

# Unequal Growth

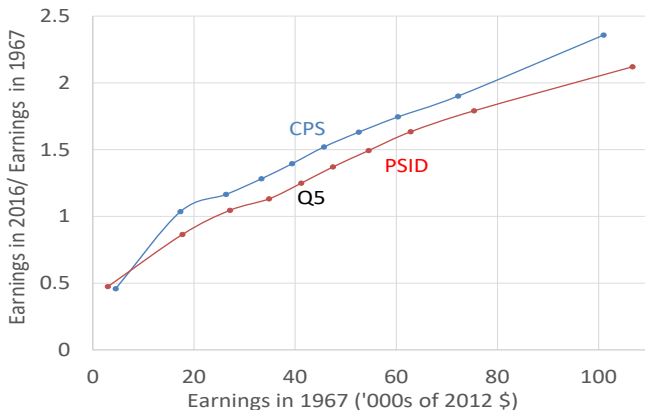
Francesco Lippi and Fabrizio Perri  
*IEEF, Luiss*      *FRB of Minneapolis*

June 2019

# Introduction

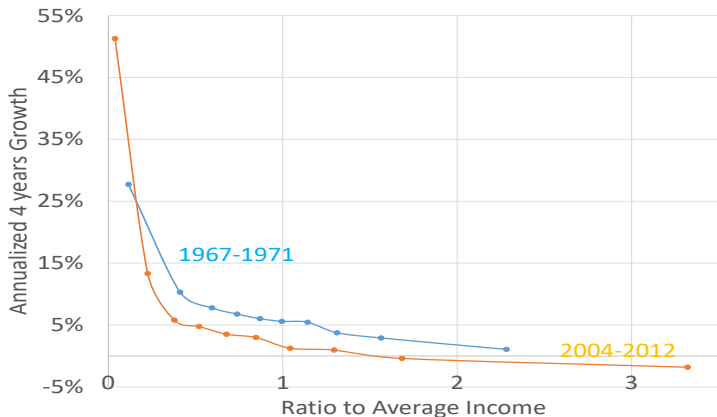
- Over past 50 years U.S. has experienced a large increase in household income inequality
- Many studies on the causes of this, much less work on its growth impact
- Changes that drive increase in income inequality are changes in income dynamics, which naturally can have a growth impact
- Building block: Changes in income dynamics that are unequal across income levels (**Unequal growth**), affect, at the same time, aggregate growth, income inequality and welfare
- Objective: Use micro data and minimal theory to connect growth and inequality, estimate these changes and assess their impact

# Unequal growth 1967-2016: a cross sectional view



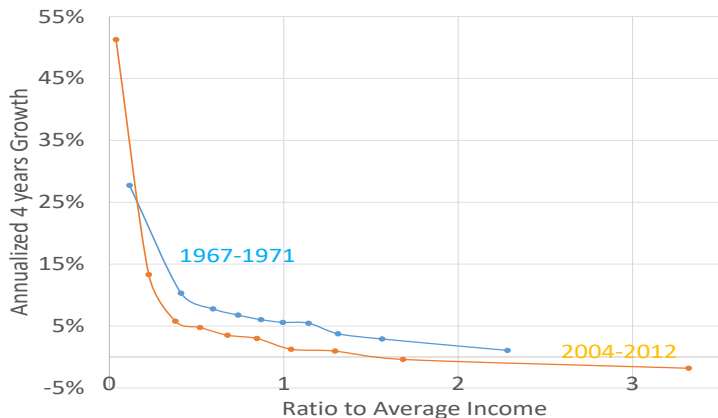
- Each point: level & growth of deciles of 1967 income distribution
- Top grew fast, bottom stagnated: **not same households across time!**

# Unequal growth 1967-2016: a panel view (PSID)



- Poor grow faster than rich (mean reversion), early and late in sample
- Same households across time!

# Unequal growth 1967-2016: a panel view (PSID)



- Poor grow faster than rich (mean reversion), early and late in sample
- Same households across time!
- How is this fig( $\beta$  convergence) consistent with previous ( $\sigma$  divergence)?
- How are these changes connected with aggregate growth?

# Outline

- A micro decomposition of aggregate growth
- Empirical analysis on decomposition
- Simple model to measure the changes driving the data, and assess impact

## Some Related literature

- **Empirical:** “Earnings, Inequality and Mobility in the United States”, Kopczuk, Saez and Song 2010, “The Nature of Countercyclical Income Risk” Guvenen, Ozkan, and Song. 2014
- **Models of Income Inequality:** “Uninsured Idiosyncratic Risk and Aggregate Saving”, Ayiagari 1994, “Dynamics of inequality”, Gabaix, Lasry, Lions and Moll 2016, “Top income inequality dynamics”, Kim and Jones 2017
- **From micro to macro:** “Misallocation and growth”, Jovanovic 2014, “The Granular Origins of Aggregate Fluctuations”, Gabaix 2011

# A micro decomposition of aggregate growth

- Let  $y_{it}$  real income of household  $i$  at time  $t$
- Aggregate growth in period  $t$  over horizon  $T$ ,  $\Gamma_{t,T}$  can be written as

$$\Gamma_{t,T} = \frac{E_i(y_{i,t+T})}{E_i(y_{i,t})} = E_i \left( \frac{y_{i,t+T}}{y_{i,t}} \frac{y_{i,t}}{E(y_{i,t})} \right)$$

- Define  $g_{i,T} = \frac{y_{i,t+T}}{y_{i,t}}$  ,  $s_{i,t} = \frac{y_{i,t}}{E(y_{i,t})}$  so that  $\Gamma_{t,T} = E_i(g_{i,T} \cdot s_{i,t})$



# A micro decomposition of aggregate growth

- Let  $y_{it}$  real income of household  $i$  at time  $t$
- Aggregate growth in period  $t$  over horizon  $T$ ,  $\Gamma_{t,T}$  can be written as

$$\Gamma_{t,T} = \frac{E_i(y_{i,t+T})}{E_i(y_{i,t})} = E_i \left( \frac{y_{i,t+T}}{y_{i,t}} \frac{y_{i,t}}{E(y_{i,t})} \right)$$

- Define  $g_{i,T} = \frac{y_{i,t+T}}{y_{i,t}}$  ,  $s_{i,t} = \frac{y_{i,t}}{E(y_{i,t})}$  so that  $\Gamma_{t,T} = E_i(g_{i,T} \cdot s_{i,t})$

$$\begin{aligned}\Gamma_T &= cov(g_{i,T}, s_i) + E(g_{i,T}) \\ &= corr(g_{i,T}, s_i)\sigma(g_{i,T})\sigma(s_i) + E(g_{i,T})\end{aligned}$$

# A micro decomposition of aggregate growth

- Let  $y_{it}$  real income of household  $i$  at time  $t$
- Aggregate growth in period  $t$  over horizon  $T$ ,  $\Gamma_{t,T}$  can be written as

$$\Gamma_{t,T} = \frac{E_i(y_{i,t+T})}{E_i(y_{i,t})} = E_i \left( \frac{y_{i,t+T}}{y_{i,t}} \frac{y_{i,t}}{E(y_{i,t})} \right)$$

- Define  $g_{i,T} = \frac{y_{i,t+T}}{y_{i,t}}$  ,  $s_{i,t} = \frac{y_{i,t}}{E(y_{i,t})}$  so that  $\Gamma_{t,T} = E_i(g_{i,T} \cdot s_{i,t})$

$$\begin{aligned}\Gamma_T &= cov(g_{i,T}, s_i) + E(g_{i,T}) \\ &= corr(g_{i,T}, s_i)\sigma(g_{i,T})\sigma(s_i) + E(g_{i,T})\end{aligned}$$

- Who grows matters for aggregate growth, and how growth takes place matter for inequality
- Similar decomposition widely used in IO (Olley and Pakes, 1996)

# Insights from decomposition

$$\begin{aligned}\Gamma_T &= cov(g_{i,T}, s_i) + E(g_{i,T}) \\ &= corr(g_{i,T}, s_i)\sigma(g_{i,T})\sigma(s_i) + E(g_{i,T})\end{aligned}$$

- Simple way to sum micro moments to evaluate a given  $\Gamma_T$ :
- Growth can be:
  - ▶ Equal ( $\sigma(g_i) = 0$  ,  $E(g_i = \bar{g})$ )
  - ▶ Unequal ( $\sigma(g_i) > 0$ ). In this case inequality  $\sigma(s_i)$  and mobility  $cov(g_i, s_i)$  matter for  $\Gamma_T$
- Whether growth is equal or unequal has welfare consequences

**Warning:**  $Cov(g_i, s_i), E(g_i)$  .. not independent primitives: structural changes in income dynamics change (at same time) all terms: need a theory!

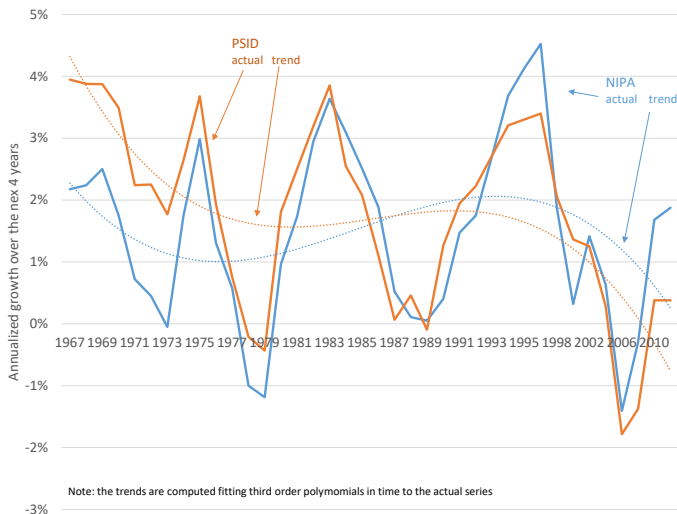
# Plan

- (1) measure  $\text{corr}(g_i, s_i)$ ,  $\sigma(g_{it})$ ,  $\sigma(s_{it})$  and  $E(g_i)$  over 1967-2016
- (2) simple mechanism to understand driving force of changes

# Panel Study of Income Dynamics (PSID)

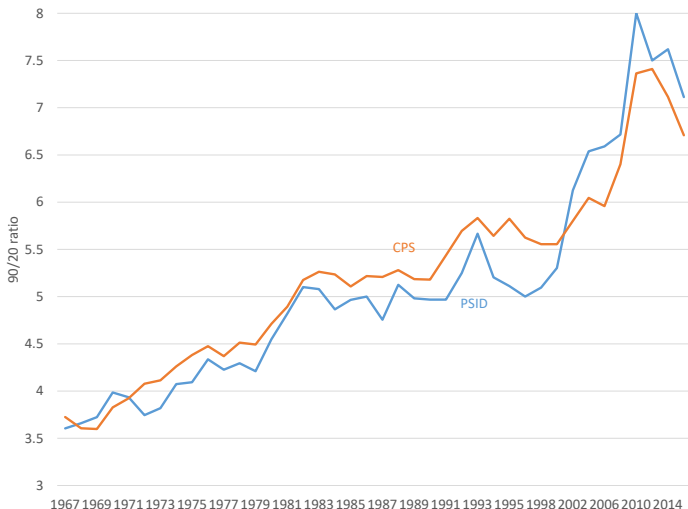
- Long panel of about 5,000 HH, representative of U.S. population
- **Panel** essential to identify change of individual dynamics (vs composition)
- 1967-2016 (Annual until 1996, bi-annual after)
- Publicly available
- **Panel** data must aggregate up to macro outcomes

# PSID v/s NIPA: 4y growth of real labor income pc



- Aggregate PSID matches well macro NIPA Dynamics (including recent growth slowdown)

# PSID v/s CPS: Cross sectional inequality



- PSID matches well cross sectional inequality in labor income from much larger sample (CPS)

## Mapping decomposition to panel data

Let  $T = 4$  years,  $y_{j,i,t}$  be real (PCE deflated) income of HH  $j$ , in decile  $i$  in year  $t$  and  $P_t$  total population in sample in year  $t$

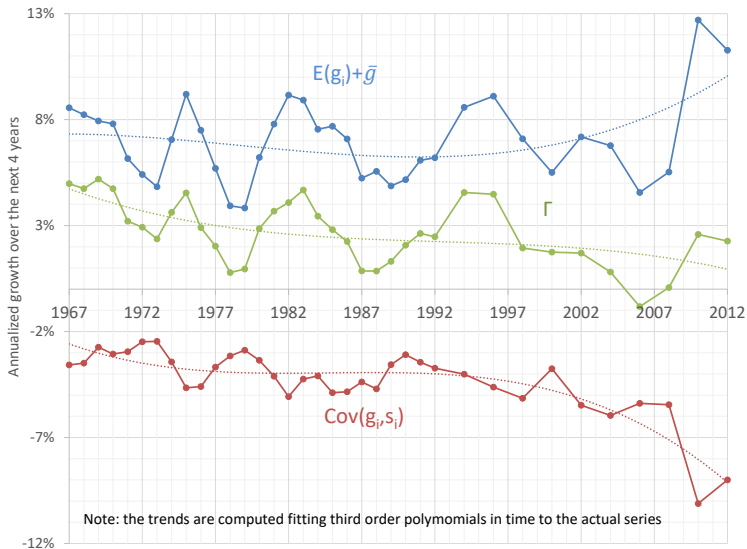
$$\text{then } g_{i,t+T} = \frac{\sum_j y_{j,i,t+T}}{\sum_j y_{j,i,t}} \frac{P_t}{P_{t+T}} \quad \text{and} \quad s_{i,t} = \frac{\sum_j y_{j,i,t}}{\sum_i \sum_j y_{j,i,t}}$$

Aggregating by income deciles (quintiles) useful with measurement error

- Income measure: Labor Earnings of all household members
- Sample restrictions: Households with head 25-60, with income above 20% of the pvtly line, no imputed labor income, which are in sample in year  $t$  and  $t + 4$  (avg. sample per year  $\simeq 3500$ )
- Similar patterns for hholds with 25-40 head (age composition)

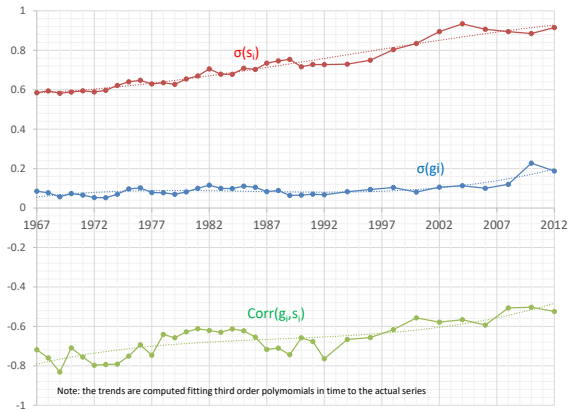


# Aggregate growth decomposition (PSID)



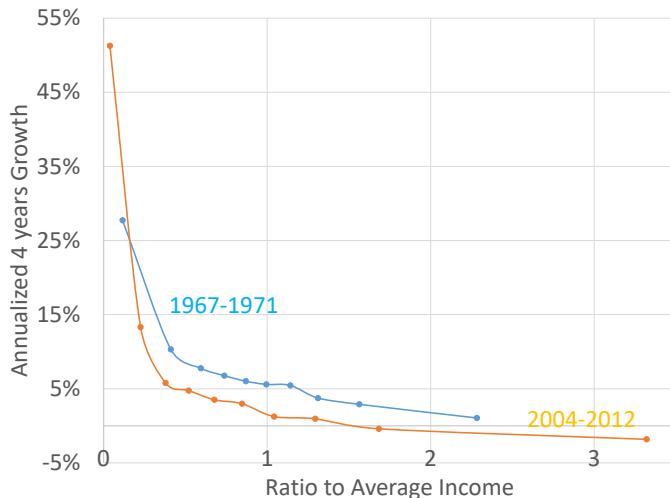
- $\Gamma$  declines,  $E(g_i)$  does not, Implies:  $cov_t \downarrow$

# Covariance decomposition (PSID)



- Increasing  $\sigma(s_i)$  measure of increasing income inequality
- $\text{Corr}(g_i, s_i)$  increasing (toward 0) signals less rank mobility

# Why is correlation increasing?

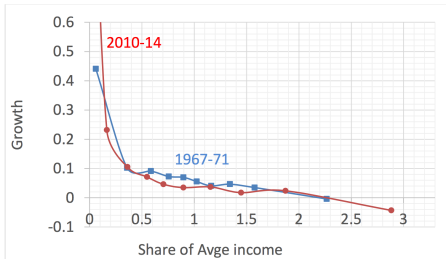


- Relation between  $g_i$  and  $s_i$ , becoming less linear (spike for low  $s$ , flatter for high  $s$ )

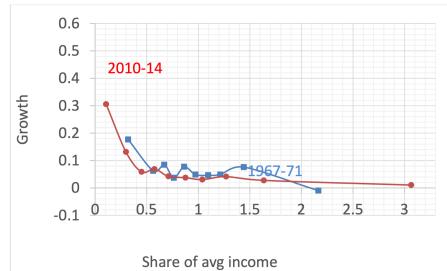
# Robustness of growth decomposition

Cut sample by HH head education:  
at most High-school                      College or more

Heads with HS degree or less



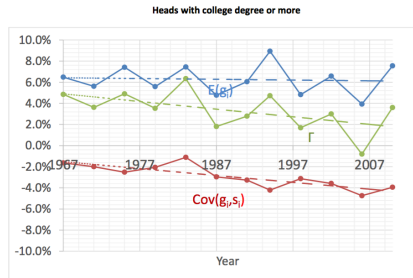
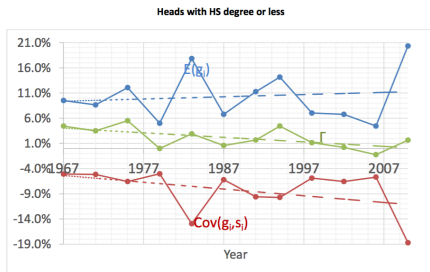
Heads with college degree or more



# Robustness of growth decomposition (1)

Cut sample by HH head education:  
at most High-school

College or more



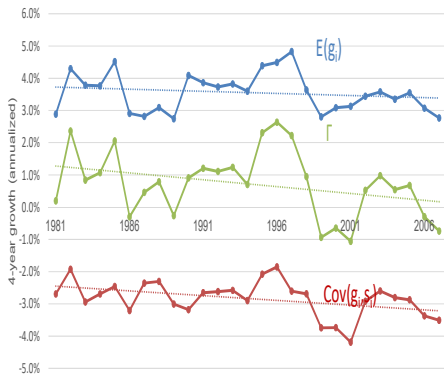
Patterns robust to several more demographics (e.g. age, race)

# Robustness of growth decomposition (2)

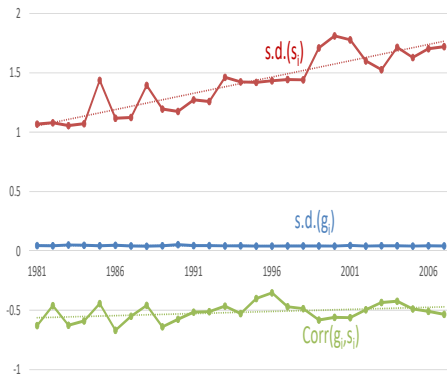
Administrative data from SIPP users

Larger sample (20x), higher quality data, indiv v/s hholds, 1980-2012

Growth decomposition



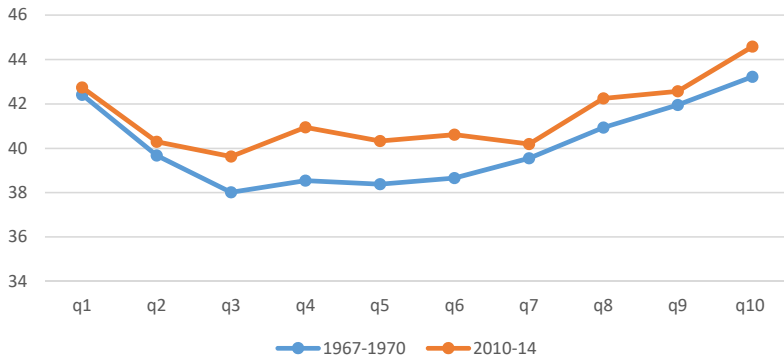
covariance decomposition



## Who is in the different deciles?

- Before writing a model for  $(g_i, s_i)$ , show some characteristics of different deciles of income distribution.

## Age of different quantiles

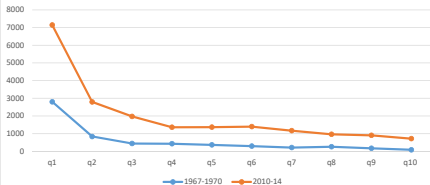


- The poor fast growers are not all young
- Mean reversion not all explained by demographic (Some household become poor-fast growers because of shocks)

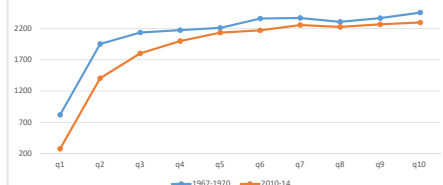


# Hours and transfers

Transfer Income

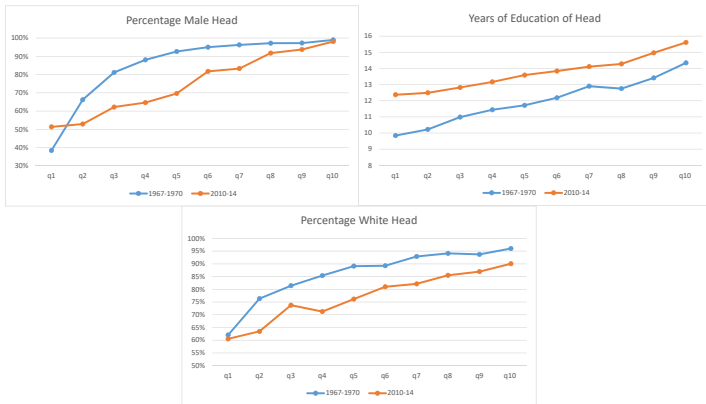


Hours worked by Head



- Poor fast-growers work much less hours and receive more transfers, suggesting they are experiencing (temporary) shock to their ability/willingness to work (Low hours mostly explained by extensive margin)

# White, Male and College Educated



- All lines increasing, suggesting the importance of permanent differences (fixed effects) across deciles.

# The theory

- Is there a simple can change in income dynamics that can account for the changes documented in the decomposition?
- And can this change explain changes in aggregate growth?

# A Bewley-Aiyagari Model

- Continuum of infinitely lived households
- Log of household  $i$  **earning potential** is

$$y_{it} = e_{it} + \alpha_i + g_{it}$$

$$e_{it} = \rho e_{it-1} + \varepsilon_{it}, \varepsilon_{it} \sim N(\mu(s_{it}), \sigma_{\varepsilon t}^2 g(s_{it}))$$

$$\alpha_i \sim N(0, \sigma_\alpha)$$

$$g_{it} = h(s_{it}) + g_{it-1} \quad h(s_{it}) = \gamma + \beta \frac{1 - s_{it}}{1 + s_{it}}$$

- $e_{it}$  standard autoregressive part. Variance of shocks  $g(s_{it})$  declining in income  $s_{it}$  (Meghir and Pistaferri, 2004)
- $\alpha_i$  is household fixed effect
- $g_{it}$  is growth factor,  $\gamma$  is equal growth,  $\beta$  captures unequal growth

## Extensive margin

- Household works iff

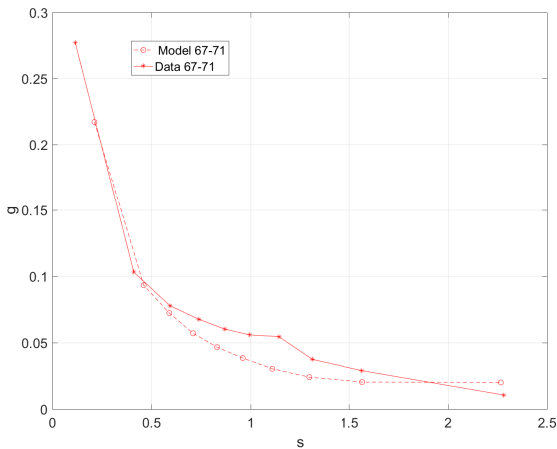
$$\begin{aligned}y_{it} &> \phi_t \\ \phi_t &= \phi_{t-1} + \gamma\end{aligned}$$

- When household work: earnings = earning potential
- Earning potential evolves when household does not work
- $\phi_t$  chosen to match increase of non participant household in data (in our PSID sample from 3% to 6%)

## Exercise

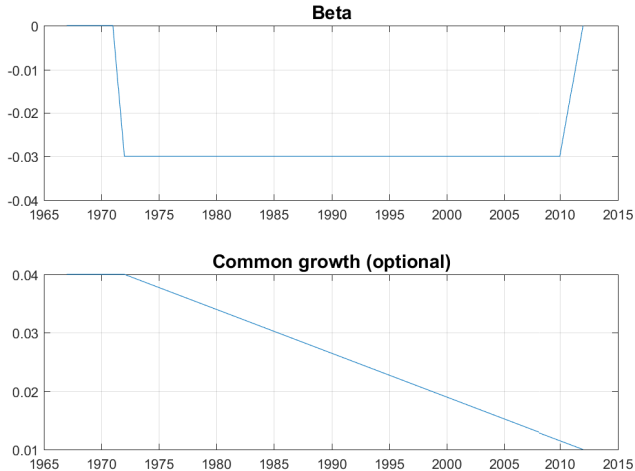
- Set  $\beta=0$ , calibrate all parameters to initial steady state (1967-1972)
- Calibrate a temporary decline in  $\beta$  (rich growing faster than poor), to match increase in income inequality (std  $s_{it}$ )
- Assess empirical performance, growth and welfare impact of this change.

## Initial steady state



- Given  $\rho \simeq 0.6$ , from many micro studies, fixed effects needed to match flat right part
- Extensive margin plus increasing shock variance for low  $s_i$  needed to match spike on left part

# Impulse

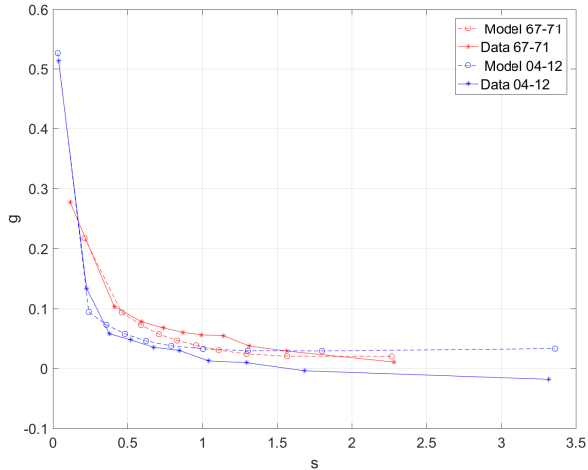


Change in  $\beta$  implies that hhold with  $s_i = 2$  grows 1% per year faster than hhold at  $s_i = 1$  (mean income)



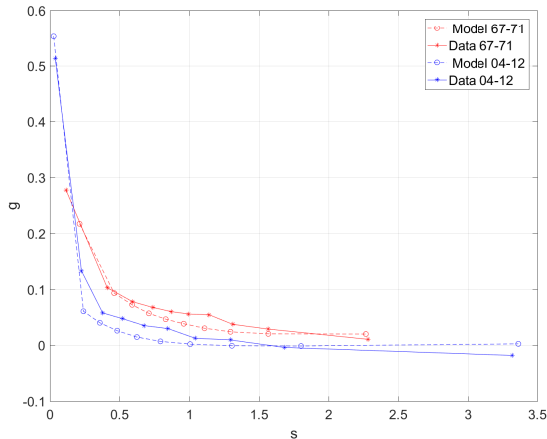
# Growth by decile of the income distribution

## Model vs Data (no common growth decline)



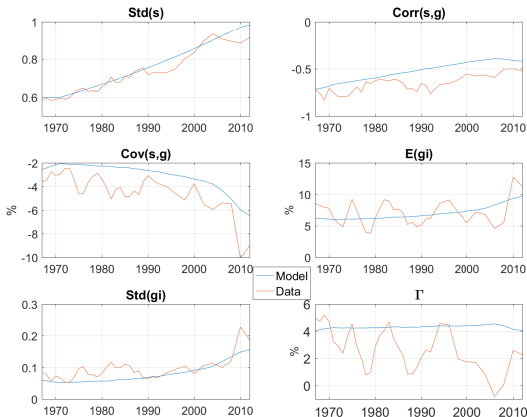
# Growth by decile of the income distribution

## Model vs Data (with common growth decline)



- Common growth decline of 3% needed to account for the full change

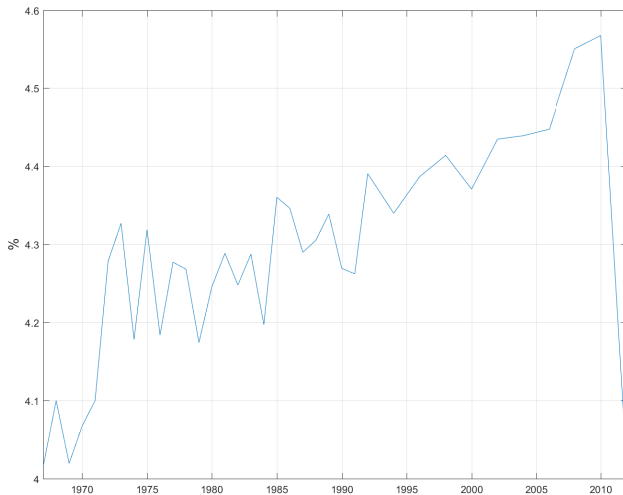
# Time series patterns: Model v/s data



- Model qualitatively accounts for time series patterns of  $cov(s_i, g_i)$  and  $corr(s_i, g_i)$

# Aggregate growth impact

## Growth with $\bar{g} = 0$



Average growth contribution over 40 years is less than 0.5% per year

## Welfare impact of the increase in unequal growth ( $\beta$ ) (prelim)

	Ex ante welfare
Complete Mkts (Or strong public redistribution)	+
Incomplete Mkts + curvature	- -

Reason for the negative effect in IM

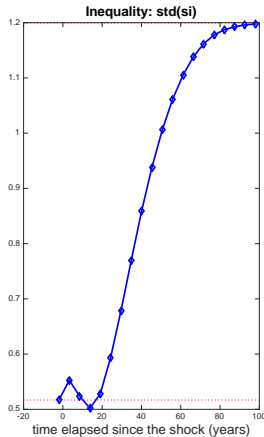
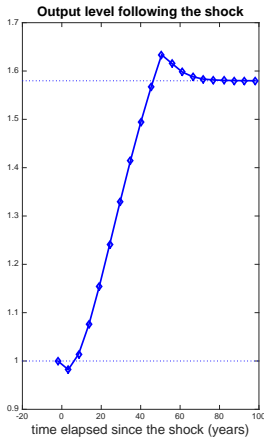
- Unequal growth leads to increase in permanent income inequality (Bowlus Robin, 2004, Abbott and Gallipoli, 2019, Straub, 2019)
- Increase in risk at the bottom of the distribution, where is more costly.

## A Pareto model

- Show that unequal growth (i.e. more growth concentrated in the top of the distribution) can account for the facts in a model of the income process where distribution is Pareto (v/s log normal)
- In that model the growth impact of unequal growth is larger (1%)

# Implication for Transition

Effects triggered by changes in inequality (shape of distribution)



About a 0.9% output growth per year over the first 40 years

## Closing remarks and open issues

- Explore a statistical connection between inequality and growth
- $\Gamma_T = cov(g_{i,T}, s_i) + E(g_{i,T})$   
Use it to inform simple income process: Increase in **unequal growth** can account for patterns of inequality and has a non trivial effect on growth (+) and welfare (-)
- **Takeaway**: not inequality drives growth; but, micro changes that drive up inequality, also impact aggregate growth



## Closing remarks and open issues

- Explore a statistical connection between inequality and growth
- $\Gamma_T = cov(g_{i,T}, s_i) + E(g_{i,T})$   
Use it to inform simple income process: Increase in **unequal growth** can account for patterns of inequality and has a non trivial effect on growth (+) and welfare (-)
- **Takeaway**: not inequality drives growth; but, micro changes that drive up inequality, also impact aggregate growth

### Open issues

- What has driven the increase in unequal growth (SBTC certainly part of it, maybe other factors, like reduced access to opportunities (Fogli and Guerrieri, 2019), playing a role
- What has driven the large (and early) decline in equal growth?

## Additional slides

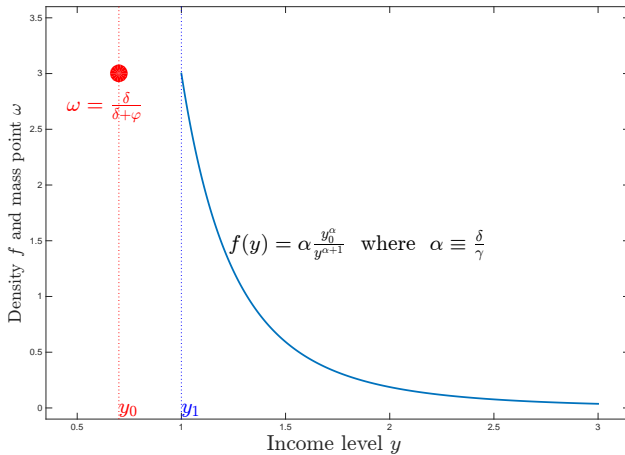
# Simple model of “type depend. growth”, Gabaix et al.

Minimal assumptions for unequal growth:

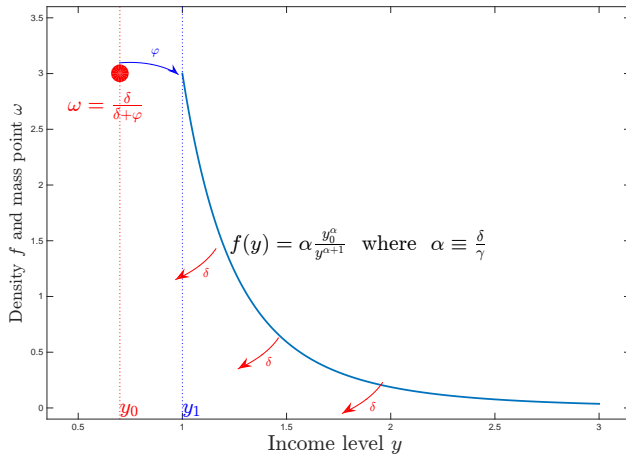
Environment: Income produced by successful projects/jobs

- New projects created at rate  $\varphi$ ; die at rate  $\delta$
- Income from first successful project is  $y_1$  grows at rate  $\gamma$
- Fraction  $\omega \equiv \frac{\delta}{\delta + \varphi}$  of agents w/o project w. constant income  $y_0$

## Model in a nutshell (steady state)

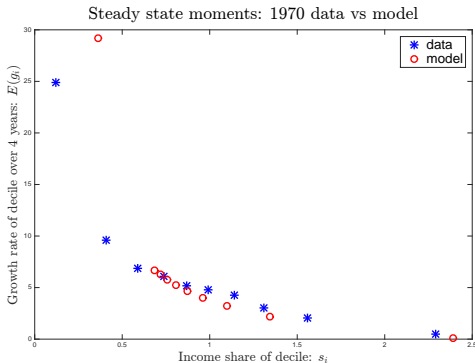


# Model in a nutshell (steady state)



# Model calibrated to early 1970's

Assumes steady state , so that  $\Gamma_t = \bar{g}_t$  , hence  $E(g_i) = -cov(s_i, g_i)$



- $\{\delta, \varphi, \gamma, y_0\}$  chosen to match  $std(s_i), std(g_i), cov(s_i, g_i), mobility$
- Captures tail of rich agents and growth spikes at the bottom

## Transition after permanent shock

- Suppose parameters once and for all change at  $t = 0$
- Old active projects keep old params (growth  $\gamma$ , die at rate  $\delta$ )
- Agents w/o projects immediately face  $\tilde{\delta}, \tilde{\varphi}, \tilde{\gamma}$
- Compute *transition* CDF,  $F(y, t)$  and implied  $\{cov(t), \sigma_{s_i}(t), \sigma_{g_i}(t)\}$ 
  - observable moments  $t$  periods after the shock occurred
- Calibration:
  - choose  $\delta, \varphi, \gamma$  to match steady state moments in 1970
  - choose  $\tilde{\delta}, \tilde{\varphi}, \tilde{\gamma}$  to match moments after  $t = 40$  years

## Tool: characterise dynamics of cross sectional distribution $f(y, t)$

- $t \in (0, \infty)$  time elapsed since shock

– fraction of agents who **low growth**:  $\tilde{\omega}(t)$

$$\tilde{\omega}(t) = \tilde{\omega} + (\omega - \tilde{\omega} + \chi) e^{-(\tilde{\delta} + \tilde{\varphi})t} - \chi e^{-\delta t} \quad \text{where} \quad \chi \equiv \frac{(\tilde{\delta} - \delta)(1 - \omega)}{\tilde{\varphi} + \tilde{\delta} - \delta}$$

– fraction of agents with **high growth**:

$$\eta(t) = 1 - \tilde{\omega}(t) - (1 - \omega)e^{-\delta t}$$

– density of agents with **new project**:  $\tilde{f}(y, t)$  solves KFE

$$\frac{\partial}{\partial t} \tilde{f}(y, t) = -\frac{\partial}{\partial y} (\tilde{f}(y, t) \tilde{\gamma} y) - \delta \tilde{f}(y, t) \quad \text{s.t.} \quad \int_{y_1}^{y_1 e^{\tilde{\gamma} t}} \tilde{f}(y, t) = \eta(t)$$



## Characterising transition (in closed form)

Solving the PDE (using eigenvalue-eigenfunction decomposition) gives

$$\tilde{f}(y, t) = (1 - \tilde{\omega}) \frac{\tilde{\alpha} y_1^{\tilde{\alpha}}}{y^{1+\tilde{\alpha}}} - e^{-\delta t} (1 - \omega - \chi) \frac{\frac{(\tilde{\delta}-\delta)}{\tilde{\gamma}} y_1^{\frac{(\tilde{\delta}-\delta)}{\tilde{\gamma}}}}{y^{1+\frac{(\tilde{\delta}-\delta)}{\tilde{\gamma}}}} + e^{-(\tilde{\delta}+\tilde{\varphi})t} (\omega - \tilde{\omega} + \chi) \frac{\frac{\tilde{\varphi}}{\tilde{\gamma}} y_1^{-\frac{\tilde{\varphi}}{\tilde{\gamma}}}}{y^{1-\frac{\tilde{\varphi}}{\tilde{\gamma}}}}$$

where exponents are “eigenvalues” (as in Gabaix et al. 2016)

## Characterising transition (in closed form)

Solving the PDE (using eigenvalue-eigenfunction decomposition) gives

$$\tilde{f}(y, t) = (1 - \tilde{\omega}) \frac{\tilde{\alpha} y_1^{\tilde{\alpha}}}{y^{1+\tilde{\alpha}}} - e^{-\delta t} (1 - \omega - \chi) \frac{\frac{(\tilde{\delta} - \delta)}{\tilde{\gamma}} y_1^{\frac{(\tilde{\delta} - \delta)}{\tilde{\gamma}}}}{y^{1 + \frac{(\tilde{\delta} - \delta)}{\tilde{\gamma}}}} + e^{-(\tilde{\delta} + \tilde{\varphi})t} (\omega - \tilde{\omega} + \chi) \frac{\frac{\tilde{\varphi}}{\tilde{\gamma}} y_1^{-\frac{\tilde{\varphi}}{\tilde{\gamma}}}}{y^{1 - \frac{\tilde{\varphi}}{\tilde{\gamma}}}}$$

where exponents are “eigenvalues” (as in Gabaix et al. 2016)

– distribution of incomes  $y$  at time  $t$

$$\tilde{f}(y, t) = (1 - \omega) h(y) \quad \text{for } y \in (y_1, \infty)$$

use it to compute moments  $\{cov(t), \sigma_{s_i}(t), \sigma_{g_i}(t)\}, \quad \forall t$

# Model calibration: fit and parameters

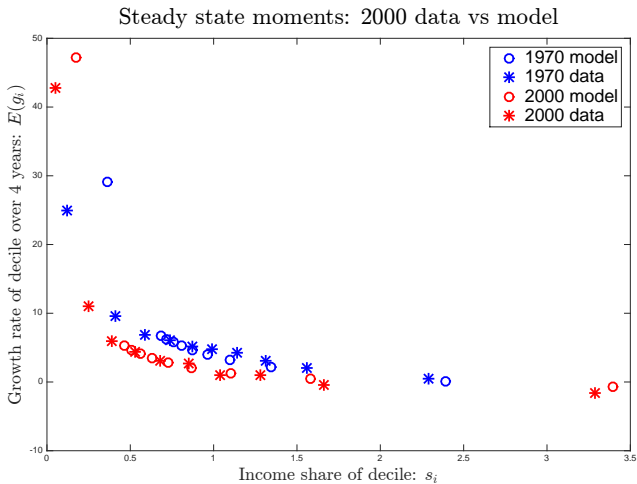
Target moments: data vs model

	$cov(g_i, s_i)$	$std(s_i)$	$std(g_i)$	Persistence at d10
1967-71	-0.033	0.62	0.07	0.60
model fit	-0.024	0.53	0.08	0.60
2004-2012	-0.066	0.94	0.13	0.68
model fit	-0.052	0.88	0.15	0.68
Calibr. Targets	NO	YES	YES	YES

Calibration Parameters chosen to match moments (st-st and transition)

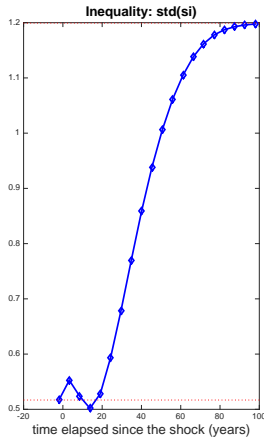
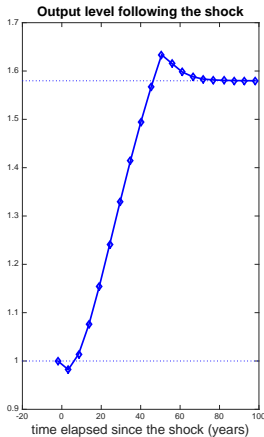
	$\delta$	$\gamma$	$\varphi$	$y_0$
pre-shock	0.13	0.049	2.0	0.25
post -shock	0.10	0.068	1.1	0.25

# Cross-sectional model fit



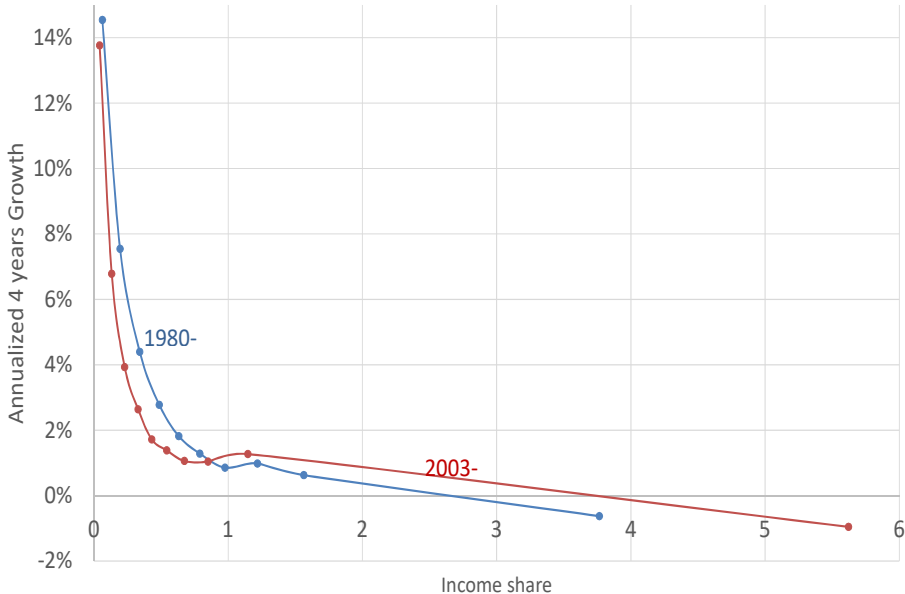
# Implication for Transition

Effects triggered by changes in inequality (shape of distribution)



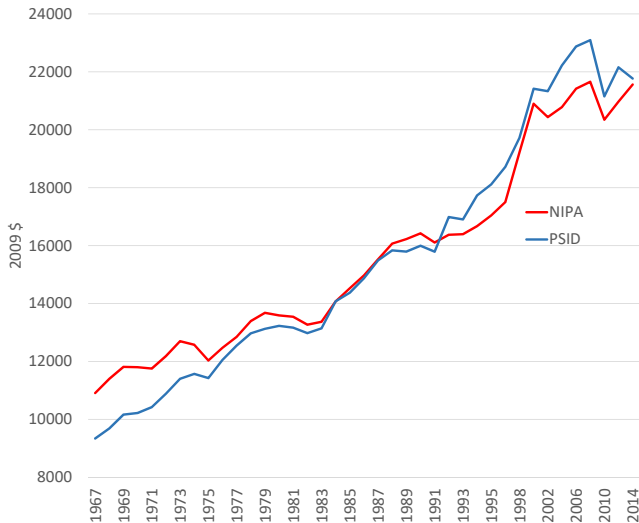
About a 0.9% output growth per year over the first 40 years

# Income Growth and Income level in SIPP data



# PSID v/s NIPA

## Wages and Salaries per capita (Constant 2009 \$)



- For labor income PSID matches NIPA Dynamics *and* Levels