# Unequal Growth

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

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# Introduction

Two major changes of the U.S. economy over past 50 years

- Increase in Household Income Inequality
- Slowdown in Aggregate Growth

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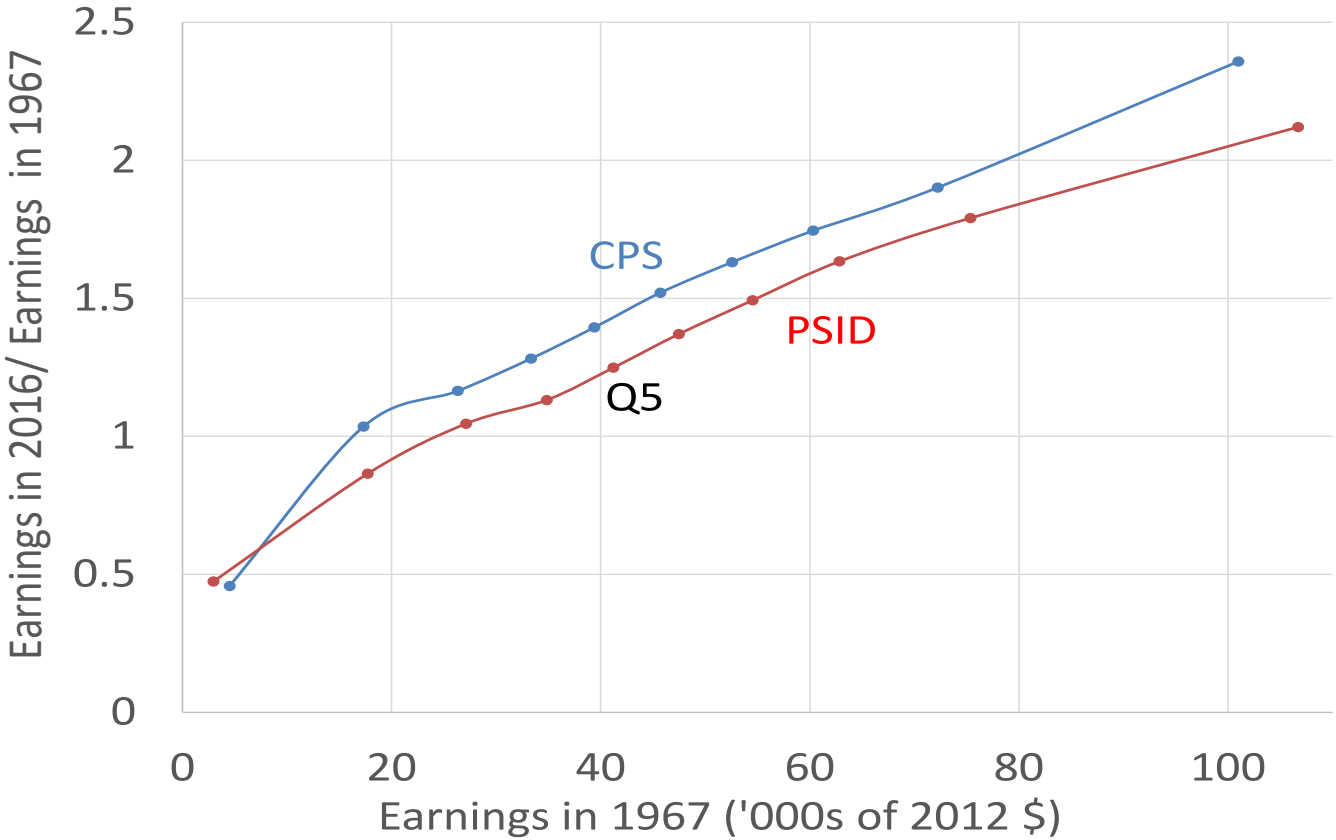
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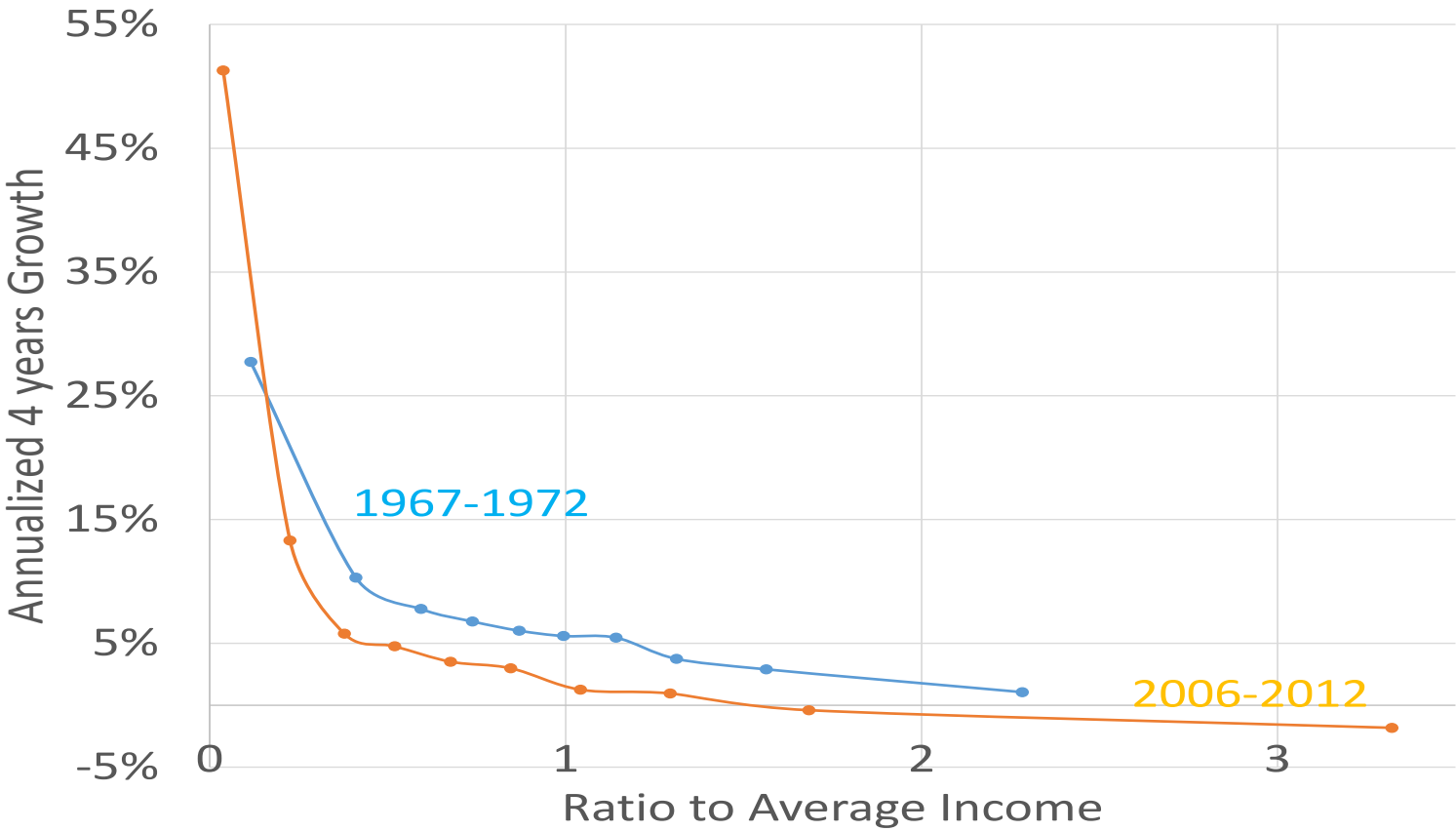
- This paper aims to link the two, empirically and theoretically
- Building block: If income growth is systematically unequal across income levels (Gibrat Law fails), aggregate income growth depends on income distribution

# Unequal growth 1967-2016: a cross sectional view



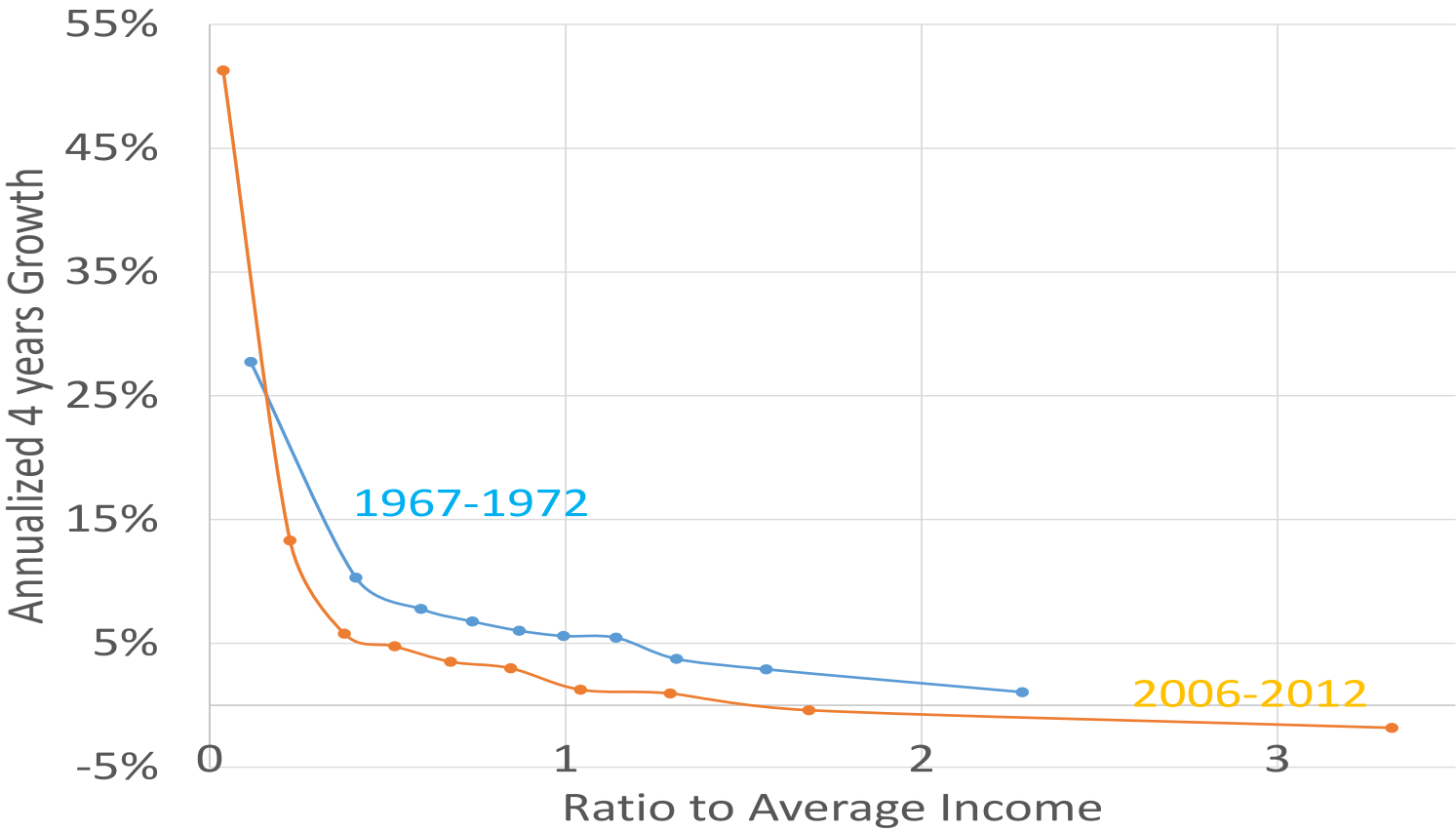

- Each point: level & growth of deciles of 1967 income distribution
- Top grew fast, bottom stagnated: not same households across time!

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




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

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

# Setup: aggregate micro income dynamics

Change in households' income dynamics triggers

- Micro changes (previous two figures)
- Macro changes (aggregate growth)
- Inequality interacts with aggregate growth since Gibrat's law fails (income growth varies with income level)

# Outline

- A micro decomposition of aggregate growth
- Empirical analysis on micro decomposition
- Simple model to interpret the data

# Some Related literature

- Background: “Inequality and Growth”, Benabou, 1996, and many others
- 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
- Inequality theory: “Dynamics of inequality”, Gabaix, Lasry, Lions and Moll 2016
- “Top income inequality dynamics”, Kim and Jones 2017
- Aggregate: “Misallocation and growth”, Jovanovic 2014
- “The Granular Origins of Aggregate Fluctuations”, Gabaix 2011

# A micro decomposition of aggregate growth

Let $y_{i,t}$ income of household/individual $i$ at time $t$

- Aggregate growth in period $t$ over horizon $T$, $\Gamma_{t,T}$ can be written as

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

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- Distribution of growth opportunities matters for aggregate growth
- For pc income with households of diff. size use: $g_{i,T} = \frac{y_{i,t+T}}{y_{i,t}}\frac{P_t}{P_{t+T}}$
- Similar decomposition widely used in IO (Olley and Pakes, 1996)

# Insights from decomposition

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- Simple way to sum micro moments to assess distributional impact of a given aggregate growth $\Gamma_T$:
  - Individual growth, $E(g_{i,T})$
  - Income inequality, $\sigma(s_i)$
  - Rank mobility, $corr(g_{i,T}, s_i)$
  - Income instability, $\sigma(g_{i,T})$

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- Suggests alternative mechanisms behind growth slowdown
  - Change of a common growth factor $\alpha$: Change in $E(g_i + \alpha)$, not $cov(g_i, s_i)$
  - Change in $cov(g_i, s_i)$ for given $E(g_i)$

# Inequality and Growth

$$\Gamma = E(g_i) + corr(g_i, s_i)\sigma(g_i)\sigma(s_i)$$

Covariance, and thus $\Gamma$, depends on patterns of inequality

- If $corr(g_i, s_i) < 0$, $Cov$ (and $\Gamma$) decreasing in income inequality, $\sigma(s_i)$

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  Intuition

  - Higher $\sigma(s_i)$ (*ceteris paribus*) implies more poor with (faster than avg.) growth and more rich with (slower than avg.) growth
  - Since rich larger: $\Gamma \downarrow$

- Warning: $Cov(g_i, s_i), E(g_i)$ .. not independent primitives: need a theory!

# Plan

- (1) measure $corr(g_i, s_i)$, $\sigma(g_{it})$, $\sigma(s_{it})$ 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

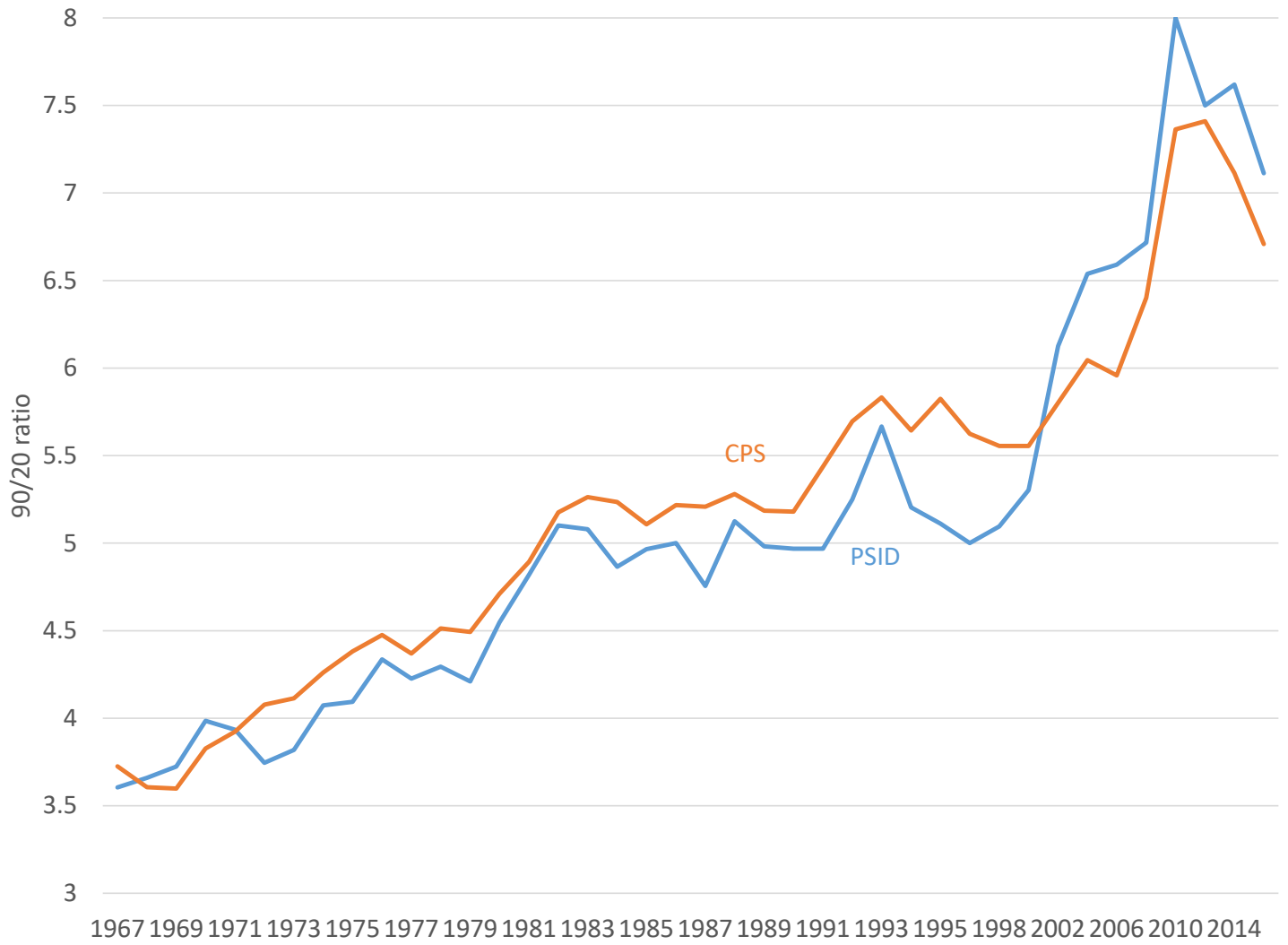
- Panel data must aggregate up to macro outcomes

# 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

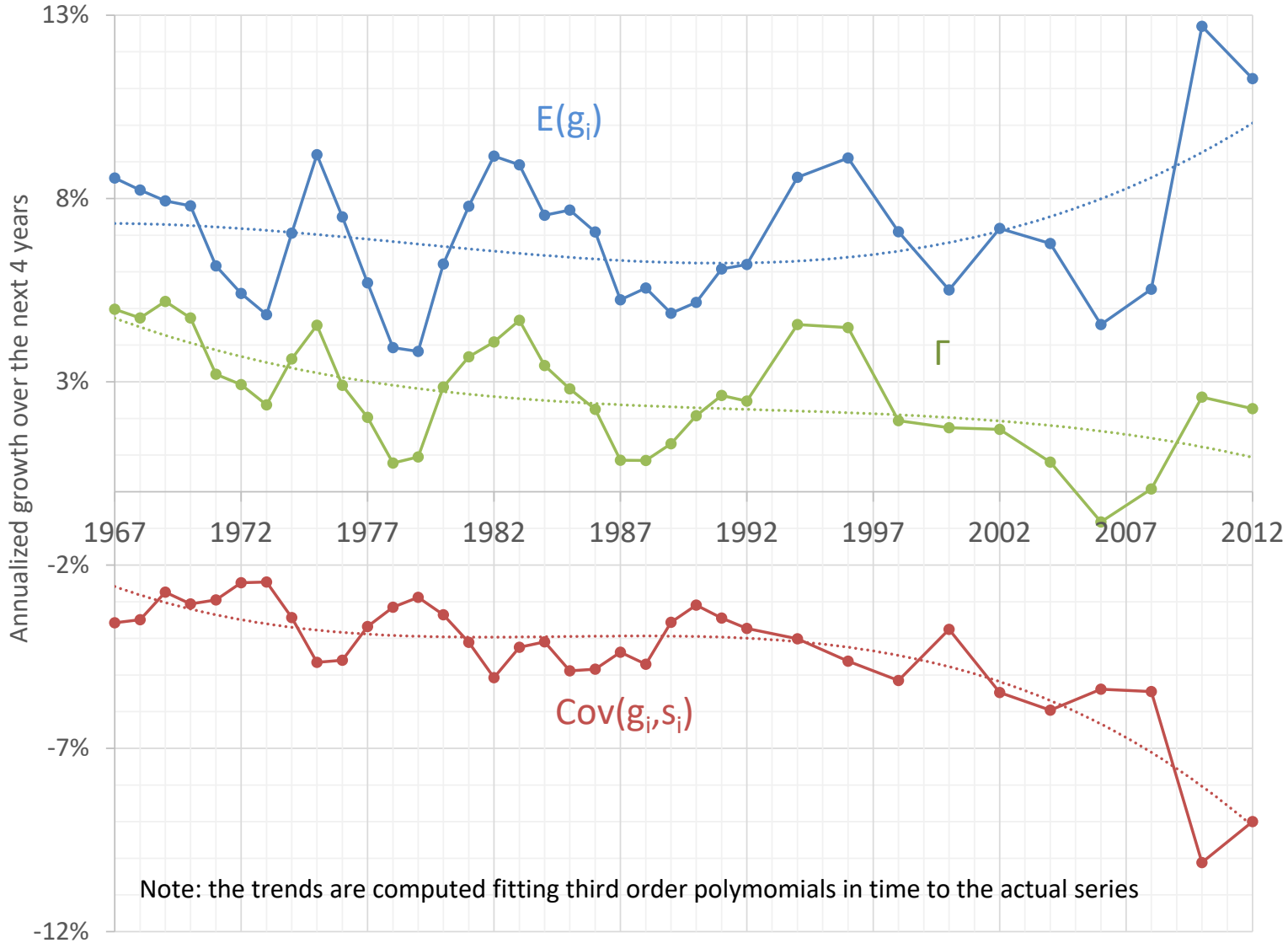
Let $T = 4$ years and $y_{j,i,t}$ be income of HH $j$, in decile $i$ in year $t$.

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

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 pvty 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)

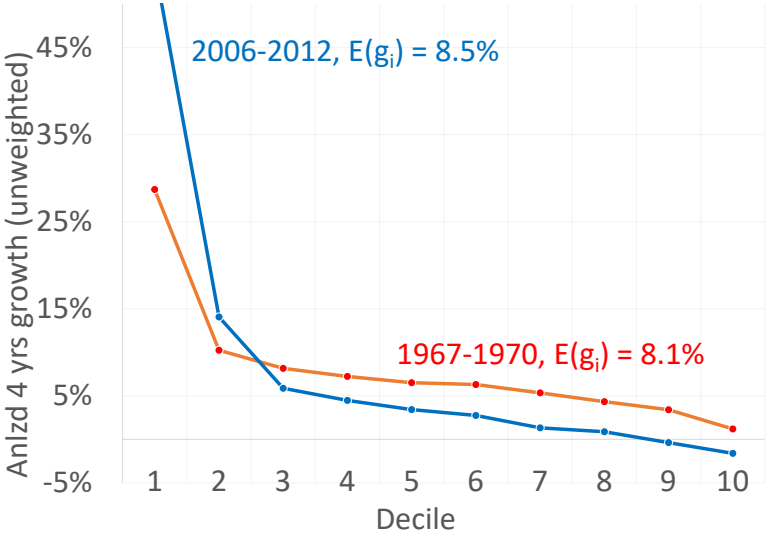
# Aggregate growth decomposition (PSID)



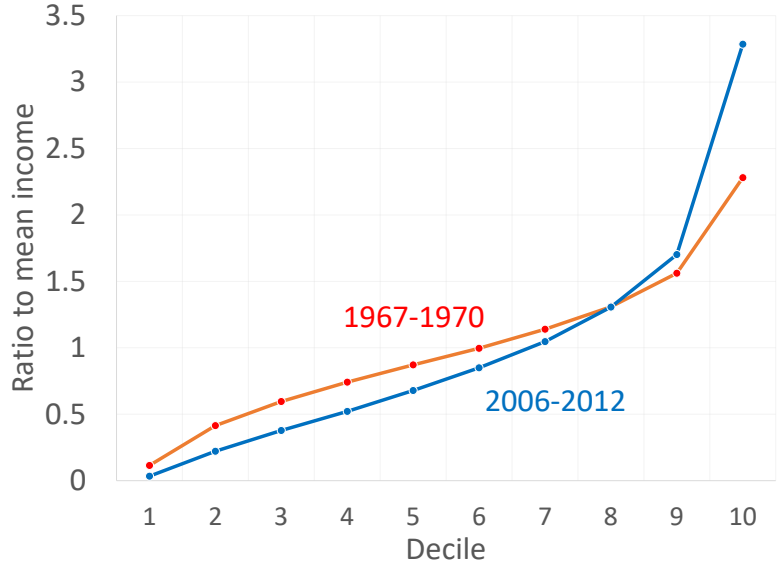

- $\Gamma$ declines, $E(g_i)$ almost flat. Implies: $cov_t \downarrow$

# Contribution to growth by decile

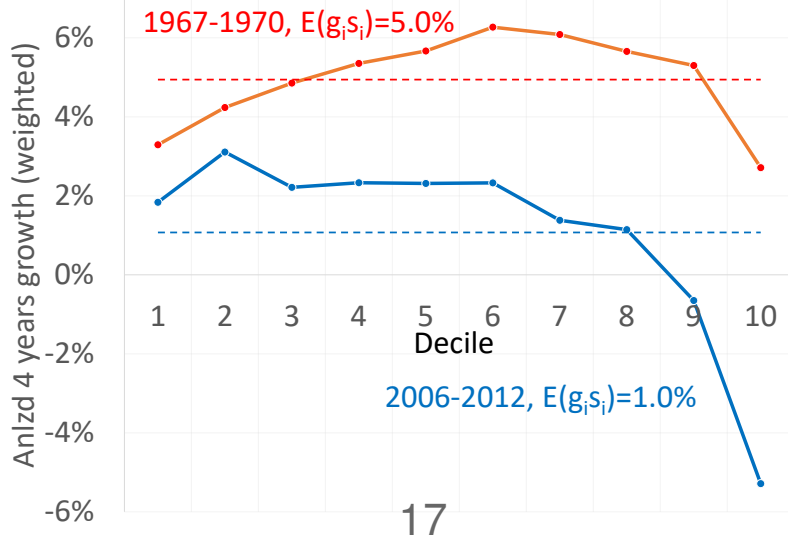
$g_i$




$s_i$



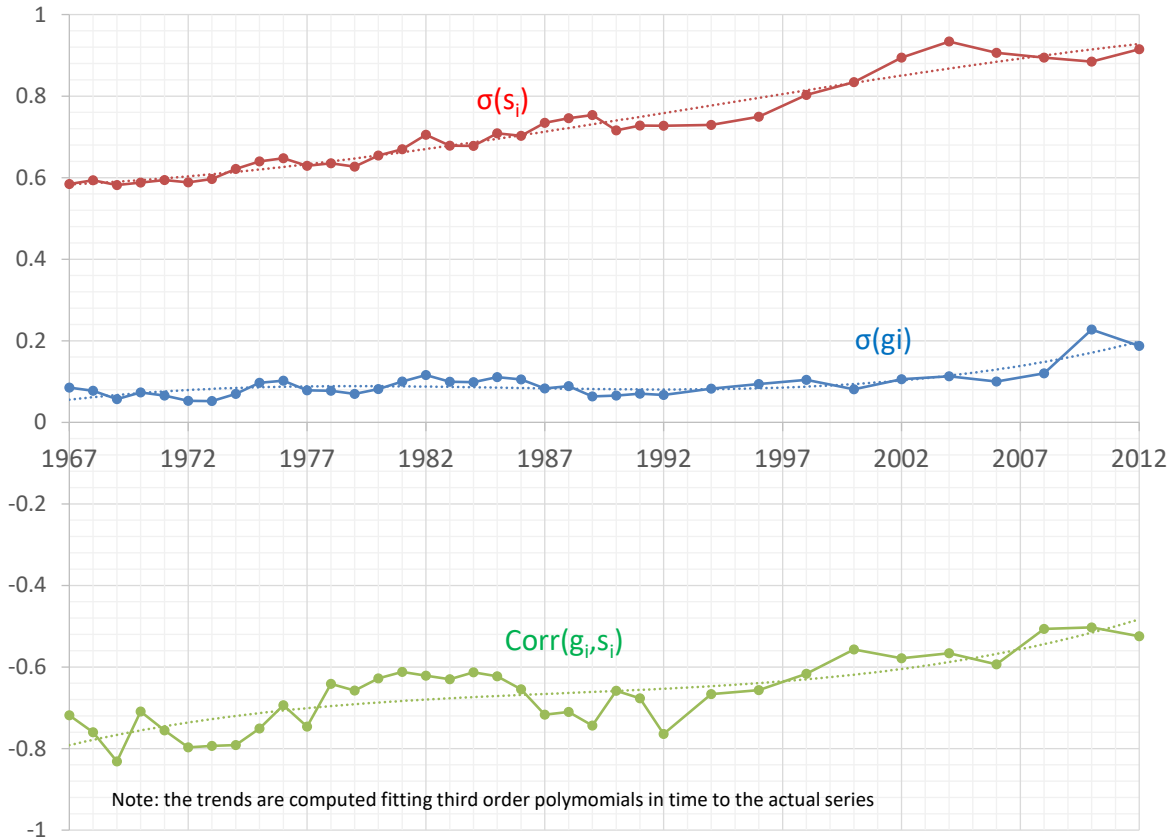

## Contribution to aggregate growth $g_i \cdot s_i$



# Some intuition

- Trends
  - U.S. becoming a more unequal society
  - Bottom growing faster, top/middle growing slower
- Causes for growth decline
  - Slow (and slower) growing top/middle has a larger share of income
  - Fast (and faster) growing bottom has a smaller share
- All decile contribute to decline in growth
- Most decline in aggregate growth accounted for (in a statistical sense), by falling covariance

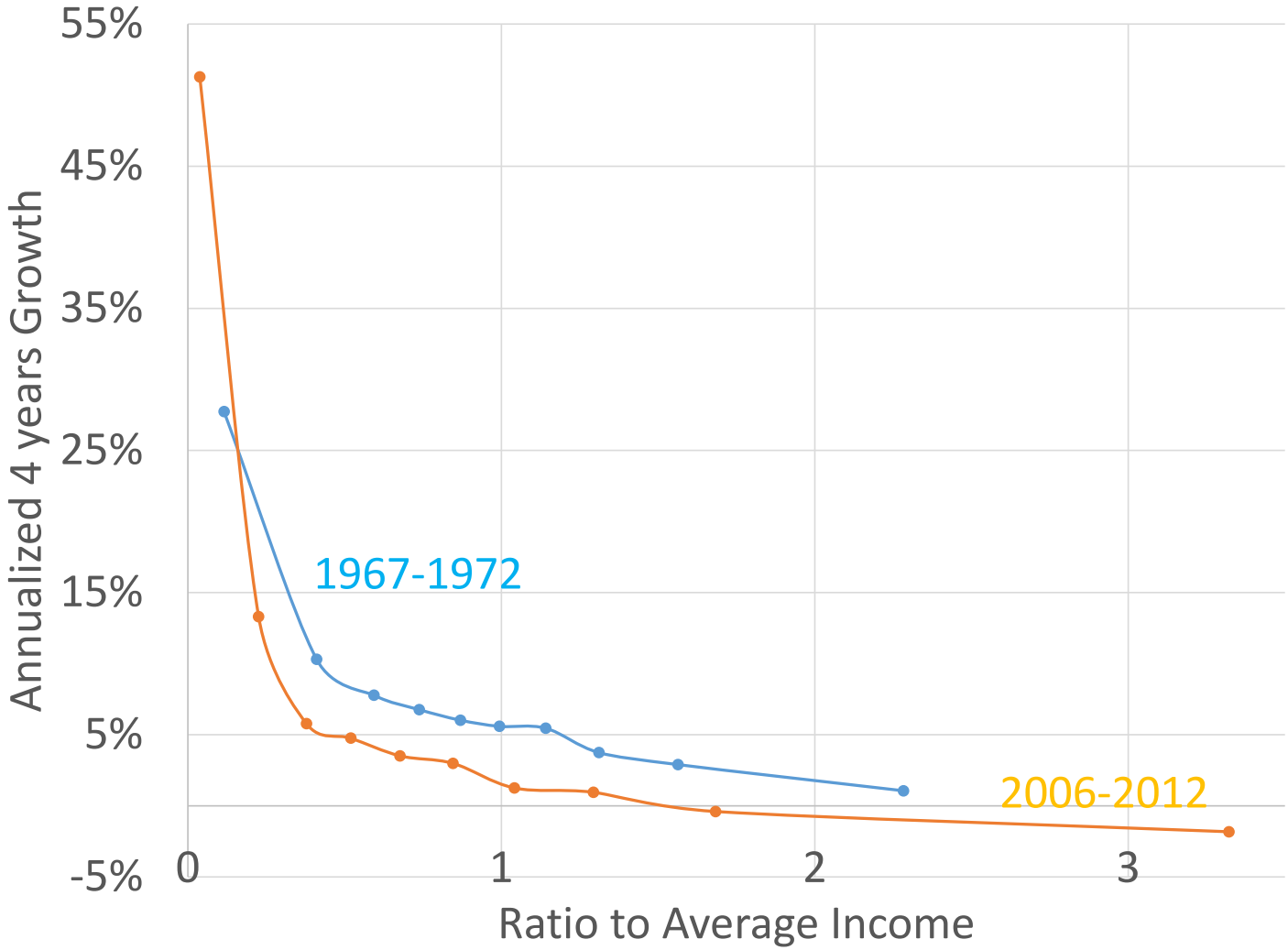
# Covariance decomposition (PSID)




$Corr(g_i, s_i)$ increasing (toward $0$) signals growth/level relation getting weaker

- less rank mobility
- less impact of increasing inequality on growth

# Why is correlation increasing?

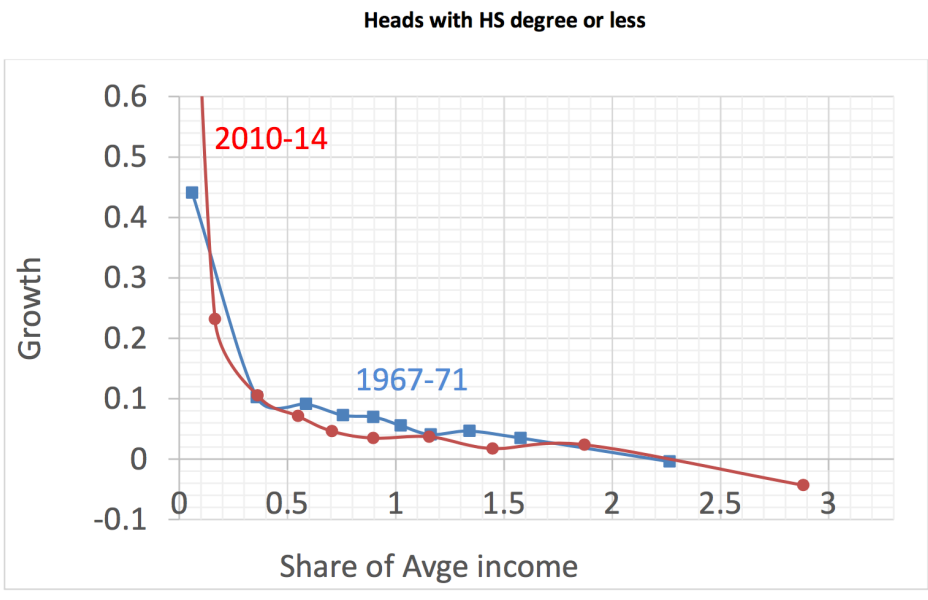



- Relation between $g_i$ and $s_i$, becoming less linear

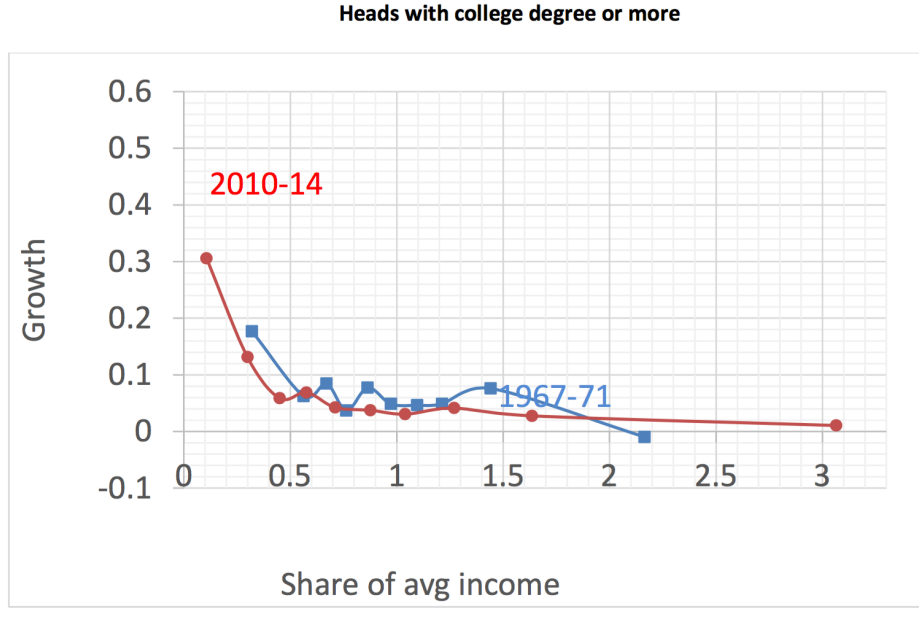
# Robustness of growth decomposition

Cut sample by HH head education:

## at most High-school



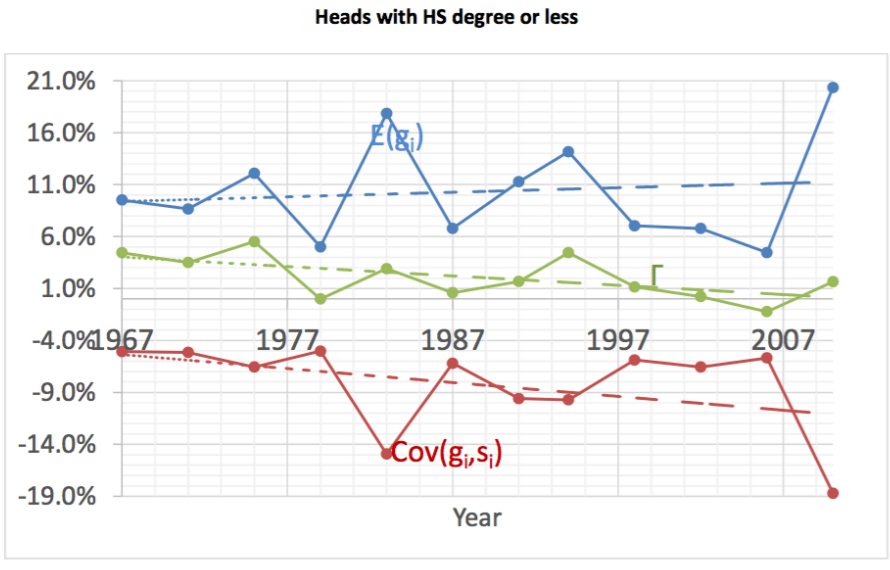

## College or more



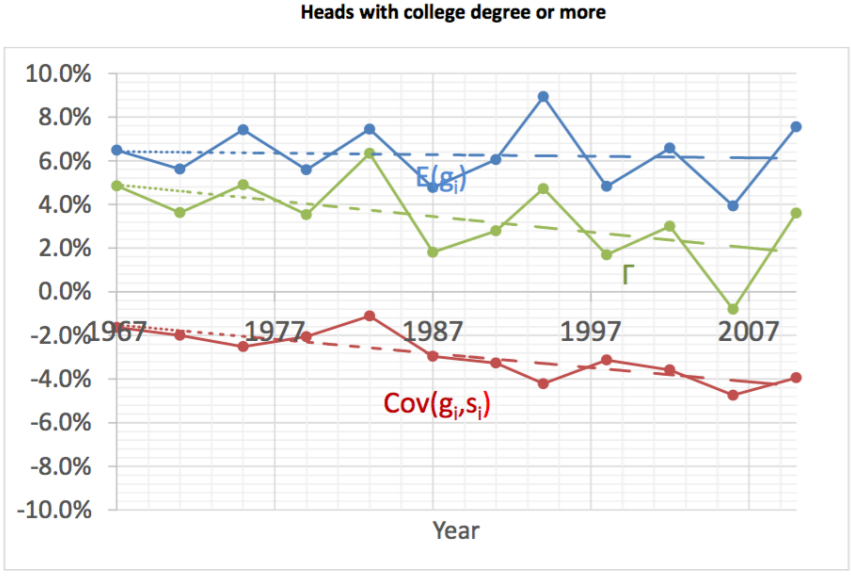
# Robustness of growth decomposition (1)

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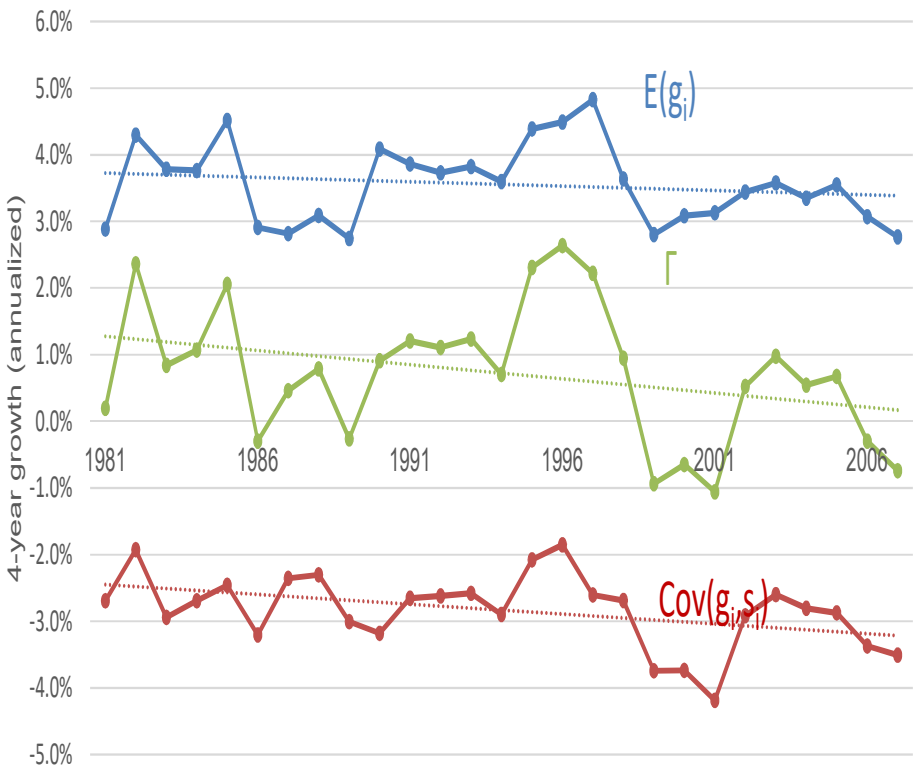



Patterns robust to several more demographics (e.g. age, race)

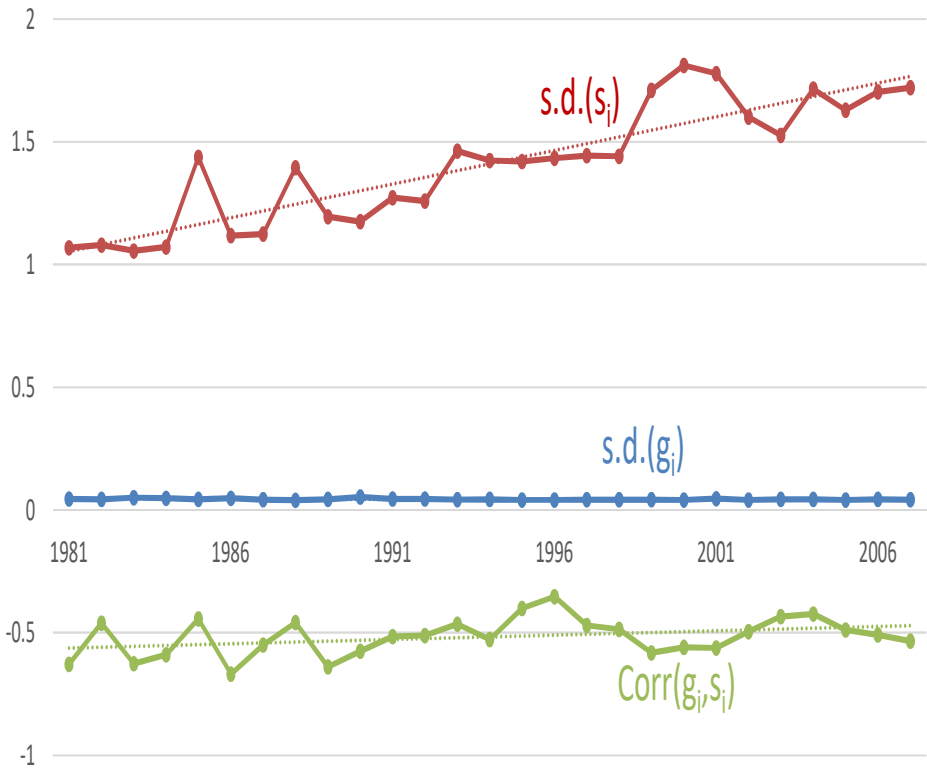
# Robustness of growth decomposition (2)

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

## Growth decomposition




## covariance decomposition



# A broad brush characterization (stylized facts)

$$\Gamma_t = \underbrace{corr(g_i, s_i)\sigma(g_{it})\sigma(s_{it})}_{cov} + E(g_i)$$

- $\Gamma_t$ declines over time (between 1% and 4%)
  - – significant contribution of $\Delta cov_i(g_{it}, s_{it})$
  - – small/no decline in "average" x-section growth $E(g_i)$

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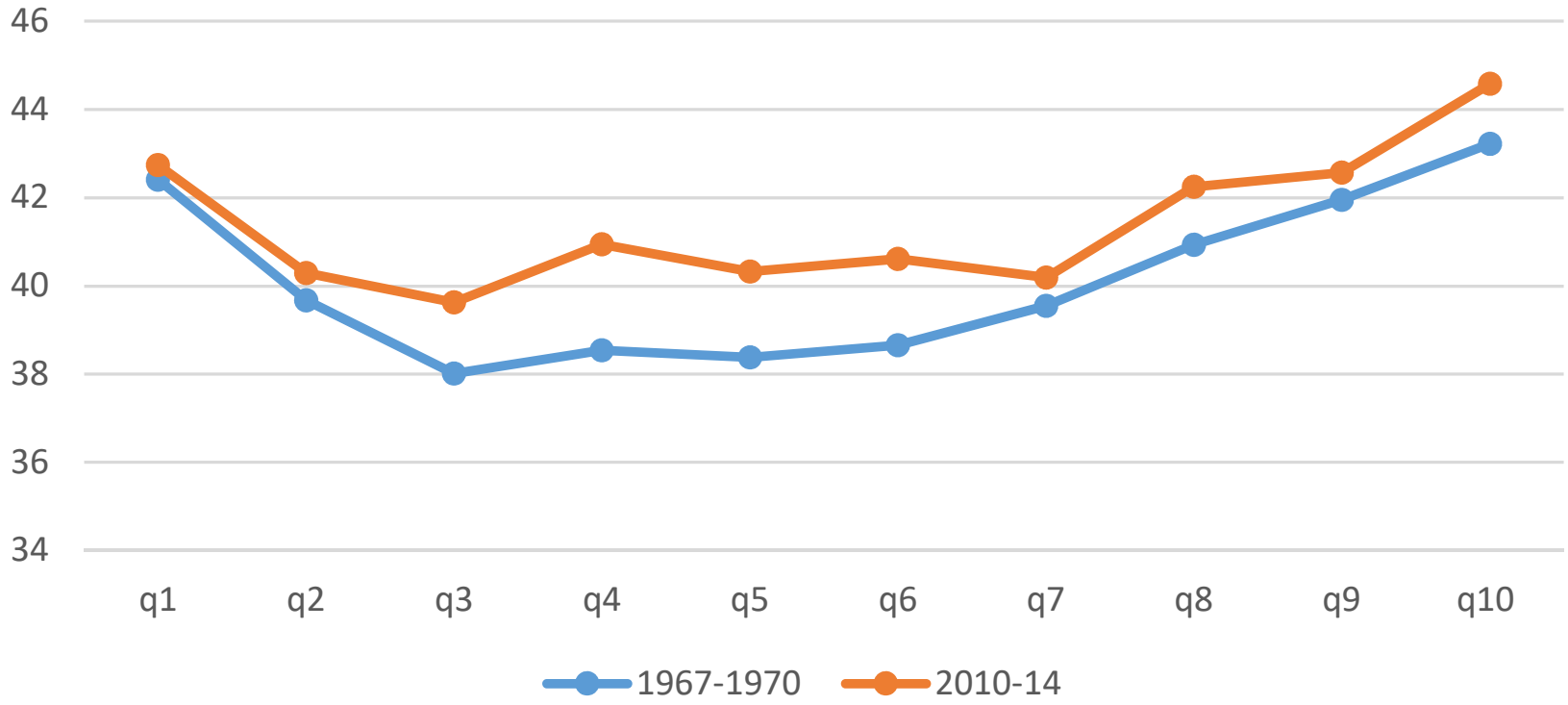
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  - – significant contribution of $\Delta cov_i(g_{it}, s_{it})$
  - – small/no decline in "average" x-section growth $E(g_i)$
- The reduction of $\Gamma_t$ and of $cov_t$ is persistent
- Reduction of $cov(g_{it}, s_{it})$ results mostly from
  - – large increase in $\sigma(s_{it})$ (from 0.6 to 0.95) + $corr(g_{it}, s_{it}) < 0$

# Who are the poor fast growers?

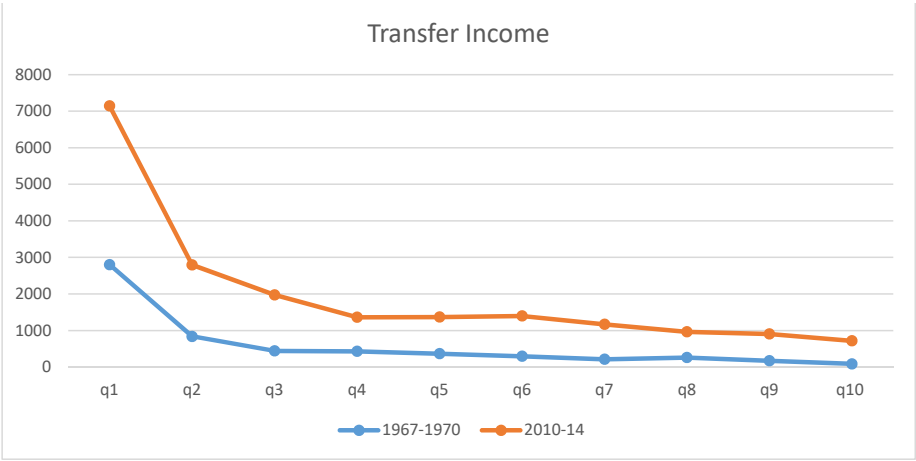
- Before writing a model for $(g_i, s_i)$, show some characteristics of different deciles of income distribution.
- And is their type changing?

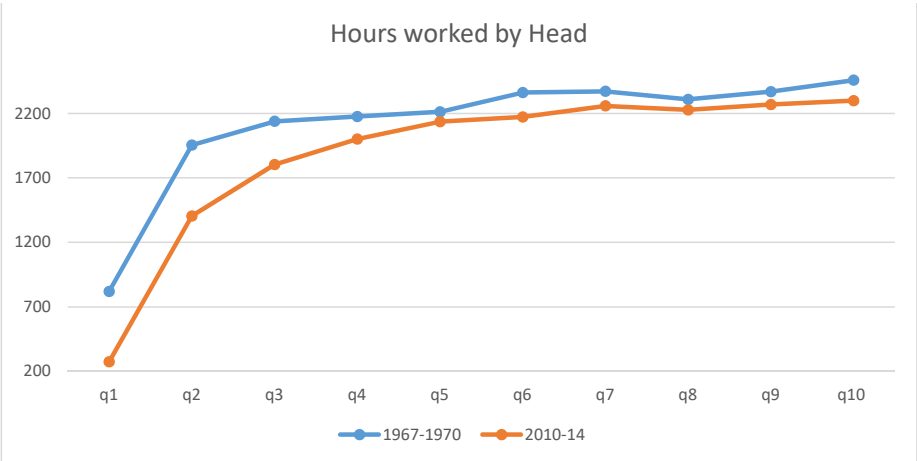
# Age of different quantiles




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

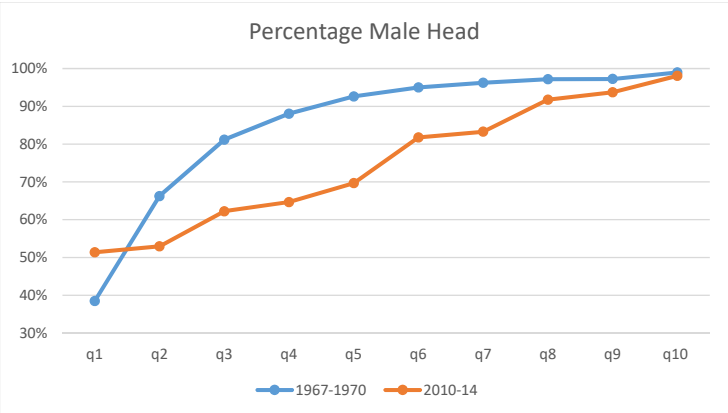
# Hours and transfers

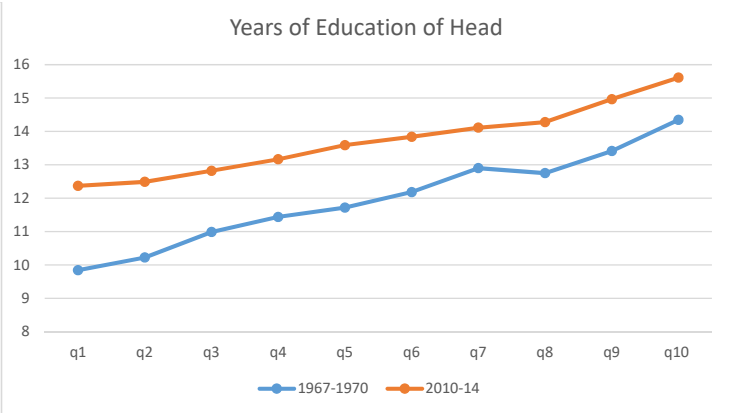


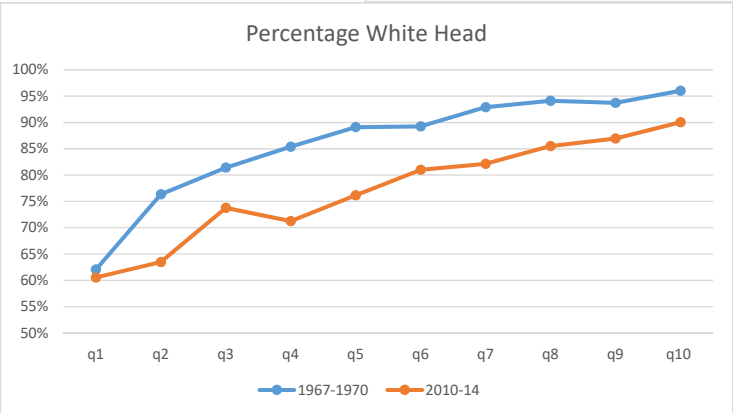




- Poor fast-growers work much less hours and receive more transfers, suggesting they are experiencing (temporary) shock to their ability to work
- For poor fast growers hours are becoming lower and transfers becoming larger!

# White, Male and College Educated?




- Blue line shows in early years, poor-fast growers mostly non-white, non-male, non-educated
- Orange line same slope but flatter, showing that poor-fast growers (i.e. household experiencing shocks) more diffused across demographic strata.

# Suggestions from data

- Micro data is calling for a mechanism that puts more households at risk of becoming a poor fast grower, but also of becoming very rich slow grower
- Want to study aggregate consequences of these changes

# A simple model of unequal growth

Qualitative analysis:

- Structural mechanism for $\{\Gamma_t, \sigma(s_i)_t, cov_t\}$ dynamics

# A simple model of unequal growth

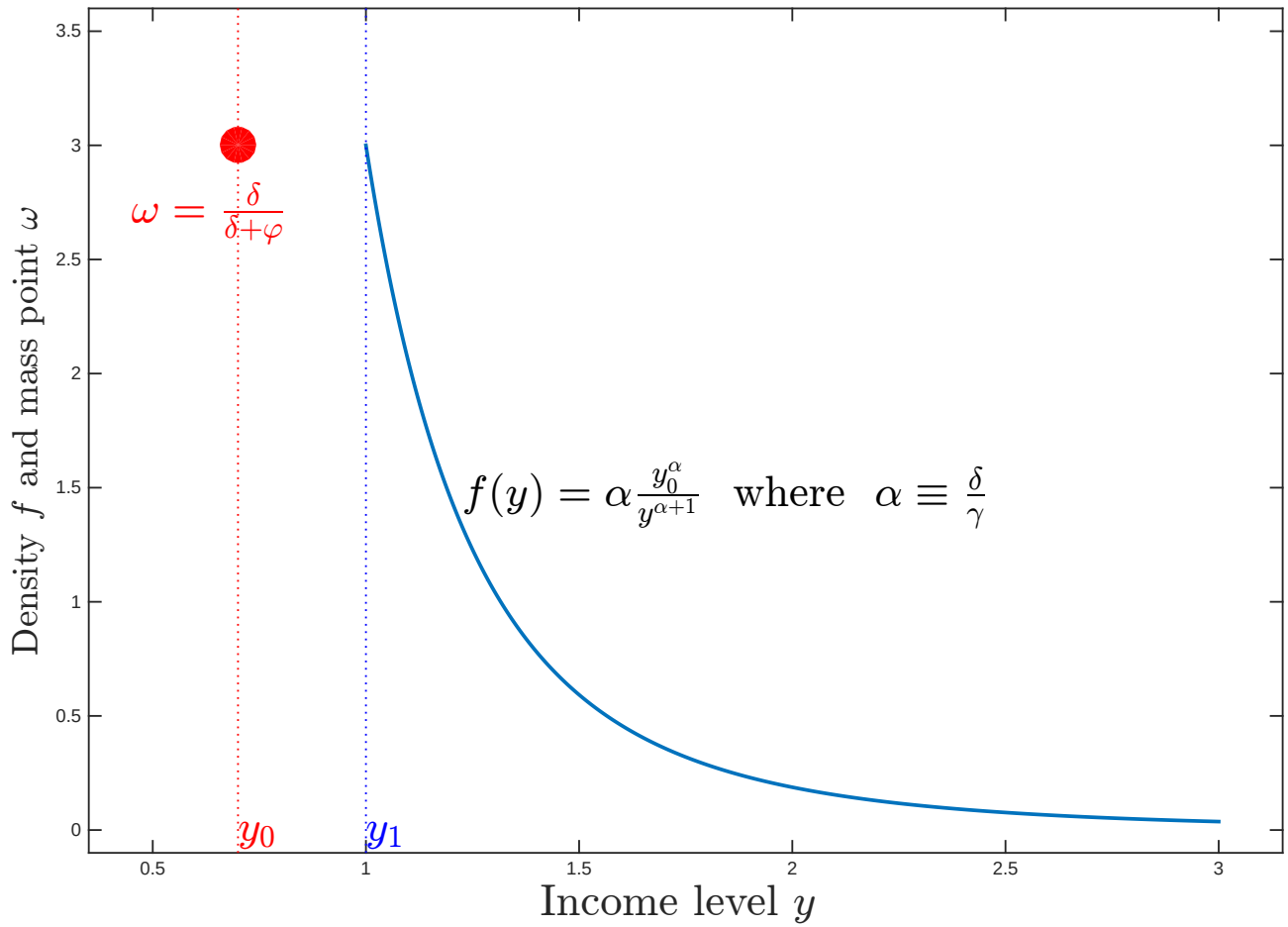
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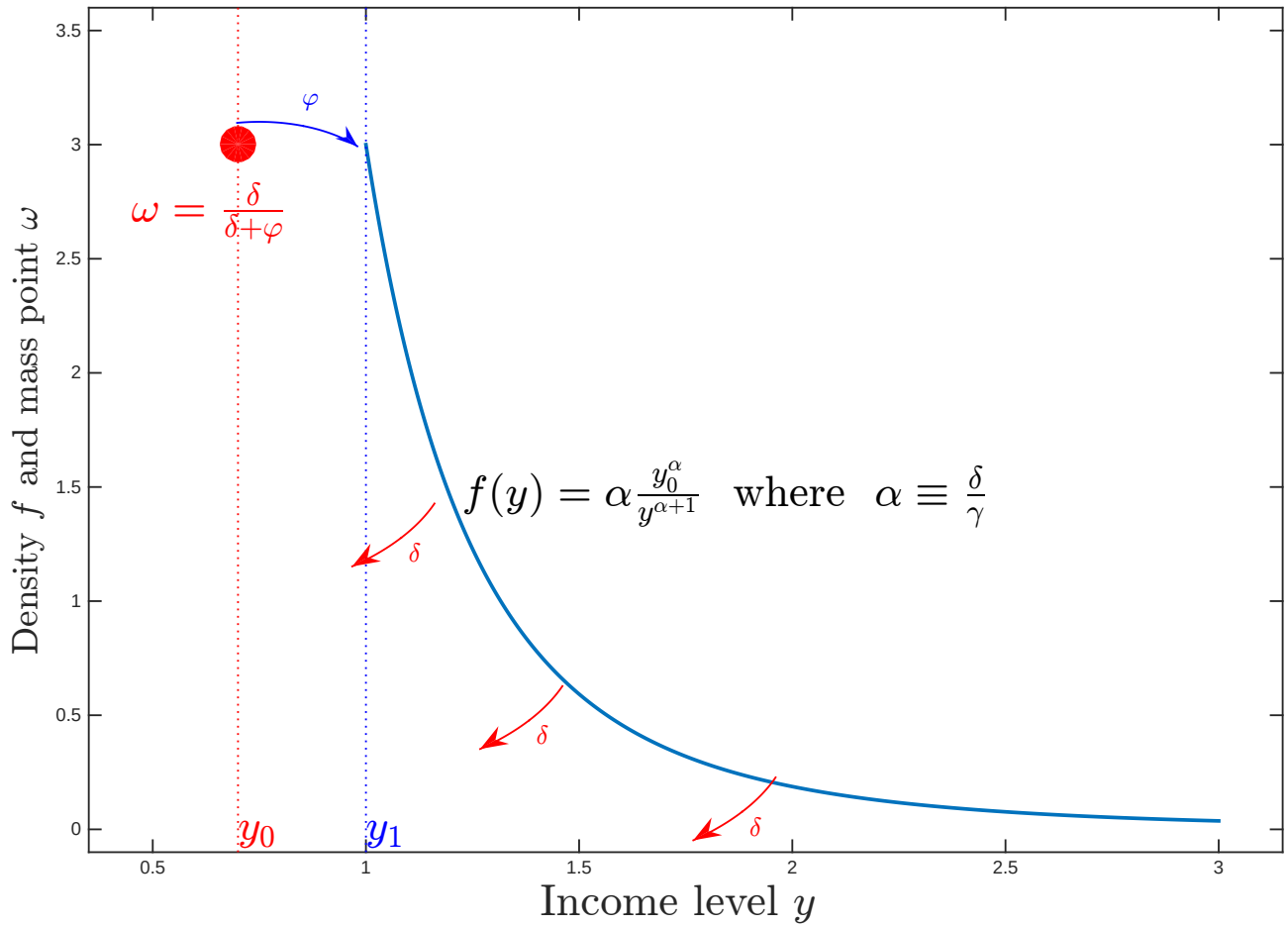
Environment: Income produced by successful projects/jobs

- New projects created at rate $\varphi$; die at rate $\delta$
- Income from first successful project is $y_1$ grows at rate $\gamma$ (state $\pi = 1$)
- Fraction $\omega \equiv \frac{\delta}{\delta+\varphi}$ of agents w/o project ($\pi = 0$), income $y_0$

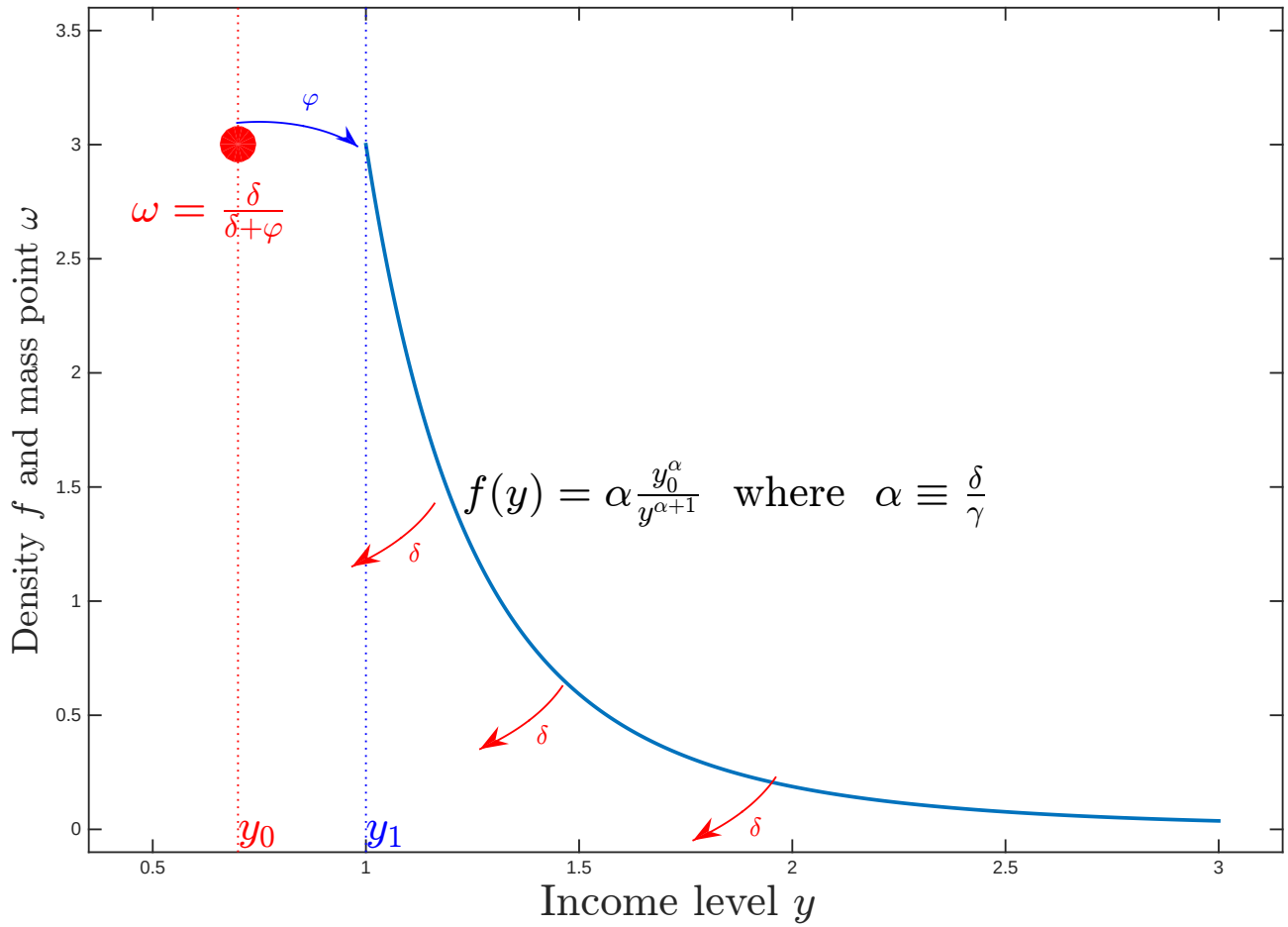
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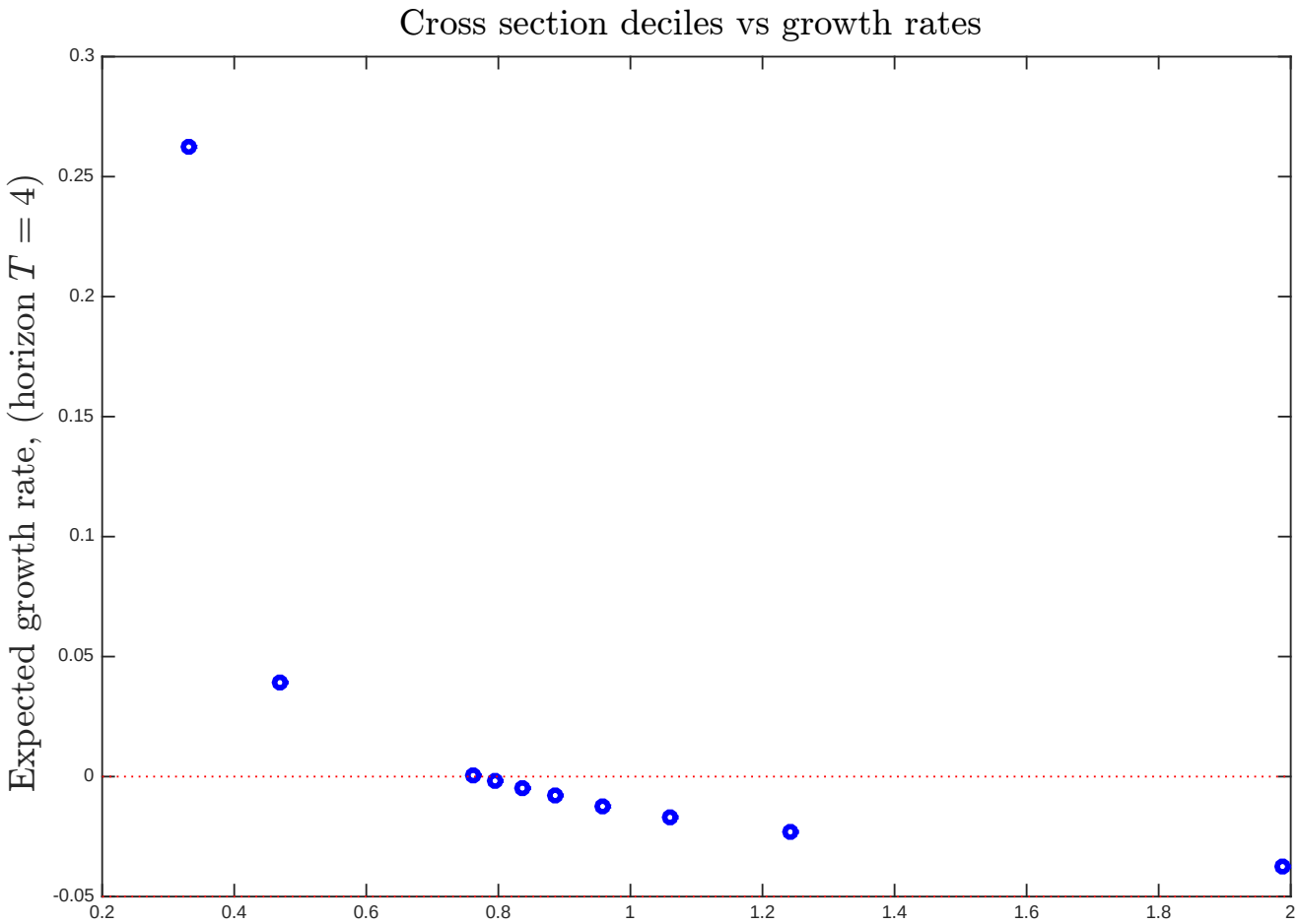


# Model in a nutshell (steady state)




(1) Pareto income distribution (2) Mean Reversion

# Model in a nutshell (unequal growth)




- Rich households on average grow slower

# Model's essentials

- Steady state w/o growth $\Gamma = 1$ (remove common growth factor)
- New StSt yields non-trivial dynamics: $\{\Gamma_t, cov(t), \mathbb{E}(g_{i,t}), \sigma(s_i, t)\}$
- Stylized mechanism gives (analytic) dynamics behind data

# Transition following change in fundamental parameters

- Suppose two parameters change: $\tilde{\varphi}, \tilde{\gamma}$
  Example: harder to succeed ($\varphi \downarrow$), new projects grow faster ($\gamma \uparrow$)

- Also: exogenous downward trend in income of poor $y_0$
  data: income of poorest decile falls by 2% p.y. over 1967-2016 (non participation important)

- Gradual convergence to new steady state

- Analytics of *transition* give: $\{\Gamma(t), \mathbb{E}(g_{i,t}), cov(t), \sigma_{s_i}(t)\}$
  – observable moments $t$ periods after the shock occurred

# Characterise transition after shocking $\varphi$ and $\gamma$

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

– fraction of agents who **do not grow**: $\tilde{\omega}(t)$

$$\tilde{\omega}(t) = \tilde{\omega} + (\omega - \tilde{\omega})\, e^{-(\delta+\tilde{\varphi})t} \quad \text{where} \quad \omega_i = \frac{\delta}{\delta + \varphi_i}$$

– fraction of agents with **NEW project** (i.e. with $\tilde{\gamma}$): $\eta(t)$

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

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

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

# Characterising transition in closed form!

Solving the PDE (using eigenvalue-eigenfunction decomposition) gives

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

where $\delta + \tilde{\varphi}$ is the "dominant eigenvalue" (as in Gabaix et al. 2016)

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

$$f(y,t)\begin{cases}\tilde{f}(y,t) & \text{for} \quad y \in (y_1, y_m(t)) \\ \tilde{f}(y,t) + (1-\omega)\frac{\alpha y_1^{\alpha}}{y^{1+\alpha}} & \text{for} \quad y \in (y_m(t), y_M(t)) \\ (1-\omega)\frac{\alpha y_1^{\alpha}}{y^{1+\alpha}} & \text{for} \quad y \in (y_M(t), \infty)\end{cases}$$

where $y_m(t) = y_1 e^{\gamma t} \quad , \quad y_M(t) = y_1 e^{\tilde{\gamma} t}$

# Transition dynamics: Three scenarios

- Scenario 1
  - reduce $\varphi$ (more difficult to succeed)
- Scenario 2
  - increase $\gamma$ (better growth potential)
  - reduce $\varphi$ (more difficult to succeed)
- Scenario 3
  - Adds gradual fall in $y_0(t)$ to Scenario 2

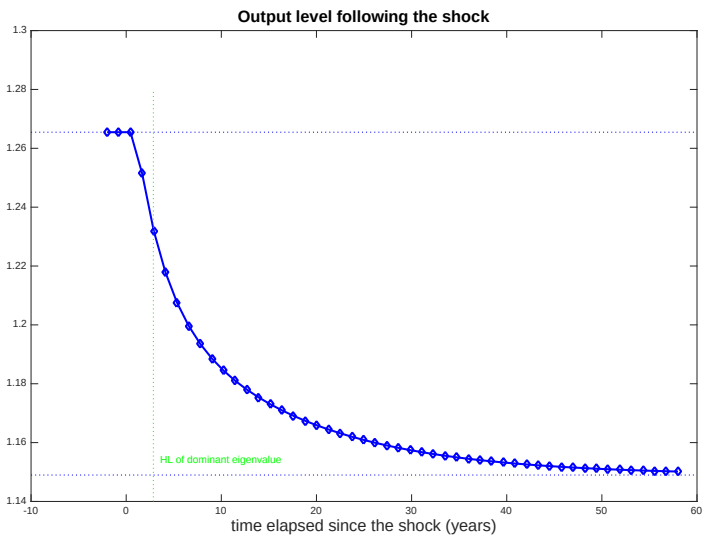
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- Three scenarios stylized features of globalization?

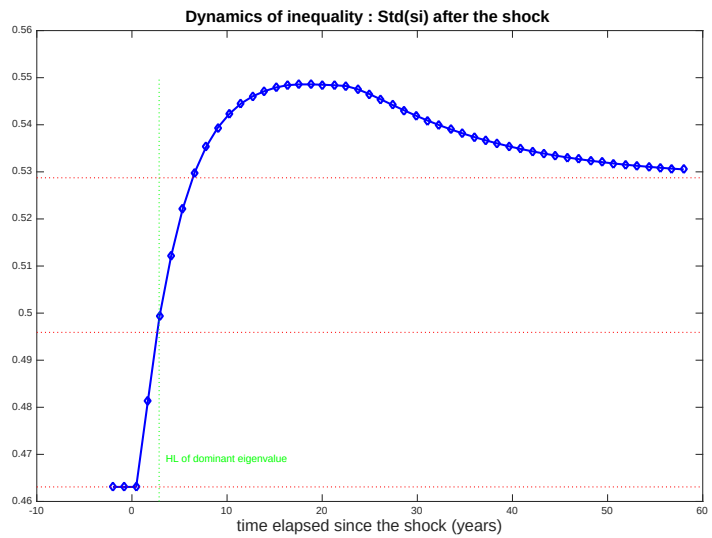
# Transition dynamics (scenario 1)

Shock lowers $\varphi$: harder to have a successful project

GDP Level

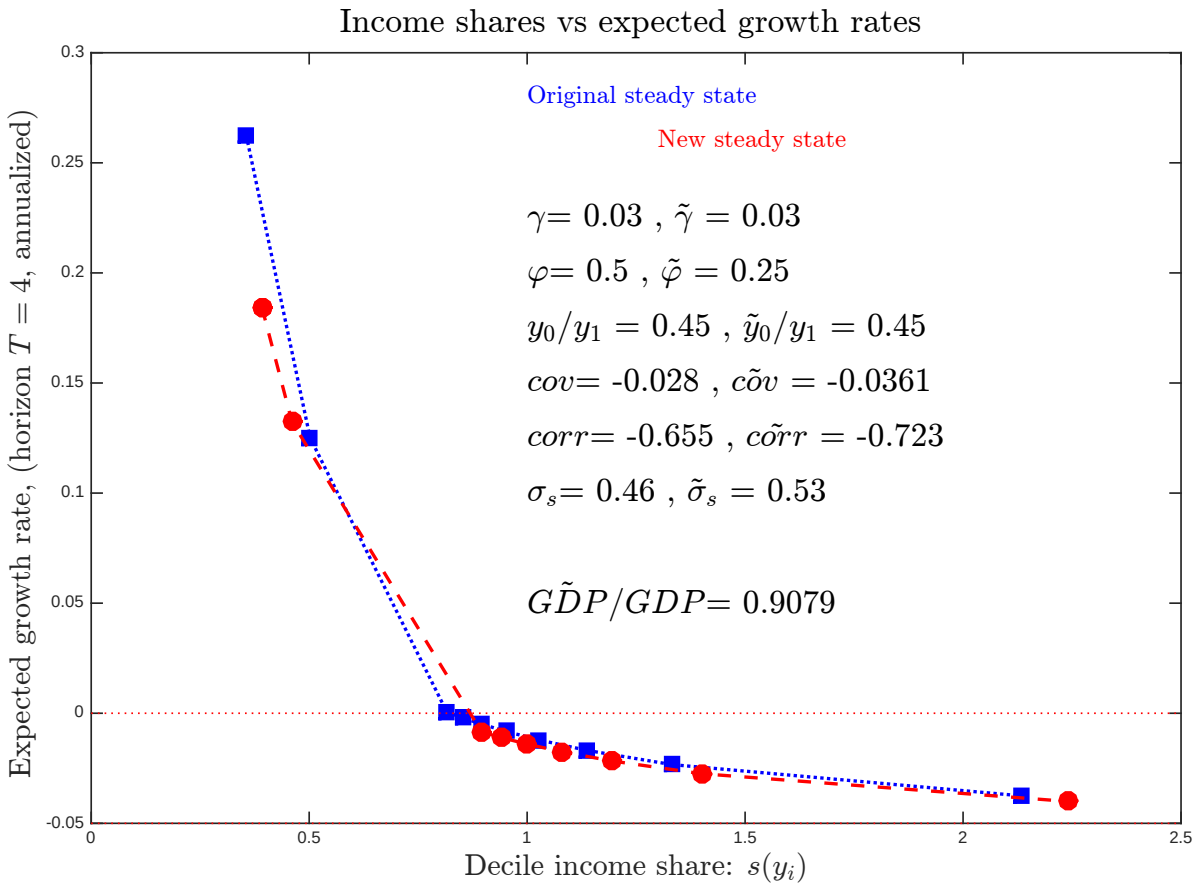



Inequality ($\sigma_s$)




Mean annualized growth effect over first 10 years is -0.66%

# Cross sectional moments in Scenario 1

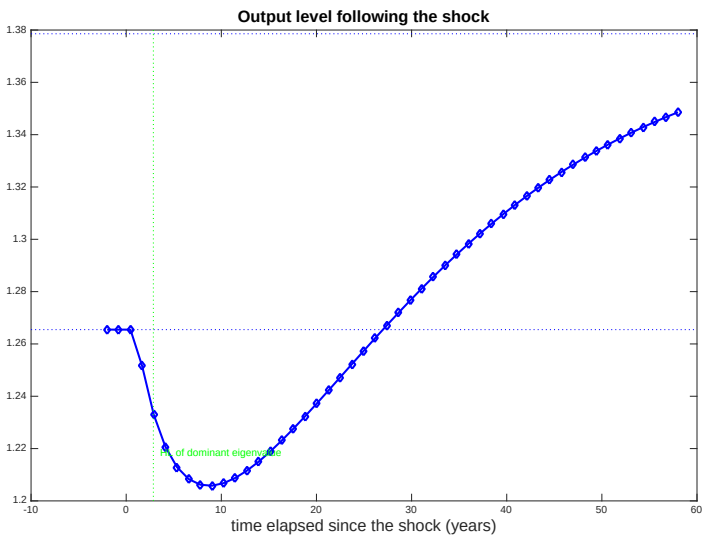



- Growth and covariance fall, inequality rises but too little, fall in growth concentrated at the bottom

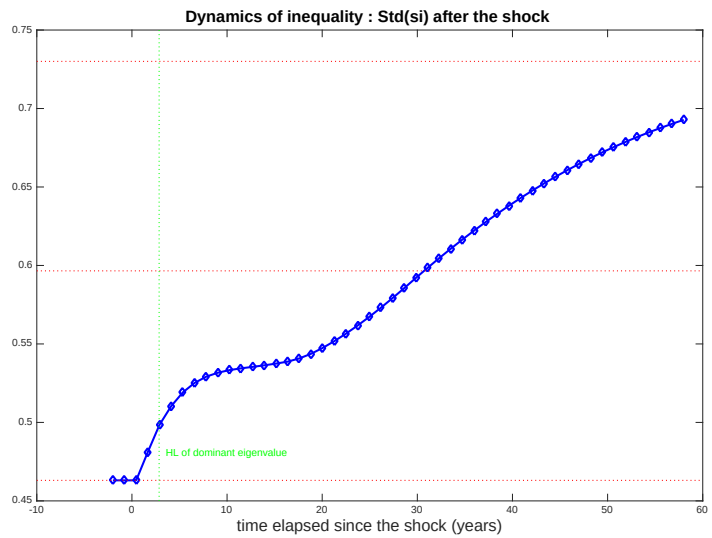
# Transition dynamics (scenario 2)

Shock triggers higher $\gamma$ and lower $\varphi$ (constant $y_0$)

GDP Level

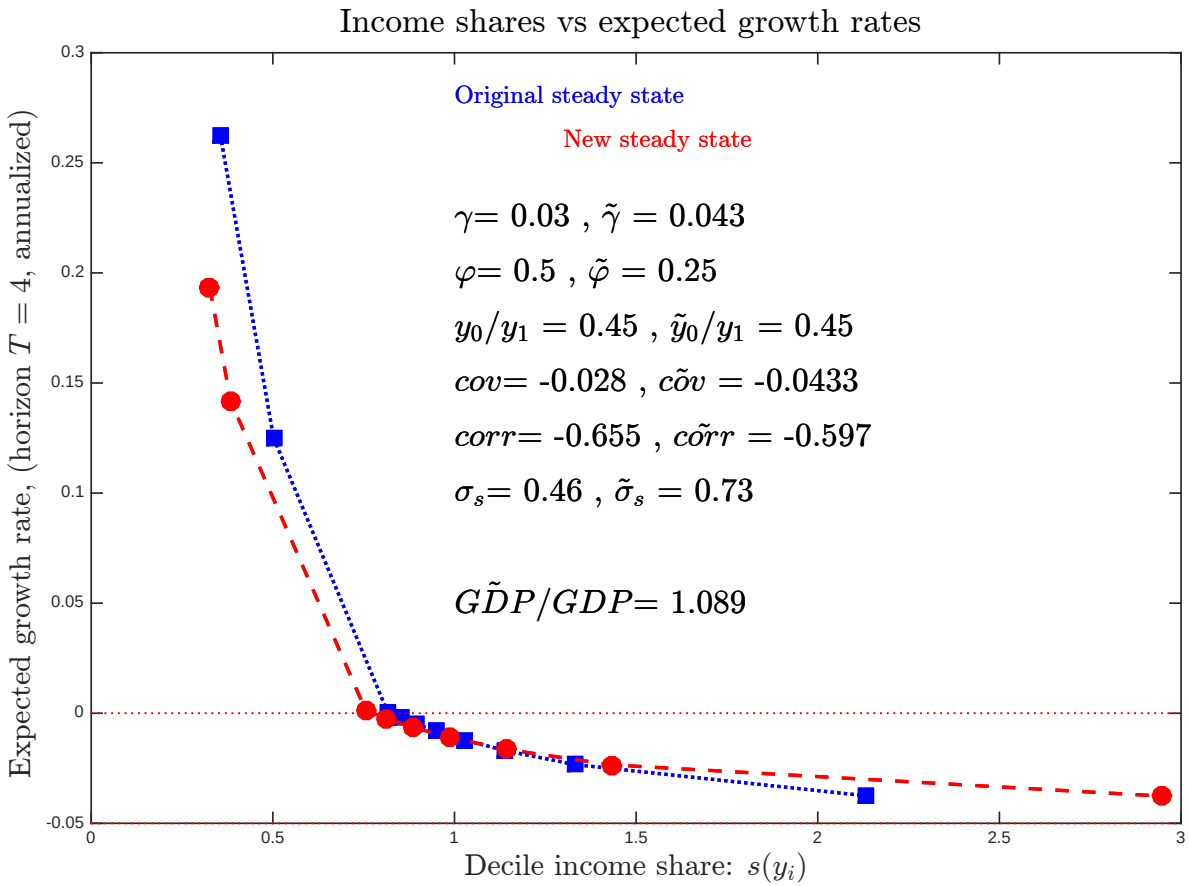



Inequality ($\sigma_s$)




Mean annualized growth effect over first 10 years is -0.45%

# Cross sectional moments in Scenario 2

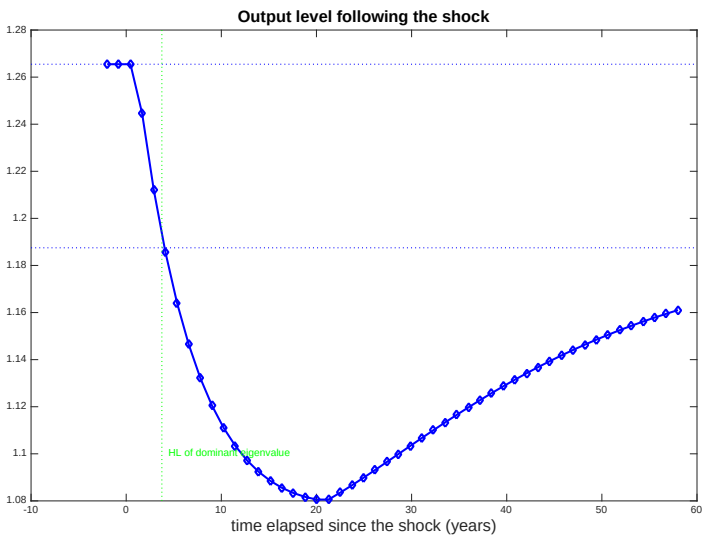



- Larger increase in ineq., fall in cov., increase in corr! Fall in growth still concentrated at the bottom

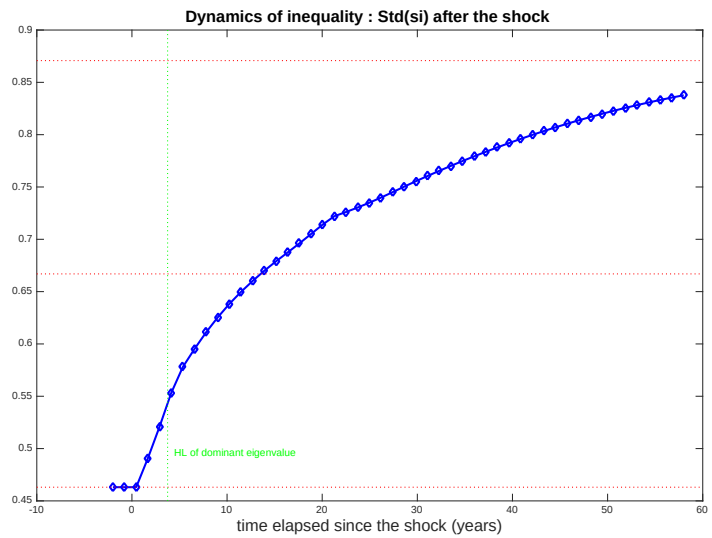
# Transition dynamics (scenario 3)

Shock triggers higher $\gamma$ and lower $\varphi$ & falling $y_0$

GDP Level

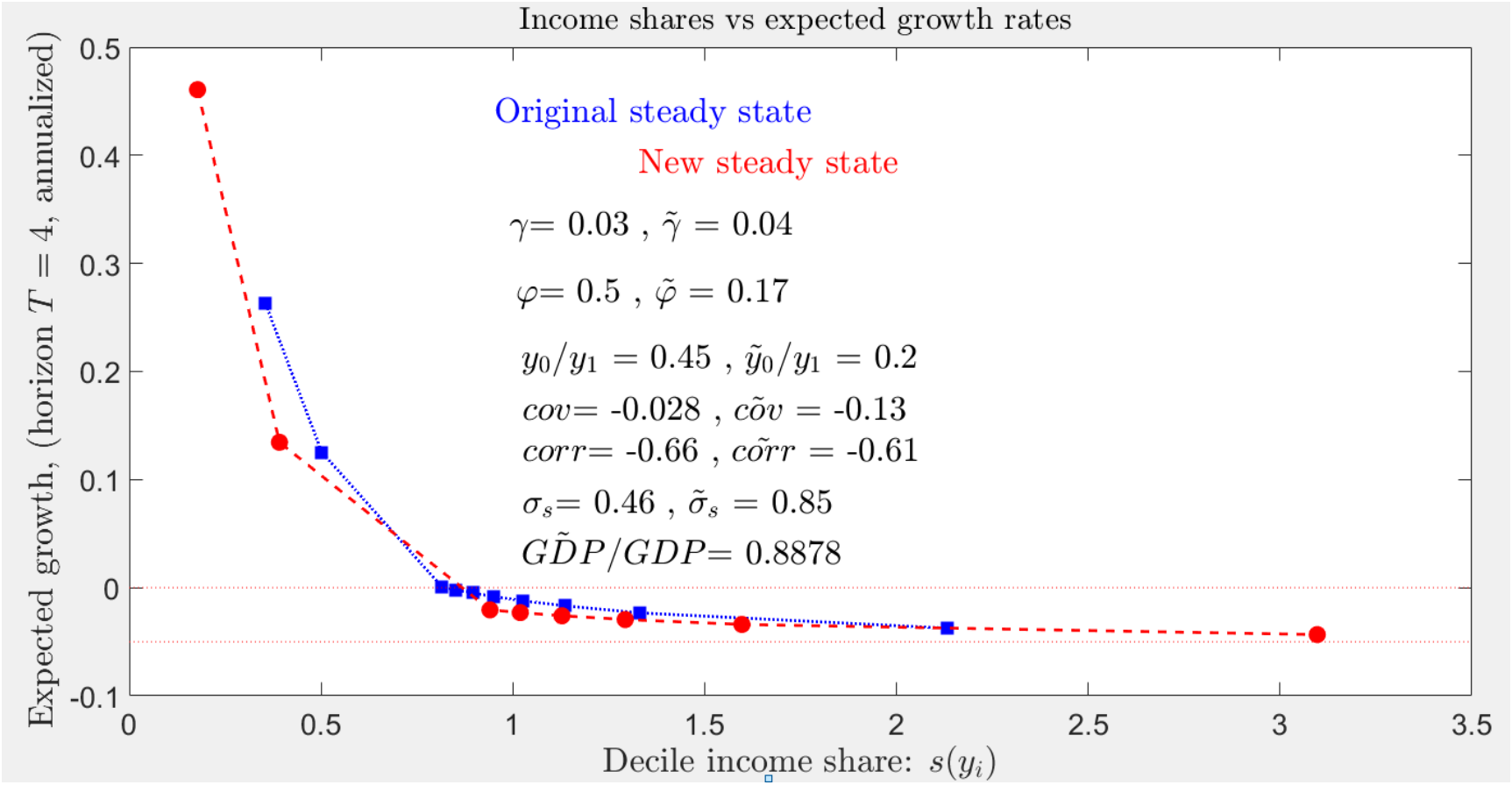



Inequality ($\sigma_s$)




Mean annualized growth effect over first 10 years is -1.2%

# Cross sectional moments in Scenario 3




- Qualitative success

# Summarizing model results

Positives

- Pareto income distribution
- Mean reversion (higher growth rates for poor)
- Persistent growth slowdown accounted by fall in covariance
- Provides insights on what structural change are needed to explain the facts
- Explain $\beta$ convergence and $\sigma$ divergence

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- Pareto income distribution
- Mean reversion (higher growth rates for poor)
- Persistent growth slowdown accounted by fall in covariance
- Provides insights on what structural change are needed to explain the facts
- Explain $\beta$ convergence and $\sigma$ divergence

Negatives

- Mechanical (no choices)
- Quantitative fit could be improved

# Closing remarks and open issues

- $\Gamma_T = cov(g_{i,T}, s_i) + E(g_{i,T})$
- Empirically: large deviations from Gibrat's low: $Cov(g_i, s_i) < 0$
- Most US growth decline over past 40 year accounted by $Cov(g_i, s_i)$
- Empirically $Cov(g_i, s_i) \downarrow$ results mostly from $\sigma(s_i) \uparrow$

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- Key shocks: bigger opportunities $\gamma \uparrow$ and risks $\varphi \downarrow y_0 \downarrow$
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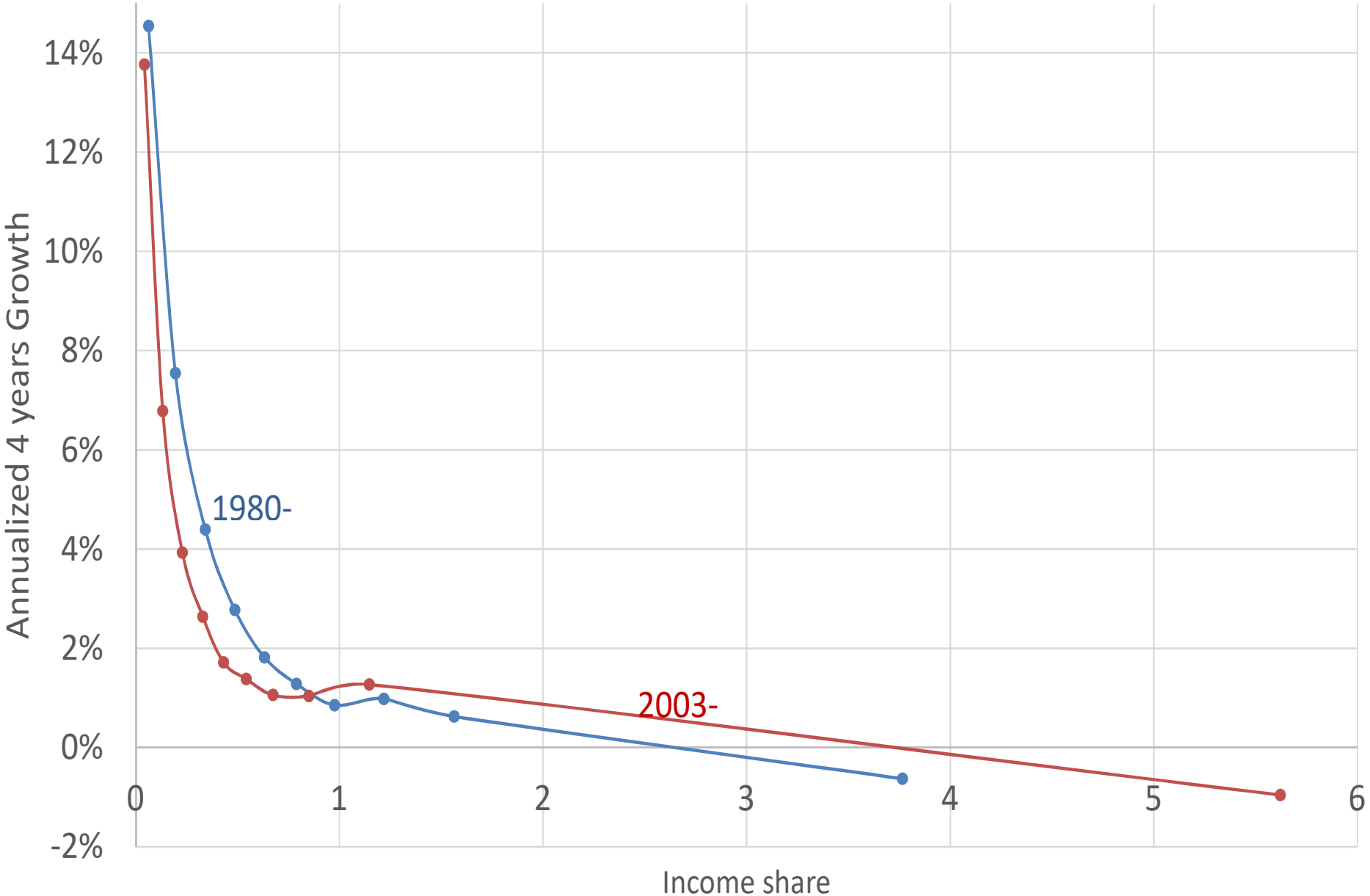
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Open issues

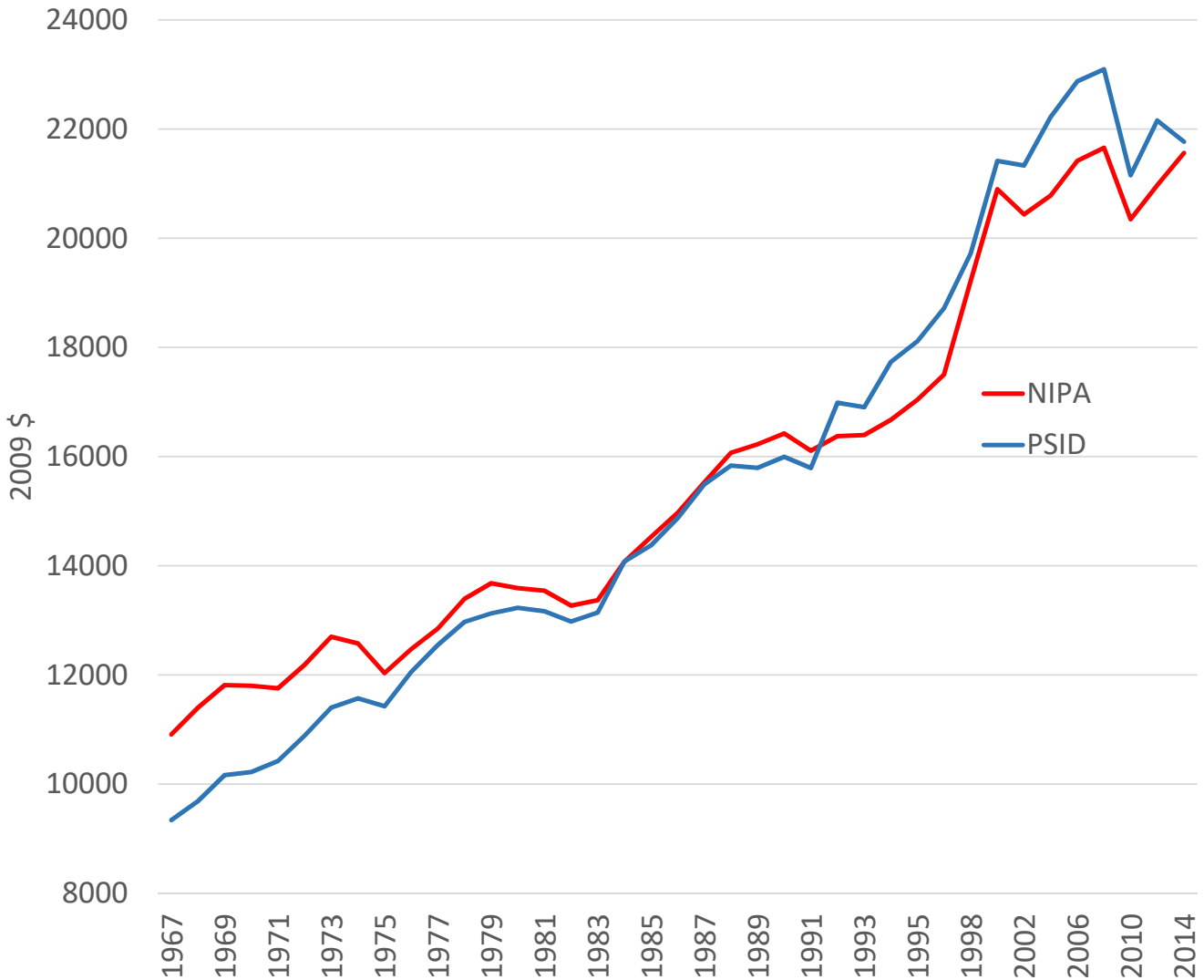
- Can the model generate micro and macro dynamics quantitatively consistent with data?
- What is the welfare impact of these changes (higher inequality, reduction in rank mobility)?

# Additional slides

# Income Growth and Income level in SIPP data

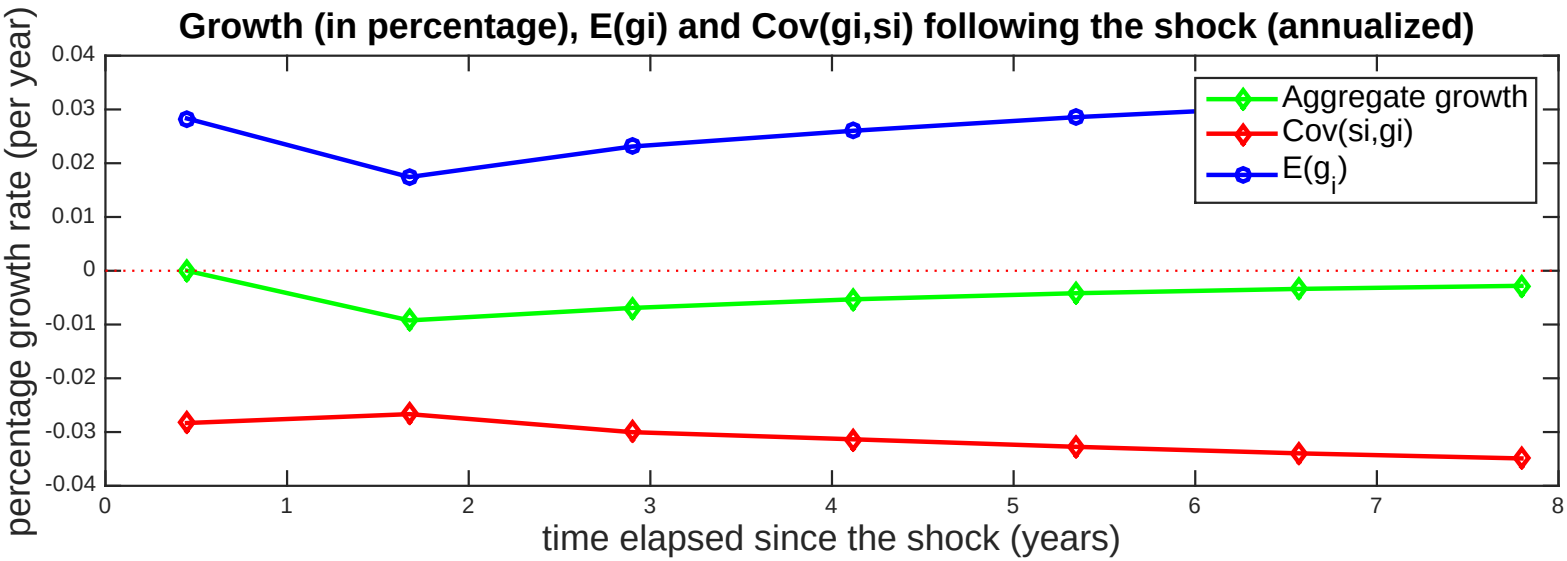


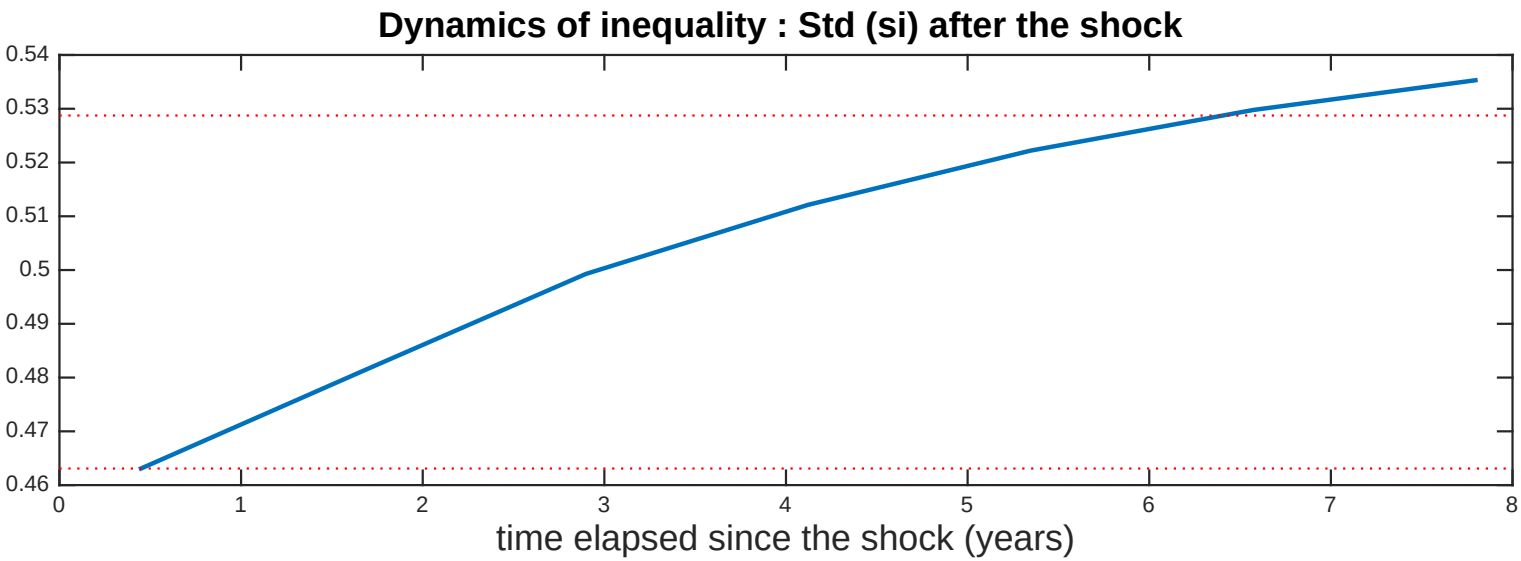
# PSID v/s NIPA
## Wages and Salaries per capita (Constant 2009 $)



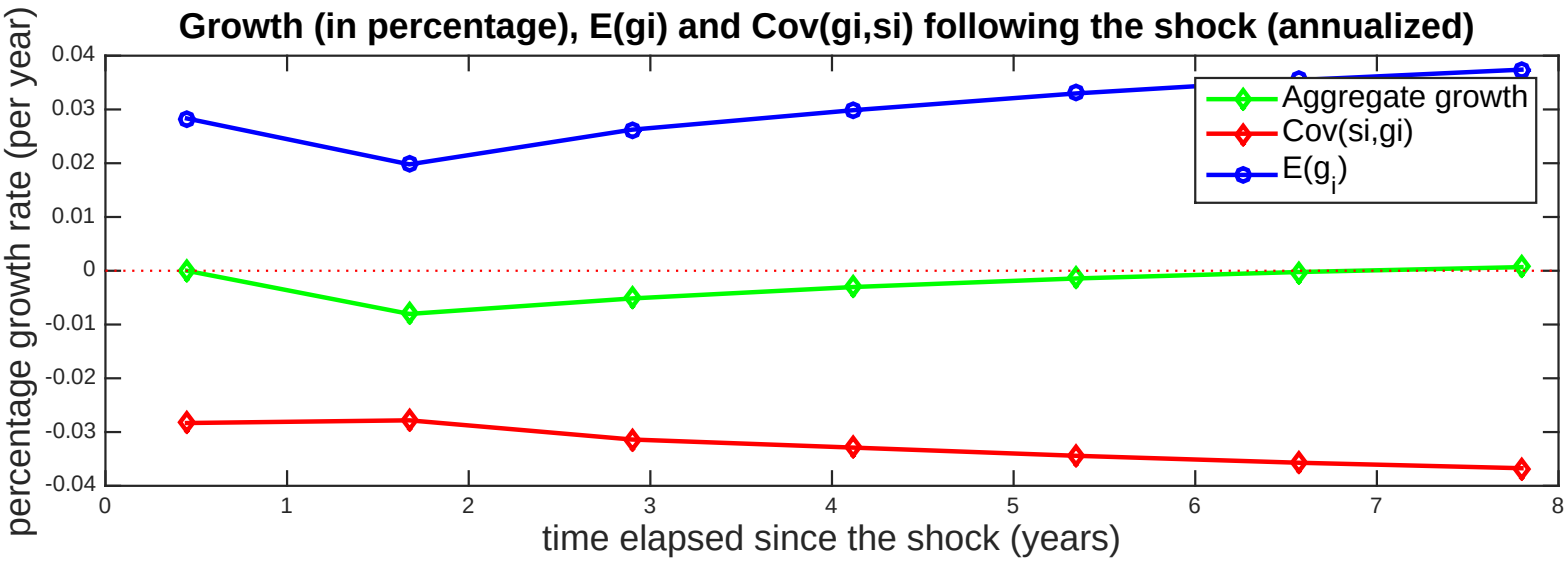

- For labor income PSID matches NIPA Dynamics *and* Levels

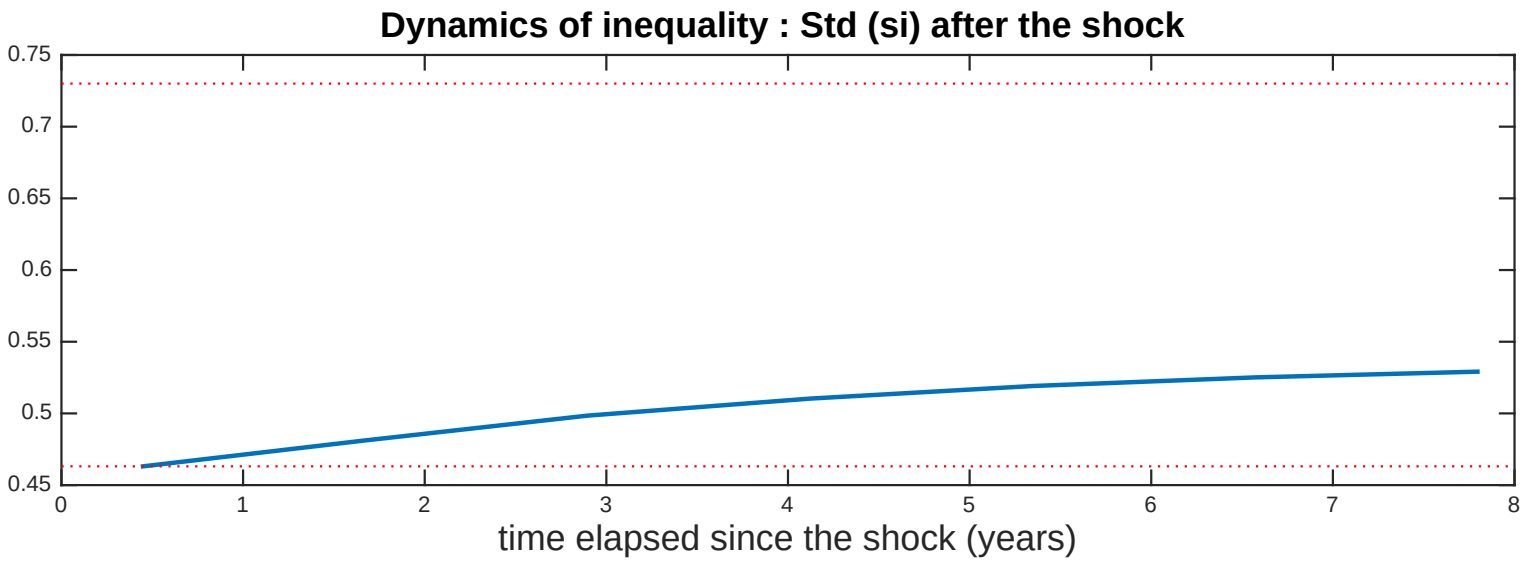
# Transition dynamics (scenario 1)



# Transition dynamics (scenario 2)



# Transition dynamics (scenario 3)

