Income Inequality and Income Risk: Old Myths vs. New Facts

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1 This lecture summarizes research conducted jointly with Jae Song, Serdar Ozkan, Fatih Karahan, Greg Kaplan, Nick Bloom, Till von Wachter, Luigi Pistaferri, David Price, Sergio Salgado, David Domeij, Rocio Madera, Chris Busch, and Priscilla Fialho.
Blind Men and the Elephant

It’s a Fan!

It’s a Spear!

It’s a Wall!

It’s a Rope!

It’s a Snake!

It’s a Tree!
Motivation

- Nature of income inequality/risk: critical for many questions in social sciences.

- Survey-based US panel datasets have important limitations:
  - small sample size
  - large measurement (survey-response) error
  - non-random attrition
  - top-coding, etc.

- → myths about income inequality and income risk.
Example of a New Data Set

SSA Master Earnings File:

- Population sample: **Universe of all individuals** with a U.S. Social Security number
- Currently covers 36 years: **1978 to 2013**
- Basic demographic info: sex, age, race, place of birth, etc.
- Earnings data:
  - Salary and wage earnings from W-2 form, Box 1
    - **No topcoding**
    - **Unique employer identifier** (EIN) for each job held in a given year.
    - 4–5 digit **SIC codes** for each employer
  - Self-employment earnings from IRS tax forms (Schedule SE)
One Baseline Sample

- **Individuals:** 10% representative panel of US population from 1978 to 2013

- Salary and wage workers (from W-2 forms)
  - exclude self-employed (data top coded before 1994)
  - Focus on workers aged 25–60
  - Key Advantages:
    - Very large sample size (400+ million individual-year observations)
    - No survey response error (W-2 forms sent from employer directly to SSA)
    - No sample attrition
    - No top-coding (earnings measure includes exercised stock options and vested restricted stock units)

- **Firms:** Full population (100%) of US firms.
Five Myths
Five Myths

1. **Long-run trends:**
   - Myth #1: Rise in income inequality partly (or largely) driven by rising within-firm inequality (e.g., CEO pay)
   - Myth #2: Income risk has been trending up in the past 40 years.

2. **Business cycle:**
   - Myth #3: Income risk over the business cycle is... mostly about countercyclical variance of shocks
   - Myth #4: Top 1% are largely immune to business cycle risk

3. **Life-cycle:**
   - Myth #5: Idiosyncratic income shocks can be modeled fairly well with a lognormal distribution.
Long-Run Trends in Inequality and Risk
Rise in Income Inequality

- 20+ years of research into the determinants of rising wage inequality.

- Conventional wisdom:
  - 1/3 is observables (education and age)
  - 2/3 residual or unobservables (innate ability? search frictions?)

- Today:
  - Rising between-firm or within-firm inequality?

\[
\Delta \text{var}(w^j_t) \equiv \Delta \text{var}_j(\bar{w}_j) + \Delta \text{var}_j(w^j_t - \bar{w}_j)
\]

- Results from “Firming Up Inequality” with Song, Price, Bloom, von Wachter (2015)
Where Do the Wage Gains Go?

- Piketty and Saez (2003, QJE) wrote an influential paper documenting rise of aggregate income share held by top 1%.

- Today: Media and public debate equate inequality with the fortunes of top 1%

- As an example, Paul Krugman (NY Times, Feb 23 2015):

  *As for wages and salaries . . . all the big gains are going to a tiny group of individuals holding strategic positions in corporate suites...*

- Our findings: This view misses the “big picture”.

Fact #1: Rise in Inequality is Fractal
Our findings

1. **Result 1**: Inequality Rose Across the *Entire* Wage Distribution.
   
   – Contradicts typical media accounts that rising inequality == rising top income shares.

2. **Next question**: What is the role of employer’s in rising inequality?
Fact #1: What is the Role of Employers?
Fact #1: What is the Role of Employers?

![Graph showing the role of employers in earning distribution](image-url)
1. **Result 1:** Inequality rose across the entire wage distribution. Contradicts typical media accounts that rising inequality == rising top income shares.

2. **Result 2:** Almost all of the rise in wage inequality happened across firms, i.e., by rising gap in the average pay across firms.
   - Almost no change in pay inequality within employers, except in mega-firms.
   - Q: What is driving the rise in between-firm inequality?
     - **Answer:** 1/2 rising segregation, 1/2 increased sorting.

3. **Next question:** Is the CEO pay driving rising inequality?
Rise in Income Inequality

The primary reason for increased income inequality in recent decades is the rise of the supermanager.

Piketty (2013, p. 315)

Wage inequalities increased rapidly in the United States and Britain because US and British corporations became much more tolerant of extremely generous pay packages after 1970.

Piketty (2013, p. 332)

A key driver of wage inequality is the growth of chief executive officer earnings and compensation.

Mishel and Sabadish (2014)
Fact #1A: Top Paid Workers vs Firm Pay

By Individual’s Percentile: Top 1%, 1982–2012

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Myths vs. Facts
Fact #1B: Dodd-Frank: CEO/median pay

![Graph showing changes in CEO/median pay over time.](image_url)

- **Highest-Paid Empl**
- **5th-Highest Paid**
- **10th-Highest Paid**
- **25th-Highest Paid**
- **50th-Highest Paid**
- **100th-Highest Paid**
- **Median at Firm**

Subgroup: 100 ≤ Firm Size < 10k
Fact #1B: Mega Firms (10,000+ FTE)

![Graph showing changes in highest-paid employees since 1981 for firms with 10,000+ FTE.](image-url)

Subgroup: 10000 ≤ Firm Size

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Myths vs. Facts
Fact #1C: Rise in Inequality

The graph shows the log change in individual total wages from 1982 to 2012 across different percentiles of the wage distribution.
Rise in Inequality *Without Top Executives*

Myths vs. Facts
Rise in Inequality *Without Top Executives*

![Graph showing the rise in inequality without top executives](image)

- **Indv Total Wage**
- **Indv Total Wage (Non-Top 1 Employees)**
- **Indv Total Wage (Non-Top 5 Employees)**

**Log Change, 1982–2012**

**Percentile of Indv Total Wage**

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- Myths vs. Facts

Page 22 / 65
Rise in Inequality: **1000+ FTE**

![Graph showing the rise in inequality](image)

- **Indv Total Wage**
- **Indv Total Wage (Non–Top 1 Employees)**
- **Indv Total Wage (Non–Top 5 Employees)**

**Log Change, 1982−2012**

**Percentile of Indv Total Wage**

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Myths vs. Facts
Top 1% Inequality: Baseline

[Graph showing the distribution of individual total wages across percentiles, with lines representing different categories: Indv Total Wage, Indv Total Wage (Non–Top 1 Employees), and Indv Total Wage (Non–Top 5 Employees).]

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Myths vs. Facts
24 / 65
Top 1% Inequality: \textbf{1000+ FTE}

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Myths vs. Facts
Robustness

- This pattern is pervasive. It holds within
  - most industries (44 of 49 Fama-French industries)
  - US regions (Census regions, counties)
  - across firms of different sizes
Myth #2:

The volatility of income shocks... has increased significantly over the past 40 years.
Myth #2: Upward Trend in Income Risk

- This conclusion has been reached by virtually all papers that use PSID data.

- Moffitt and Gottschalk (1995) documented it first in a now-famous paper, and it has been confirmed by a large subsequent literature.

- Opening quote from Ljungqvist and Sargent (2008, ECMA):

  A growing body of evidence points to the fact that the world economy is more variable and less predictable today than it was 30 years ago... [There is] more variability and unpredictability in economic life

Figure 10: Permanent, Transitory, and Total Variances for those 30-39 with Education Greater than 12

Source: Moffitt and Gottschalk (2012)
Fact #2: No Upward Trend in Volatility

- Administrative data: the opposite conclusion emerges robustly.

- See, e.g., Congressional Budget Office (2007); Sabelhaus and Song (2010); Guvenen et al. (2014)

- In fact, volatility of earnings changes has been declining within most
  - industries
  - age groups
  - gender groups
  - U.S. regions
  - etc.
Fact #2: No Upward Trend in Volatility

Cross Sectional Dispersion by Sex (25 to 65 yrs)
Fact #2: No Upward Trend in Volatility

Cross Sectional Dispersion by Sex (30 to 50 yrs)
Robustness

- Declining wage volatility holds within every private industry, with the exception of agriculture (2% of employment).

- It is also robust to alternative measures of dispersion (top end: P90-50, bottom end, P50-10, and so on)
Risk and Inequality Over the Business Cycle
Business Cycle Variation in Shocks

Myth #3:

The variance of idiosyncratic shocks rises substantially during recessions.
Myth #3: Countercyclical Shock Variances

\[ y_{t+k} - y_t \]

Density

Recession

Expansion

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Myths vs. Facts
Countercyclical Variance

- Constantinides and Duffie (1996): countercyclical variance can generate interesting and plausible asset pricing behavior.

- Existing indirect parametric estimates find a tripling of the variance of persistent innovations during recessions (e.g., Storesletten et al (2004)).

- Our direct and non-parametric estimates show no change in variance over the cycle.
Fact #3: No Change in Variance

Storesletten et al (2004)'s benchmark estimate: 1.75
Fact #3: Procyclical Skewness

\[ y_{t+k} - y_t \]

Density

Expansion

Recession
Fact #3: Procyclical Skewness

Kelley’s Skewness Measure of $y_{t+k} - y_t$, $k = 1, 5$
Robustness

- In ongoing work (with Busch, Domeij, and Madera), we find precisely the same patterns for Sweden and Germany.

- Moving from individual to household income, as well as incorporating government policy has little effect on countercyclical left-skewness in the US.

- Gov’t policy more effective in Germany and Sweden.
Firm-level Data

- Salgado, Guvenen, Bloom (2016): examine firm level variables in a panel of firms covering 44 countries:
  - growth rate of sales, profits, employment, inventories
  - stock prices

- Robust evidence of procyclical skewness for all variables in 90% of the countries.

Firm Variables: Procyclical Skewness

Skewness: Kelly (normalized to mean 0, SD 1)

GDP growth deciles

Sales

Employment

Stock Returns

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Myths vs. Facts
Firm Variables: Slightly Countercyclical Dispersion

The chart illustrates the dispersion of firm variables across GDP growth deciles. The dispersion is measured as the difference between the 90th and 10th percentiles (P90-P10), normalized to mean 0 and SD 1. The graph shows the comparison between Micro Sales, Micro Returns, Macro GDP, and Macro Returns across different GDP growth deciles.

- **Micro Sales** and **Micro Returns** exhibit a slight countercyclical pattern, with higher dispersion in lower GDP growth deciles.
- **Macro GDP** and **Macro Returns** display a more cyclical pattern, with higher dispersion in higher GDP growth deciles.

This visual representation helps in understanding the economic outcomes of firms during periods of economic growth and downturns.
Is Business Cycle Risk Predictable?

Myth #4:

Business cycle risk is mostly *ex-post* risk
Fact #4: Business Cycle Risk is Predictable

Mean Log Income Change During Recession

Percentiles of 5-Year Average Income Distribution ($Y_{t-1}$)
Myth #4:

The top 1% are largely immune to the pain of business cycles.
Fact #4: The “Suffering” of the Top 1%
Fact #4: 1-Year Income Growth, Top 1%

Year | Log 1-Year Change in Mean Income Level |
-----|--------------------------------------|
1980 | -0.4 |
1985 | -0.3 |
1990 | -0.2 |
1995 | -0.1 |
2000 | 0.1  |
2005 | 0.2  |
2010 | 0.3  |

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Myths vs. Facts
Fact #4: 5-Year Income Growth, Top 0.1%
Risk and Inequality Over the Life Cycle
Distribution of Income Shocks

Myth #5:

It is OK to model income growth...

...as a lognormal distribution

⇒ it is OK to assume...

...zero skewness and no excess kurtosis

\[
\begin{align*}
y_t &= z_t^i + \varepsilon_t^i \quad \varepsilon_t^i \sim \mathcal{N}(0, \sigma^2_\varepsilon) \\
z_t^i &= \rho z_t^i + \eta_t^i \quad \eta_t^i \sim \mathcal{N}(0, \sigma^2_\eta)
\end{align*}
\]
Kurtosis
Myth #5: Lognormal Histogram of $y_{t+1} - y_t$
Fact #5: Excess Kurtosis

Kurtosis: 28.5

Kurtosis: 3.0

N(0,0.43^2)

US Data, Ages 35-54, P90 of \( \bar{Y} \)
Fact #5: Excess Kurtosis

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Fact #5: Excess Kurtosis

Ages 25-29
Ages 30-34
Ages 35-39
Ages 40-54

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Myths vs. Facts
Skewness
Fact #5: Skewness of $y_{t+1} - y_t$
Double Pareto Tails of Earnings Growth

Log Density

- US Data
- \( \mathcal{N}(0, 0.51^2) \)
- Slope: 1.40
- Slope: -2.18

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Myths vs. Facts
Guvenen-Karahan-Ozkan-Song (2016):
- the welfare costs of idiosyncratic fluctuations are 25-40% of lifetime consumption compared to 10-12% with Gaussian shocks. (RRA=2)

Constantinides-Ghosh (2015, JF), Golosov-Troshkin-Tsyvinski (2016, AER), Schmidt (2016), Kaplan-Moll-Violante (2016) find substantially different results when higher-order moments are taken into account.
Recap: Five Myths

1. **Long-run trends:**
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Final Thoughts

- Public funding for collecting micro panel data for research purposes is woefully inadequate.

- To provide perspective:
  - NASA’s annual budget: ~20 Billion dollars
  - International Space Station total cost: ~150 Billion dollars.
  - All worthy efforts. Now consider this:
  - US gov’t transfer payments in 2014: ~1.9 trillion dollars.

  - For micro research on distributional issues, PSID’s annual budget (only US panel with consumption data): ~3 million dollars!

- Increased public funding for good quality data is essential for good quality economic research.
Final Thoughts, cont’d

- We have played the “blind men and the elephant” for too long.

- There is hope: fantastic new datasets becoming accessible:
  - Earnings: from IRS, SSA, and LEHD through various calls for proposals.
  - Administrative data for Europe is especially impressive.

- Challenges: Data on consumption.. still very limited.
  - Still there is hope: Private companies (Mint.com, Credit agencies) and research products (Michigan-Berkeley project) are becoming more useful for researchers.

- I hope these new facts will feed back into theory and policy work.
References


