Unequal Growth

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

- Increase in Household Income Inequality
- Slowdown in Aggregate Growth
Introduction

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• Increase in Household Income Inequality

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

- 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
- **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
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

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

- 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 $\Gamma_{t,T} = E_i(g_{i,T} \cdot s_{i,t})$
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$$\Gamma_T = cov(g_{i,T}, s_i) + E(g_{i,T})$$

$$= corr(g_{i,T}, s_i)\sigma(g_{i,T})\sigma(s_i) + E(g_{i,T})$$
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- Distribution of growth opportunities matters for aggregate growth
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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

\[ \Gamma_T = \text{cov}(g_{i,T}, s_i) + E(g_{i,T}) \]
\[ = \text{corr}(g_{i,T}, s_i)\sigma(g_{i,T})\sigma(s_i) + E(g_{i,T}) \]

- 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, \( \text{corr}(g_{i,T}, s_i) \)
  - 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 \( \text{cov}(g_i, s_i) \)
  - Change in \( \text{cov}(g_i, s_i) \) for given \( E(g_i) \)
\[ \Gamma = E(g_i) + corr(g_i, s_i)\sigma(g_i)\sigma(s_i) \]

Covariance, and thus \( \Gamma \), depends on patterns of inequality

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

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  **Intuition**
  
  - Higher \( \sigma(s_i) \) (\textit{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 $\text{corr}(g_{it}, s_i)$, $\sigma(g_{it})$, $\sigma(s_{it})$ 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
• 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 $t$.

then

$$ g_{i,t+T} = \frac{\sum_j y_{j,i,t+T}}{\sum_j y_{j,i,t}} \frac{P_t}{P_{t+T}} $$

and

$$ s_{i,t} = \frac{\sum_j y_{j,i,t}}{\sum_i \sum_j y_{j,i,t}} $$

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 poverty line, no imputed labor income, which are in sample in year $t$ and $t + 4$ (avg. sample per year $\simeq 3500$)
- Similar patterns for households with 25-40 head (age composition)
• $\Gamma$ declines, $E(g_i)$ almost flat. Implies: $\text{cov}_t \downarrow$
Contribution to growth by decile

\[ g_i \]

2006-2012, \( E(g_i) = 8.5\% \)

1967-1970, \( E(g_i) = 8.1\% \)

\[ S_i \]

\[ 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad 6 \quad 7 \quad 8 \quad 9 \quad 10 \]

Ratio to mean income

1967-1970

2006-2012

Contribution to aggregate growth \( g_i \cdot S_i \)

1967-1970, \( E(g_iS_i) = 5.0\% \)

2006-2012, \( E(g_iS_i) = 1.0\% \)

\[ 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad 6 \quad 7 \quad 8 \quad 9 \quad 10 \]

Analyzed 4 years growth (weighted)
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)

\[ \text{Corr}(g_i, s_i) \] 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)

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

- $E(g_i)$
- $\Gamma$
- $\text{Cov}(g_i, s_i)$

Covariance decomposition

- $\text{s.d.}(s_i)$
- $\text{s.d.}(g_i)$
- $\text{Corr}(g_i, s_i)$
A broad brush characterization (stylized facts)

\[ \Gamma_t = \text{corr}(g_i, s_i) \sigma(g_{it}) \sigma(s_{it}) + E(g_i) \]

- \( \Gamma_t \) declines over time (between 1% and 4%)
  - significant contribution of \( \Delta \text{cov}_t(g_{it}, s_{it}) \)
  - small/no decline in “average” x-section growth \( E(g_i) \)
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- 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?
• The poor fast growers are not all young
• Mean reversion not all explained by demographic (Some household become poor-fast growers because of shocks)
• 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

Qualitative analysis:

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

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 $y_0$
Model in a nutshell (steady state)

\[ f(y) = \alpha \frac{y_0^\alpha}{y^{\alpha+1}} \text{ where } \alpha \equiv \frac{\delta}{\gamma} \]
Model in a nutshell (steady state)

The income level distribution is often characterized by a Pareto distribution. The density function of the income distribution is given by:

\[ f(y) = \alpha \frac{y_0^\alpha}{y^{\alpha+1}} \]

where \( \alpha \equiv \frac{\delta}{\gamma} \). The parameter \( \omega = \frac{\delta}{\delta + \varphi} \) describes the density of income levels and mass points.
Model in a nutshell (steady state)

$$f(y) = \alpha \frac{y_0^\gamma}{y^\gamma + 1} \quad \text{where} \quad \alpha \equiv \frac{\delta}{\gamma}$$

(1) Pareto income distribution \hspace{1cm} (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: $\{\Gamma(t), \mathbb{E}(g_{i,t}), \text{cov}(t), \sigma_{s_i}(t)\}$
  – 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: $\tilde{\omega}(t)$

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

- 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

$$\frac{\partial}{\partial t} \tilde{f}(y, t) = - \frac{\partial}{\partial y} (\tilde{f}(y, t) \tilde{\gamma} y) - \delta \tilde{f}(y, t) \text{ s.t. } \int_{y_1}^{y_1 e^{\tilde{\gamma}t}} \tilde{f}(y, t) = \eta(t)$$
Characterising transition in closed form!

Solving the PDE (using eigenvalue-eigenfunction decomposition) gives

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

where \(\delta + \tilde{\varphi}\) is the “dominant eigenvalue” (as in Gabaix et al. 2016)
Characterising transition in closed form!

Solving the PDE (using eigenvalue-eigenfunction decomposition) gives

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

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

– distribution of incomes \(t\) at time \(t\) :

\[
\begin{align*}
\tilde{f}(y, t) & \quad \text{for } y \in (y_1, y_{m(t)}) \\
\tilde{f}(y, t) + (1 - \omega) \frac{y_1^{\alpha}}{y^{1+\alpha}} & \quad \text{for } y \in (y_{m(t)}, y_{M(t)}) \\
(1 - \omega) \frac{y_1^{\alpha}}{y^{1+\alpha}} & \quad \text{for } y \in (y_{M(t)}, \infty)
\end{align*}
\]

where \(y_{m(t)} = y_1 e^{\gamma t}\), \(y_{M(t)} = y_1 e^{\tilde{\gamma} t}\)
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
Transition dynamics: Three scenarios

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- Three scenarios stylized features of globalization?
Transition dynamics (scenario 1)

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

GDP Level

Inequality ($\sigma_s$)

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

\[ \gamma = 0.03, \tilde{\gamma} = 0.04 \]
\[ \varphi = 0.5, \tilde{\varphi} = 0.17 \]
\[ \frac{y_0}{y_1} = 0.45, \frac{\tilde{y}_0}{y_1} = 0.2 \]
\[ \text{cov} = -0.028, \text{cðv} = -0.13 \]
\[ \text{corr} = -0.66, \text{cðr} = -0.61 \]
\[ \sigma_s = 0.46, \tilde{\sigma}_s = 0.85 \]
\[ \frac{G\tilde{D}P}{GDP} = 0.8878 \]
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
Summarizing model results

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Negatives

- Mechanical (no choices)
- Quantitative fit could be improved
Closing remarks and open issues

- $\Gamma_T = \text{cov}(g_i, T_i, s_i) + E(g_i, T_i)$
- Empirically: large deviations from Gibrat’s law: $\text{Cov}(g_i, s_i) < 0$
- Most US growth decline over past 40 years accounted by $\text{Cov}(g_i, s_i)$
- Empirically $\text{Cov}(g_i, s_i) \downarrow$ results mostly from $\sigma(s_i) \uparrow$

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)?
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- Simple model: links inequality and growth changes
- Key shocks: bigger opportunities $\gamma \uparrow$ and risks $\varphi \downarrow, y_0 \downarrow$
- qualitatively consistent with $\Gamma \downarrow, \text{Cov} \downarrow$ and $\sigma(s_i) \uparrow$
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- Takeaway: not inequality drives growth; but, micro changes that drive up inequality, also impact aggregate growth
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Additional slides
Income Growth and Income level in SIPP data

Annualized 4 years Growth

Income share

1980-2003-
PSID v/s NIPA
Wages and Salaries per capita (Constant 2009 $)

- For labor income PSID matches NIPA Dynamics and Levels
Transition dynamics (scenario 1)

Growth (in percentage), $E(g_i)$ and $Cov(g_i,si)$ following the shock (annualized)

Dynamics of inequality: $\text{Std } (si)$ after the shock
Transition dynamics (scenario 2)

Growth (in percentage), E(g_i) and Cov(g_i,si) following the shock (annualized)

Dynamics of inequality : Std (si) after the shock
Transition dynamics (scenario 3)

Growth (in percentage), $E(g_i)$ and $Cov(g_i, s_i)$ following the shock (annualized)

Dynamics of inequality : Std ($s_i$) after the shock