What Do Data on Millions of U.S. Workers Say About Life Cycle Income Risk?

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-The 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.

Motivation

- Large variation in individual earnings trajectories over the career
  - surprises/successes: finding an attractive job, getting promotions, raises, etc.
  - as well as disappointments: unemployment, failing in one career and changing, health shocks, and so on.
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1. Earnings dynamics is largely driven by earnings risk and the nature of earnings risk is important for many questions:
   - Effectiveness of self-insurance, wealth and consumption inequality, optimal taxation, welfare costs of business cycles, etc.
2. Earnings dynamics is informative for various theories of the labor market
   - the role of search frictions, importance of job mobility, etc.

- A large literature on estimating statistical models of earnings dynamics:
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Open Questions

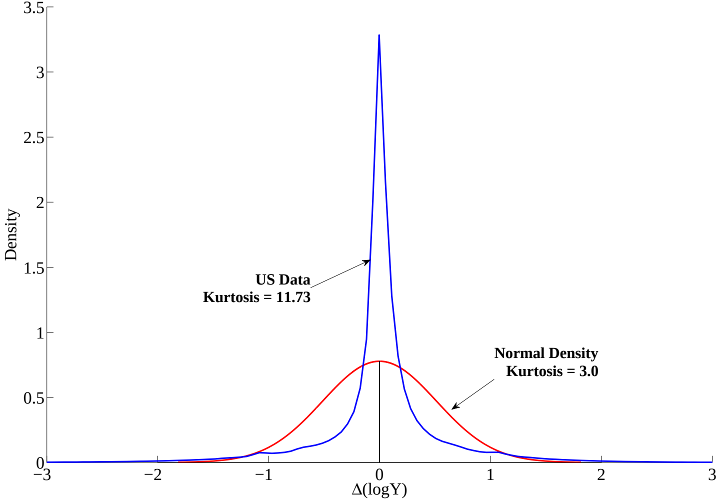
1. What does the distribution of earnings changes look like?

A. Is it approximately lognormal?

B. How about higher-order moments?

> Symmetric or skewed? any excess kurtosis?

Open Questions



Open Questions

1. What does the distribution of earnings changes look like?

2. How does this distribution vary?

A. across "different income groups"?

B. over the life cycle? Karahan and Ozkan (2013, RED)

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2. How does this distribution vary?

3. Dynamics of earnings?

A. Very persistent/permanent vs. moderately persistent with heterogenous income profiles?

B. Do positive and negative changes have similar persistence?

C. Do large and small changes have similar persistence?

Open Questions

1. **What does the distribution of earnings changes look like?**

2. **How does this distribution vary?**

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Existing Work

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2. Employ covariance matrix estimation (CME), developed for a data-constrained environment
   - Ignores higher order moments, which we find to be very important.
   - Selecting among rejected models is very hard:
     - moments that are missed do not have clear economic interpretations.
   - *Notable exceptions:* Meghir and Pistaferri (2004), Browning et al (2010), and Altonji et al (2013)

This Paper

Uses a unique, confidential, and very large administrative panel dataset with 5 million individuals to:

1. Document new empirical facts on life-cycle earnings dynamics
2. Estimate lifecycle earnings dynamics
   - by matching economically important moments (as opposed to the "covariance matrix of income residuals")
   - Provide a reliable "user's guide" for earnings process specifications.
3. Study consumption/savings implications in a standard incomplete markets model.
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Road Map

- Describe the SSA data
- Document new empirical facts on life cycle earnings dynamics
- A new process for earnings dynamics
- Life-cycle model of consumption and savings
- Conclude

Data: 10% Random Sample from SSA

- We draw our sample directly from SSA's Master Earnings File (MEF).
- MEF contains all individuals in the US with a Social Security number.
- Labor income data from W-2 forms for salaried/wage workers.
  - Self-employed workers are excluded.
- We draw a representative sample of US males covering 33 years: 1978 to 2010
- We focus on individuals aged 25–60.

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Compared to Survey Data

- Very large sample size. Allows us to study variation between and within very finely defined groups and higher order moments.
- No survey response error (possible under-reporting).
- No sample attrition.
  - Allows us to control for compositional changes.
- No top-coding:
  - In PSID, CPS, etc., using extreme observations is tricky.
  - Here, income observations in tens of millions of $ per year.
- Drawback: Lack of hours data and no information on hourly wages!!

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NEW EMPIRICAL FACTS

Three Sets of Empirical Facts

1. Cross-sectional moments of earnings growth
2. Short- and long-run dynamics of earnings growth
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Three Sets of Empirical Facts

1. **Cross-sectional moments of earnings growth**
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Moments of $F(y_{t+1} - y_t | \bar{Y}^i_{t-1}, age_{t-1})$

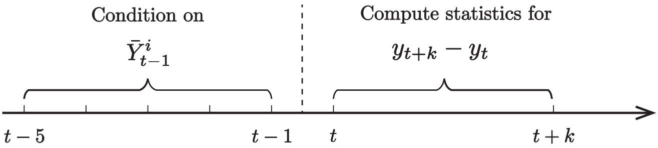
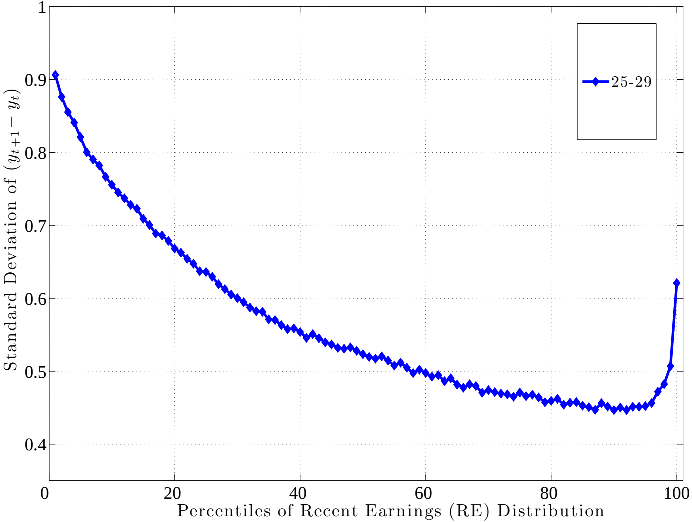


Figure: Timeline For Rolling Panel Construction

Standard Deviation

I.a Standard Deviation of $y_{t+1} - y_t$



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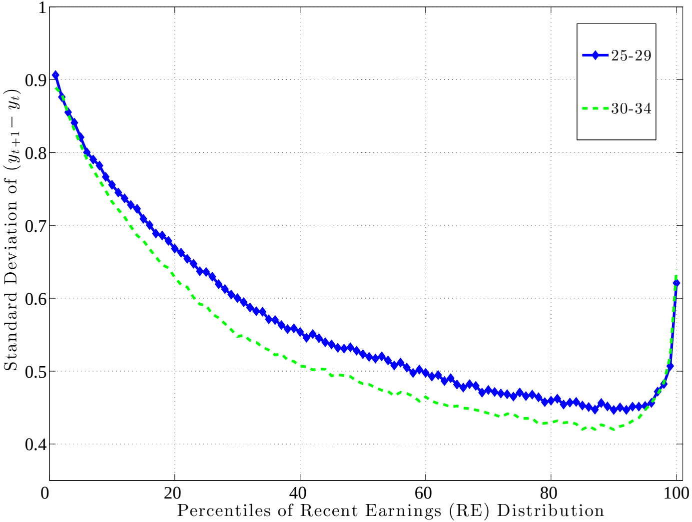

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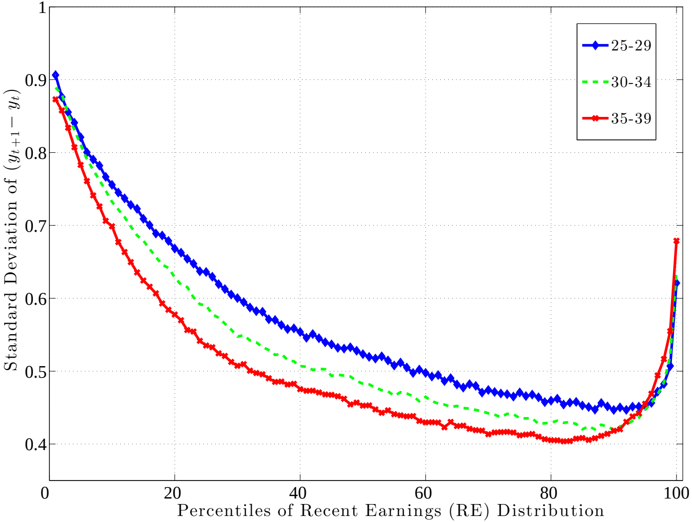

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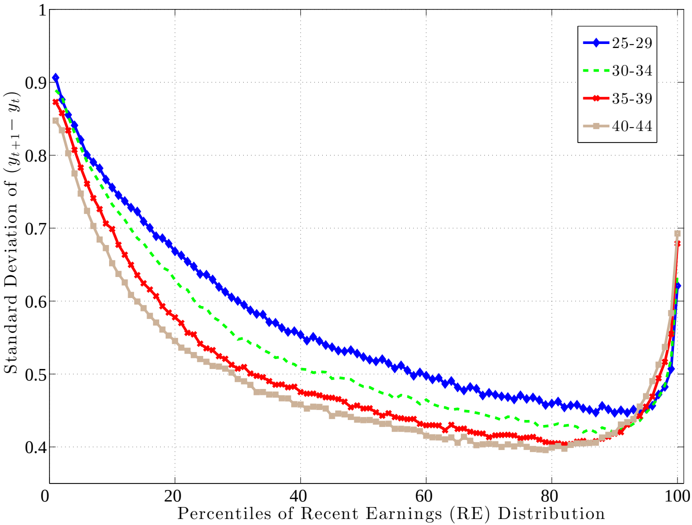

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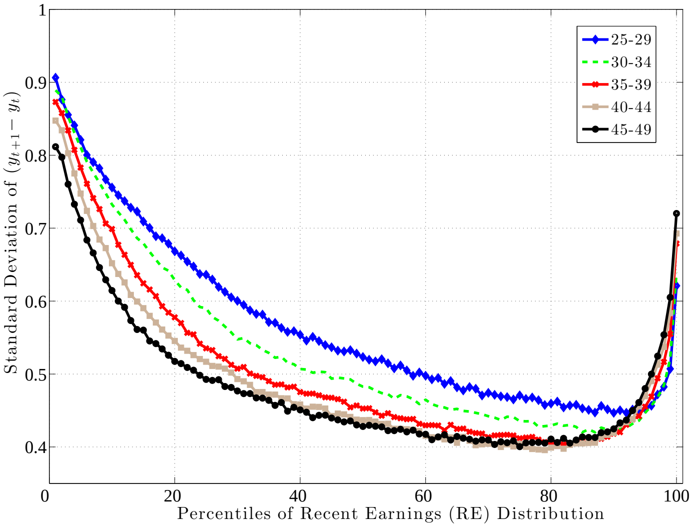

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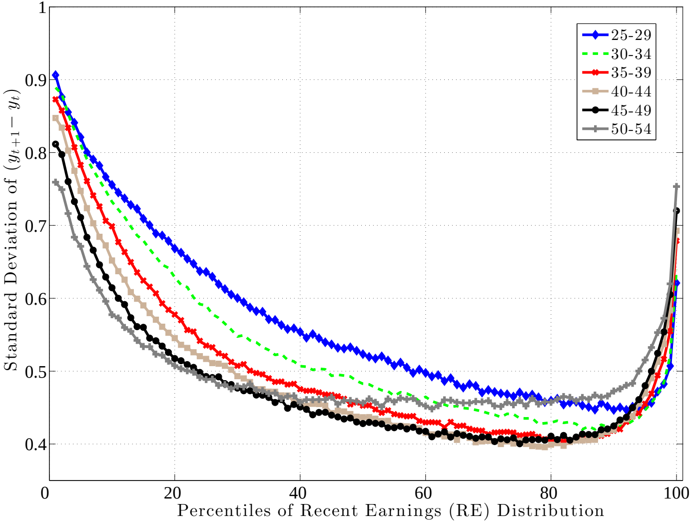
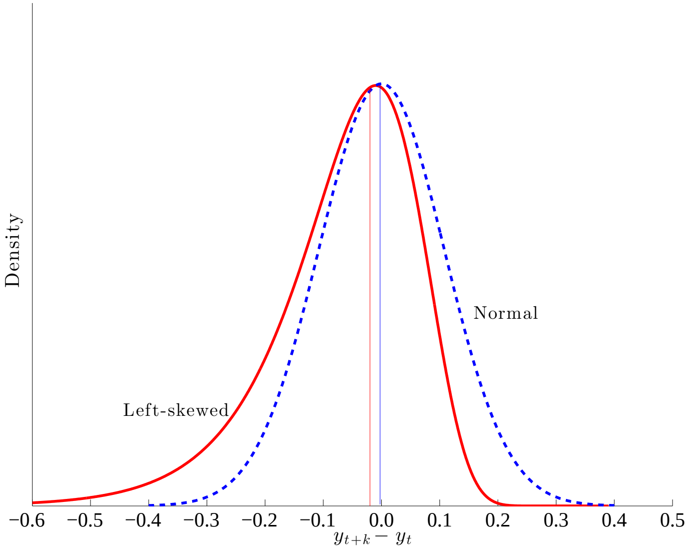
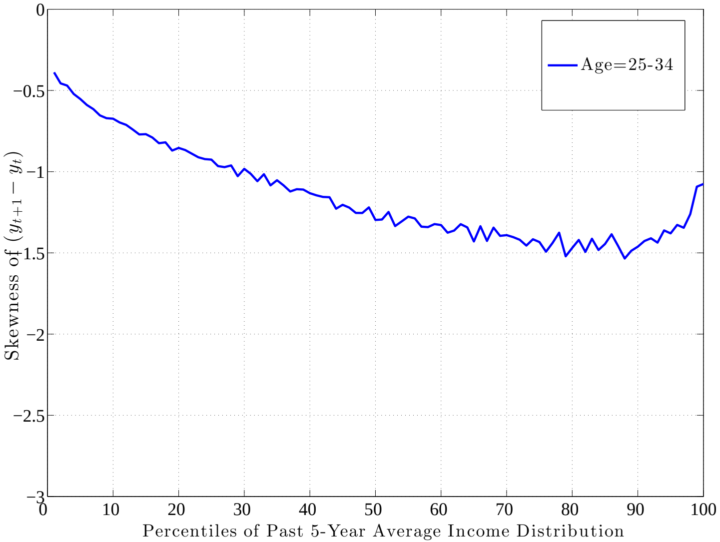


Skewness

Left-Skewness



I.B Skewness of $y_{t+1} - y_t$



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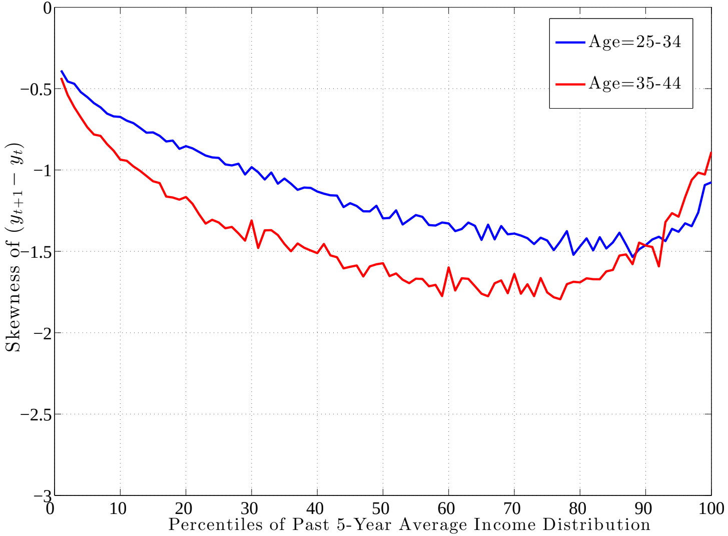

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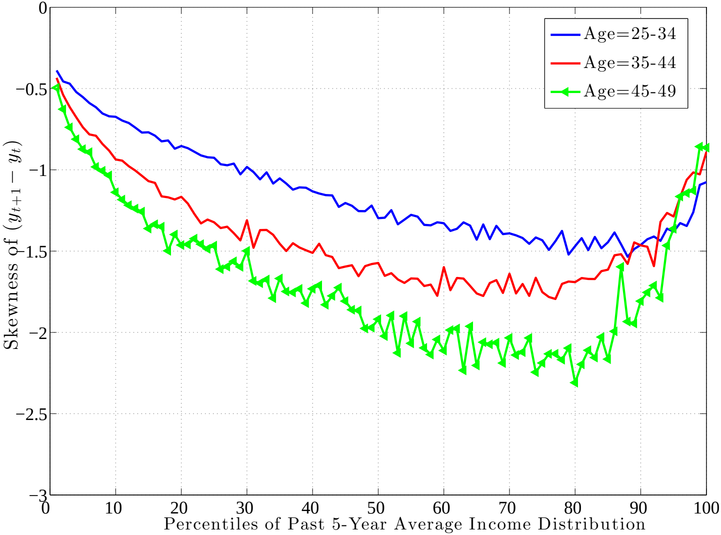

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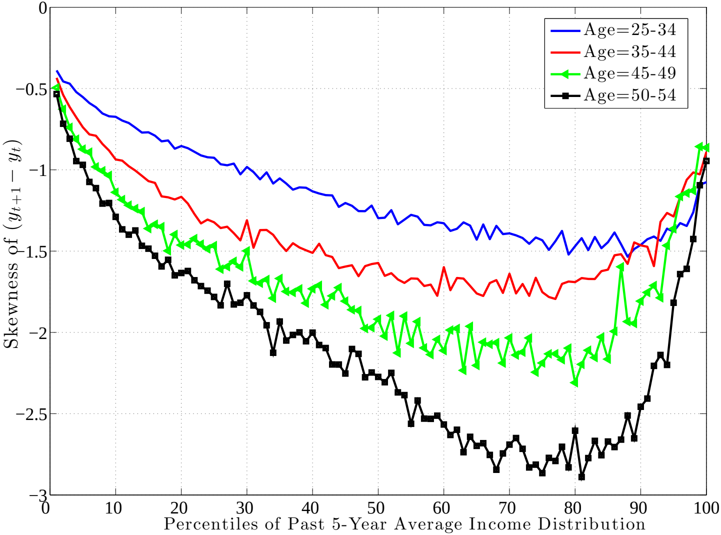
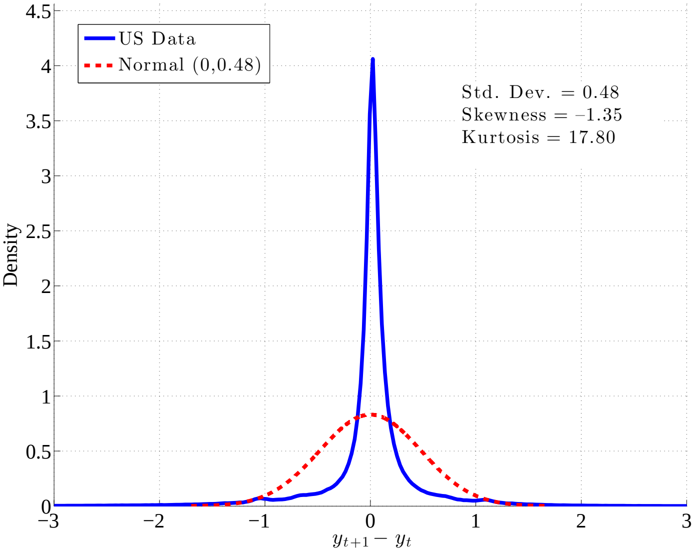


Kurtosis

I.c Histogram of $y_{t+1} - y_t$



I.c Distribution of Income Changes

	$\text{Prob}(\lvert y^i_{t+1} - y^i_t \rvert < x)$		
x :	Data*	$\mathcal{N}(0, 0.48^2)$	Ratio
0.05	0.35	0.08	4.38
0.10	0.54	0.16	3.38
0.20	0.71	0.32	2.23
0.50	0.86	0.70	1.22
1.00	0.94	0.96	0.98
$\lvert y^i_{t+1} - y^i_t \rvert > 1.5$	0.023	0.002	11.5

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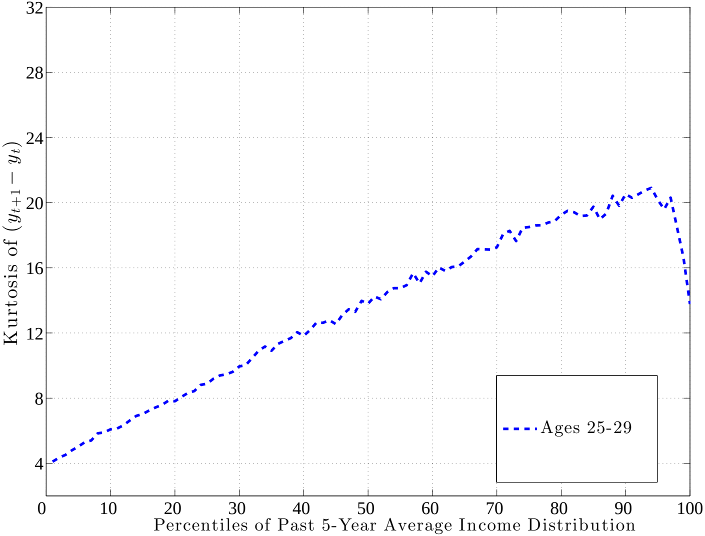
I.C Kurtosis of $y_{t+1} - y_t$



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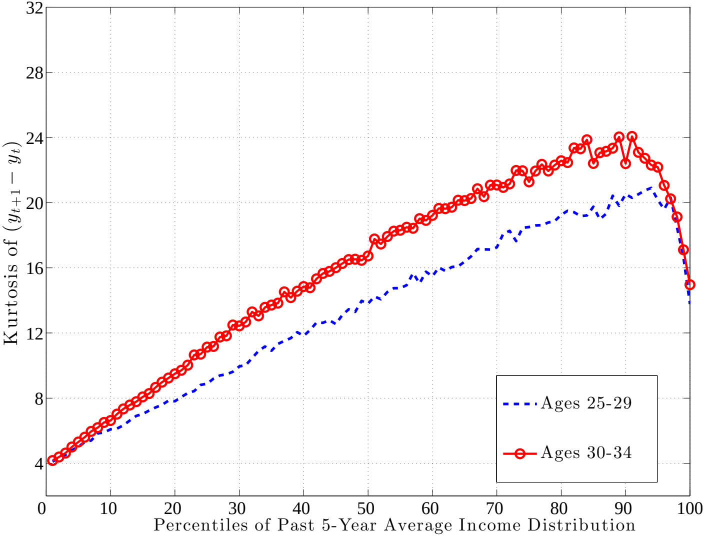

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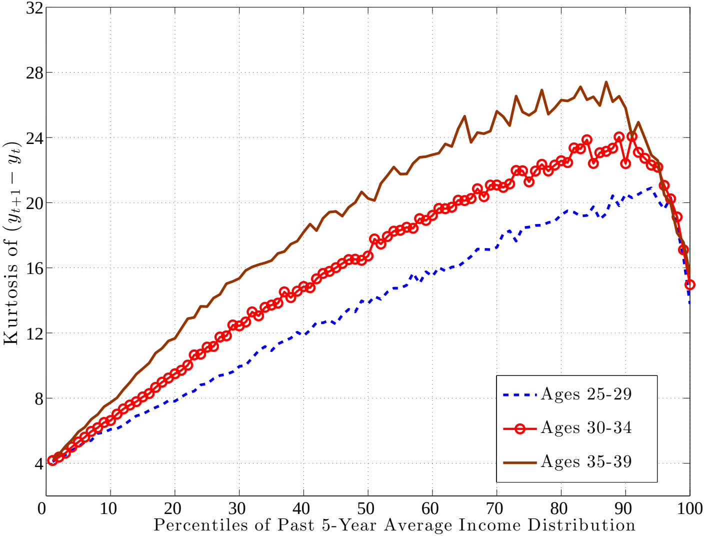

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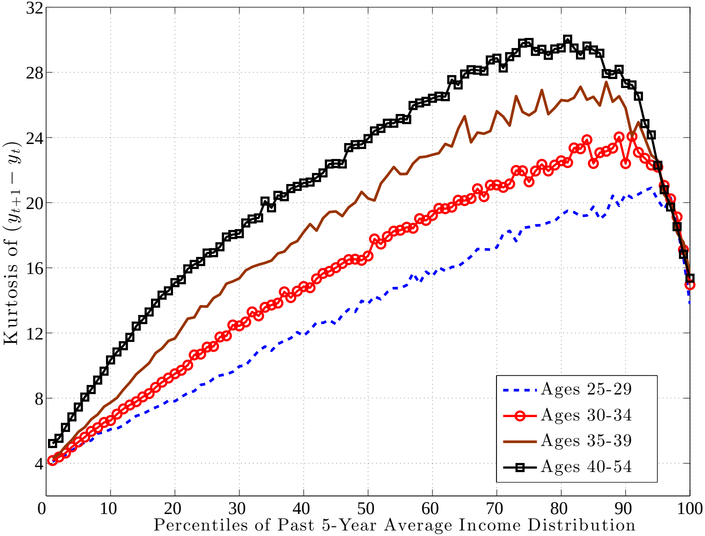

Search Models and Earnings Dynamics

- Kapon, Karahan, Ozkan, and Song (2016) study higher order moments using search models.
  - An equilibrium search model with on-the-job search.
  - EE, EU, UE transitions generate tail events.
- Job mobility declines with age and wage.
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Search Models and Earnings Dynamics

Main results in Kapon, Karahan, Ozkan, and Song (2016):

- The model can capture higher order moments and its variation [with some bells and whistles].
- The structure of the model, along with the documented facts, identifies firm productivity distribution [i.e. the “job ladder”] nonparametrically.

Three Sets of Empirical Facts

1. Cross-sectional moments of earnings growth$\surd$
2. **Short- and long-run dynamics of earnings growth**
3. Average income growth over the life cycle

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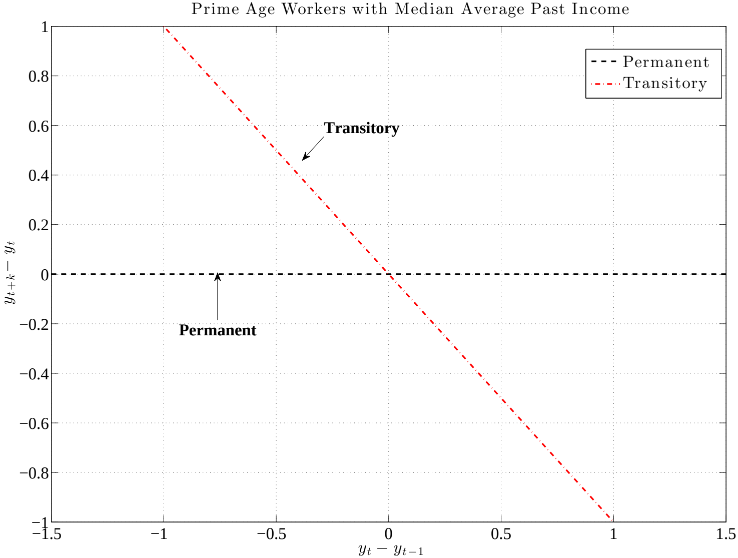

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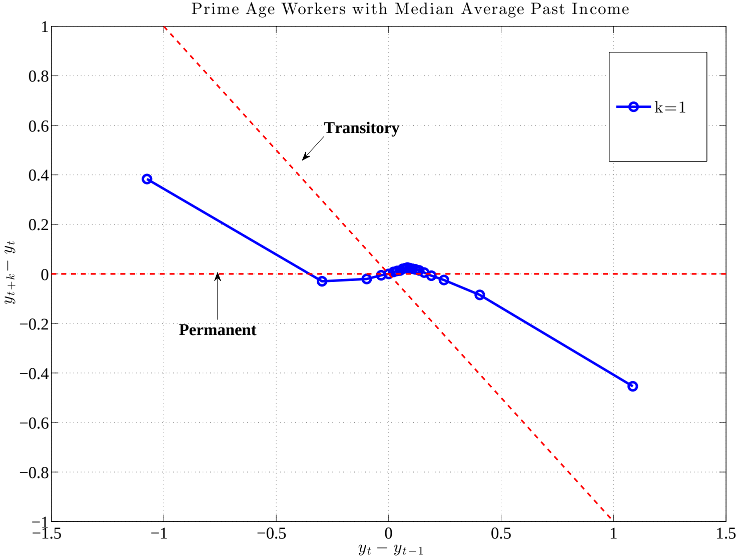

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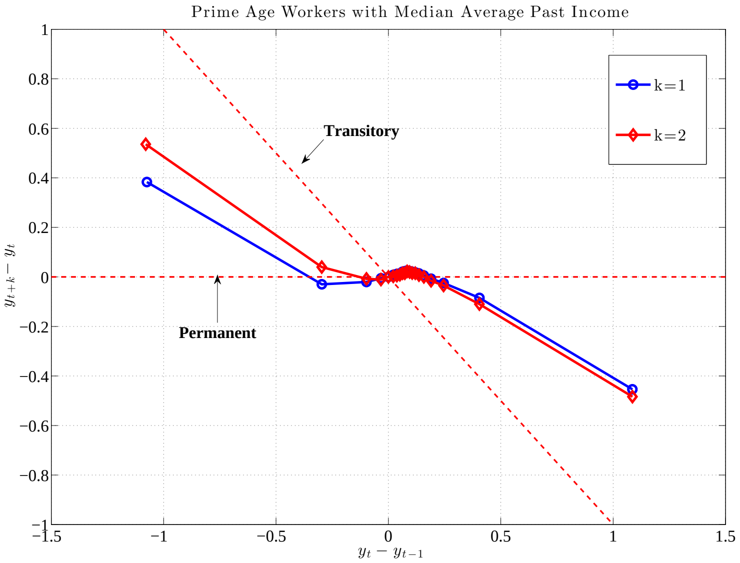

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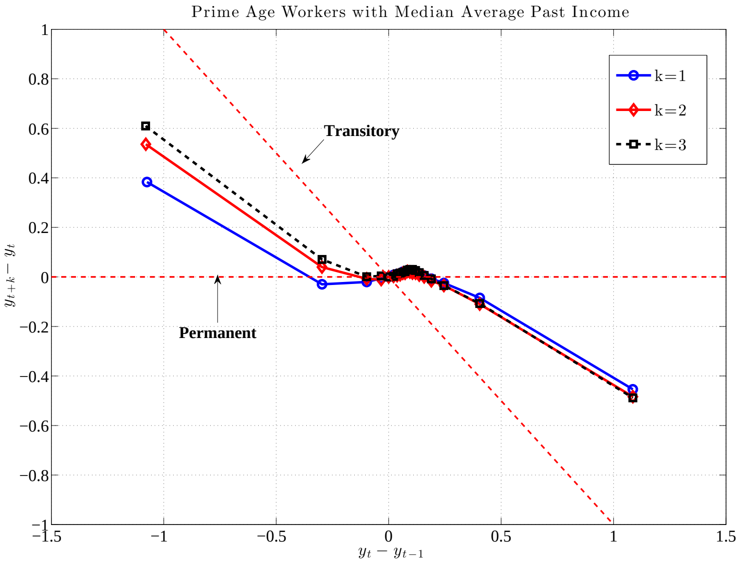

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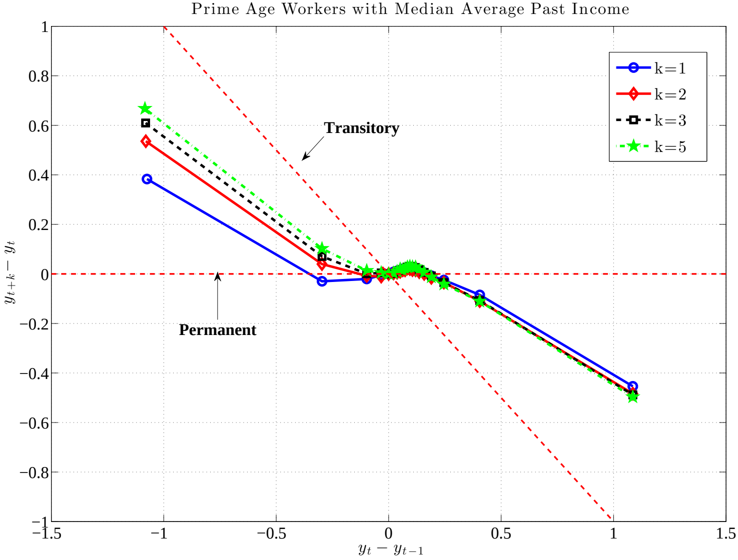

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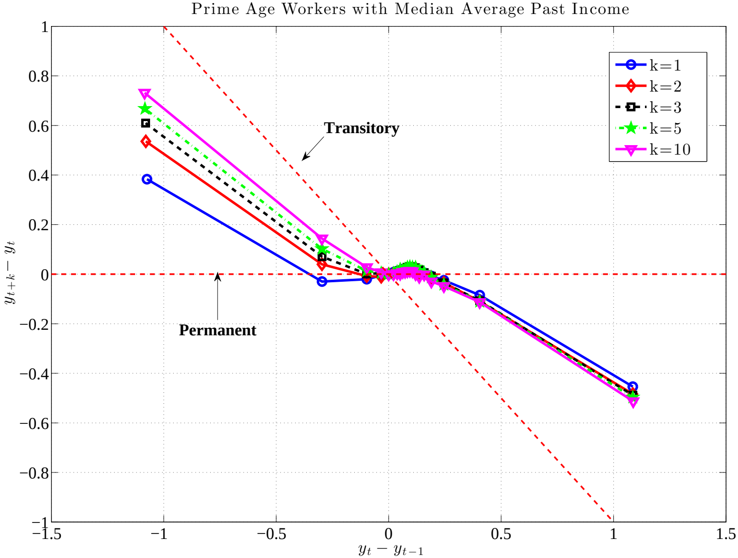

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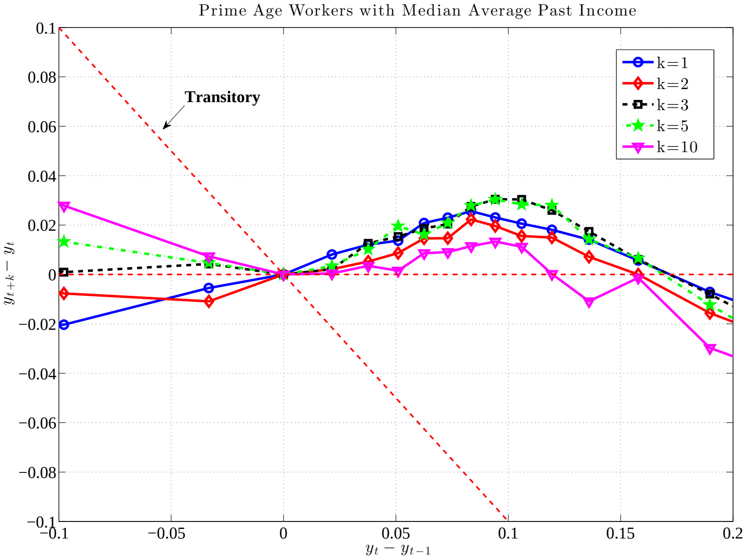

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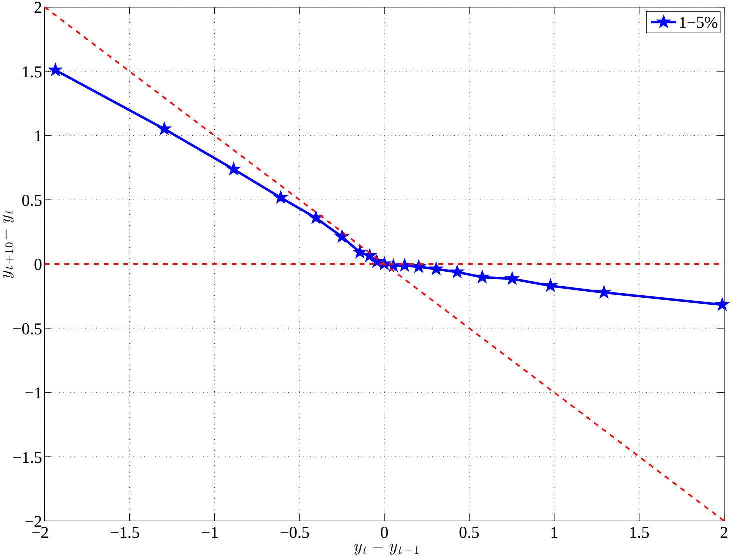

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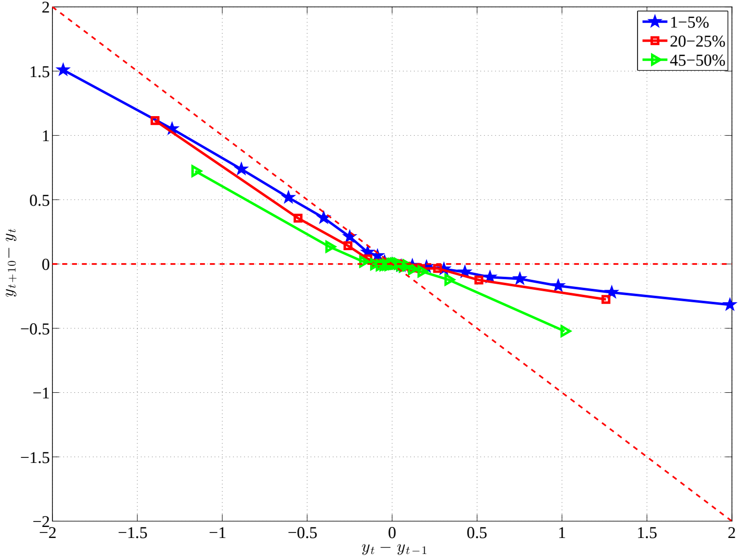

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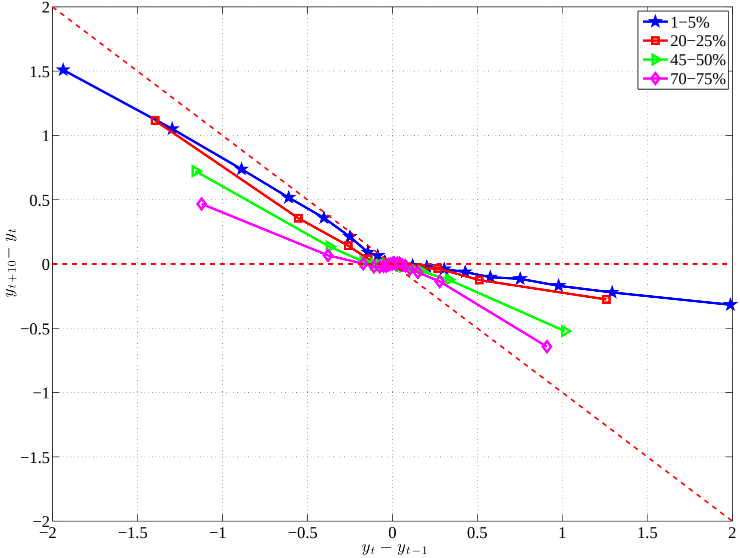

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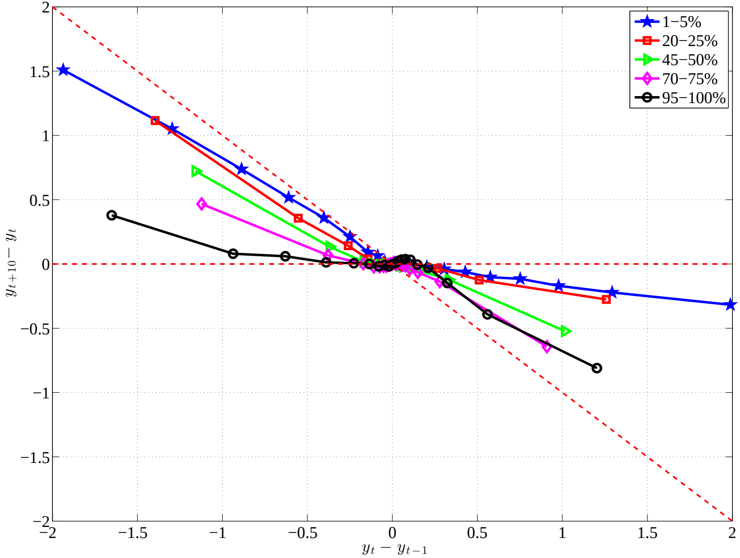

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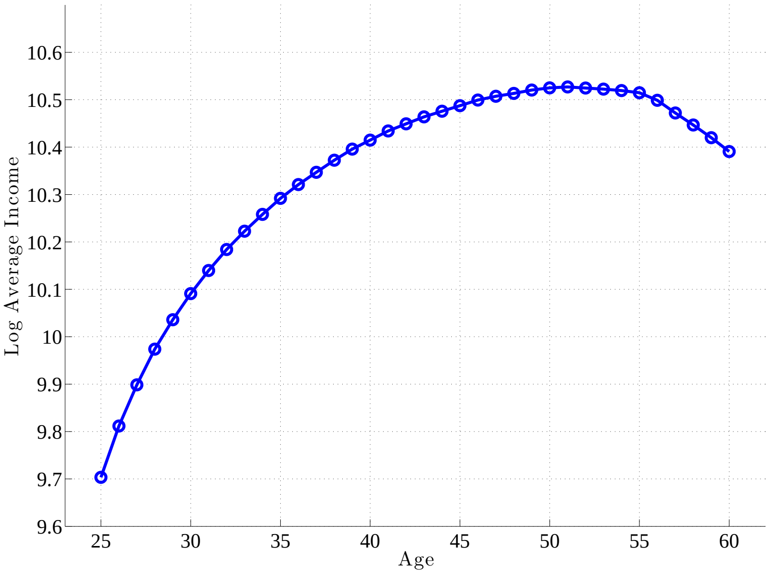

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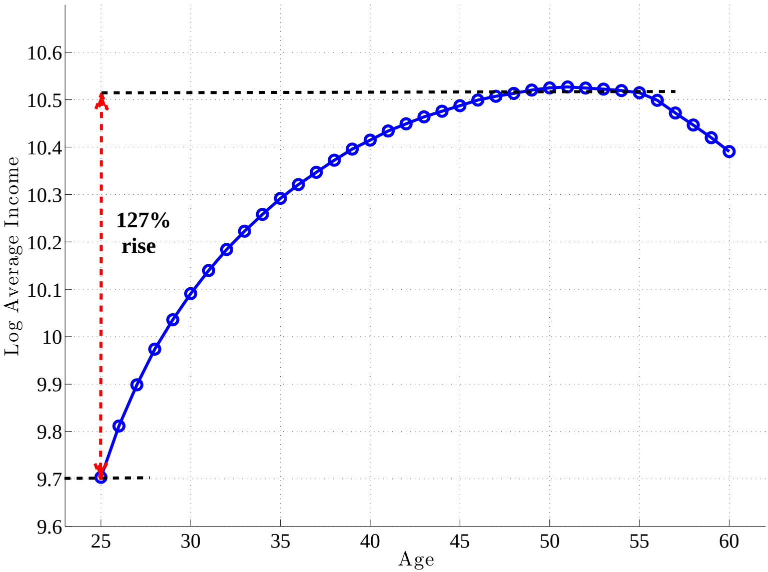

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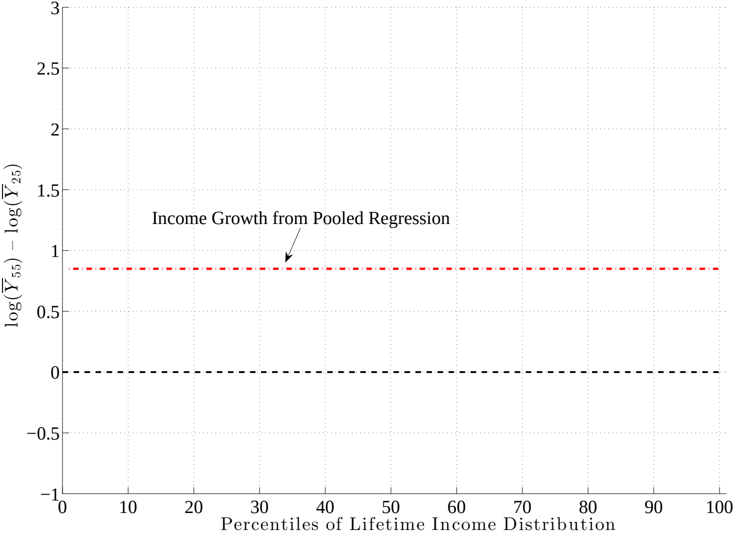

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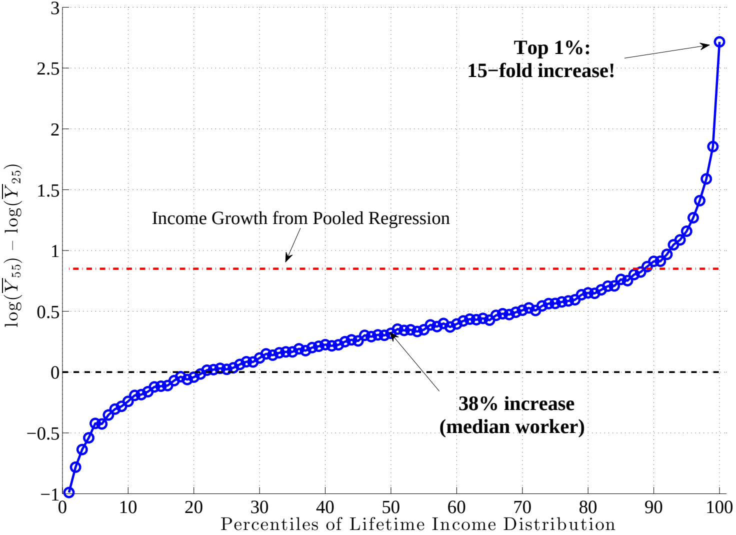

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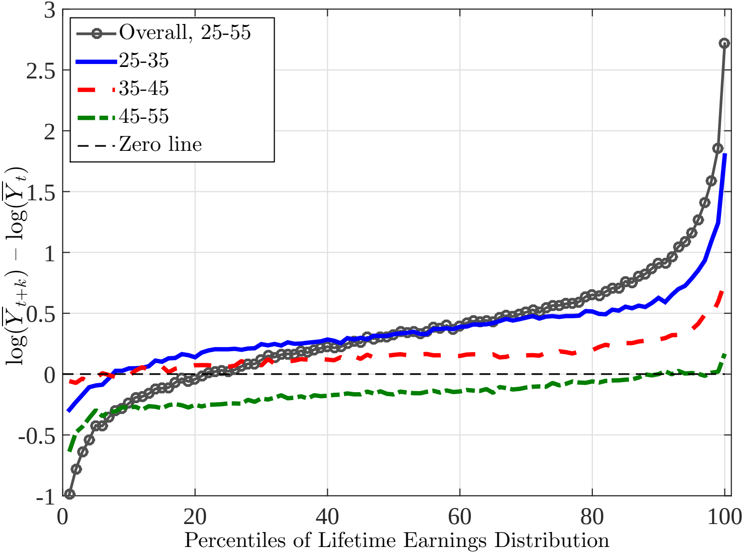

INCOME PROCESS

Econometric Specification

$$Y_t^i = \underbrace{\left(1-\nu_t^i\right)}_{\text{unemp. shck.}} \exp\left(g\left(t\right) + \underbrace{\left[\alpha^i + \beta^i t\right]}_{\text{HIP}} + \underbrace{z_{1,t}^i + z_{2,t}^i}_{\text{mixture of AR(1)s}} + \varepsilon_t^i \right)$$

$$z_{j,t}^i = \rho_j z_{j,t-1}^i + \eta_{j,t}^i, \text{ for } j = 1, 2$$

$$\nu_t^i \sim \min\left\{1, \text{Exponential}\left(\lambda\right)\right\} \text{ with prob. } p_{\nu t}(z_{1,t}^i + z_{2,t}^i)$$

Annual earnings of individual i at age t, Y_t^i is composed of:

1. a heterogeneous income profiles (HIP) component of linear form;
2. a mixture of two AR(1) processes, z_1 and z_2,
3. an i.i.d. shock ε
4. a non-employment shock $\nu > 0$ with probability $p_{\nu t}$, $\nu \sim \min\left\{1, Exp(\lambda)\right\}$;
    - $p_{\nu t}$ is a linear function of age and sum of persistent components.

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$$\text{for } j = 1,2: \quad \eta_{jt}^i \sim \begin{cases} -\frac{p_{jt}^i}{1-p_{jt}^i}\mu_j & \text{with prob } 1\text{-}p_{jt}^i(z_{t-1}^i) \\ \mathcal{N}(\mu_j, \sigma_j^i) & \text{with prob } p_{jt}^i(z_{t-1}^i) \end{cases}$$

- $z_{j,t}^i$ receives a new innovation with probability $p_{jt}^i \in [0,1]$
- $p_{jt}^i(z_{t-1}^i)$ is a linear function of age and sum of persistent components.
- η_{jt}^i has zero mean.
- variance of each innovation, σ_j^i is individual-specific.

Estimation Results: Summary

- We estimate this specification (and simpler versions) by targeting the previously shown moments employing SMM.
- Unemployments shocks are important; without them fit significantly worsens.
- HIP case: z_2 is not unit root though quite persistent, $\rho_2 \sim 0.96$; z_1 is only moderately persistent, $\rho_1 \simeq 0.56$.
- Large heterogeneity in individual specific variance of innovations.
  - σ_1^i ~ [0.06,0.78] and σ_2^i ~[0.13,1.05]
- Removing HIP component does not worsen the fit significantly.
  - Serially correlated shocks compensate for the lack of HIP.

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Probability of Shocks over the Life Cycle

	Age groups		
	25–34	35–49	45–59
p_{z_1} ($\rho_z = 0.56$)	0.101	0.186	0.292
p_{z_2} ($\rho_x = 0.96$)	0.264	0.201	0.187
p_ν (nonemp.)	0.088	0.065	0.059
Pr (any shock)	0.351	0.369	0.458

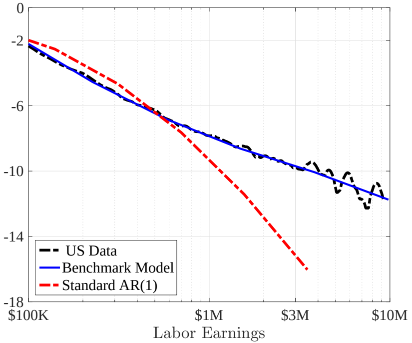
- The overall likelihood of receiving a either type of shock is fairly low.
- Probability of drawing η_1 (η_2) is increasing (decreasing) over the life cycle.
- Non-employment is slightly more likely when young.

Probability of Shocks over the Income Distribution

	RE (Percentile) groups			
	10	50	90	100
p_{z_1} ($\rho_z = 0.56$)	0.110	0.197	0.254	0.477
p_{z_2} ($\rho_x = 0.96$)	0.476	0.185	0.100	0.044
p_ν (nonemp.)	0.208	0.050	0.020	0.014
Pr (any shock)	0.563	0.364	0.341	0.515

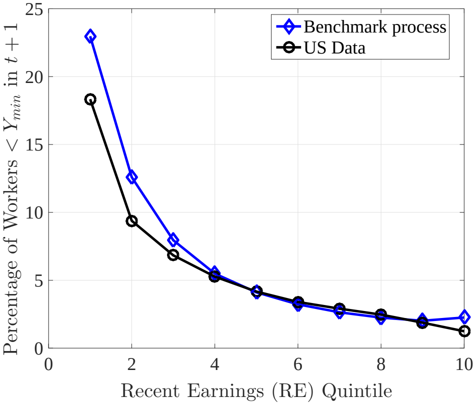
- η_1 is more likely to hit high-income (in particular, top 1%) individuals and vice versa for η_2.
- Non-employment risk is much more likely for low-income.
- For low-income, the correlation of ν_t and ν_{t+1} is 0.60.

Log Density of Earnings



- Non-Gaussian income process can capture the very long tails of the earnings distribution.

Unemployment Risk by Income



- Large heterogeneity in non-employment rates in non-employment rate across income groups.

CONSUMPTION-SAVINGS

Life-Cycle Incomplete Markets Model

$$
\begin{aligned}
V_t^i\left(a_t^i, z_{1,t}^i, z_{2,t}^i; \Upsilon^k\right) &= \frac{\left(c_t^i\right)^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_t\left[V_{t+1}^i\left(a_{t+1}^i, z_{1,t+1}^i, z_{2,t+1}^i; \Upsilon^k\right)\right] \\
\text{s.t.} & \\
\Upsilon^i &\equiv \left(\alpha^i, \beta^i, \sigma_1^i, \sigma_2^i\right) \\
c_t^i + a_{t+1}^i &= a_t^i R + Y_t^{\mathrm{disp},i}, \qquad \forall t, \\
Y_t^{\mathrm{disp},i} &= \max\left\{\underline{Y}, Y_t^i\right\}^{1-\tau}, \qquad t = 1, \ldots, T_W, \\
Y_t^{\mathrm{disp},i} &= \left(\widetilde{Y}_R^k\right)^{1-\tau}, \qquad t = T_W + 1, \ldots, T, \\
a_{t+1}^i &\geq \bar{A}_t^k, \qquad \forall t,
\end{aligned}
$$

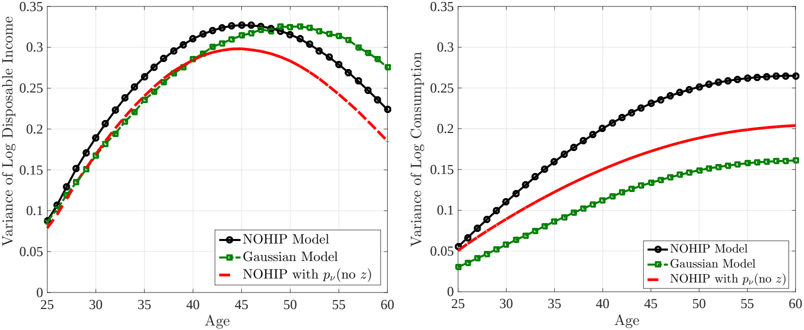
- type-spefic borrowing limit, $\bar{A}_t^k$.
- τ: calibrated to match US progressive tax schedule.
- $\tilde{Y}_R^k$: type-specific retirement pension calibrated to US.
- Two values of $\underline{Y}$, \$2,000 and \$10,000.
- Income process is not discretized, $z_{1,t}^i, z_{2,t}^i$ are continuos.

Welfare Costs of Idiosyncratic Shocks

Model	Benchmark	NOHIP	p_ν (no z)	Gaussian
	(1)	(2)	(3)	(4)
$\underline{Y} = \$10,000$	25.3%	18.1%	14.4%	11.3%
$\underline{Y} = \$2,000$	40.1%	34.5%	24.8%	12.5%

- Welfare costs of Benchmark much larger than Gaussian.
  - Especially when consumption floor is low.
- When unemployment shocks are iid within age, welfare costs decline.
- When rank types k; welfare costs for 90th percentile 26%, whereas the 10th percentile is a mere 2.4%.

Income and Consumption Inequality



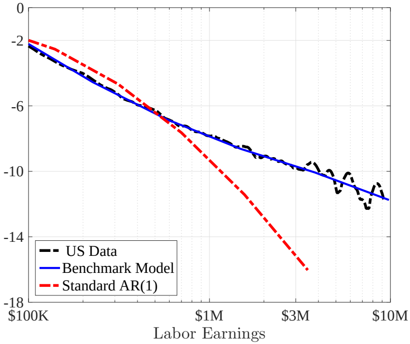
- The increase in consumption inequality is steeper for the NOHIP.
  - Non-Gaussian shocks are harder to insure against.

Wealth Inequality

	U.S. Data	Simulated Model: Benchmark	Simulated Model: NOHIP	Simulated Model: Gaussian
	(1)	(2)	(3)	(4)
Gini	0.85	0.69	0.66	0.58
Top 10%	50.8%	47.4%	41.6%	37.9%
Top 1%	37.0%	10.0%	9.2%	7.0%
Top 0.1%	14.8%	2.2%	2.2%	1.1%

- Benchmark process exhibits the highest wealth inequality; Gaussian exhibits the lowest.
  - Improvement is not nearly large enough to capture the top wealth inequality.
- Higher-order risk can explain wealth accumulation of the top 10% excluding the top 1%.

Log Density of Earnings



- Non-Gaussian income process can capture the very long tails of the earnings distribution.

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.
- Important consumption/savings implications
  - Higher welfare costs of idiosyncratic risk.
  - Larger top 10% wealth inequality.

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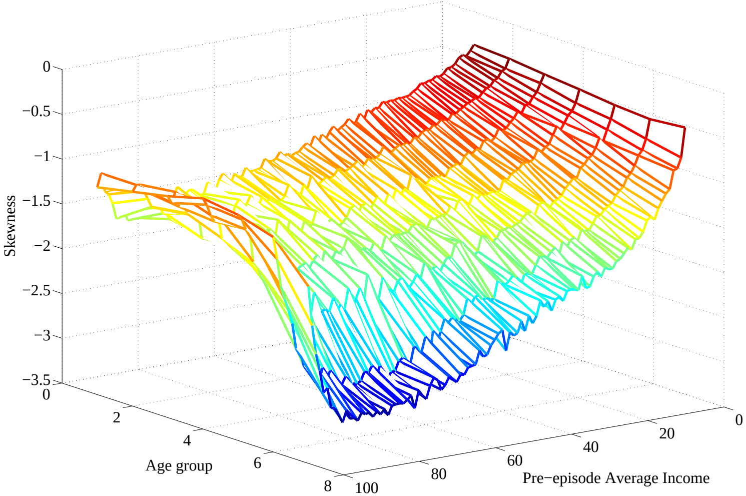
Ongoing Research

- Karahan, Kapon, and Ozkan (2015) show that hourly and weekly wages display excess kurtosis and left skewness in the CPS data.
  - How about household (after tax/transfers) income? IRS data.
- We study quantitative implications for household finance.
  - Karahan and Ozkan (2015) study portfolio choice and consumption insurance implications.
  - Gordon, Karahan and Ozkan (2015) study implications for unsecured credit.
- Karahan, Ozkan and Peterman (2015) study implications for optimal taxation in a Ramsey setting.

3-D Skewness of $y_{t+1} - y_t$



3-D Kurtosis of $y_{t+1} - y_t$