Earnings Distribution

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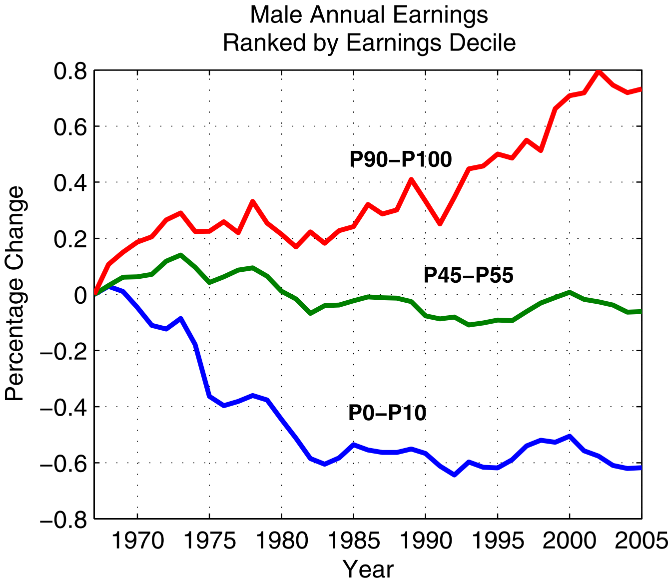
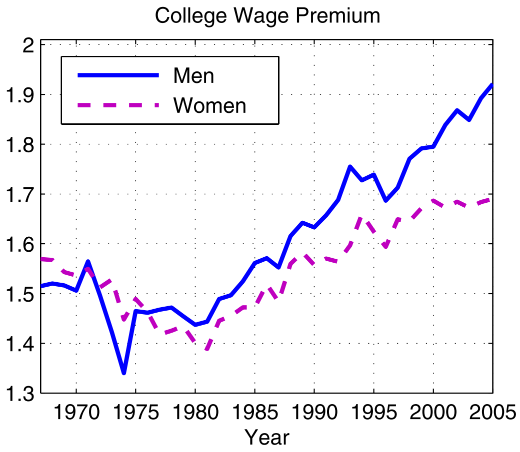
Facts: Earnings Distribution

Data from Heathcote et al. (2010)



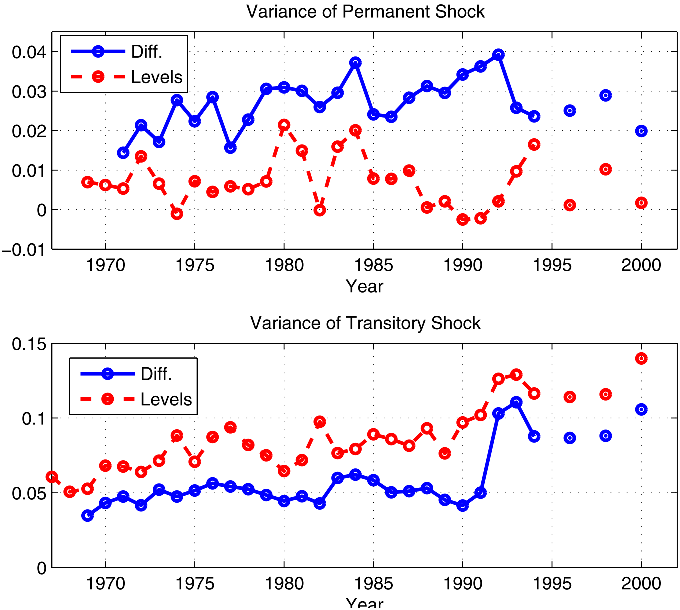
Rising college premium



College premium and college labor supply are rising at the same time

The most common interpretation: **Skill-biased technical change** (Katz and Murphy, 1992).

Shock Variances



Shock variances

This is from a model with permanent and transitory shocks.

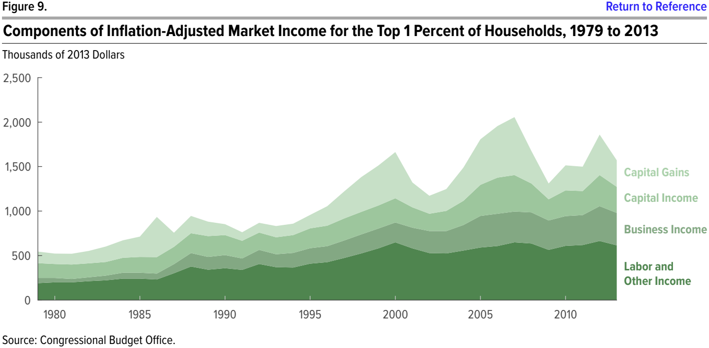
Conclusion depends on whether the model is estimated in levels or differences.

Suggests that the model is mis-specified.

Most of the literature thinks that persistent and transitory shock variances have increased.

But some recent work using tax data finds that mostly persistent shocks have increased (Debacker et al., 2013).

Top 1%



Source: Congressional Budget Office (2016)

A rising share of top incomes comes from earnings.

Skill Premium

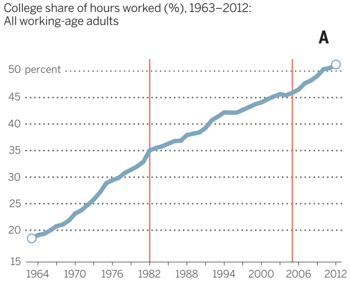
The skill premium

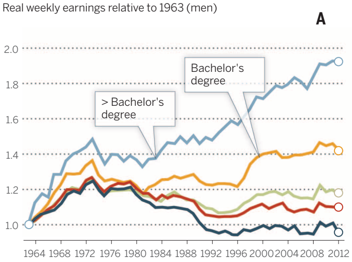
The college wage premium has been rising, even as the supply of college educated labor has been rising.

A common interpretation: skill biased technical change.

The "race between education and technology" (Goldin and Katz, 2008).

Data





Source: Autor (2014)

Canonical model

Katz and Murphy (1992).

Skilled and unskilled workers are imperfect substitutes.

Labor aggregator:

$$Q_t = \left[\alpha_t L_{St}^{\rho} + (1-\alpha_t) L_{Ut}^{\rho}\right]^{1/\rho} \tag{1}$$

SBTC increases $\alpha_t/(1-\alpha_t)$ over time.

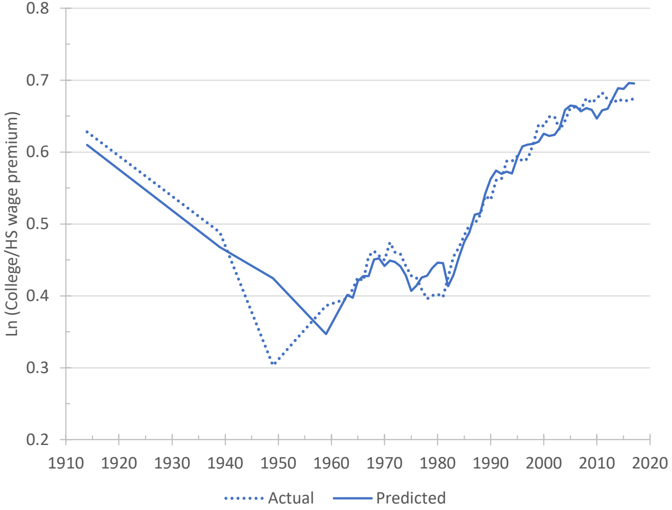
Assume that workers are paid their marginal products:

$$\ln(w_{St}/w_{Ut}) = \frac{1}{\sigma}\left[D_t - \ln(L_{St}/L_{Ut})\right] \tag{2}$$

Measurement:

- labor supplies: hours worked college / non-college.
- D_t: linear time trend (at times with complications)

Fit



Source: Autor et al. (2020)

Notes

There is fairly wide agreement that the basic story sounds right.

Unresolved:

- Does the rising relative productivity of skilled labor reflect technology or human capital?
- Is SBTC the driving force or the result of rising education?
- Acemoglu (2002, 2003) argues in favor of endogenous technological skill bias.

What do data in other countries say?

Labor market polarization

The share of middle income jobs has declined over time (Autor and Dorn, 2013).

Figure 6. Employment Growth Has Polarized Between High- and Low-Paid Occupations

CHANGES IN OCCUPATIONAL EMPLOYMENT SHARES AMONG WORKING-AGE ADULTS, 1980–2015

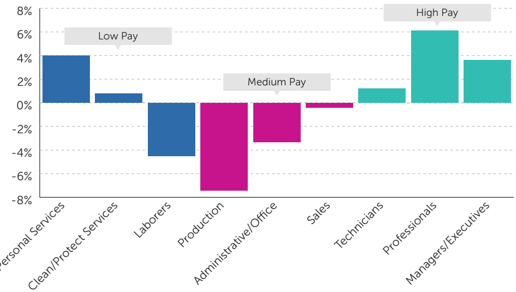


Figure is constructed using U.S. Census of Population data for 1980, 1990, and 2000, and pooled American Community Survey (ACS) data for years 2014 through 2016, sourced from IPUMS (Ruggles et al., 2018). Sample includes working-age adults ages 16 – 64 excluding those in the military. Occupational classifications are harmonized across decades using the classification scheme developed by Dorn (2009).

Source: (Autor, 2020)

Roys and Taber (2019) argue that this does not affect the wage distribution much.

Earnings Processes

The canonical model

Earnings as a function of experience:

$$y_{i,t} = f(t) + z_{i,t} \tag{3}$$

All households share the same experience profile f.

Shocks:

$$z_{i,t} = \rho z_{i,t-1} + \eta_{i,t} \tag{4}$$

$$\eta_{i,t} \sim N\left(0, \sigma_\eta^2\right) \tag{5}$$

Estimating this yields $\rho \approx 1$.

Earnings shocks are highly persistent and therefore hard to insure against.

Guvenen (2007)

Argues in favor of "HIP":

$$y_{i,t} = f(t) + \beta_i t + z_{i,t} \tag{6}$$

Estimating this yields $\rho \approx 0.8$.

Shocks are less persistent. Self-insurance is easier.

RIP or HIP

How to distinguish between the two models?

Estimating β_i versus ρ from earnings data only is surprisingly hard.

- Estimation uses the autocovariance matrix of earnings.
- Both processes yield similar matrices.

One idea: use consumption data.

- They reveal whether earnings dispersion is due to heterogeneity or shocks.

Guvenen (2007)

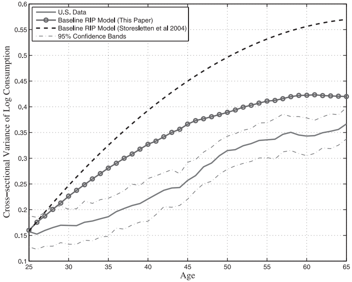


FIGURE 7. AGE-INEQUALITY PROFILE OF CONSUMPTION: US DATA VERSUS RIP MODEL

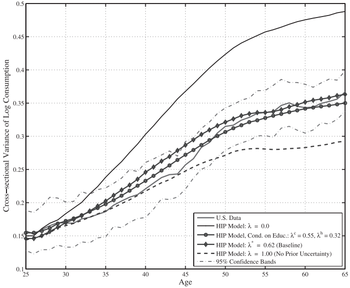


FIGURE 8. AGE-INEQUALITY PROFILE OF CONSUMPTION: US DATA VERSUS HIP MODEL

HIP fits better than RIP.

The general point

Earnings data cannot tell whether dispersion is due to heterogeneity or shocks.

But the distinction is fundamentally important for model implications:

- self-insurance and value of social insurance
- wealth inequality

Consumption data are useful, but hard to interpret.

- Guvenen and Smith (2014) is an ambitious attempt.

Panel data limitations

Earnings processes are estimated from panel data.

They undersample the rich.

E.g.: PSID roughly misses the top 1%.

Alternatives:

- administrative data
- make up earnings processes from cross-sectional data (Castaneda et al., 2003)

Castaneda et al. (2003)

Goal: Match earnings and wealth distribution in a "standard" Aiyagari model.

Key features:

1. Stochastic aging: a computational trick
   similar to perpetual youth
2. Perfect altruism
   agents effectively live forever
3. A "superstar" earnings state

Earnings process

Calibration does not use information on persistence of earnings.

The earnings process is "cooked" to match the wealth distribution.

The lower 3 earnings states "look like" something estimated from the PSID

- though persistence is very high

The top earnings state is very high and very rare.

TABLE 5

RELATIVE ENDOWMENTS OF EFFICIENCY LABOR UNITS, $e(s)$, AND THE STATIONARY DISTRIBUTION OF WORKING-AGE HOUSEHOLDS, $\boldsymbol{\gamma}_{\varepsilon}^{*}$

	$s = 1$	$s = 2$	$s = 3$	$s = 4$
$e(s)$	1.00	3.15	9.78	1,061.00
$\boldsymbol{\gamma}_{\varepsilon}^{*}$ (%)	61.11	22.35	16.50	.0389

Earnings process

The top state has lowish persistence.

TABLE 4

TRANSITION PROBABILITIES OF THE PROCESS ON THE ENDOWMENT OF EFFICIENCY LABOR UNITS FOR WORKING-AGE HOUSEHOLDS THAT REMAIN AT WORKING AGE ONE PERIOD LATER, $\mathbf{\Gamma}_{\varepsilon\varepsilon}$ (%)

	To s'			
From s	$s' = 1$	$s' = 2$	$s' = 3$	$s' = 4$
$s = 1$	96.24	1.14	.39	.006
$s = 2$	3.07	94.33	.37	.000
$s = 3$	1.50	.43	95.82	.020
$s = 4$	10.66	.49	6.11	80.51

Intuition:

- households win the lottery once every 250 years
- lottery winners save everything because the top state is so transitory

Reservations

The paper shoes that it is **possible** to write down a standard life-cycle model that matches wealth concentration based on an earnings process with the right amount of cross-sectional inequality.

It does not show that a life-cycle model generates the right wealth distribution when a "**realistic**" earnings process is imposed.

The Castaneda approach has been widely adopted in the literature.

Yanran will explain what goes wrong with it.

Administrative data

Administrative data have

- large samples
- no measurement error
- no truncation
- no top coding

Social security records

Guvenen et al. (2015)

- 200 million individual earnings histories
- starting in 1978

Can estimate a mostly non-parametric earnings process.

Key findings:

1. Kurtosis: most earnings shocks are small, but a few are very large.
2. Age variation: persistence and size of shocks vary with age.
3. Positive shocks are transitory
4. Negative shocks are persistent (but not for low income workers)

De Nardi et al. (2020) explores what this implies in a life-cycle model.

Administrative data

Song et al. (2019): matched employer-employee data.

Firms play a big role for rising earnings inequality

- 2/3 of rising dispersion is between firms
- mostly due to stronger sorting of workers into firms

Structural Models

Structural models

Very few attempts at developing structural models of the earnings distribution.

Ben-Porath human capital models:

- Huggett et al. (2011), Guvenen and Kuruscu (2010)

Skill biased technical change: Lee and Wolpin (2010)

This topic clearly deserves more research.

Guvenen and Kuruscu (2010)

Goal: A structural model that accounts for changes in wage distribution since the 1970s.

Key facts:

1. Rising overall wage inequality, starting in 1970s
2. Rising college premium, starting in 1980s

The idea:

- SBTC accelerates in 1970s
- Skilled wage growth rises
- Skilled workers invest more in human capital
- Initially skilled wages fall, then they rise
- Within group wage inequality then rises as well

Model

Start from a life-cycle model like Huggett (1996).

Add a Ben-Porath human capital accumulation block.

Output is produced from skilled and unskilled labor:

$$Y_t = Z_t \left(\theta_{L,t} L_t^{\rho} + \theta_{H,t} H_t \right) \tag{7}$$

L, H: total efficiency units of labor provided by each skill type.

Model

Human capital is produced from time only:

$$h_{t+1} = h_t + A([\theta_{L,t} l + \theta_{H,t} h_t] i_t)^\alpha \tag{8}$$

Note: θ's are the same in both technologies (why?)

Households maximize lifetime earnings.

- This has a closed form solution.

Skill weights drift up (H) or down (L) by κ in each period (SBTC)

Thought Experiment

Start in steady state

Then skill weights drift for T periods

After that, converge to new steady state

The period of rising skill weights starts in 1970 and ends in 1995 (data picking)

Compare model implication with data on wage distribution, skill premium, ...

Calibration

Calibration Targets

1. Avg college wage premium over 1970-95;
2. avg cross-sectional variance of wages;
3. mean wage growth over life-cycle
4. var(log wage 1995)

These 3 moments are supposed to identify the joint distribution of (h_0, l, A) (!)

Results

The model matches (roughly) the time series of wage inequality

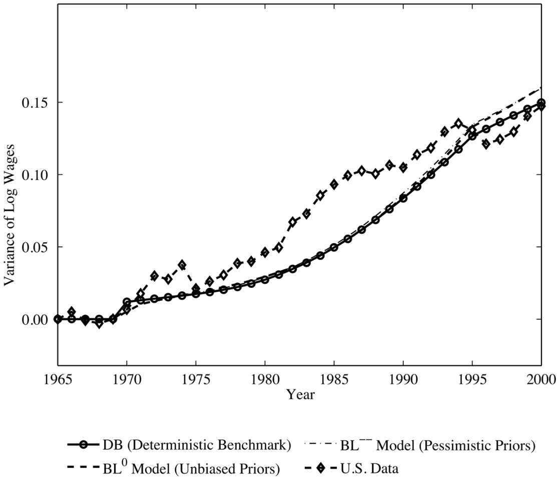


Fig. 3. The evolution of overall wage inequality: model versus U.S. data, 1965–2000

Results: College Premium

The model matches that the college premium initially falls and then rises

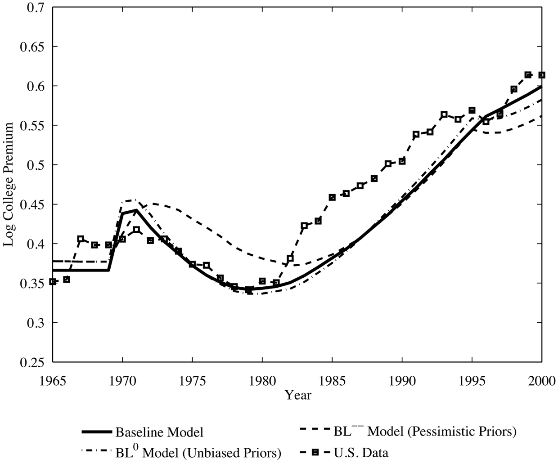


Fig. 4. The evolution of the college premium: model versus U.S. data, 1965–2000

Results: College Premium By Age

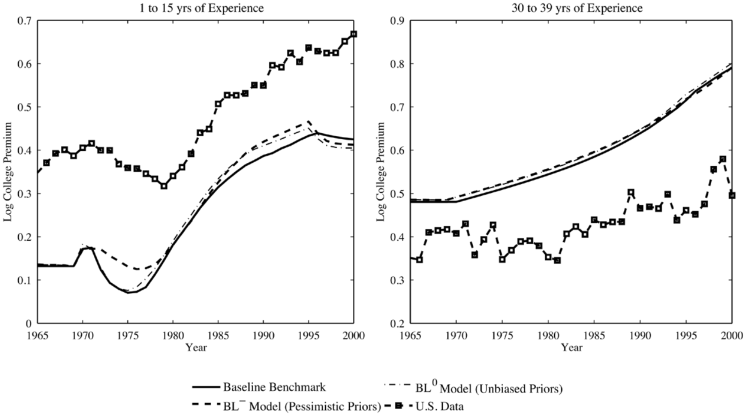


Fig. 7. The college premium by experience level: model versus U.S. data

The model matches that the college premium evolves differently for young / old workers.

Results: Within Group Inequality

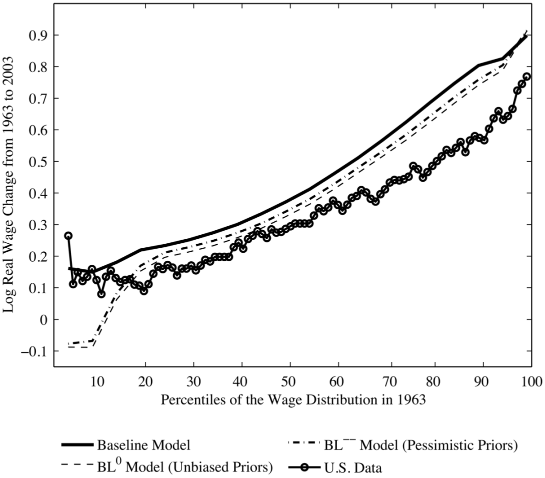


Fig. 8. Log real wage changes by percentile: model versus U.S. data, 1963–2003

Problems

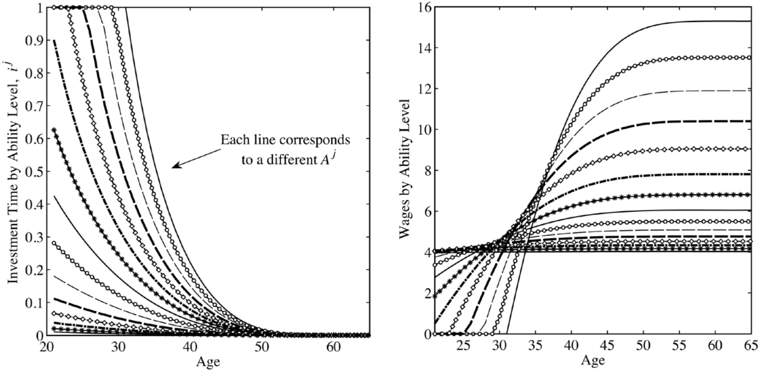


Fig. 1. Cross-sectional differences in investment time and wages over the life cycle

Cross-sectional heterogeneity in h investment is enormous (because of the near linear techology)

Problems

Getting big changes in wage distribution requires enormous changes in h investment

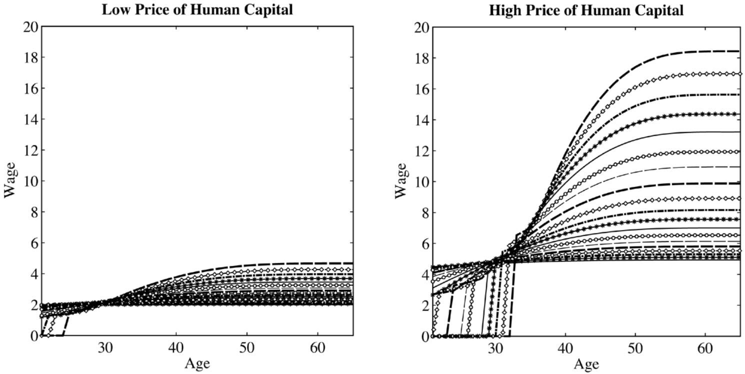


Fig. 12. Large rise in cross-sectional wage inequality: small rise in lifetime wage inequality

Thoughts

This is a really nice idea - clear connection between story and data.

The paper tries to do too much with one driving force (SBTC).

The model needs shocks - you can't talk about inequality without shocks.

More data could be used for identification of key parameters

- endowment distribution
- curvature of Ben-Porath technology

This is an opportunity to do better:

Needed: a quantitative theory of the wage distribution over time.

An alternative view

Much of the literature looks for models of time-varying returns to experience

- including Guvenen and Kuruscu (2010)

An alternative interpretation: cohort effects and time varying skill premiums.

A simple model where

- the skill premium depends on the relative supply of skilled labor (as in Katz and Murphy (1992))
- cohort effects depend on cohort schooling (selection)

fits data on

- cross-sectional returns to experience
- college wage premium (by age)

quite well (Hendricks, 2017)

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