# Rising Inequality: Transitory of Persistent?

*New Evidence from a Panel of US Tax Returns*

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# Transitory vs. persistent inequality


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## *Rising Inequality: Transitory or Persistent? New Evidence from a Panel of U.S. Tax Returns*


**ABSTRACT** We use a new, large, and confidential panel of tax returns to study the persistent-versus-transitory nature of rising inequality in male labor earnings and in total household income, both before and after taxes, in the United States over the period 1987–2009. We apply various statistical decomposition methods that allow for different ways of characterizing persistent and transitory income components. For male labor earnings, we find that the entire increase in cross-sectional inequality over our sample period was driven by an increase in the dispersion of the persistent component of earnings. For total household income, we find that most of the increase in inequality reflects an increase in the dispersion of the persistent income component, but the transitory component also appears to have played some role. We also show that the tax system partly mitigated the increase in income inequal-

# Transitory vs. persistent inequality

Goal of this paper:

- Decompose the variance in income into its component sources
- Particular focus on the variance not explained by business cycles, age, or other observables
- Show how this has changed over time
- Do this in a way that incorporates the upper tail of the income distribution
- Show the effects of the tax system on income inequality

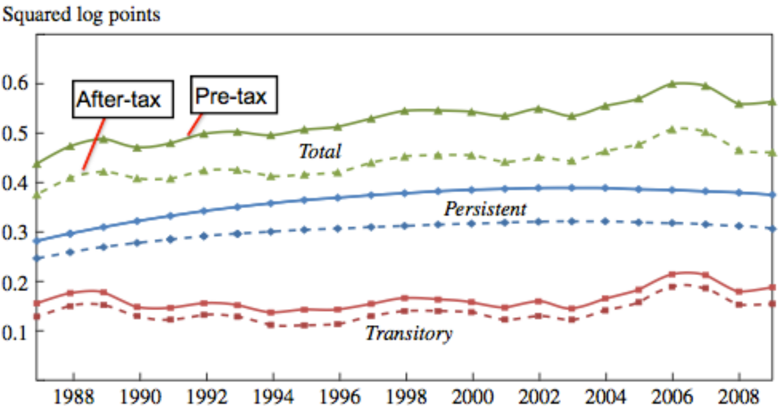
# Transitory vs. persistent inequality

What to we mean by transitory versus persistent?

- Transitory shocks to income are those that affect your income for only a short period of time
  - → e.g., A one-time bonus
- Persistent shocks are those that last for a longer period of time (i.e., several years)
  - → Some could be permanent
    - e.g., a step up in pay scale due to an advanced degree
  - → Some are just persistent
    - e.g., an increase in demand for a particular skill over several years

# Transitory vs. persistent inequality

**Figure 9.** ECM Decomposition of Cross-Sectional Variance in Pre-Tax and After-Tax Household Income, All Households, 1987–2009




Source: Authors' calculations using SOI data.

# Transitory vs. persistent inequality

Why important to decompose?

- May say something about cause of inequality
  - $\rightarrow$ E.g., if permanent component driving increase, then not increases in mobility
- Says something about welfare effects
  - $\rightarrow$ E.g., if transitory shocks driving increase, these can be insured against by saving/borrowing

# Transitory vs. persistent inequality

DHPRV (2013) use a number of methods to decompose the variance in earnings:

- Non-parametric methods
  - → Volatility (i.e., standard deviation in percentage changes) in income over different time horizons
  - → Variance decomposition
    - Find variance in income over some time horizon (e.g. 5 years) - call this the "persistent" variance.
    - Find variance of (income less mean income over the time horizon) - call this the "transitory" variance
- Parametric Methods
  - → Error components models

# Model of Income

Let $y^i_{a,t} =$ log income of individual $i$ at age $a$ in year $t$

Income is determined as:

$$y^i_{a,t} = g(\zeta; X^i_{a,t}) + \xi^i_{a,t}, \tag{1}$$

where:

- $\zeta$ is a vector of (possibly year dependent) parameters
- $X^i_{a,t}$ is a vector of observed characteristics
- $g(\cdot)$ is the component of log income that is common to all individuals conditional on $X^i_{a,t}$
- $\xi^i_{a,t}$ is the unobserved error term

# Error-Components Model

ECMs put structure on this error term to estimate the process underlying this unobserved component of income.

Assume (for the stationary model of residual earnings):

$$\xi^i_{a,t} = \alpha^i + p^i_{a,t} + \tau^i_{a,t} \tag{2}$$

- $\alpha^i$ is the permanent component (i.e., an unobserved fixed effect)
- $p^i_{a,t}$ is the persistent component
- $\tau^i_{a,t}$ is the transitory component

# ECM

Some further structure:

- The persistent component follows an AR(1) process:

$$p^i_{a,t} = \psi p^i_{a-1,t-1} + \eta^i_{a,t} \tag{3}$$

- The transitory component follows an MA(2) process:

$$\tau^i_{a,t} = \varepsilon^i_{a,t} + \theta_1 \varepsilon^i_{a-1,t-1} + \theta_2 \varepsilon^i_{a-2,t-2} \tag{4}$$

- Shocks are distributed as:

$$\alpha^i \sim \text{i.i.d.}(0, \sigma^2_\alpha), \eta^i_{a,t} \sim \text{i.i.d.}(0, \sigma^2_\eta), \varepsilon^i_{a,t} \sim \text{i.i.d.}(0, \sigma^2_\varepsilon)$$

# ECM

Some notes:

- This is a lot of structure to put on the model
- It is somewhat flexible (e.g., it may turn out that the process is MA(1) and thus $\theta_2 = 0$)
- But do note that the parameters are not index by $t$, so assuming some stationarity (this is relaxed in DHPRV (2013))
- Looking at the data will help inform the parametric specification (i.e., plot residuals - what to they look like? What does the auto-covariance structure look like? Are the relationships stable over time?)

# Identification (1)

What would this model of the error term imply for the structure of the data?

1. $E(\xi^i_{a,t}) = E(\alpha_i + p^i_{a,t} + \tau^i_{a,t}) = 0$
2. $cov(\xi^i_{a,t}, \xi^i_{a+k,t+k}) = E(\xi^i_{a,t} * \xi^i_{a+k,t+k}) - \underbrace{E(\xi^i_{a,t})}_{=0}\underbrace{E(\xi^i_{a+k,t+k})}_{=0} =$

   $E(\xi^i_{a,t} * \xi^i_{a+k,t+k})$

# Identification (2)

Further expansion of the $cov(\xi^i_{a,t}, \xi^i_{a+k,t+k})$:

$$
\begin{aligned}
cov(\xi^i_{a,t}, \xi^i_{a+k,t+k}) &= E(\xi^i_{a,t} * \xi^i_{a+k,t+k}) \\
&= E\left[(\alpha_i + p^i_{a,t} + \tau^i_{a,t})(\alpha_i + p^i_{a+k,t+k} + \tau^i_{a+k,t+k})\right] \\
&= E\Big[\alpha^i\alpha^i + \alpha^i p^i_{a,t} + \alpha^i \tau^i_{a,t} + \alpha^i p^i_{a+k,t+k} + p^i_{a,t} p^i_{a+k,t+k} + \\
&\qquad \tau^i_{a,t} p^i_{a+k,t+k} + \alpha^i \tau^i_{a+k,t+k} + p^i_{a,t}\tau^i_{a+k,t+k} + \tau^i_{a,k}\tau^i_{a+k,t+k}\Big] \\
&= \underbrace{E(\alpha^i\alpha^i)}_{=var(\alpha^i)} + \underbrace{E(\alpha^i p^i_{a,t})}_{=0} + \underbrace{E(\alpha^i \tau^i_{a,t})}_{=0} + \underbrace{E(\alpha^i p^i_{a+k,t+k})}_{=0} + \\
&\qquad \underbrace{E(p^i_{a,t} p^i_{a+k,t+k})}_{=cov(p^i_{a,k} p^i_{a+k,t+k})} + \underbrace{E(\tau^i_{a,t} p^i_{a+k,t+k})}_{=0} + \underbrace{E(\alpha^i \tau^i_{a+k,t+k})}_{=0} + \\
&\qquad \underbrace{E(p^i_{a,t}\tau^i_{a+k,t+k})}_{=0} + \underbrace{E(\tau^i_{a,k}\tau^i_{a+k,t+k})}_{=cov(\tau^i_{a,k}, \tau^i_{a+k,t+k})}
\end{aligned}
$$

# Identification (3)

$$cov(\xi^i_{a,t}, \xi^i_{a+k,t+k}) = var(\alpha^i) + \underbrace{cov(p^i_{a,k} p^i_{a+k,t+k})}_{\rho^k var(p^i_{a,t})} + cov(\tau^i_{a,k} \tau^i_{a+k,t+k})$$

$$= \sigma^2_\alpha + \rho^k var(p^i_{a,t}) + cov(\tau^i_{a,k}, \tau^i_{a+k,t+k})$$

where,

$$cov(\tau^i_{a,k} \tau^i_{a+k,t+k}) = \begin{cases} \sigma^2_\varepsilon, & \text{if } k = 0, a = 1 \\ (1+\theta_1^2)\sigma^2_\varepsilon, & \text{if } k = 0, a = 2 \\ (1+\theta_1^2+\theta_2^2)\sigma^2_\varepsilon, & \text{if } k = 0, a \geq 3 \\ \theta_1\sigma^2_\varepsilon, & \text{if } k = 1, a = 1 \\ (\theta_1+\theta_1\theta_2)\sigma^2_\varepsilon, & \text{if } k = 1, a \geq 2 \\ \theta_2\sigma^2_\varepsilon, & \text{if } k = 2 \\ 0, & \text{if } k > 2 \end{cases}$$

# Identification (4)

and

$$var(p^i_{a,t}) = \begin{cases} \sigma^2_\eta \frac{1-\psi^{2a}}{1-\psi^2} & \text{if } a \geq 2, t = \text{First year in data} \\ \sigma^2_\eta, & \text{if } a = 1 \\ \psi^2 var(p^i_{a-1,t_-1}) + \sigma^2_\eta & \text{if } a \geq 2, t \neq \text{First year in data} \end{cases}$$

# Identification (5)

Theoretical covariances:

$$\begin{aligned} cov(a,t,k;\Theta) = \sigma_\alpha^2 + \psi^k var(p_{a,t}^i) + &\\ &\mathbb{1}[k=0](1+\mathbb{1}[a\geq 2]\theta_1^2 + \mathbb{1}[a\geq 3]\theta_2^2)\sigma_\varepsilon^2 + \\ &\mathbb{1}[k=1](\theta_1 + \mathbb{1}[a\geq 2]\theta_1\theta_2)\sigma_\varepsilon^2 + \\ &\mathbb{1}[k=2]\theta_2\sigma_\varepsilon^2 \end{aligned}$$

- Analytical solution for the covariances that we observe in the data
- $\implies$ moment conditions (for each $a$, $t$, $k$):

$$g_{a,t,k}(\Theta_0) = E\left[\underbrace{cov(\xi_{a,t}^i, \xi_{a+k,t+k}^i)}_{\text{covariances from data}}\right] - cov(a,t,k;\Theta_0) = 0$$

# GMM Estimator

We will use the sample analogue of the theoretical moment conditions:

$$\tilde{g}_{a,t,k}(\Theta_0) = \frac{\sum_{i=1}^{n}(\xi_{a,t}^{i}\xi_{a+k,t+k}^{i})}{n-1} - cov(a,t,k;\Theta_0) = 0$$

Define $g(\Theta)$ as the vector containing all the $g_{a,t,k}(\Theta)$ moment conditions.

The GMM estimator is then:

$$\hat{\Theta} = arg\min_{\Theta} g(\Theta)^T W g(\Theta),$$

where $W$ is a weighting matrix