

Trends in Earning Volatility for U.S. Men: 1979-2017

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2022 Southern Economic Association Annual Meeting

November 26

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Two types of income volatility

Volatility measures the degree of change in an economic variability from one period to the next

- ① Variance of income change or income growth (Gross Volatility):
Bloom et al. (2017), Carr & Wiemers (2018), Braxton et al. (2021),
Carr & Wiemers (2021), Moffitt et al. (2022)
- ② Permanent and transitory variances: Moffitt & Gottschalk (2012),
Hryshko et al. (2017), Moffitt & Zhang (2018), Braxton et al. (2021)

- Trends in transitory variance also fall into the income risk category of income mobility, according to Jäntti & Jenkins (2015)
- A gross volatility study is straightforward and does not require delicate model assumptions
- But, trends in permanent and transitory variances provide more useful policy implications (ex., consumption, inequality, welfare).

Implication of variance decomposition

Increase in permanent variance

- Causes income distribution to widen over time
- Rankings are preserved
- Possible determinants: Labor demand shift from skill biased technology and international trade

Increase in transitory variance

- Shuffles income rankings
- Implies higher income risk
- Possible determinants: Worker-firm attachment, labor market competitiveness, regulation, and temporary employment

- The gross volatility analysis in this article contributes to the recent effort to reconcile discrepancies across studies (Moffitt et al., 2022)
- The first study that investigates a permanent-transitory variance of earnings in the Current Population Survey (CPS) by constructing a pseudo panel.

The Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS)

- The publicly-available version downloaded from the Center for Economic and Policy Research (CEPR)
- Ranges from 1979 to 2017
- Restrict to men between ages 30 and 59, who are not full-time students, with positive earned income and non-missing educational attainment information
- Drop zero-weighted samples
- Converted to 2017 CPI-U-RS dollars
- Trim the top 4% to eliminate top-coded incomes

Descriptive Statistics: CPS Cross-Section

	Mean	Standard Deviation	Minimum	Maximum
Age	43	8.424	30	59
Married (%)	0.74	0.437	0	1
Race:				
White (%)	0.78	0.415	0	1
Black (%)	0.08	0.275	0	1
Hispanic (%)	0.09	0.283	0	1
Others (%)	0.05	0.219	0	1
Education:				
Less than high school (%)	0.12	0.329	0	1
High school (%)	0.33	0.472	0	1
Some college (%)	0.25	0.432	0	1
College (%)	0.19	0.391	0	1
Advanced (%)	0.11	0.308	0	1
Employment:				
Full time, full year (%)	0.82	0.385	0	1
Working hours per week	43.56	9.46	1	99
Working weeks	48.82	8.87	1	52
Wage and Salary (2017 Dollars)	56,584	33,668	1	200,000

Data overview: CPS cross-section

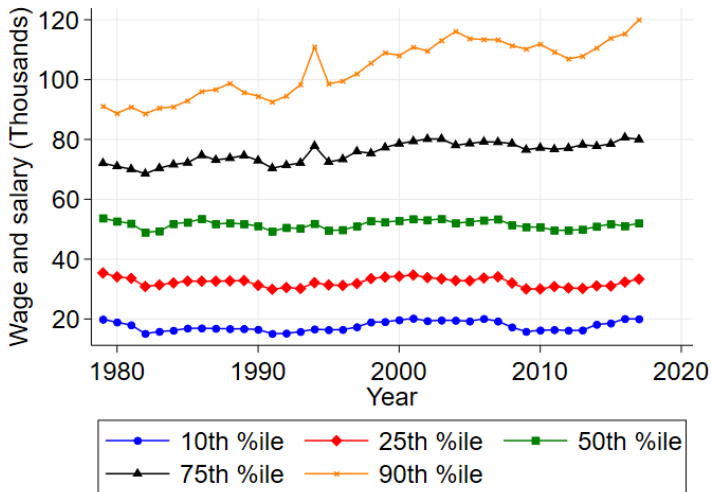


Figure: Male earnings by percentiles

Cross-sectional variance

- Researchers disagree about the degree of the rise in cross-sectional variance (those above the 90th percentile)
 - Partially results from methodological choices for imputing income sources that are not directly observed.
- However, the rise in cross-sectional variance is still a conventional view on U.S. income (Bloom et al., 2017).
- On the other hand, researchers disagree on trends in earnings volatility.

Data: Pseudo panel

- In the CPS, individuals are followed at most two years.
- To investigate longer-term earnings patterns, a **pseudo panel** is constructed:
Each individual is classified into only one cohort where the characteristics for creating cohorts are exogenous and time-invariant.
- Based on an individual's year of birth, education level, and race

Methodology: Obtain residuals

- Regress log earnings on education, an age polynomial, and interactions between age and education variables, separately by calendar year \rightarrow Obtain residuals $\hat{\epsilon}_{ct}$

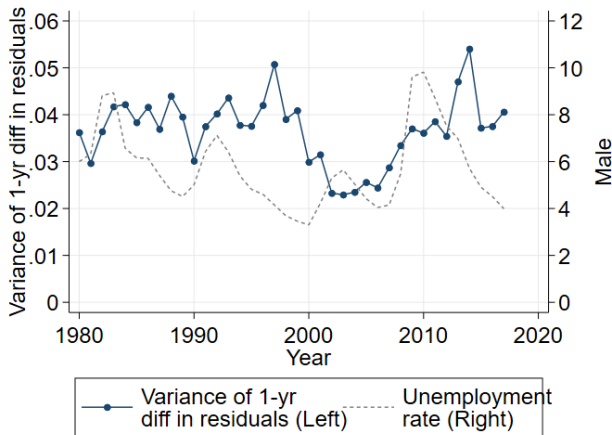
$$y_{ct} = \beta_{0t} + \mathbf{X}'_{ct}\beta_{1t} + \mathbf{Y}'_{ct}\beta_{2t} + \mathbf{Z}'_{ct}\beta_{3t} + \epsilon_{ct} \quad (1)$$

- y_{ct} is log earnings for cohort c and time t
- \mathbf{X}_{ct} is a vector of five education dummy variables
- \mathbf{Y}_{ct} is an age polynomial (cubic)
- \mathbf{Z}_{ct} is interaction between education dummies and age
- The regressions are weighted by the square root of the cohort size

Result: Gross volatility

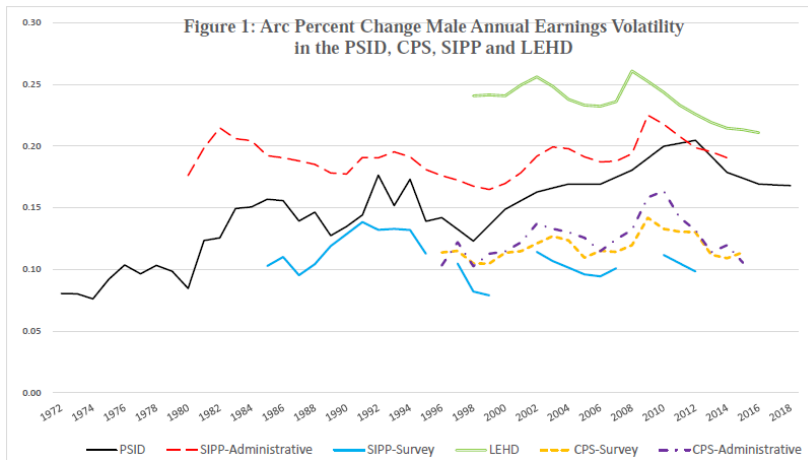
Gross volatility = The variance of first-differenced residuals

Figure: Gross volatility of male log earnings residuals



Result: Gross volatility

Figure: Gross Volatility (Moffitt et al., 2022)



Methodology: Extended Semiparametric (ESP) Model

- Developed by Moffitt & Zhang (2018) (Hereafter MZ)
- The model overcomes one criticism on the widely used error component (EC) model, under which estimates are often sensitive to parametric assumption.
- The ESP model is non-parametric with respect to the dynamic evolution of permanent and transitory variances but maintains a traditional linear framework of the EC model.

$$\epsilon_{cat}^{\hat{}} = \underbrace{\alpha_t \mu_{ca}}_{\text{Permanent Component}} + \underbrace{\beta_t \nu_{ca}}_{\text{Transitory Component}} \quad (2)$$

$\epsilon_{cat}^{\hat{}}$: Log earnings residual for cohort c at age a and year t

α_t and β_t : Calendar time shifts

Note: Parameters to be estimated are colored red.

Methodology: Extended Semiparametric (ESP) Model

Permanent Component:

$$\mu_{ca} = \mu_{c0} + \sum_{s=1}^a \omega_{cs} \quad (3)$$

Transitory Component:

$$\nu_{ca} = \xi_{ca} + \sum_{s=1}^{a-1} \psi_{a,a-s} \xi_{c,a-s} \text{ for } a \geq 2 \quad (4)$$

$$\nu_{c1} = \xi_{c1} \text{ for } a = 1 \quad (5)$$

$$|\psi_{a,a-s}| < 1$$

ω_{cs} : Permanent shocks

$\xi_{c,a-s}$: Transitory shocks

$$\mu_{c0} \sim N(0, \text{Var}(\mu_{c0}))$$

Note: Parameters to be estimated are colored red.

Methodology: Extended Semiparametric (ESP) Model

- ω and ξ are nonparametric functions of age a
- ψ are nonparametric functions of age a and leg length b

$$\text{Var}(\omega_{ca}) = e^{\sum \delta_j (a-25)^j} \quad (6)$$

$$\text{Var}(\xi_{ca}) = e^{\sum \gamma_j (a-25)^j} \text{ for } a \geq 2 \quad (7)$$

$$\text{Var}(\xi_{c1}) = k e^{\sum \gamma_j (1-25)^j} \text{ for } a = 1 \quad (8)$$

$$\psi_{a,a-b} = [1 - \pi(a-25)][\sum e^{-\lambda_j b}] + \sum \eta_j D(b=j) \quad (9)$$

- The degree of the expansion is chosen by generalized cross-validation (GCV)

Note: Parameters to be estimated are colored red.

Methodology: Generalized method of moments (GMM)

- The GMM estimator finds close matches for **population variances and autocovariances** in equations (2)-(9) to **their sample counterparts** from log earning residuals $\hat{\epsilon}_{ct}$
- Estimation with the weighing matrix can lead to biases in finite samples (Doris et al., 2011)
 - An identity matrix can be chosen as an alternative (Altonji et al., 2013)
 - Minimum distance method

Result: ESP model estimates

Table: Estimates of the ESP Parameters

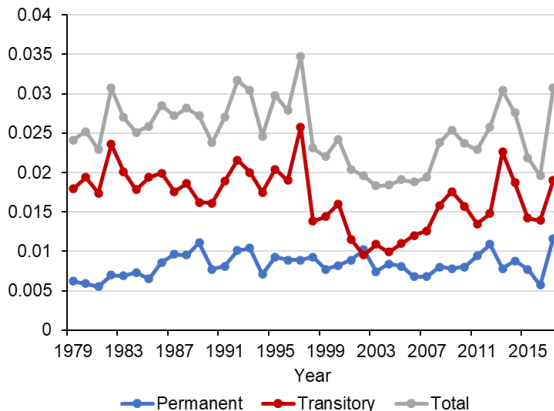
	Coefficient	Standard Error
$Var(\mu_{i0})$	0.0062	0.0001
λ	0.0551	0.0029
η_0	-11.5137	0.4775
π	-0.1468	0.0048
k	1.5188	0.0997
η_1	-2.3291	0.0579
δ_0	-15.4304	29.0889
δ_1	-0.0074	2.1871
γ_0	-8.6724	0.0877
γ_1	0.0344	0.0005
η_2	-0.2634	0.0083

Result: ESP model estimates

Total variance = $Var(\epsilon_{cat}^{\hat{}})$

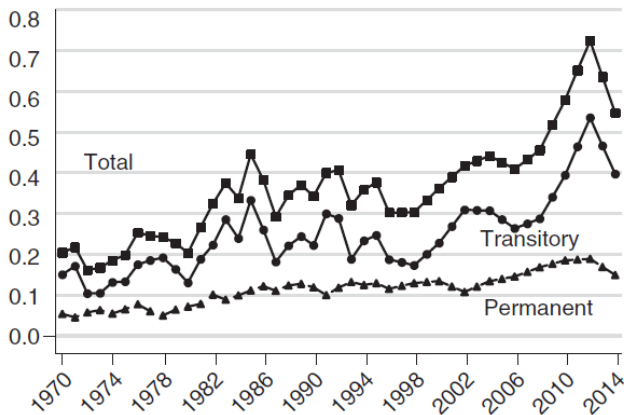
Permanent variance = $Var(\hat{\alpha}_t \mu_{ca})$, Transitory variance = $Var(\hat{\beta}_t \nu_{ca})$

Figure: Fitted permanent, transitory, and total variances of log earnings residuals:
Ages 30-39



Result: ESP model estimates

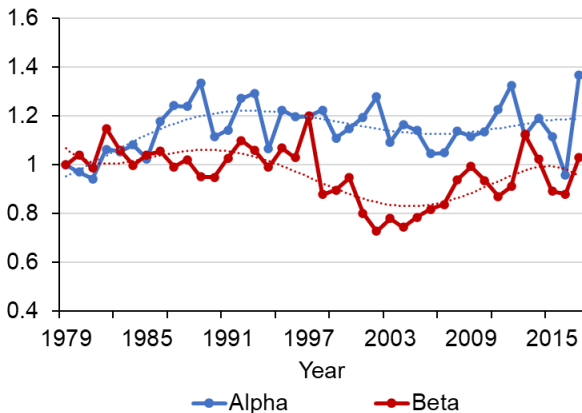
Figure: Fitted Variances of Log Earning Residuals: Age 40-49 (Moffitt and Zhang, 2018)



Result: ESP model estimates

$$\hat{\epsilon}_{cat} = \alpha_t \mu_{ca} + \beta_t \nu_{ca}$$

Figure: Extended semiparametric (ESP) model estimates of alpha and beta



Note: The trend line is fit from a fifth order polynomial.

Gross volatility

- An essential difference between our work and MZ is the decreasing trend in gross volatility that preceded the Great Recession
- Researchers disagree with the trend in gross volatility from the mid-1980s to the late 1990s, possibly caused by characteristics of data sets (e.g., a heaviness in low tail) and difference in trimming method (real dollar trim vs. percentile trim)
- Consistent with the recent study (Moffitt et al., 2022) that shows little evidence of any significant trend in male earnings volatility since the mid-1990s except a counter-cyclical pattern.

Permanent and transitory variance

- The increase of α in the 1980s corresponds to rises in the return to education and other indices of skill differentials (Moffitt & Gottschalk, 2012)
- Our estimates of β resemble those from MZ in that they increased in years around the Great Recession (countercyclicality)
- The transitory variance: About 74% of the total variance until the late 1990s, and 52% in 2002. Resumed to increase and was about 70% surrounding the Great Recession.

- Use the restricted-use version CPS
 - To protect the confidentiality of respondents, incomes in the CPS are top coded. The restrict-use version has higher top-coding thresholds.
- The article focuses on the income volatility of prime-age men, and extensions to other sub-demographic levels – such as females, immigrants, or minorities – are not explored yet.