# Anatomy of Lifetime Earnings Inequality Heterogeneity in Job Ladder Risk vs Human Capital

Fatih Karahan

Serdar Ozkan

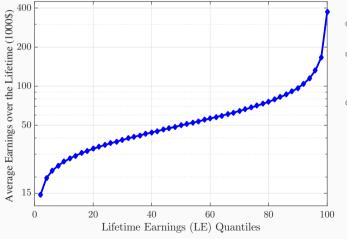
Jae Song

New York Fed

IZA Workshop: Heterogeneity and the Labor Market

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- 1. Large differences in lifetime earnings (LE) of males
- LE: Total labor (wage/salary) income between age 25 and 55.
- Rank into 50 equally sized LE quantiles.

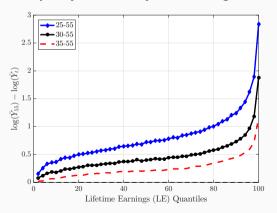


- ∘ P90/P10~4;
- Larger differences at the top: P100/P10≃14.
- Pareto Tail of LE distribution:

$\frac{S(p/10)}{S(p)}$	ζ
0.29	2.2

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- 1. Large differences in lifetime earnings (LE) of males
- 2. Inequality starts early in life, but growth differences over the life time is key.



#### Average earnings growth: 25 to 55

- $\circ \ \text{Top} \simeq 2000\%$
- $\circ$  Median  $\simeq$  200%
- $\circ$  Bottom $\simeq 10\%$

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- 1. Large differences in lifetime earnings (LE) of males
- 2. Inequality starts early in life, but growth differences over the life time is key.
- 3. If there were no differences in earnings growth:
- P90/P10 would have been halved.
- The effects are much larger at the top of the distribution: P100/P10≈2.5 (vs. 14).

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### **Possible Explanations of Earnings Growth Differences**

#### Heterogeneity in:

- o Ability to accumulate human capital (Huggett, Ventura, Yaron 2011 AER)?
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- Job ladder (Topel and Ward 1992, Bagger et. al. 2014 AER)? Do high-LE workers:
  - o make more job-to-job transitions?
  - o make larger jumps when they switch?
  - $\circ~$  face lower unemployment risk and fall of the ladder (the slippery slope–Jarosch 2015)?

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### **Possible Explanations of Earnings Growth Differences**

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  - o make more job-to-job transitions?
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  - $\circ~$  face lower unemployment risk and fall of the ladder (the slippery slope–Jarosch 2015)?
- Unexplained ex-post productivity shocks?

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#### What We Do and Find?

- **1. Empirically** investigate the career paths of different LEs.
- Twice more #employers at the bottom than above the median
- Switch jobs due to different reasons: Higher unemp. risk at the bottom, more job-to-job transitions at the top
- Little heterogeneity in earnings growth among stayers in the bottom 2/3 of the LE

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- Little heterogeneity in earnings growth among stayers in the bottom 2/3 of the LE
- 2. Quantitatively estimate a model with heterogeneity in job ladder risk and learning ability:
- $\circ$  Large ex-ante differences in unemp. risk, job finding and contact rate below-median LE $\Rightarrow$
- 80% of differences between the bottom and the median LE vanish if same ex-ante job ladder risk.
- Median and top LE differences are driven by Pareto-distributed learning ability.

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### **Today**

- 1. Facts
- 2. Job Ladder Model
- 3. Estimation Results
- 4. Conclusion

### **Facts**

#### **SSA Data**

- We draw our sample from SSA: all individuals in the US with a SSN.
- Labor income data from W-2 forms for wage/salary workers.
- o Employees are linked to their employers via EINs.
- Sample period covers 36 years between 1978 to 2013 for 1953–1960 cohorts.
- o Drawback: Annual data.
  - It is typical that a worker has more than one EIN in a year.
  - Complicates the identification of job changes.
  - o Cannot distinguish between E-U-E vs. E-E or U vs. N.

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### **Sample of Workers with Labor Force Attachment**

- Focus on males between ages 25–55.
- Exclude individuals that are full-year non-employed
  - o for more than 1/4 of life time.
  - o in two consecutive calendar years or more.

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  - $\circ$  i.e., SE income above 10% of wage income and  $Y_{min,t}$ .
  - o in more than 1/8 of life time.
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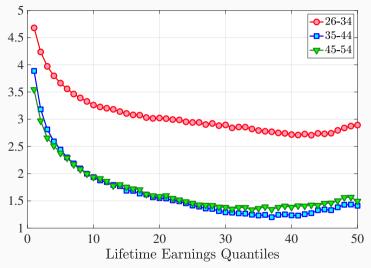
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  - o in more than 1/8 of life time.
  - in two consecutive calendar years or more.
- Compute lifetime earnings (25–55) and rank into 50 equally-sized groups.
  - More than 12000 observations in each group.

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### **Number of Employers Over the Career**



- Twice more #employers at the bottom than above median
- Bottom LE less likely to settle into stable jobs.
- Bottom LE: higher unemployment risk.

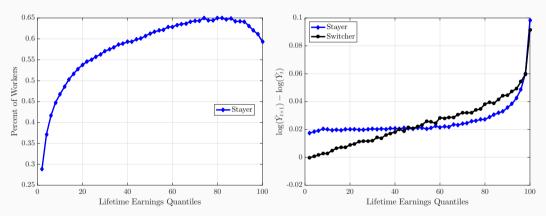
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### **Earnings Growth: Stayers vs Switchers**

- Classify workers in a given year as stayers vs switchers.
  - Several plausible definitions.
- o A worker is a **stayer** between year t and t + 1 if
  - o income from the same employer 4 years in a row, t 1 to t + 2.
  - $\circ$  that employer pays at least 90% of his wage/salary income in t and t+1.
- Switchers are very heterogenous:
  - UE, EU, EUE, or EE.

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### Stayers vs. Switchers



- Higher-LE are more likely to stay.
- Pronounced heterogeneity among switchers (below 75th LE percentile).

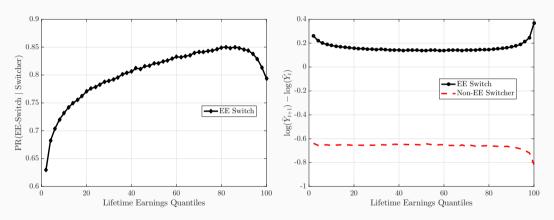
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#### Switchers: E vs U

- What drives the differences among switchers?
- Switchers are very heterogenous.
  - UE, EU, EUE, or EE
  - The annual nature of the data makes it hard to separate these.
- Different parts of the earnings growth distribution is more informative about different types of switches:
  - $\circ$  **U-switcher**: Workers experience  $Y_{t+1} < 0.75 * Y_t$  more likely to go through nonemployment
  - **E-switchers** those that experience  $Y_{t+1} > 0.75 * Y_t$ 
    - o includes EE and UE workers.

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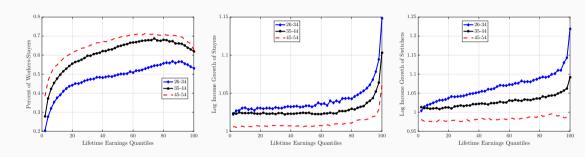
### **E** vs. **U** Switchers



- $\circ$  Small differences among **E** and **U** (except top groups).
- Heterogeneity is mainly due to composition: Higher LEs are more likely to be E.

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### **Life-Cycle Variation**



- Workers are more likely to stay as they age.
- Stayer and Switcher income growth declines over the life cycle.

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### Taking stock: What do we learn?

- \* These empirical findings guide us when developing the structural model.
- \* The model has to capture the heterogeneity in income growth due to:
- Bottom vs median LE: differences in switcher income growth.
  - Large heterogeneity in switcher growth and
  - More likely to be switchers.
- Median vs top LE: differences in stayer income growth.
  - Large heterogeneity in stayer income growth and
  - More likely to be stayer.
- Large heterogeneity in worker flows, also confirmed using high-frequency SIPP data

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**Job Ladder Model** 

#### **Model Overview**

- A life-cycle job ladder model with two-sided heterogeneity à la Bagger, Postel-Vinay and Robin (2014) that features:
  - on the job search and employer competition (à la Bertrand)
  - Perpetual youth (Blanchard-Yaari)
- Allow for lots of worker heterogeneity:
  - o unemployment risk,
  - job finding rate, the contact rate for employed workers,
  - on-the-job training ability (returns to experience),

Recalls for unemployed workers (à la Fujita and Moscarini 2016).

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### **Worker Productivity**

Worker productivity is given by

$$h_t^i = \alpha_i + \beta_i \tau_{i,t} + \gamma \tau_{i,t}^2 + \epsilon_{i,t}$$

- Ex-ante heterogeneity in permanent productivity  $\alpha_i$  and learning ability (returns to experience)  $\beta_i$ .
  - $\circ \tau_{i,t}$  actual experience
  - $\circ \ \alpha_i \sim \mathcal{N}\left(\mu_{\alpha}, \sigma_{\alpha}^2\right), \ \beta_i \sim \textit{Pareto}(\psi_{\textit{W}}, \varsigma_{\textit{W}}).$
  - $\circ \ \alpha_i$  and  $\beta_i$  are correlated.
- AR(1) idiosyncratic shocks,  $\epsilon_{i,t} = \rho \epsilon_{i,t-1} + \epsilon_{i,t}$ 
  - $\circ~$  with probability  $\pi$ ,  $\varepsilon_{it}\sim\mathcal{N}\left(0,\sigma_{arepsilon}^{2}
    ight)$  and with probability  $1-\pi$ ,  $\varepsilon_{it}=0$ .

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### **Production Technology**

- Workers draw firm productivity from  $p_t^i \sim Pareto(\psi_F, \varsigma_F)$ .
  - experimented with other distributions.
- o Once in a match, produce a single divisible good sold in a competitive market.
- $\circ \:$  The log-output per period of a match,  $extbf{ extit{y}}_t^{ij} = extbf{ extit{p}}_t^i + extit{ extit{h}}_t^i$
- $\circ$  Unemployment risk and meeting probabilities are functions of worker fixed effect  $\alpha_i$  and vary over the life-cycle.

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### **Wage Setting**

- ∘ Bargain over the piece rate,  $R \in [0, 1]$ ,  $W_t^{ij} = Re^{p_t^j + h_t^i}$ .
- This setup generates
  - o job-to-job changes with wage cuts (for better future earnings growth)
  - o endogenous large wage increases on the job due to employer competition.
- Recalls also help us generate large wage cuts for stayers, very prevalent in the data.

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**Estimation Results** 

### **Estimation Methodology**

- $\circ\,$  Estimate using Simulated Method of Moments.
  - o Create an employer-employee panel mimicking the SSA sample.

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### **Targeted moments**

1. Higher-order moments (skewness and kurtosis) of 1-year earnings growth.

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#### **Targeted moments**

- 1. Higher order moments (skewness and kurtosis) of 1-year earnings growth.
  - o conditional on LE and age,
  - Separately for stayers and switchers.
- 2. fraction of stayers and non-stayers conditional on LE income and age, their average income growth.

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### How to Identify the Different Sources of Earnings Growth?

Earnings growth among people differs for several reasons

- **1.** Heterogeneity in returns to experience:  $\beta$
- **2.** Speed of climbing the ladder:  $\lambda_0, \lambda_1, \delta$
- **3.** Productivity shocks/unexplained variation:  $\epsilon$

Key insight: exploit differences earnings growth between stayers and switchers.

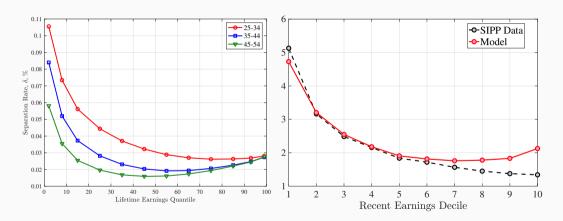
- o If job ladder is not important, they should experience similar growth, driven by  $\beta$ .
- Differences in the distribution of earnings growth between stayers and switchers over the LE are informative about the nature of the job ladder risk.

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# Estimation Results

Parameter Estimates

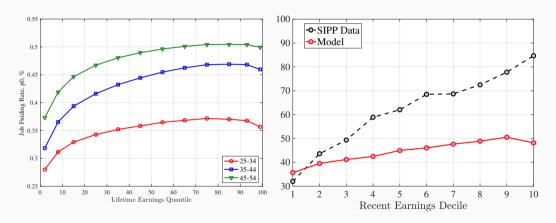
## **Heterogeneity in Unemployment Risk**



o Large heterogeneity in EU by income and age, overall consistent with the data.

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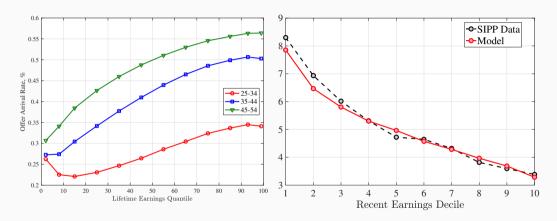
### **Heterogeneity in Job Finding Rate**



- o The model generates an increasing pattern of UE w.r.t. RE
- The variation is much less pronounced compared to the data.

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### **Heterogeneity in the Contact Rate**



- $\circ$   $\lambda_1$  is increasing by LE, whereas EE is declining (matches the SIPP).
- o Higher offer arrival rate by income in the NY Fed SCE data.

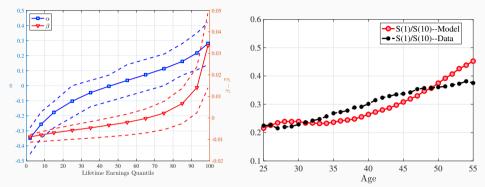
### **Heterogeneity in the Contact Rate**

Recent earnings groups	1-25%	26-50%	51-75%	76-94%	95+%
Total Number of Contacts	0.18	0.18	0.13	0.26	0.43
<b>Unsolicited Contacts</b>	0.09	0.02	0.04	0.11	0.43

Note: Respondents age 25-55. Individuals who report 25 or more contacts in the last 4 weeks are dropped from the sample. We assign zero contacts for those reporting a positive number of contacts but none corresponding with either (i) an employer directly online or through email, (ii) an employer directly through other means, including in-person, or (iii) an employment agency or career center (including a career center at a school or university).

 $\circ\,$  Higher offer arrival rate by income in the NY Fed SCE data.

### Ex-ante Heterogeneity ( $\alpha, \beta$ )



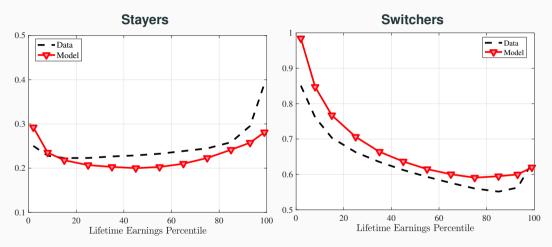
- ∘ Higher LE workers have higher  $\alpha$  and  $\beta$ ,  $corr(\alpha, \beta)$  ∼ 0.40.
- $\circ$  Pareto tails of  $\beta$  distribution needed to capture the large growth at the top.
- Along with Pareto firm distribution, Pareto  $\beta$  generates fractal top inequality:  $\frac{S(p/10)}{S(p)} = \frac{S(p'/10)}{S(p')}$

# Estimation Results

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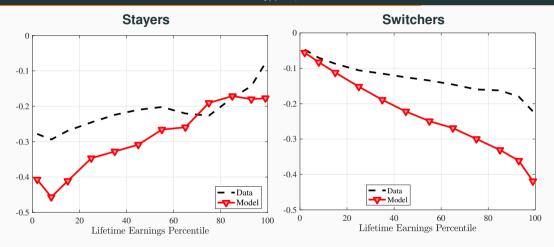
**Model Fit** 

# Standard Deviation of Arc Percent Growth, $2\frac{Y_{t+1}-Y_t}{Y_{t+1}+Y_t}$



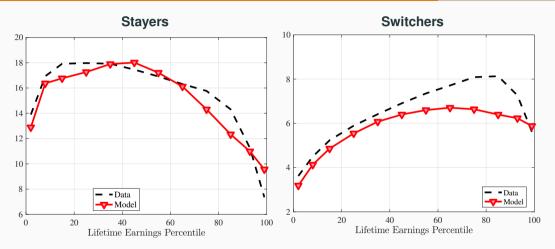
o Captures the variation over the LE and between stayers and switchers.

# Skewness of Arc Percent Growth, $2\frac{Y_{t+1}-Y_t}{Y_{t+1}+Y_t}$



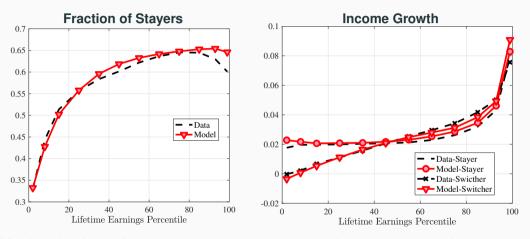
Captures the variation over the LE and between stayers and switchers.

# Kurtosis of Arc Percent Growth, $2\frac{Y_{t+1}-Y_t}{Y_{t+1}+Y_t}$



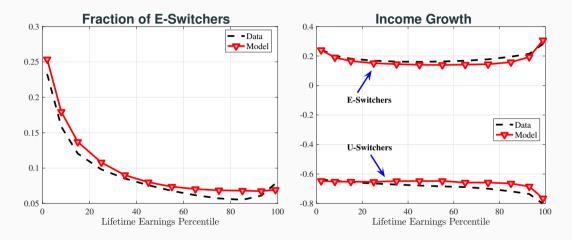
o Captures the levels and patterns of kurtosis between stayers and switchers fairly well.

### **Fraction of Stayers and Income Growth**



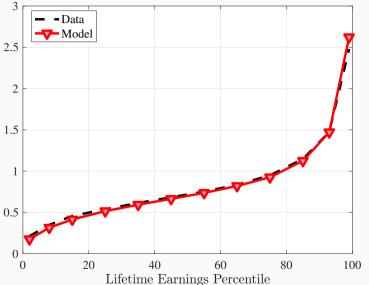
Matches the share of stayers and captures stayer and switcher income growth.

#### Fraction of E-Switchers and Income Growth



Matches the fraction of E-switchers and their income growth remarkably well.

### Earnings Growth Between 25 and 55—Not Targeted

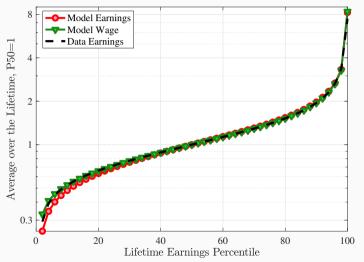


 The model captures earnings growth differences well throughout the LE distribution.

### **Estimation Results**

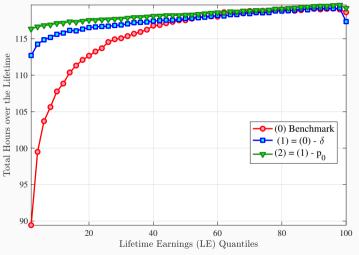
**Decomposition of Lifetime Earnings** 

### **Lifetime Earnings and Wages**



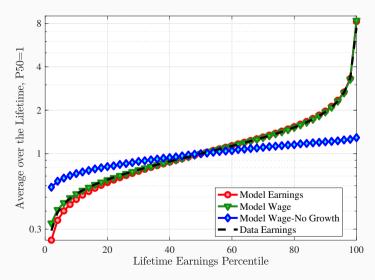
- matches lifetime earnings inequality.
- most inequality due to wages.
- except at the bottom: lifetime employment is lower.

### **Lifetime Employment**

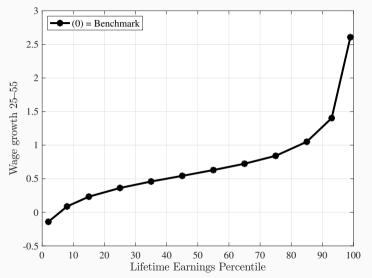


- 25% lower employment at the bottom.
- mostly due to higher unemployment risk and (somewhat) lower job finding rate.
- Little role to ex-post luck.

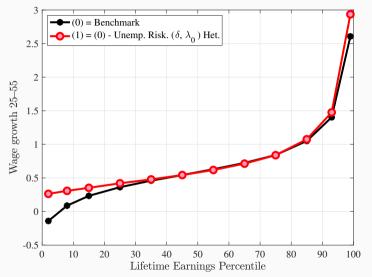
### **Lifetime Earnings and Wages**



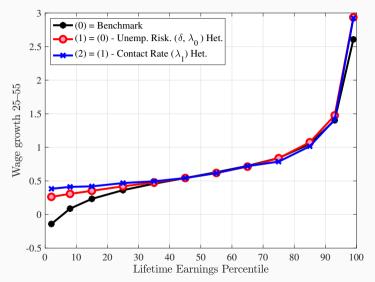
- Most of the wage inequality is due to differences in wage growth.
- What explains the differences in wage growth?



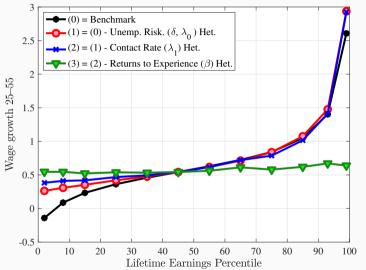
- We shut down each heterogeneity one after another, until we eliminate all differences.
- We keep the rankings of workers the same (i.e., not sorting again under new parameters).



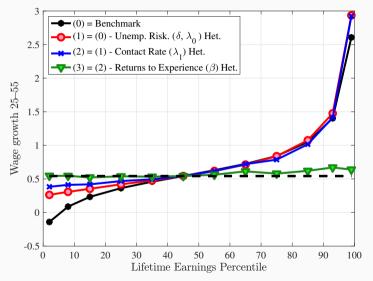
- Suppose all workers face the same unemployment risk,  $\delta$  and job finding rate  $\lambda_0$  as the  $\alpha=0$ .
- Large effect at bottom.
- Also significant effect at the top.



- Suppose now all workers also receive same number of outside offers  $\lambda_1$  as  $\alpha = 0$ .
- 80% of differences between the bottom and median vanish.



- Suppose now all workers also face the same returns to experience β.
- Above the median growth differences vanish.
- Sizable effect at the bottom.



- The rest due to ex-post productivity and job ladder shocks.
- Luck plays a very limited role.

## Conclusion

#### **Conclusions**

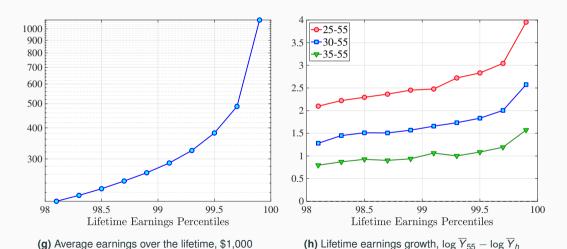
- We studied the reasons behind the vast heterogeneity in lifetime earnings.
- 2 different mechanisms for different parts of the LE: "Jobs" vs "Careers"
  - Below median LE: mainly heterogeneity in job ladder risk.
  - Above median LE: mostly heterogeneity in returns to experience.
- Ex-ante vs. ex-post debate: Ex-ante differences are more important than we think.

# Appendix

### **Appendix**

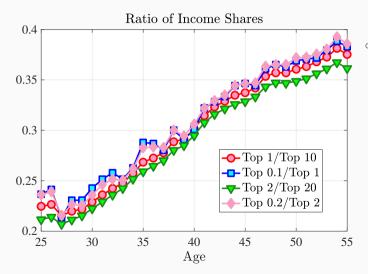
**Top Earnings Inequality** 

### **Lifetime Earnings Inequality in top 1%**



Note: The left panel shows the average annual earnings over the life cycle for each LE group. The right panel

### **Top Income Shares over the Life Cycle**



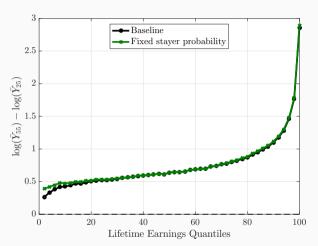
 The earnings distribution has Pareto tails at each age with a declining pareto tail index (growing inequality).

**Appendix Decomposition from the Data** 

### A simple decomposition of earnings growth

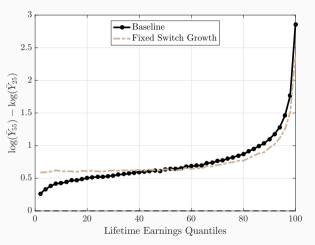
- o Differences in lifetime income growth can be due to heterogeneity in:
  - 1. Probability of being a stayer,
  - 2. Switcher income growth,
  - **3.** Stayer income growth.
- Shut down heterogeneity one at a time by assigning the level corresponding to median LE workers
- Compute the resulting income growth profile.

### **Stayer Probability Heterogeneity**



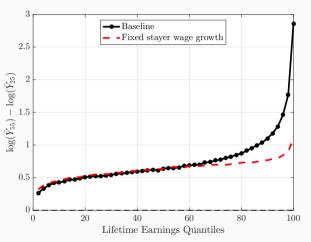
- o Heterogeneity in stayer probability plays a very small role.
  - Above median no heterogeneity in stayer probability.
  - Below median stay and switch growth are similar.

### **Switcher Income Growth Heterogeneity**



 Heterogeneity in switcher income growth is important below median, less so above median.

### **Stayer Income Growth Heterogeneity**



- Heterogeneity in stayer income growth is the main determinant of above median.
- o Little heterogeneity in stayer income growth below median.

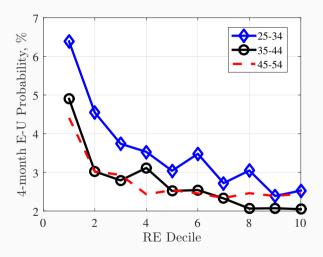
# Appendix

**Evidence From SIPP** 

#### **SIPP Data**

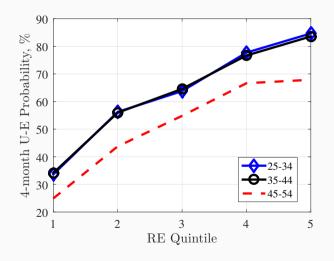
- o SSA does not allow us to distinguish between E-U-E, vs. E-E as well as E-N vs. E-U.
- o SIPP allows computation of flow probabilities.
- o Cannot compute lifetime earnings. Rank people by past income (over 2 years instead).
- Rankings within age groups.

#### 4-Month E-U Probabilities



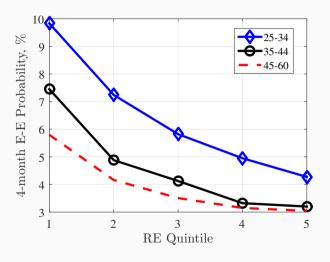
o Unemployment risk is lower for people with higher wages.

#### 4-Month U-E Probabilities



o Job finding rates are higher at the top of the income distribution.

#### 4-Month E-E Probabilities



o Job-to-job switches are more common at the bottom.

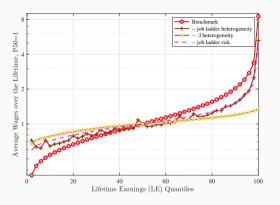
# Appendix

**Model Decomposition** 

#### Identification

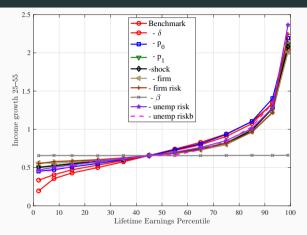
- Inequality at the beginning of life informs us on  $\alpha$ .
- Wage growth of job stayers most informative about  $\beta$ .
- The left tail of the earnings change distribution of job switchers is due to long nonemployment spells  $(\delta, \lambda_0)$ .
- Fraction of EE-switchers informative about  $\lambda_1$ .
- Wage growth of (EE-)switchers informative about the firm distribution.
- $\circ$  Wage growth of stayers informative about the distribution of  $\epsilon_{it}$ .

### **Decomposition of Lifetime Wages**



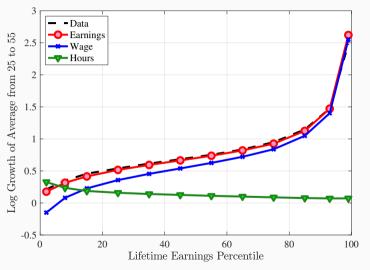
- Heterogeneity in job ladder risk and its ex-post idiosyncratic risk as well as alpha heterogeneity are important below median.
- Beta heterogeneity explains most of the income growth heterogeneity above median.

### **Decomposition of Earnings Growth**



- o Job ladder heterogeneity/risk is important below median.
- Beta heterogeneity explains most of the income growth heterogeneity above median.

### **Decomposition of Earnings Growth**



- Over the life cycle hours grow as workers settle into stable jobs (especially bottom LE).
- Wage growth is lower than earnings growth.