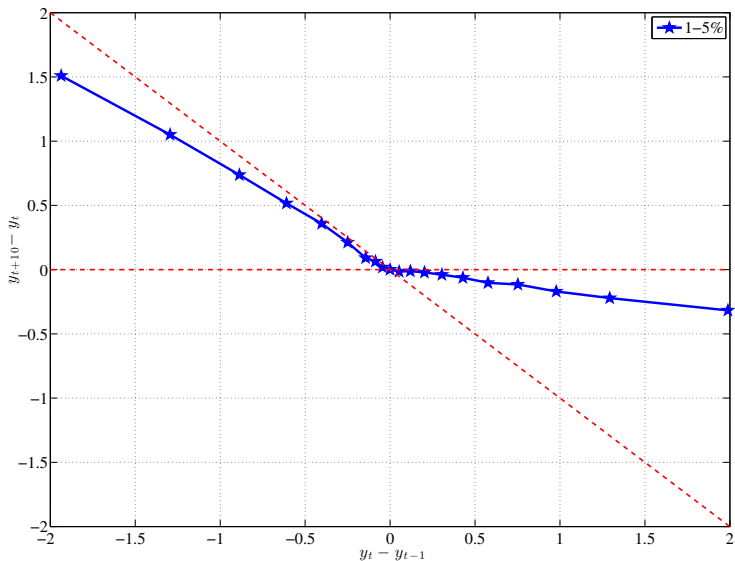
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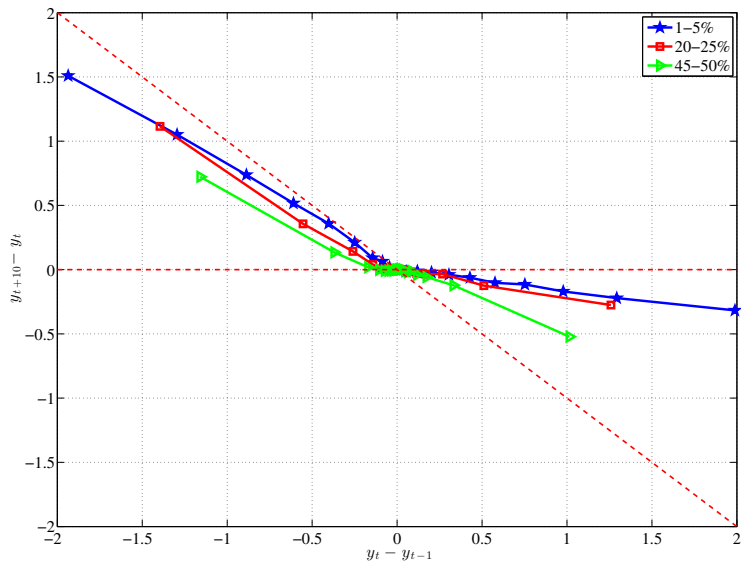
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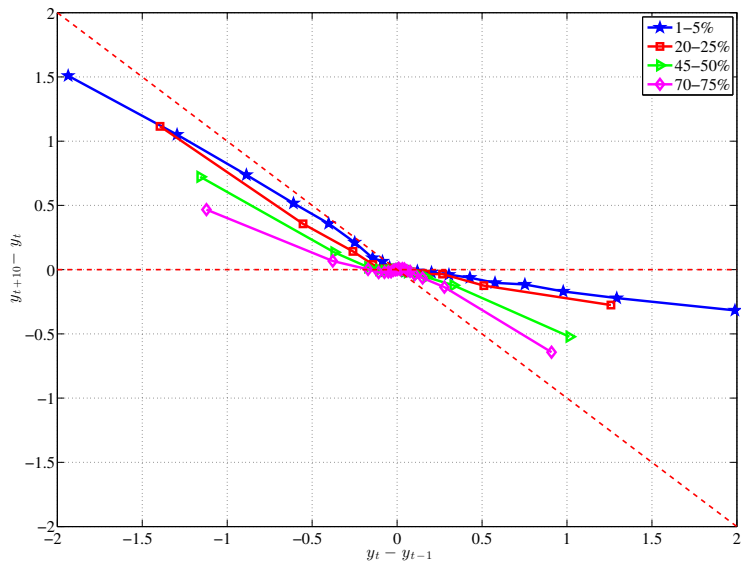
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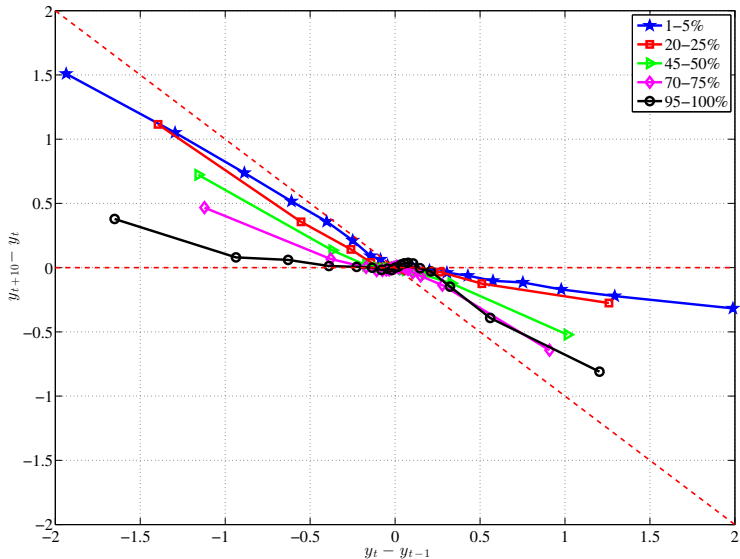
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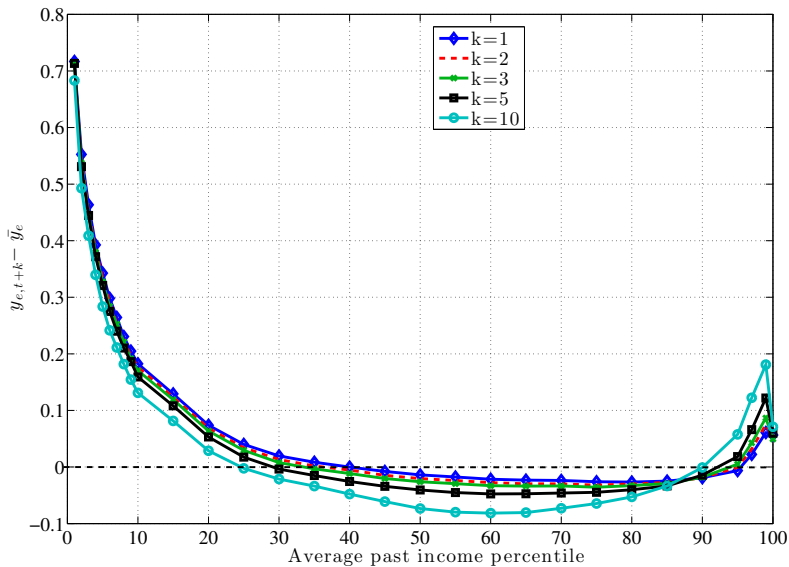
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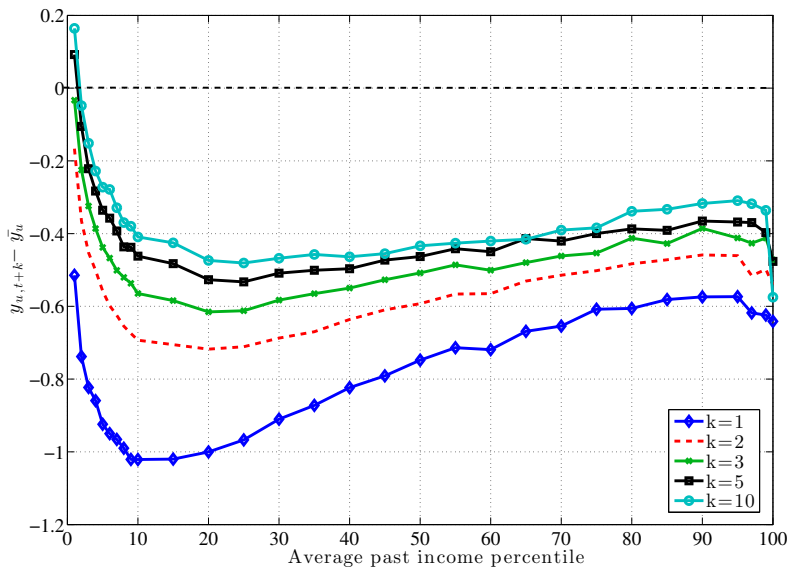
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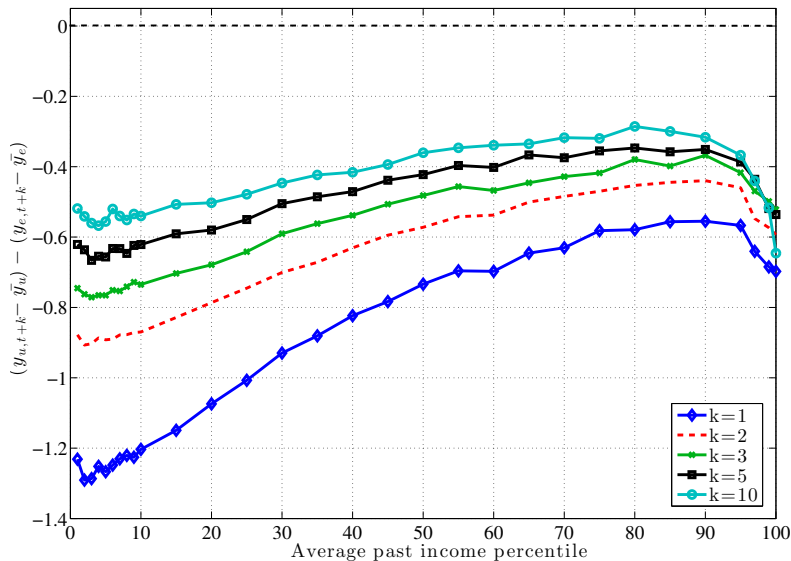
PRIME-AGE WORKERS: EMPLOYED



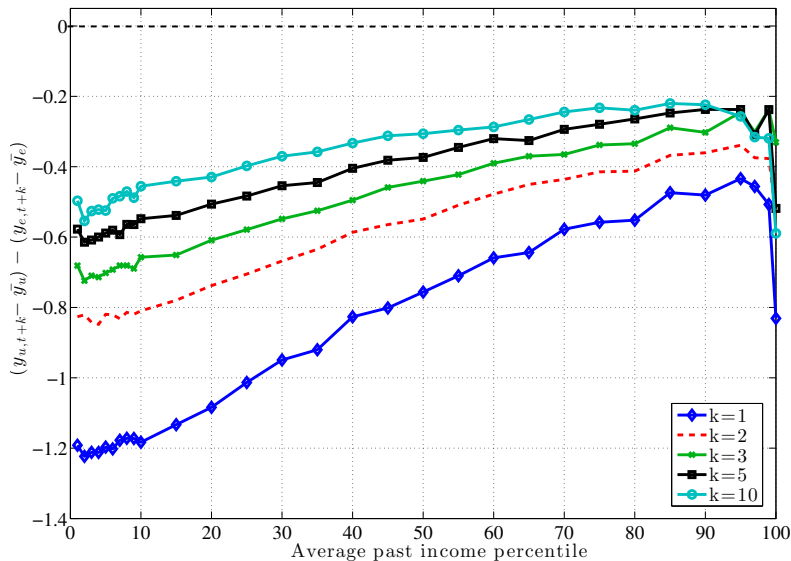
PRIME-AGE WORKERS: UNEMPLOYED



PRIME-AGE WORKERS: DIFF. IN DIFF.



YOUNG WORKERS: DIFF. IN DIFF.



ESTIMATION

ECONOMETRIC SPECIFICATION

$$y_t^i = \underbrace{\left[\alpha^i + \beta^i t + \gamma^i t^2 \right]}_{\text{HIP}} + \underbrace{z_{1,t}^i + z_{2,t}^i}_{\text{mixture of AR(1)s}} + \underbrace{\varepsilon_t^i}_{\text{i.i.d.}}$$

$$z_{1,t}^i = \rho_1 z_{1,t-1}^i + \eta_{1,t}^i$$

$$z_{2,t}^i = \rho_2 z_{2,t-1}^i + \eta_{2,t}^i$$

where for $j = 1, 2$:

$$\eta_{jt}^i = \begin{cases} 0 & \text{w.p. } 1 - p_j \\ \sim \mathcal{N}(0, \sigma_j) & \text{w.p. } p_j \end{cases}$$

and

$$\sigma_j(t, z_{t-1}) = \max(0, \sigma_{j,0} + \mathbf{a}_j \times z_{t-1} + \mathbf{b}_j \times t + \mathbf{c}_j \times z_{t-1} \times t)$$

ESTIMATION RESULTS

Parameters	Group 1	Group 2	Group 2
Fractions	0.10	0.80	0.10
mean(α)	2.21	2.95	3.57
mean(β) $\times 100$	4.31	9.44	12.27
quadratic	-0.25	-0.25	-0.25
σ_α	-0.74	0.00	0.63
$\sigma_\beta \times 100$	1.02	1.35	0.68
$\sigma_{\alpha\beta}$	-0.02	-0.41	0.21
ρ_1		0.11	
ρ_2		0.77	
ρ_1		0.25	
ρ_2		0.54	
σ_1	$1.07 + 0.65z_{t-1} + 0.32t + 0.148tz_{t-1}$		
σ_2	$0.07 - 0.15z_{t-1} - 0.15t - 0.21tz_{t-1}$		
σ_ϵ		0.03	

WHAT TO USE IN CALIBRATION?

- These estimated processes are complex and richly parameterized.
 - How to use them for calibration?
- We intend to construct Markov transition matrices that summarize these processes.
- Civalo-Guvenen-Stefanides (2013) explore how to do this for processes with excess kurtosis and large skewness.
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- Within-job earnings changes are small.
 - Every once in a while: find a better job or lose the job.
- Job mobility declines with age and wage.
 - **Kurtosis** goes up with age and wage
 - **Variance** of income changes decline with age and wage
- **Skewness**: Job losses contribute to the left tail.
 - Larger left tail for older people and for high wage people.
- These insights are mostly missed in income dynamics literature.

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CONCLUSIONS

- **Striking new regularities and patterns in individual earnings.**
- Existing specifications do not capture these salient features of the data.
- We propose a richer specification that captures many of these patterns.
- Excess kurtosis and mixture of AR(1)s can explain an important puzzle in the CME literature.
 - Ongoing research (Guvenen-Tonetti aims to show this more rigorously.)
- New benchmarks and targets for calibration.

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