

# The Dynamics of Inequality

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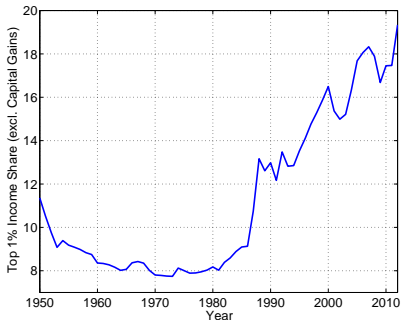
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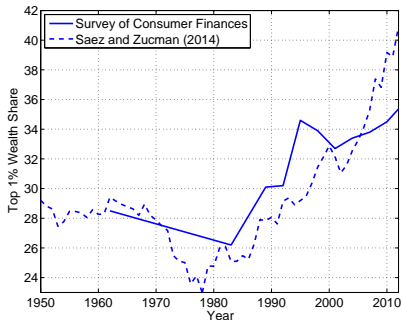
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# Question



(a) Top Income Inequality



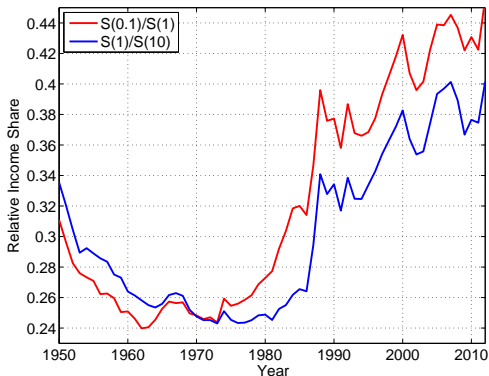
(b) Top Wealth Inequality

- In U.S. past 40 years have seen (Piketty, Saez, Zucman & coauthors)
  - rapid rise in top income inequality
  - rise in top wealth inequality (rapid? gradual?)
- **Why?**

## Question

- **Main fact** about **top inequality** (since Pareto, 1896): upper tails of income and wealth distribution follow **power laws**
- Equivalently, top inequality is **fractal**
  - ① ... top 0.01% are  $X$  times richer than top 0.1%, ... are  $X$  times richer than top 1%, ... are  $X$  times richer than top 10%, ...
  - ② ... top 0.01% share is fraction  $Y$  of 0.1% share, ... is fraction  $Y$  of 1% share, ... is fraction  $Y$  of 10% share, ...

## Evolution of “Fractal Inequality”



- $\frac{S(p/10)}{S(p)}$  = fraction of top  $p\%$  share going to top  $(p/10)\%$ 
  - e.g.  $\frac{S(0.1)}{S(1)}$  = fraction of top 1% share going to top 0.1%
- Paper: same exercise for wealth

# This Paper

- **Starting point:** existing theories that explain top inequality **at point in time**
  - differ in terms of underlying economics
  - but share basic mechanism for generating power laws: **random growth**
- **Our ultimate question:** which specific economic theories can also explain observed **dynamics** of top inequality?
  - income: e.g. falling income taxes? superstar effects?
  - wealth: e.g. falling capital taxes (rise in after-tax  $r - g$ )?
- **What we do:**
  - study **transition dynamics** of cross-sectional distribution of income/wealth in theories with random growth mechanism
  - contrast with data, **rule out** some theories, **rule in** others

# Main Results

- Transition dynamics of standard random growth models **too slow** relative to those observed in the data
  - analytic formula for speed of convergence
  - transitions particularly slow in **upper tail** of distribution
  - jumps cannot generate fast transitions either
- Two parsimonious deviations that generate **fast transitions**
  - ① heterogeneity in mean growth rates
  - ② “superstar shocks” to skill prices
- Both only consistent with particular economic theories
- Rise in top **income** inequality due to
  - ~~simple tax stories, stories about  $\text{Var}(\text{permanent earnings})$~~
  - **rise of “superstar” entrepreneurs or managers**
- Rise in top **wealth** inequality due to
  - ~~increase in  $r - g$  due to falling capital taxes~~
  - **rise in saving rates/RoRs of super wealthy**

# Literature: Inequality and Random Growth

- **Income distribution**

- Champernowne (1953), Simon (1955), Mandelbrot (1961), Nirei (2009), Toda (2012), Kim (2013), Jones and Kim (2013), Aoki and Nirei (2014),...

- **Wealth distribution**

- Wold and Whittle (1957), Stiglitz (1969), Cowell (1998), Nirei and Souma (2007), Benhabib, Bisin, Zhu (2012, 2014), Piketty and Zucman (2014), Piketty and Saez (2014), Piketty (2015)

- **Dynamics** of income and wealth distribution

- Blinder (1973), but no Pareto tail
- Aoki and Nirei (2014)

- **Power laws are everywhere**  $\Rightarrow$  results useful there as well

- firm size distribution (e.g. Luttmer, 2007)
- city size distribution (e.g. Gabaix, 1999)
- ...

# Plan

- ① **Random growth theories** of top inequality
    - a simple theory of top income inequality
    - stationary distribution
  - ② **Slow transitions** in the baseline model
  - ③ Models that generate **fast transitions**
    - heterogeneous mean growth rates
    - “superstar shocks” to skill prices
- **Today’s presentation:** focus on top income inequality
  - **Paper:** analogous results for top wealth inequality



# A Random Growth Theory of Income Dynamics

- Continuous time
- Continuum of workers, heterogeneous in human capital  $h_{it}$
- die/retire at rate  $\delta$ , replaced by young worker with  $h_{i0}$
- Wage is  $w_{it} = \omega h_{it}$
- Human capital accumulation involves
  - investment
  - luck
- “Right” assumptions  $\Rightarrow$  wages evolve as

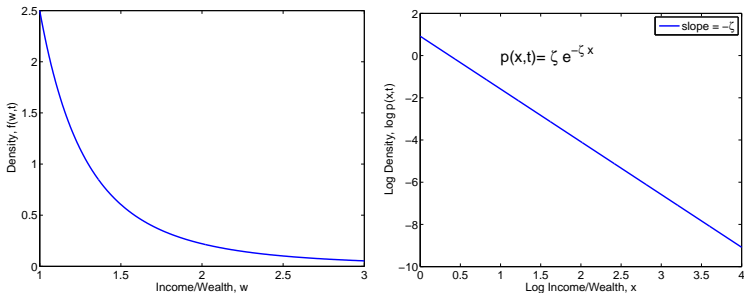
$$d \log w_{it} = \mu dt + \sigma dZ_{it}$$

- **growth rate** of wage  $w_{it}$  is **stochastic**
- $\mu, \sigma$  depend on model parameters
- $Z_{it}$  = Brownian motion, i.e.  $dZ_{it} \equiv \lim_{\Delta t \rightarrow 0} \varepsilon_{it} \sqrt{\Delta t}, \varepsilon_{it} \sim \mathcal{N}(0, 1)$
- A number of alternative theories lead to same reduced form

# Stationary Income Distribution

- **Result:** The stationary income distribution has a Pareto tail

$$\Pr(\tilde{w} > w) \sim Cw^{-\zeta}$$



- ... with tail exponent

$$\zeta = \frac{-\mu + \sqrt{\mu^2 + 2\sigma^2\delta}}{\sigma^2}$$

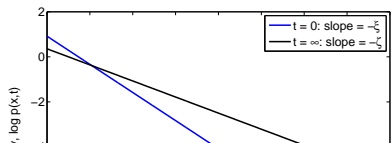
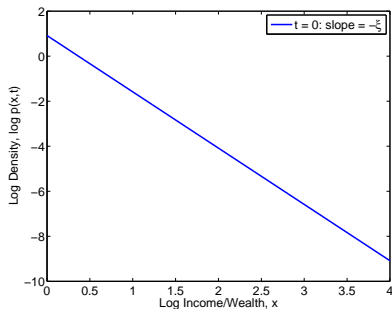
- Tail inequality  $\eta = 1/\zeta$  increasing in  $\mu, \sigma$ , decreasing in  $\delta$

## Other Theories of Top Inequality

- We confine ourselves to theories that generate power laws
  - random growth
  - models with superstars (assignment models) – more later
- Example of theories that do not generate power laws, i.e. do not generate **fractal feature** of top income inequality:
  - theories of rent-seeking (Benabou and Tirole, 2015; Piketty, Saez and Stantcheva, 2014)
  - someone should write that “rent-seeking  $\Rightarrow$  power law” paper!

## Transitions: The Thought Experiment

- $\sigma \uparrow$  leads to increase in stationary tail inequality
- But what about dynamics? Thought experiment:
  - suppose economy is in Pareto steady state
  - at  $t = 0$ ,  $\sigma \uparrow$ . Know: in long-run  $\rightarrow$  higher top inequality



## Transitions: Tools

- Convenient to work with  $x_{it} = \log w_{it}$

$$dx_{it} = \mu dt + \sigma dZ_{it}$$

- Need additional “friction” to ensure existence of stat. dist.
  - income application: death/retirement at rate  $\delta$
  - alternative: reflecting barrier
- Distribution  $p(x, t)$  satisfies

$$p_t = -\mu p_x + \frac{\sigma^2}{2} p_{xx} - \delta p + \delta \delta_0$$

where  $\delta_0 =$  Dirac delta function (point mass at  $x = 0$ )

- Useful to write in terms of differential operator  $\mathcal{A}^*$

$$p_t = \mathcal{A}^* p + \delta \delta_0, \quad \mathcal{A}^* p = -\mu p_x + \frac{\sigma^2}{2} p_{xx} - \delta p$$

- $\mathcal{A}^*$  = “transition matrix” for continuous-state process

## Average Speed of Convergence

- **Proposition:**  $p(x, t)$  converges to stationary distrib.  $p_\infty(x)$

$$\|p(x, t) - p_\infty(x)\| \sim ke^{-\lambda t}$$

- without reflecting barrier, rate of convergence is

$$\lambda = \delta$$

- with reflecting barrier, rate of convergence is

$$\lambda = \frac{1}{2} \frac{\mu^2}{\sigma^2} \mathbf{1}_{\{\mu < 0\}} + \delta$$

- For given amount of top inequality  $\eta$ , speed  $\lambda(\eta, \sigma, \delta)$  satisfies

$$\frac{\partial \lambda}{\partial \eta} \leq 0, \quad \frac{\partial \lambda}{\partial \sigma} \geq 0, \quad \frac{\partial \lambda}{\partial \delta} > 0$$

- **Observations:**

- **high inequality** goes hand in hand with **slow transitions**
- half life is  $t_{1/2} = \ln(2)/\lambda \Rightarrow$  precise quantitative predictions

- **Rough idea:**  $\lambda =$  2nd eigenvalue of “transition matrix”  $\mathcal{A}^*$

## Rough Idea of Proof [▶ back](#)

- To understand, suppose  $x_{it}$  = finite-state Poisson process
  - $x_{it} \in \{x_1, \dots, x_N\} \Rightarrow$  distribution = vector  $p(t) \in \mathbb{R}^N$
  - dynamics

$$\dot{p}(t) = \mathbf{A}^T p(t),$$

where  $\mathbf{A} = N \times N$  (diagonalizable) transition matrix

- Denote eigenvalues by  $0 = |\lambda_1| < |\lambda_2| < \dots < |\lambda_N|$  and corresponding eigenvectors by  $(v_1, \dots, v_N)$
- **Theorem:**  $p(t)$  converges to stationary dist. at rate  $|\lambda_2|$
- Proof sketch: decomposition

$$p(0) = \sum_{i=1}^N c_i v_i \quad \Rightarrow \quad p(t) = \sum_{i=1}^N c_i e^{\lambda_i t} v_i$$

- Example: symmetric two-state Poisson process with intensity  $\phi$

$$\mathbf{A} = \begin{bmatrix} -\phi & \phi \\ \phi & -\phi \end{bmatrix}, \quad \Rightarrow \quad \lambda_1 = 0, \quad |\lambda_2| = 2\phi$$

Intuitively, speed  $|\lambda_2| \nearrow$  in switching intensity  $\phi$

## Rough Idea of Proof

- Here: generalize this idea to continuous-state process
- Consider Kolmogorov Forward equation for  $x_{it}$ -process

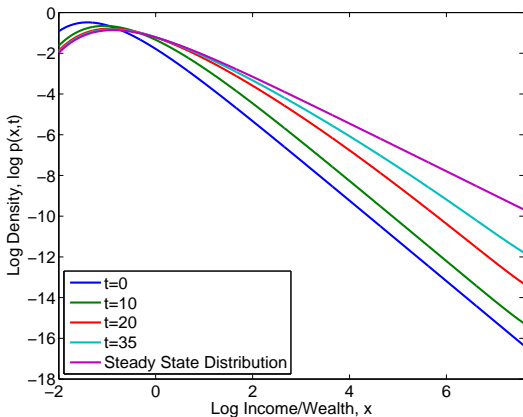
$$p_t = \mathcal{A}^* p + \delta \delta_0, \quad \mathcal{A}^* p = -\mu p_x + \frac{\sigma^2}{2} p_{xx} - \delta p$$

- Exact generalization of finite-state  $\dot{p}(t) = \mathbf{A}^T p(t)$
- **Proof** has two steps:
  - ① realization that speed = second eigenvalue of operator  $\mathcal{A}^*$
  - ② analytic computation:  $|\lambda_2| = \frac{1}{2} \frac{\mu^2}{\sigma^2} \mathbf{1}_{\{\mu < 0\}} + \delta$



## Transition in Upper Tail

- So far: **average** speed of convergence of whole distribution
- But care in particular about speed in **upper tail**
- Show: transition can be much **slower** in upper tail



## Instructive Special Case: Steindl Model

- The special case  $\sigma = 0, \mu > 0$  can be solved cleanly
  - $x_t$  grows at rate  $\mu$ , gets reset to  $x_0 = 0$  at rate  $\delta$
  - stationary distribution  $p(x) = \zeta e^{-\zeta x}, \zeta = \delta/\mu$
- Can show: for  $t, x > 0$  density satisfies

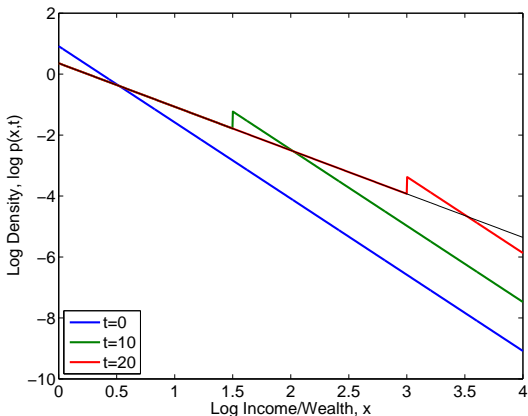
$$\frac{\partial p(x, t)}{\partial t} = -\mu \frac{\partial p(x, t)}{\partial x} - \delta p(x, t), \quad p(x, 0) = \alpha e^{-\alpha x} \quad (*)$$

- **Result:** the solution to (\*) is

$$p(x, t) = \zeta e^{-\zeta x} \mathbf{1}_{\{x \leq \mu t\}} + \alpha e^{-\alpha x + (\alpha - \zeta)t} \mathbf{1}_{\{x > \mu t\}}$$

where  $\mathbf{1}_{\{.\}}$  = indicator function

## Instructive Special Case: Steindl Model



### Observations:

- 1 transition is slower in upper tail: it takes time  $\tau(x) = x/\mu$  for the local PL exponent to converge to its steady state value  $\zeta$
- 2 initially, tail exhibits parallel shift

## Transition in Tail: General Case

- Distribution  $p(x, t)$  satisfies a Kolomogorov Forward Equation

$$p_t = -\mu p_x + \frac{\sigma^2}{2} p_{xx} - \delta p + \delta \delta_0 \quad (*)$$

- Can solve this, but not particularly instructive
- Instead, use so-called “Laplace transform” of  $p$

$$\hat{p}(\xi, t) := \int_{-\infty}^{\infty} e^{-\xi x} p(x, t) dx = \mathbb{E} \left[ e^{-\xi x} \right]$$

- $\hat{p}$  has natural interpretation:  $-\xi$ th moment of income/wealth  
 $w_{it} = e^{x_{it}}$ 
  - e.g.  $\hat{p}(-2, t) = \mathbb{E}[w_{it}^2]$

## Transition in Upper Tail

- **Proposition:** The Laplace transform of  $p$ ,  $\hat{p}$  satisfies

$$\hat{p}(\xi, t) = \hat{p}_\infty(\xi) + (\hat{p}_0(\xi) - \hat{p}_\infty(\xi)) e^{-\lambda(\xi)t}$$

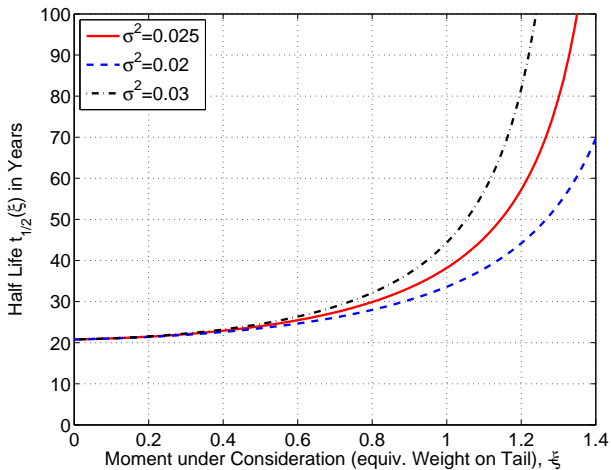
with moment-specific speed of convergence

$$\lambda(\xi) = \mu\xi - \frac{\sigma^2}{2}\xi^2 + \delta$$

- Hence, for  $\xi < 0$ , the higher the moment  $-\xi$ , the slower the convergence (for high enough  $|\xi| < \zeta$ )
- Key step: Laplace transform transforms PDE (\*) into ODE

$$\frac{\partial \hat{p}(\xi, t)}{\partial t} = -\xi\mu\hat{p}(\xi, t) + \xi^2\frac{\sigma^2}{2}\hat{p}(\xi, t) - \delta\hat{p}(\xi, t) + \delta$$

## Transition in Upper Tail



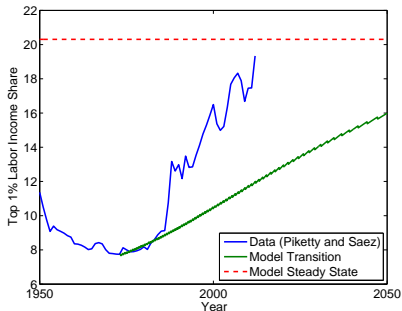
# Dynamics of Income Inequality

- Recall process for log wages

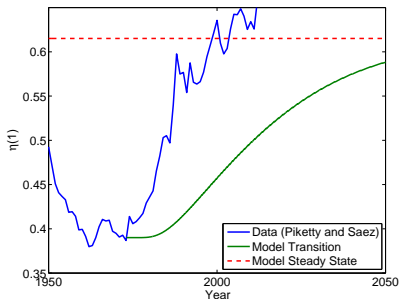
$$d \log w_{it} = \mu dt + \sigma dZ_{it} \quad + \text{ death at rate } \delta$$

- $\sigma^2 = \text{Var}(\text{permanent earnings})$
- **Literature:**  $\sigma$  has increased over last forty years
  - documented by Kopczuk, Saez and Song (2010), DeBacker et al. (2013), Heathcote, Perri and Violante (2010) using PSID
  - but Guvenen, Ozkan and Song (2014):  $\sigma$  flat/decreasing in SSA data
- **Can increase in  $\sigma$  explain increase in top income inequality?**

# Dynamics of Income Inequality: Model vs. Data



(a) Top 1% Labor Income Share



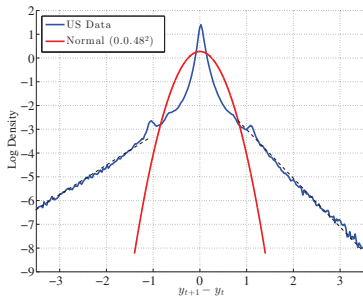
(b) Pareto Exponent

- Experiment  $\sigma^2 \uparrow$  from 0.01 in 1973 to 0.025 in 2014 (Heathcote, Perri and Violante, 2010)
- Note: PL exponent  $\eta = 1 + \log_{10} \frac{S(0.1)}{S(1)}$  (from  $\frac{S(0.1)}{S(1)} = 10^{\eta-1}$ )



## Jumps Don't Help Either

- Standard random growth model: income innovations are log-normally distributed
- Recent research: not a good description of the data, e.g. Guvenen-Karahan-Ozkan-Song:



- Natural question: can jumps generate fast transitions?
- Answer: no! While useful descriptively, jumps do not increase the speed of convergence

## Jumps Don't Help Either

- Extend income process to

$$dx_{it} = \mu dt + \sigma dZ_{it} + \text{jumps with intensity } \phi \text{ drawn from } f$$

- **Proposition:** With jumps, speed of convergence is

$$\lambda(\xi, \phi) := \xi\mu - \xi^2 \frac{\sigma^2}{2} + \delta - \phi(\widehat{f}(\xi) - 1)$$

$$\widehat{f}(\xi) := \int_{-\infty}^{\infty} e^{-\xi g} f(g) dg,$$

Jumps have no effect whatsoever on average speed of convergence

$$\lambda = \delta$$

and they slow down the speed of convergence in the tail

$$\xi < 0 \quad \Rightarrow \quad \lambda(\xi, \phi) \text{ decreasing in } \phi$$

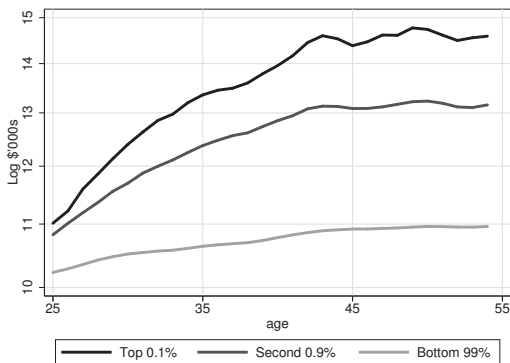
## OK, so what drives top inequality then?

Two candidates:

- ① heterogeneity in mean growth rates
- ② deviations from Gibrat's law, e.g. due to changes in skill prices

# Heterogeneity in Mean Growth Rates

(A) Mean earnings by age



- Guvenen, Kaplan and Song (2014): between age 25 and 35
  - earnings of top 0.1% of lifetime inc. grow by  $\approx 25\%$  each year
  - and only  $\approx 3\%$  per year for bottom 99%

## Heterogeneity in Mean Growth Rates

- Two regimes:  $H$  and  $L$

$$dx_{it} = \mu_H dt + \sigma_H dZ_{it}$$

$$dx_{it} = \mu_L dt + \sigma_L dZ_{it}$$

- Assumptions
  - $\mu_H > \mu_L$
  - fraction  $\theta$  enter labor force in  $H$ -regime
  - switch from  $H$  to  $L$  at rate  $\psi$ ,  $L =$  absorbing state
  - retire at rate  $\delta$
- See Luttmer (2011) for similar model of firm dynamics
- **Proposition:** The dynamics of  $\hat{p}(x, t) = \mathbb{E}[e^{-\xi x}]$  satisfy

$$\hat{p}(\xi, t) - \hat{p}_\infty(\xi) = c_H(\xi)e^{-\lambda_H(\xi)t} + c_L(\xi)e^{-\lambda_L(\xi)t}$$

$$\lambda_H(\xi) := \xi\mu_H - \xi^2 \frac{\sigma_H^2}{2} + \psi + \delta \gg \lambda_L(\xi)$$

and  $c_L(\xi), c_H(\xi) =$  constants

## “Superstar shocks” to skill prices

- Second candidate for fast transitions:  $x_{it} = \log w_{it}$  satisfies

$$\begin{aligned}x_{it} &= \chi_t y_{it} \\ dy_{it} &= \mu dt + \sigma dZ_{it}\end{aligned}\quad (*)$$

i.e.  $w_{it} = (e^{y_{it}})^{\chi_t}$  and  $\chi_t =$  stochastic process  $\neq 1$

- Note: implies deviations from Gibrat's law

$$dx_{it} = \mu dt + x_{it} dS_t + \sigma dZ_{it}, \quad S_t := \log \chi_t \neq 0$$

- Call  $\chi_t$  (equiv.  $S_t$ ) “**superstar shocks**”
- **Proposition:** The process (\*) has an **infinitely fast** speed of adjustment:  $\lambda = \infty$ . Indeed

$$\zeta_t^x = \zeta^y / \chi_t \quad \text{or} \quad \eta_t^x = \chi_t \eta^y$$

where  $\zeta_t^x$ ,  $\zeta^y$  are the PL exponents of incomes  $x_{it}$  and  $y_{it}$ .

- **Intuition:** if power  $\chi_t$  jumps up, top inequality jumps up

## A Microfoundation for “Superstar Shocks”

- $\chi_t$  term can be microfounded with changing skill prices in assignment models (Sattinger, 1979; Rosen, 1981)
- Here adopt Gabaix and Landier (2008)
  - continuum of firms of different size  $S \sim \text{Pareto}(1/\alpha_t)$ .
  - continuum of managers with different talent  $T$ , distribution

$$T(n) = T_{\max} - \frac{B}{\beta} n^{\beta_t}$$

where  $n := \text{rank/quantile of manager talent}$

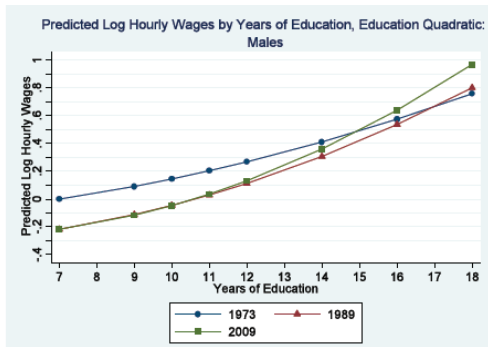
- Match generates firm value: constant  $\times TS^{\gamma_t}$
- Can show:  $w(n) = e^{a_t} n^{-\chi_t}$  ( $= e^{a_t + \chi_t y_{it}}$ ,  $y_{it} = -\log n_{it}$ )

$$\chi_t = \alpha_t \gamma_t - \beta_t$$

- Increase in  $\chi_t$  due to
  - $\beta_t, \gamma_t$ : (perceived) importance of talent in production, e.g. due to ICT (Garicano & Rossi-Hansberg, 2006)
- Other assignment models (e.g. with rent-seeking, inefficiencies) would yield similar microfoundation

# Empirical Evidence on “Superstar shocks”

- ① Acemoglu and Autor (2011): “convexification” of skill prices



- ② Recall

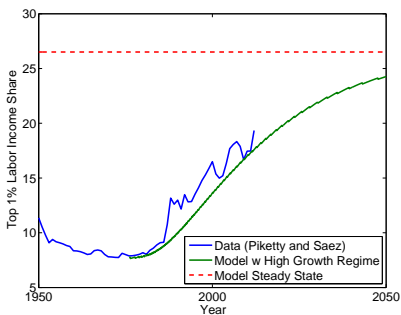
$$dx_{it} = \mu dt + x_{it} dS_t + \sigma dZ_{it}, \quad S_t := \log \chi_t \neq 0$$

Parker and Vissing-Jorgenson (2009) and Guvenen (2014) find evidence of  $S_t$  shocks at business cycle frequencies

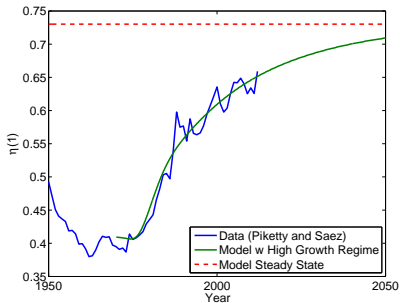


## Revisiting the Rise in Income Inequality

- Casual evidence: very rapid income growth rates since 1980s (Bill Gates, Mark Zuckerberg)
- Jones and Kim (2015): in IRS/SSA data, average growth rate in upper tail of the growth rate distribution  $\uparrow$  since late 1970s
- Experiment in model with het. growth rates: in 1973 growth rate of  $H$ -types  $\uparrow$  by 8%



(a) Top 1% Labor Income Share



(b) Pareto Exponent

## Wealth Inequality and Capital Taxes

- A simple model of top wealth inequality based on Piketty and Zucman (2015, HID), Piketty (2015, AERPP),...

$$dw_{it} = [y + (r - g - \theta)w_{it}]dt + \sigma w_{it}dZ_{it}$$
$$r = (1 - \tau)\tilde{r}, \quad \sigma = (1 - \tau)\tilde{\sigma}$$

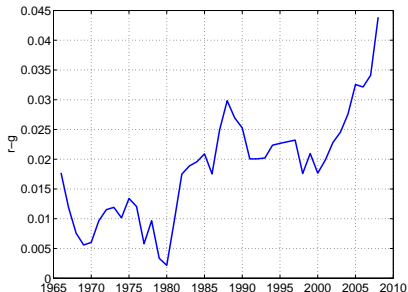
- $y$ : labor income
  - $R_{it}dt = rdt + \sigma dZ_{it}$ : after-tax return on wealth
  - $\tau$ : capital tax rate
  - $g$ : economy-wide growth rate
  - $\theta$ : MPC out of wealth
- Stationary top inequality

$$\eta = \frac{1}{\zeta} = \frac{\sigma^2/2}{\sigma^2/2 - (r - g - \theta)}$$

- **Can  $r - g$  explain observed dynamics of wealth inequality?**

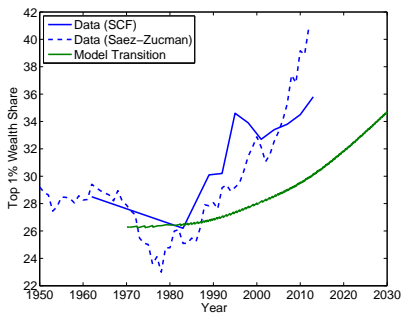
# Wealth Inequality and Capital Taxes

- Compute  $r_t - g_t = \tilde{r}_t(1 - \tau_t) - g_t$  with [details](#)
  - $\tilde{r}_t$  from Piketty and Zucman (2014)
  - $\tau_t$  = capital tax rates from Auerbach and Hassett (2015)
  - $g_t$  = smoothed growth rate from PWT

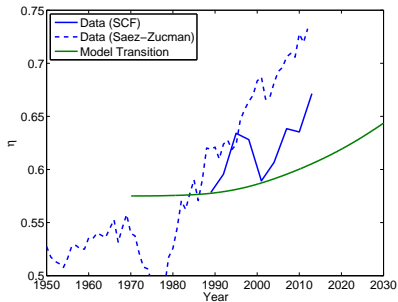


- $\sigma = 0.3$  = upper end of estimates from literature
- $\theta$  calibrated to match inequality in 1978

# Dynamics of Wealth Inequality



(a) Top 1% Wealth Share



(b) Power Law Exponent

Note: PL exponent  $\eta = 1 + \log_{10} \frac{S(0.1)}{S(1)}$  (from  $\frac{S(0.1)}{S(1)} = 10^{\eta-1}$ )

## OK, so what drives top wealth inequality then?

- Rise in **rate of returns** of super wealthy relative to wealthy (top 0.01 vs. top 1%)
  - better investment advice?
  - better at taking advantage of “tax loopholes”?
  - Kacperczyk, Nosal and Stevens (2015) provide some evidence
- Rise in **saving rates** of super wealthy relative to wealthy
  - Saez and Zucman (2014) provide some evidence

## Conclusion

- Transition dynamics of standard random growth models **too slow** relative to those observed in the data
- Two parsimonious deviations that generate **fast transitions**
  - ① heterogeneity in mean growth rates
  - ② “superstar shocks” to skill prices
- Rise in top **income** inequality due to
  - ~~simple tax stories, stories about  $\text{Var}(\text{permanent earnings})$~~
  - **rise in superstar growth (and churn) in two-regime world**
  - **“superstar shocks” to skill prices**
- Rise in top **wealth** inequality due to
  - ~~increase in  $r - g$  due to falling capital taxes~~
  - **rise in saving rates/RoRs of super wealthy**