

Dissecting Idiosyncratic Earnings Risk

Elin Halvorsen

Statistics Norway

Hans Holter

U of Oslo

Serdar Ozkan

Toronto, St. Louis Fed

Kjetil Storesletten

U of Minnesota

Presentation Slides

June 2023

Nonlinear/Non-Gaussian Earnings Dynamics

- Big data and new methods helped us to reveal new insights for income dynamics.
Guvenen *et al.* (2019); Arellano *et al.* (2017); De Nardi *et al.* (2019); Guvenen *et al.* (2014); Busch *et al.* (2015), ...
- Non-Gaussian features of income shocks
 - Left skewness and excess kurtosis

Nonlinear/Non-Gaussian Earnings Dynamics

- Big data and new methods helped us to reveal new insights for income dynamics.
Guvenen *et al.* (2019); Arellano *et al.* (2017); De Nardi *et al.* (2019); Guvenen *et al.* (2014); Busch *et al.* (2015), ...
- Non-Gaussian features of income shocks
 - Left skewness and excess kurtosis
- Asymmetric/nonlinear mean reversion: Persistence differ by
 - positive vs negative changes; low vs high income workers; age
 - Current shocks change persistence of past ones.

Open Questions

- Focus has been on **annual male earnings** (before tax-before transfer) dynamics.
Except for recent work by De Nardi *et al.* (2019); Busch *et al.* (2019).
- What's driving **asymmetric mean reversion** and **non-Gaussian features** of earnings growth?
 - **Wages** vs **Hours**?
- How much insurance against large earnings losses/gains from spouse and government?
- Do non-Gaussian features (**skewness/kurtosis**) extend to
 - household (husband+wife) earnings?
 - and to household disposable income?
- This paper: Use the Norwegian registry data to study these questions.

What Do We Do

Use the Norwegian registry data to study above questions.

1. Show that patterns for annual earnings risk are remarkably similar to the US.
2. Study the role of wages vs hours in non-Gaussian properties of earnings changes.
 - Decompose earnings changes into hours and hourly wage growth.
 - Do wage and hours growth display non-Gaussian features?
3. Document the insurance against tail shocks of earnings through spouse's income and public insurance.
 - Distribution of after after-tax and transfer household income growth.

Data and Empirical Methodology

Norwegian Registry Data

Norwegian Registry Data

- Administrative data covering the whole Norwegian population.
 - A combination of administrative registers such as annual tax records and employment register
- High quality because
 - Third-party reported: employers, banks, brokers, etc.
 - No attrition (unless someone emigrates).
- Family identifiers from the population register.
 - includes cohabitant couples.

Norwegian Registry Data: Base Sample

- Panel data between 1998 and 2014.
 - Income data goes back to 1993 but not hours.
- Today: focus on males between ages 25 and 60.
 - We do the same analysis with women.
- We use ~20M year/individual observations in our analysis
- **Labor Earnings** for wage and salary workers including bonuses and other remunerations.
 - Business income for self-employed workers: no hours data.
 - Deflate all values with the 2000 CPI.
- 2 measures of hours worked.

Hours Data: Employment Register

- Hours reported by employers between 2003 and 2014
 - On contractual working hours per week, employment duration and sector
 - Only for wage and salary workers w/ ≥ 4 hours/week contracts
 - Cover 77% of population between 25 and 60.

Hours Data: Employment Register

- Hours reported by employers between 2003 and 2014
 - On contractual working hours per week, employment duration and sector
 - Only for wage and salary workers w/ ≥ 4 hours/week contracts
 - Cover 77% of population between 25 and 60.
- Shortcomings of hours measure in the employment register:
 - overtime hours are not included,
 - fail to report employment spells correctly or update hour changes,
 - employers with irregular employments are more prone.

AKU: Panel Labor Force Survey

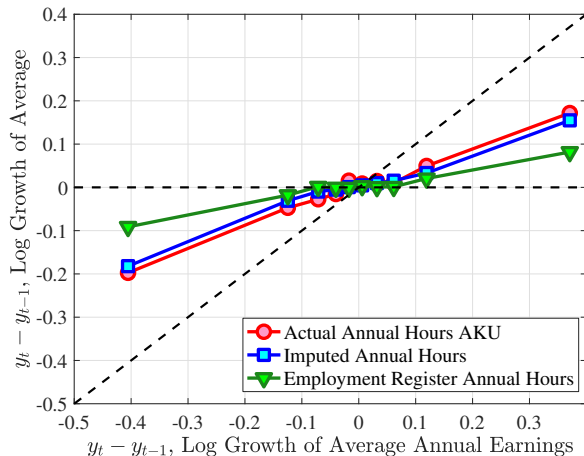
- Used in official unemployment estimates.
- For ~3200 individuals since 1972.
- Surveyed actual hours worked last week in 8 quarters in a row.
 - compute annual hours as $h_{AKU} = \sum_{t=1}^4 13 * h_t$.
- Individuals in the AKU are linked to their administrative register data.
 - Additional information from register data: part time, sick days, unemployment, etc.
- **Impute a better hours measure** in administrative register data.

Imputation of Hours in the Register Data

$$h_{AKU} = f(X_{REG}) + \epsilon$$

- Estimate a model of actual hours measure in the AKU using covariates from the register data.
- The model includes:
 - Basic demographics: Age, education, gender, marriage
 - Contractual hours measure in the register data and its lagged value
 - Number of unemployed, sick and parental days, and their lags
 - Part time vs full time and public vs private, and their lags
 - Past and recent earnings
- Tried different ML algorithms—**regression tree** (Quinlan *et al.* (1992)) performed best.
 - Sample size for training the model is not very big.
- Use $f(X_{REG})$ to impute hours for everyone in the register.

Imputation of Hours in the Register Data



- Hours changes in register data are smaller than those from AKU.
- Imputation is doing a fairly good job in replicating the AKU measure.
- Best predictors are register hours, sick/unemployment days.

	Men		Women	
Depth	3	4	3	4
Train R^2	25.7	26.8	48.8	49.7
Test R^2	22.9	22.4	48.7	48.4

Data and Empirical Methodology

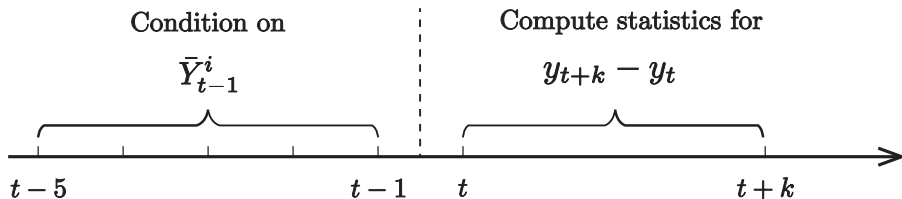
Methodology

Sample Selection and Construction of Recent Earnings

- Revolving panel of 25-60 year old workers with a reasonably strong labor market attachment.
- In year t select individuals participating in the labor market:
 - $Y_s^i > Y_s^{min}$ (5% of median earnings) in $t - 1$ and for 2 more years between $t - 2$ and $t - 5$.
- \bar{Y}_{t-1} : Average recent earnings (**RE**) between $t - 1$ and $t - 5$ net of age effects.

A Graphical Construct

- Divide the population into 3 age groups in $t - 1$: 25–34, 35–44, 45–54.
- Within each age group rank individuals according to \bar{Y}_{t-1} into 10 RE deciles.
- Within each age group, against each quantile of \bar{Y}_{t-1} (RE) on the x-axis:
 - plot moments from conditional distribution of earnings growth $\mathbb{F}(y_{t+k} - y_t | \bar{Y}_{t-1})$.



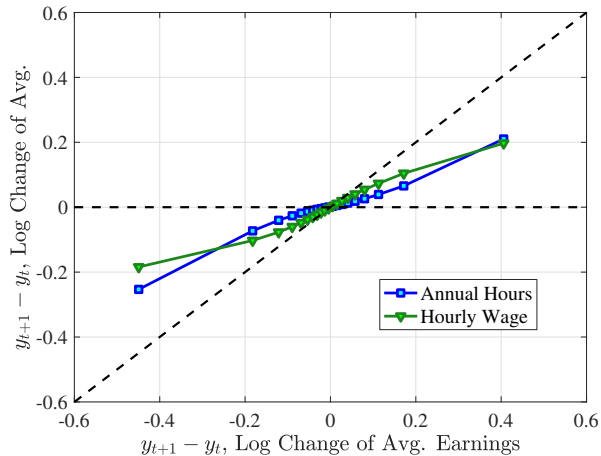
Changes in Hours vs Wages

Earnings Growth: Hours vs Wage

Annual Hours vs Hourly Wage

- Decompose changes in earnings to **hourly wage** or **hours** components.
- Group workers w.r.t. annual wage growth between $t - 1$ and t , $\Delta e_{t,1}$ into 20 equally sized bins.
 - Conditional on age (young vs prime age) and past 5-year income (RE) deciles \bar{Y}_{t-1}^i .
 - a group of prime age men
 - with median past income/recent earnings (**RE**)
 - who experience 25 log points decline in earnings between $t + 1$ and t .
- How much hourly wage and hours growth each group experience?

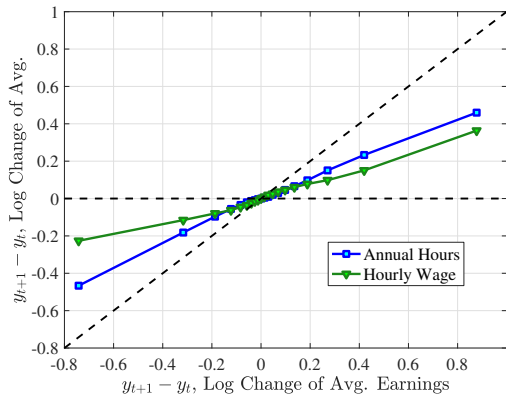
Hours vs Wage: Middle 4 RE Decile



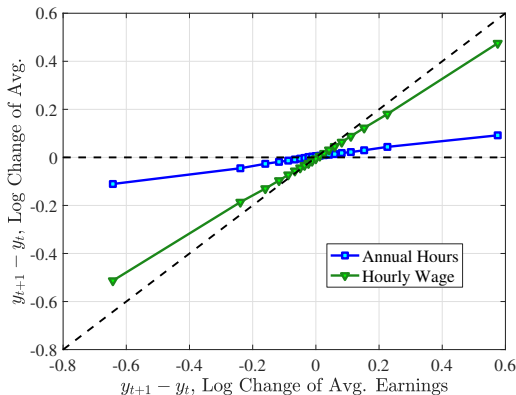
- Large earnings swings: hours and wage growth are equally important.
- Smaller earnings changes: wage growth is more important.

Hours vs Wage: Bottom vs Top RE Deciles

Bottom RE



Top RE

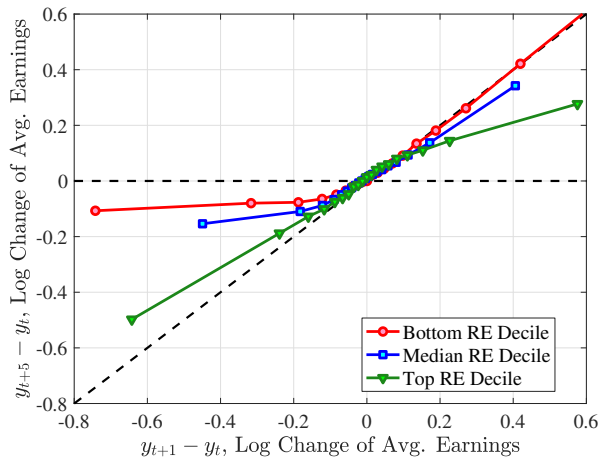


- For bottom RE group hours growth plays a more important role.
- For higher RE groups wage changes are main drivers of earnings growth.

Changes in Hours vs Wages

Asymmetric Mean Reversion

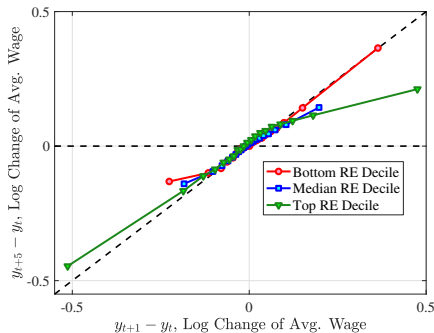
Asymmetric Mean Reversion: Dynamics of Earnings



- For bottom (and median) RE:
 - **negative** changes are transitory
 - **positive** changes are persistent.
- The opposite is true for **top RE**.
 - **negative** changes are persistent
 - **positive** changes are transitory.

Asymmetric Mean Reversion: Hours vs Wages

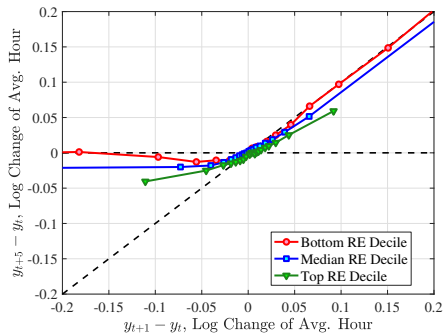
Wage Growth



Low-Earners

- **negative:** transitory hours declines
- **positive:** persist. hours&wage inc.

Hours Change



High-Earners

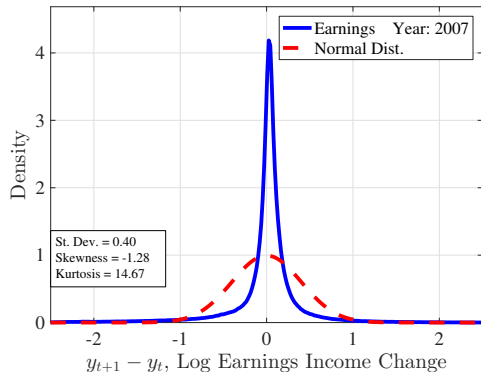
- **negative:** persistent wage declines
- **positive:** transitory wage rises.

Non-Gaussian Earnings Growth Distribution

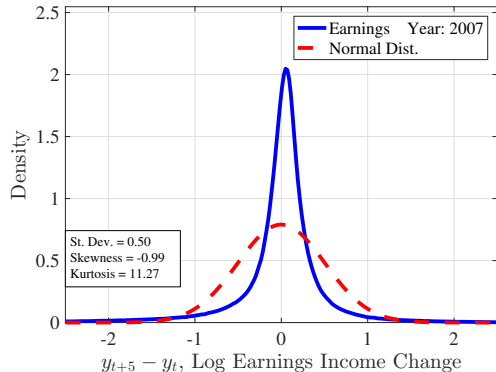
Norway vs US

Histogram of $y_{t+k} - y_t$

1-Year Growth



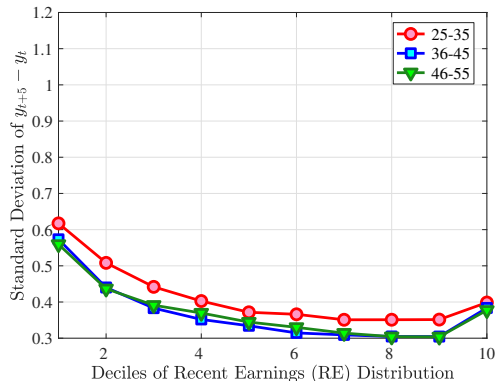
5-Year Growth



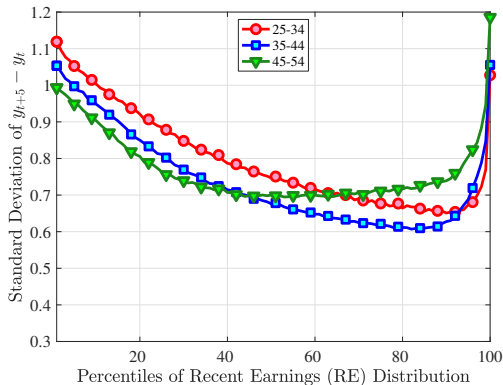
- Peaky center, narrow shoulders, long tails \Rightarrow Excess kurtosis.
- Left tail longer than right tail \Rightarrow Left (Negative) Skewness.

Standard Deviation of $y_{t+5} - y_t$

Norway



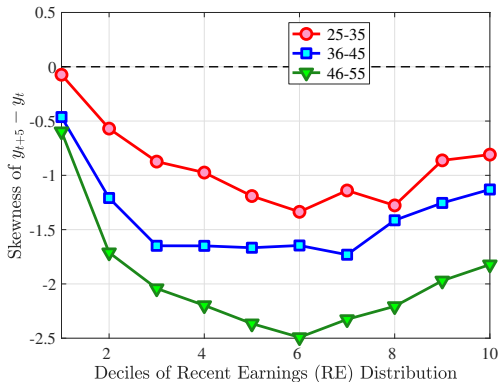
US



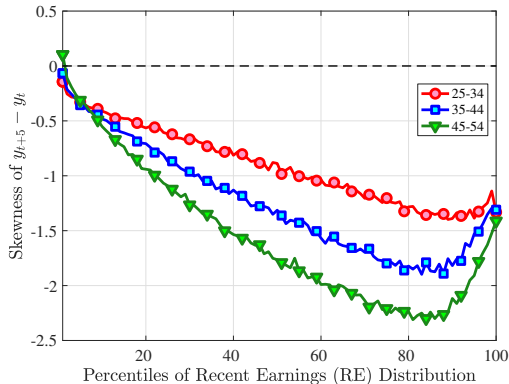
- Changes are smaller in Norway.
- RE and age variation are very similar in both countries.

Skewness of $y_{t+5} - y_t$

Norway



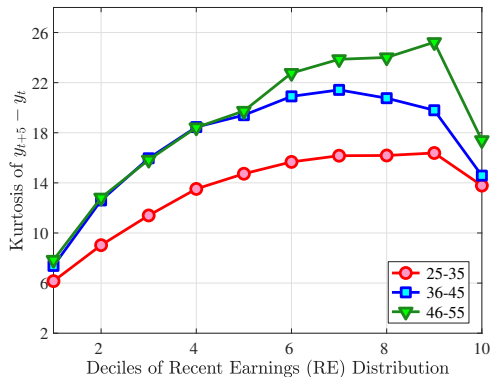
US



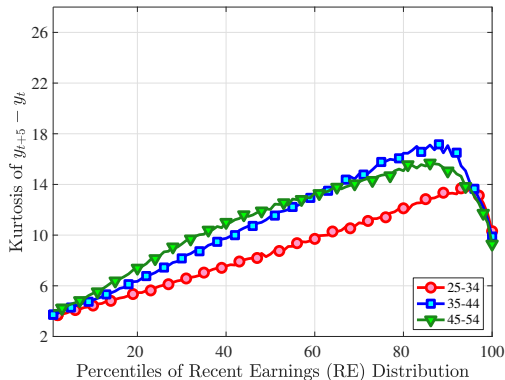
- In both economies, distributions are similarly left skewed.
- Left skewness increases by RE and age in a similar fashion.

Kurtosis of $y_{t+5} - y_t$

Norway



US



- 5-year earnings distribution exhibits higher excess kurtosis in Norway.
- Excess kurtosis follows hump-shaped pattern over RE in both.

Non-Gaussian Earnings Growth Distribution

Distribution of Hours vs Wage Growth

Distribution of Hours vs Wage Growth

- Does **hourly wage** and **annual hours** growth distribution exhibit **non-Gaussian/nonlinear** features?
- How much of the left skewness and excess kurtosis of **annual earnings growth** are driven by changes in **hourly wages** vs **hours**?

$$\log e_{t+k} - \log e_t = \Delta e_{t,k} = \Delta h_{t,k} + \Delta w_{t,k}$$

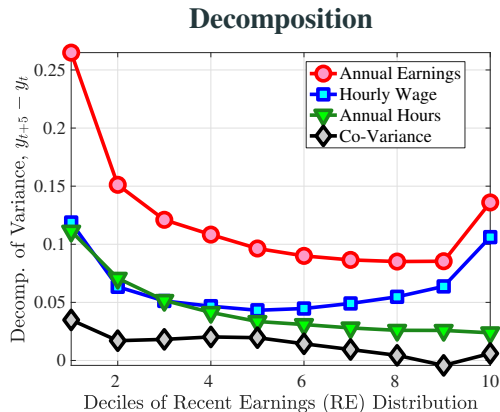
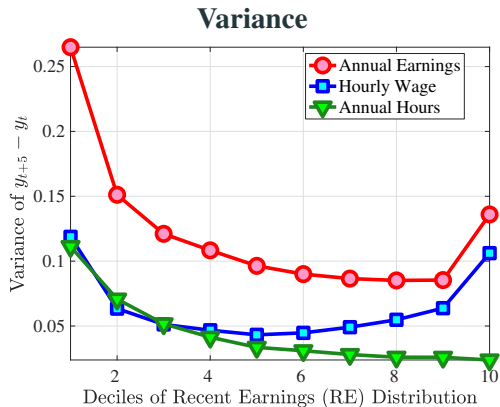
- **Skewness Decomposition**

$$s_{\Delta e_{t,k}} = \left(\frac{\sigma_{\Delta w_{t,k}}}{\sigma_{\Delta e_{t,k}}} \right)^3 \times s_{\Delta w_{t,k}} + \left(\frac{\sigma_{\Delta h_{t,k}}}{\sigma_{\Delta e_{t,k}}} \right)^3 \times s_{\Delta h_{t,k}} + \text{CO-}s_{\Delta w_{t,k}, \Delta h_{t,k}}$$

- **Kurtosis Decomposition**

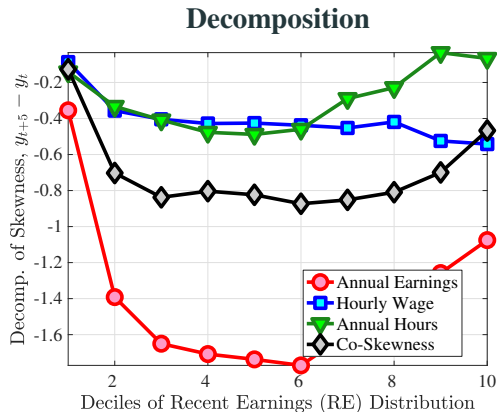
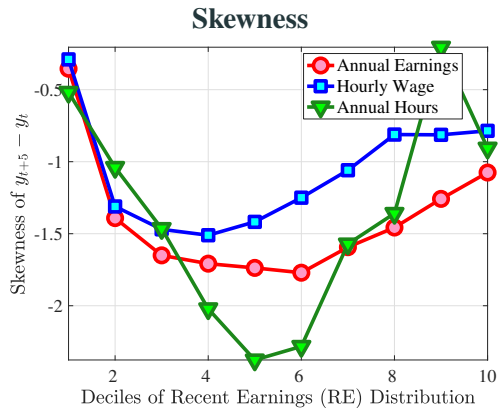
$$k_{\Delta e_{t,k}} = \left(\frac{\sigma_{\Delta w_{t,k}}}{\sigma_{\Delta e_{t,k}}} \right)^4 \times k_{\Delta w_{t,k}} + \left(\frac{\sigma_{\Delta h_{t,k}}}{\sigma_{\Delta e_{t,k}}} \right)^4 \times k_{\Delta h_{t,k}} + \text{CO-}k_{\Delta w_{t,k}, \Delta h_{t,k}}$$

Variance of $y_{t+5} - y_t$ for Prime Age Male



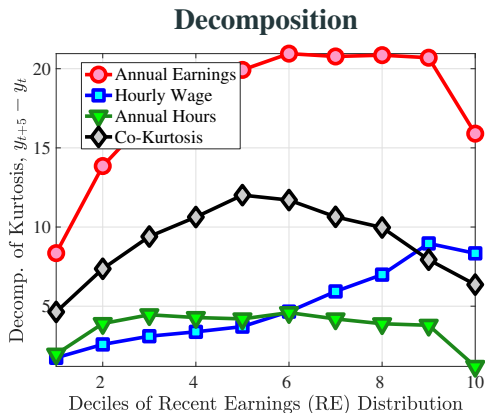
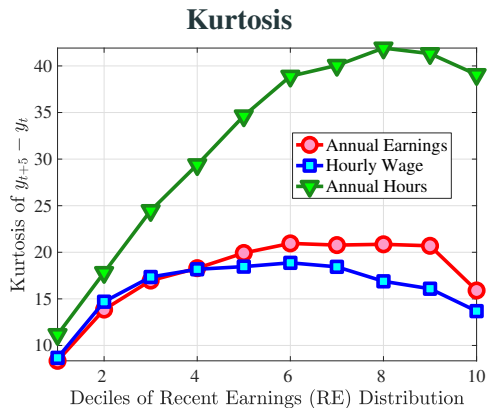
- Hourly wage is more volatile than hours especially above the median.
- Similar to the PSID (Heathcote *et al.* (2014)).

Skewness of $y_{t+5} - y_t$ for Prime Age Male



- Both hours and wage growth are left skewed.
- Wage growth and more importantly co-skewness are driving the left skewness of earnings growth.

Kurtosis of $y_{t+5} - y_t$ for Prime Age Male



- Wage and hours growth are both leptokurtic (especially hours growth).
- Excess kurtosis due to hourly wage dominates the hours.

Non-Gaussian Earnings Growth Distribution

Stayers vs. Switchers

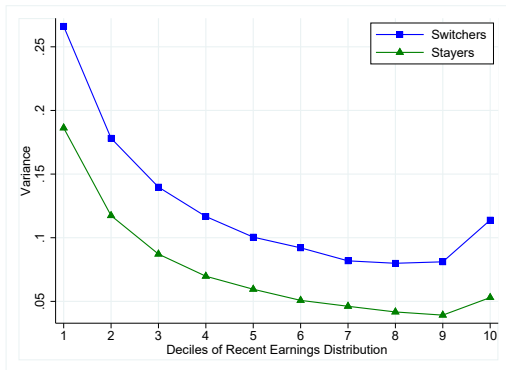
Distribution of Hours vs Wage Growth

- One of the key events leading to both large positive and negative earnings shocks is a change of employer (e.g., EE or EUE).
- How do the earnings shock distributions of job-stayers and job-switchers differ?
- Define a job-stayer as an individual who stays with the same employer in year t or $t+1$.
 - Everybody else are switchers.
- Quantify the role of stayers and switchers in higher-order moments of earnings growth. For example, for skewness:

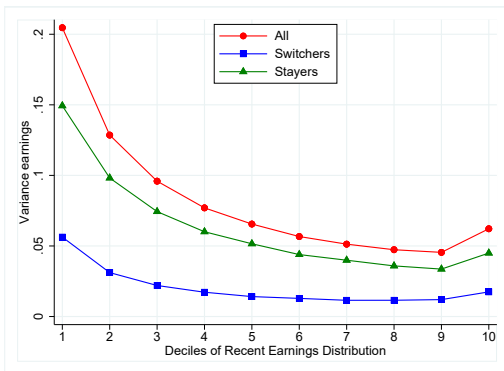
$$\text{skew}(\Delta y) = \underbrace{\frac{1}{(\text{std}(\Delta y))^3} \int_{\{i \in \text{Stay}\}} (\Delta y_i - E(\Delta y))^3 dF(\Delta y)}_{\text{skewness due to Stayers}} + \underbrace{\frac{1}{(\text{std}(\Delta y))^3} \int_{\{i \in \text{Switch}\}} (\Delta y_i - E(\Delta y))^3 dF(\Delta y)}_{\text{skewness due to Switchers}}$$

Variance: Stayers vs. Switchers

Variance



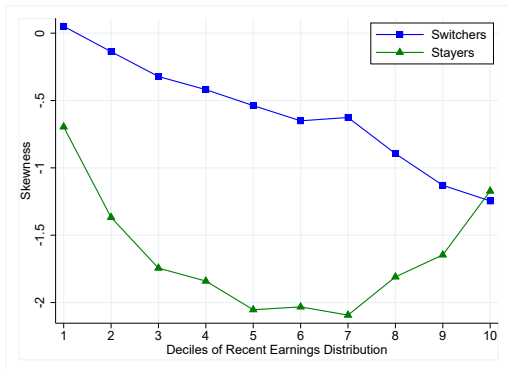
Decomposition



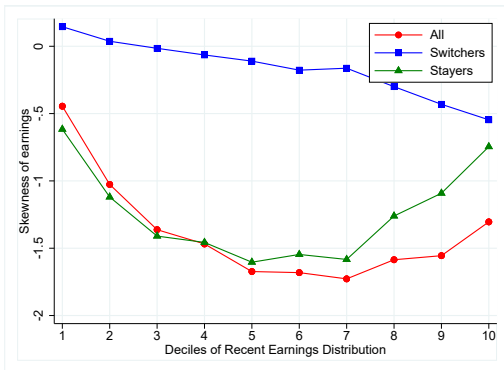
- As expected switchers experience a more volatile wage growth.
- Switcher contribution to overall volatility is low because there are fewer of them.

Skewness: Stayers vs Switchers

Variance



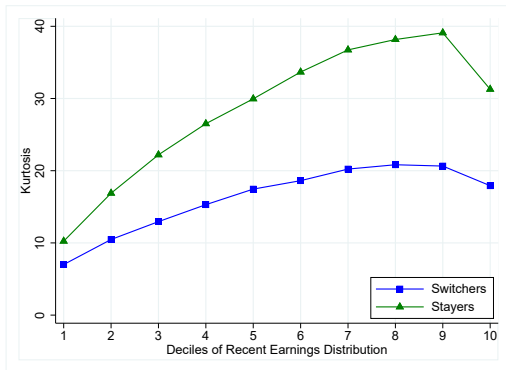
Decomposition



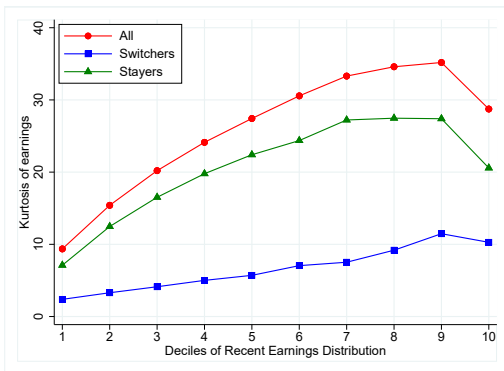
- Stayer face a more left skewed dist'n because of sick days (substitute for unemp).
- Skewness of earnings driven mainly by stayers.

Kurtosis: Stayers vs. Switchers

Variance



Decomposition



- Earnings growth for stayers is more leptokurtic (similar to the US).
- Excess kurtosis due to mainly for stayers.

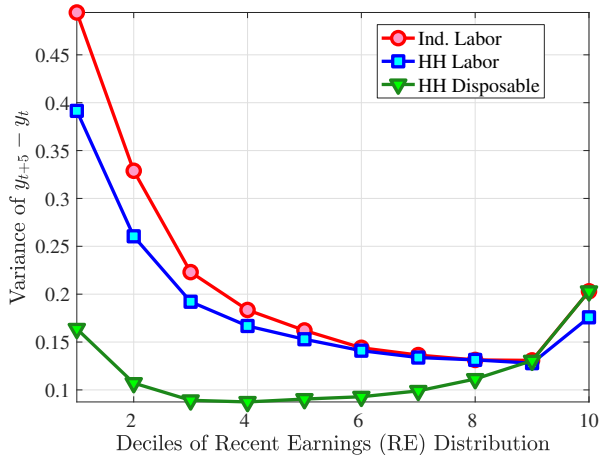
Household Income Dynamics

Distribution of Household Income Growth

Nature of Idiosyncratic Income Risk

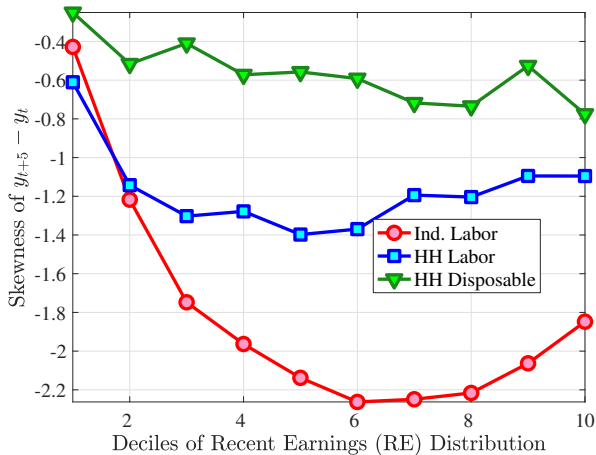
- Do non-Gaussian features of annual earnings growth distribution extend to
 - household (husband+wife) earnings?
 - After tax/after transfer disposable household income?
- For some questions nature of household income risk—before and after tax—is key.
- Plot their distributions and higher-order moments.

Variance of 5-Year Income Growth, $y_{t+5} - y_t$



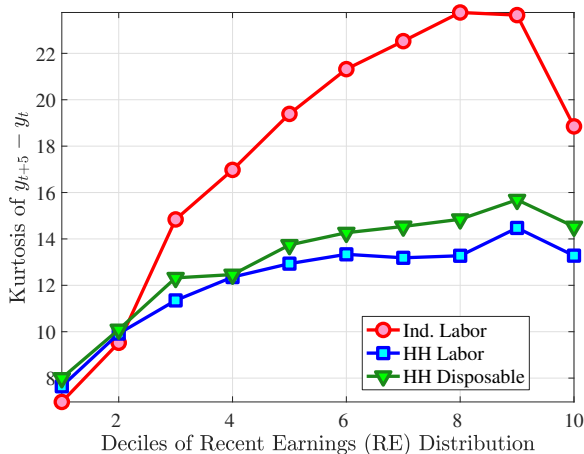
- HH labor is less volatile than individual labor.
- Taxes and transfers reduces variance substantially.

Skewness of 5-Year Income Growth, $y_{t+5} - y_t$



- Spousal income reduces negative skewness due to second earner effect (similar for the US, Pruitt and Turner (2018)).
- Public insurance reduces left tail further.

Kurtosis of 5-Year Income Growth, $y_{t+5} - y_t$



- HH labor and disposable income are still substantially leptokurtic, less so than individual earnings growth though.

Summary of Findings

1. Large earnings swings: driven equally by wages and hours.
 - Wage rates more important for for higher RE.
 - Smaller earnings changes driven by wages.
2. Nonlinear mean reversion in earnings is driven by the dynamics of hours.
3. Both wages and hours contribute to negative skewness and high kurtosis of earnings changes but hour-wage interactions most important.
4. Spousal inc. reduces the variance and skewness of disposable income growth
 - mainly through second earner effect (no behavior change)
5. Taxes/transfers provide insurance against tail shocks—more for low RE groups.

- ARELLANO, M., BLUNDELL, R. and BONHOMME, S. (2017). Earnings and consumption dynamics: a nonlinear panel data framework. *Econometrica*, **85** (3), 693–734.
- BUSCH, C., DOMEIJ, D., GUVENEN, F. and MADEIRA, R. (2015). *Higher-Order Income Risk and Social Insurance Policy Over the Business Cycle*. Working paper, University of Minnesota.
- , FIALHO, P. and GUVENEN, F. (2019). *Life-Cycle Wage and Hours Dynamics: Higher Order Moments*. Tech. rep., University of Minnesota.
- DE NARDI, M., FELLA, G., KNOEF, M. G., PAZ-PARDO, G. and VAN OOIJEN, R. (2019). *Family and Government Insurance: Wage, Earnings, and Income Risks in the Netherlands and the US*. Tech. rep., National Bureau of Economic Research.

- GUVENEN, F., KARAHAN, F., OZKAN, S. and SONG, J. (2019). *What Do Data on Millions of U.S. Workers Say About Labor Income Risk?* Working Paper 20913, National Bureau of Economic Research.
- , OZKAN, S. and SONG, J. (2014). The Nature of Countercyclical Income Risk. *Journal of Political Economy*, **122** (3), 621–660.
- HEATHCOTE, J., STORESLETTEN, K. and VIOLANTE, G. L. (2014). Consumption and labor supply with partial insurance: An analytical framework. *American Economic Review*.
- QUINLAN, J. R. *et al.* (1992). Learning with continuous classes. In *5th Australian joint conference on artificial intelligence*, World Scientific, vol. 92, pp. 343–348.