

What is driving wealth inequality in the US?

The role of productivity, taxation and skills

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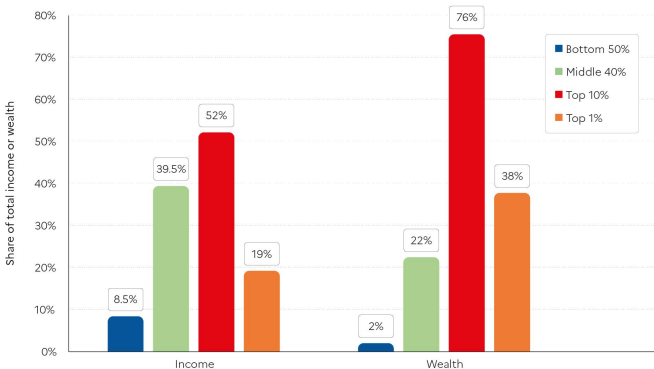
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Introduction

- Concerns on widening inequality
- Wealth disparities are larger than income disparities (Bartscher et al. 2019)
- Wealth inequality has increased at the very top (1%) of the distribution, it ranges between 25% (Europe) and 46% (Russia and Central Asia) of total wealth
- Wealth concentration $\Rightarrow$ big inheritance $\Rightarrow$ low social mobility and fair access to opportunity (Bank of America 2003)

Income and wealth inequality

Figure 1.1 Global income and wealth inequality, 2021



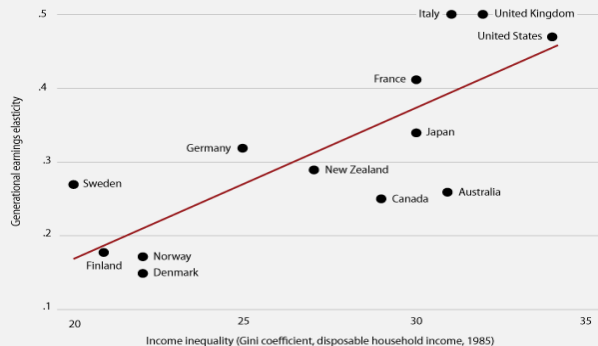
Interpretation: The global 50% captures 8.5% of total income measured at Purchasing Power Parity (PPP). The global bottom 50% owns 2% of wealth (at Purchasing Power Parity). The global top 10% owns 76% of total Household wealth and captures 52% of total income in 2021. Note that top wealth holders are not necessarily top income holders. Income is measured after the operation of pension and unemployment systems and before taxes and transfers. **Sources and series:** wir2022.wid.world/methodology

Correlation between inequality and social mobility

FIGURE 1

The Great Gatsby Curve

More inequality is associated with less mobility across the generations



Source: Miles Corak, "Inequality from Generation to Generation: The United States in Comparison." In Robert Rycroft, ed. *The Economics of Inequality, Poverty, and Discrimination in the 21st Century* (Santa Barbara, California: ABC-CLIO, 2013).

Which are the main drivers of inequality?

- ① Productivity slowdown (Piketty 2014) $\Rightarrow r - g > 0$ & inequality $\uparrow$
- ② Skill-biased technologies (Goldin and Katz 2009) $\Rightarrow$ skill premium $\uparrow$ & inequality $\uparrow$
mitigated by
- ③ Increase in educational attainments $\Rightarrow$ skill premium $\downarrow$ & inequality $\downarrow$
- ④ Flatter tax system (Gerber et al. 2009) $\Rightarrow$ inequality $\uparrow$
- ⑤ Income risk/volatility, uncertainty (Hubmer et al. 2020)

Our contributions

- We analyze the contribution of these factors to both wealth and income inequality
- Starting point: literature on inequality in DSGE models (Aiyagari 1994; Kaymak and Poschke 2016; Hubmer et al. 2019)
- **Extension 1:** we analyze inequality both *between* and *within* groups
 - Inequality has increased not only among those with different characteristics (e.g. gender, race, education and experience), but also within groups of workers
- **Extension 2:** We focus more on both *wealth* and *income* inequality
 - Bigger concentration of wealth = bigger inheritance and low social mobility (Bank of America 2023)
 - Vicious cycle: inheritance further increases wealth persistence (Adermor et al. 2018; Blandem et al. 2007; Keane and Wolpin 2001; Daruich and Kozlowski 2020)

Methodology

- Closed economy DSGE calibrated using empirical evidence from the US economy, with heterogeneous agents: skilled vs unskilled (Ahn et al. 2018)
- Why skilled and unskilled? We want to analyse inequality between different groups but also within a group of people with similar characteristics
 - Skilled/unskilled reflects high-income/low-income
- We introduce the 4 permanent shocks, which correspond to the 4 drivers
- The size of the shocks is calibrated to reproduce what we observe in US data
- We compare the predictions of our model over 1989-2010 with data
- We measure the relative contribution of each shock, as well as their interaction

Outline of this presentation

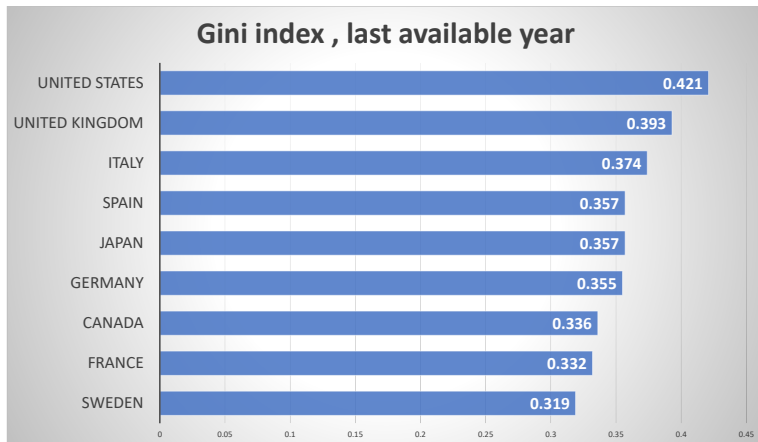
- Stylized facts to further motivate our research - Why the US?
- Model & calibration
- Results: which are the sources of rising inequality?
 - Productivity slowdown: r-g effect
 - Higher education
 - Skill-biased technological change
 - Less progressiveness in the tax system
- Conclusions & policy recommendations

Stylized facts based on the SFC

Our data source: The Survey of Consumer Finances (SFC) measures US households' wealth every 3 years

- US households are classified into 4 groups by level of education: no high school diploma, high school diploma, some college, college degree
- *Unskilled*=no high school diploma, high school diploma, some college & *Skilled*=college degree

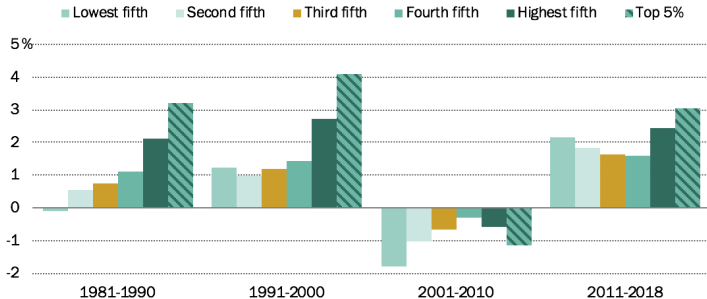
Income inequality: the US & other OECD countries



Source: OECD

Since 1981, the incomes of the top 5% of earners have increased faster than the incomes of other families

Average annual change in mean family income, by income quintile and for the top 5%



Note: Estimates of change from 2011-2018 are affected by revisions to the Current Population Survey in 2014. See Methodology for details.

Source: U.S. Census Bureau, Historical Income Tables, Table F-3.

"Most Americans Say There Is Too Much Economic Inequality in the U.S., but Fewer Than Half Call It a Top Priority"

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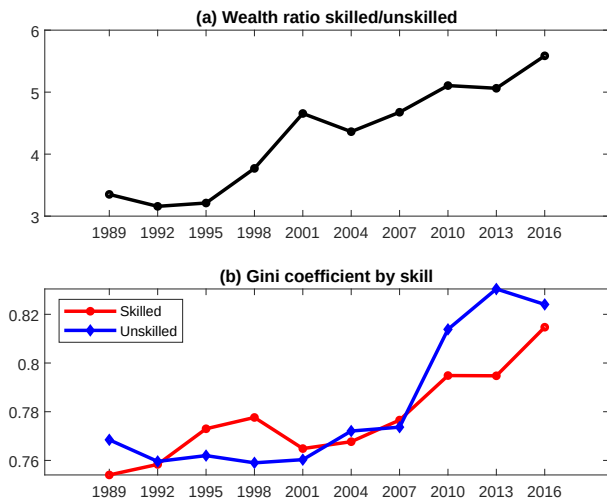
The evolution of wealth between groups (1989-2016)

- Wealth has increased since 1989, but unevenly, much more for skilled
- The wealth ratio between skilled and unskilled has widened

	All	Skilled	Unskilled	Wealth Ratio
Mean value in 1989	353.33	765.69	228.52	3.35
Mean value in 2016	689.51	1504.17	269.29	5.59

Source: SCF and authors' calculations. Mean values are in thousands of US \$

Wealth inequality has increased both between and within skill groups



Wealth inequality within skill groups, 1989–2016

- Wealth inequality increased both overall and in each skill group
- Indicators are almost identical at global and skill level (except for the interquartile ratio)

	All	Skilled	Unskilled
Gini coefficient (1989)	0.79	0.75	0.77
Gini coefficient (2016)	0.86	0.81	0.82
Inter Quartile Ratio (1989)	26.16	10.16	36.26
Inter Quartile Ratio (2016)	36.28	16.97	39.64
Top quartile share (1989)	85.17	82.39	83.01
Top quartile share (2016)	91.41	87.77	87.79

Source: SCF and authors' calculations

Model description

- ① **Households** supply labor, consume and pay taxes to max $U(\cdot)$, s.t. their budget constraint (wage + return on assets)
 - Heterogeneous agents: skilled/unskilled and patient/impatient
 - Non-linear tax system as in Heathcote et al. (2017)
- ② **Firms** produce goods using unskilled labor and a combination of skilled labor and capital
 - Firms can substitute skilled labor with capital (σ_h) and unskilled labor with skilled labor & capital (σ_l)
- ③ **Shocks**: productivity slowdown, skill-biased technological change, higher education, flatter tax reform

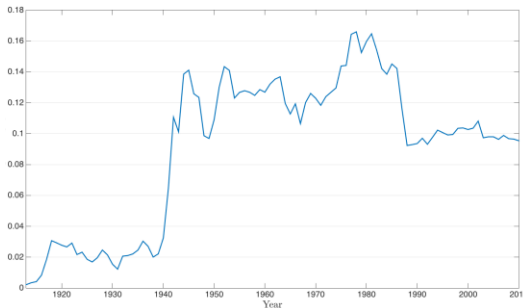
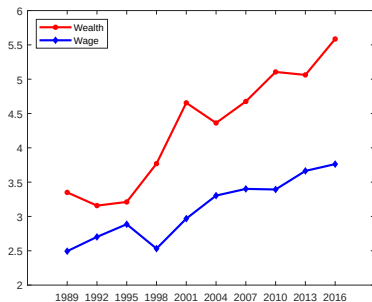
How we proceed

- ① We calibrate the model referring to the literature and replicating ratios observed in SFC 1989 data
- ② Similarly, we calibrate the 4 shocks replicating data observed in 1989-2010
- ③ We shock the model and we compute the post-shock (i) income inequality between-skills; (ii) wealth inequality between skills; (iii) wealth inequality within-skills; (iv) the wealth Gini index
- ④ We compare inequality measures produced by the model with data

Calibration of shocks

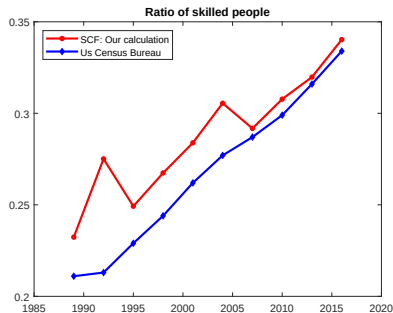
Category	Symbol	Values (1989)	Values (2010)	Source
BTC	s	2.43	3.34	SCF (Wage premium)
Growth	g	0.021	0.0089	Fernald (2014)
Tax	λ	0.18	0.13	Ferriere & Navarro (2018)
Skills	N_s	0.24	0.31	SCF (Share of skilled)

Calibration of shocks I

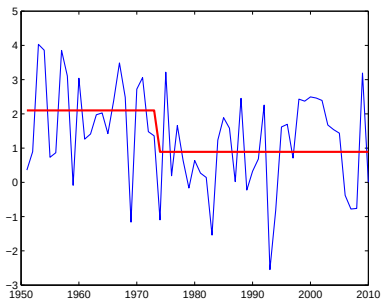


(a) The Rise in the Wage Premium (SCF) (b) Tax Progressivity (Ferriere and Navarro 2018)

Calibration of shocks II



(c) The Rise of the Share of Skilled Workers in the United States (SFC)



(d) The Changes in the US Growth Rate (Fernald 2014)

Shocks in the model equations

- ① Growth rate shock/productivity slowdown: X_t
- ② Skill-biased technological change: s

$$\tilde{y}_t = A \left(\mu F_t^{\frac{\sigma_l - 1}{\sigma_l}} + (1 - \mu)(X_t \ell_{u,t})^{\frac{\sigma_l - 1}{\sigma_l}} \right)^{\frac{\sigma_l}{\sigma_l - 1}}$$

$$F_t = \left[\zeta \left(s \tilde{k}_t \right)^{\frac{\sigma_h - 1}{\sigma_h}} + (1 - \zeta)(X_t \ell_{s,t})^{\frac{\sigma_h - 1}{\sigma_h}} \right]^{\frac{\sigma_h}{\sigma_h - 1}}$$

- ③ Higher education: $N_u + N_s = 1$
- ④ Flatter taxation: $\lambda = 0$ no progressiveness

$$T(r_t \tilde{a}_{\varsigma,t} + \tilde{w}_{q,t} z_{\varsigma,t} h_{\varsigma,t}) =$$

$$r_t \tilde{a}_{\varsigma,t} + \tilde{w}_{q,t} z_{q,t} h_{q,t} - (1 - \tau) e^{\lambda g} (\tilde{w}_{q,t} z_{q,t} h_{\varsigma,t} + r_t \tilde{a}_{q,t})^{1 - \lambda}$$

Empirical data VS model results, 1989-2010

	Wage premium	Wealth premium	Wealth top 25% skilled	Wealth top 25% unskilled	Gini
	Between ineq.	Between ineq.	Within ineq.	Within ineq.	
Data 1989	2.43	3.35	0.82	0.83	0.79
Model 1989	2.44	3.33	0.80	0.86	0.69
Data 2010	3.34 (0.91)	5.11 (1.76)	0.86	0.87	0.85 (6pp)
Model 2010					
All shocks	3.28 (0.84)	9.12 (5.79)	0.79	0.86	0.79 (10pp)
Skills	2.03	3.21	0.81	0.83	0.69
BTC	3.29	4.09	0.79	0.86	0.71
Tax	2.68	4.78	0.79	0.85	0.71
g	2.82	6.95	0.87	0.88	0.81

Empirical data VS model results, 4 shocks

- ① The model predicts a 10 pp increase in the **Wealth Gini index**, close to the 6 pp increase observed in data
- ② **Within inequality** is stable in our model, both for skilled and unskilled, while it increases in data
- ③ **Between inequality:**
 - The wealth premium increase is 5.79 in the model, more moderate in data (1.76)
 - The wage premium increase is similar in the model and data (0.84 & 0.91)

Main conclusions:

- The combination of the 4 shocks explains the evolution of inequalities in the US between 1989 and 2010
- Wealth inequality has increased more between than within skill groups

Impact of each shock in the model

① Labour force composition: higher supply of skilled workers

- The model predicts a decrease in wage and wealth premium (between inequality) in 1989-2010.
 - Why? If the share of skilled workers $> 50\%$, an increase in education reduces skill premium and inequality (Azis & Cortes, 2021)
- Conclusions: The change in labour force composition does not explain the observed increase in inequalities, neither between nor within groups.

Empirical data VS model results, 1989-2010

	Wage premium	Wealth premium	Wealth top 25% skilled	Wealth top 25% unskilled	Gini
	Between ineq. ↓	Between ineq. ↓	Within ineq.	Within ineq.	
Data 1989	2.43	3.35	0.82	0.83	0.79
Model 1989	2.44	3.33	0.80	0.86	0.69
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Model 2010	3.28	9.12	0.79	0.86	0.79
Model 2010: Skills	2.03	3.21	0.81	0.83	0.69
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Impact of each shock in the model

② Skill-biased technological change (SBTC)

- The model predicts an increase in skill premium (wider between inequality) in 1989-2010. Negligible change in within inequality.
- Conclusions: SBTC can explain increasing inequality between skill groups but not within inequality

Empirical data VS model results, 1989-2010

	Wage premium	Wealth premium	Wealth top 25% skilled	Wealth top 25% unskilled	Gini
	Between ineq.↑	Between ineq.↑	Within ineq.	Within ineq.	
Data 1989	2.43	3.35	0.82	0.83	0.79
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Impact of each shock in the model

③ Less progressive taxation

- Between inequality: Wage and wealth premium increase (0.24 & 1.45), but less than what was observed in the data (0.91 & 1.76)
- Within inequality not explained by the model with only tax shock

Empirical data VS model results, 1989-2010

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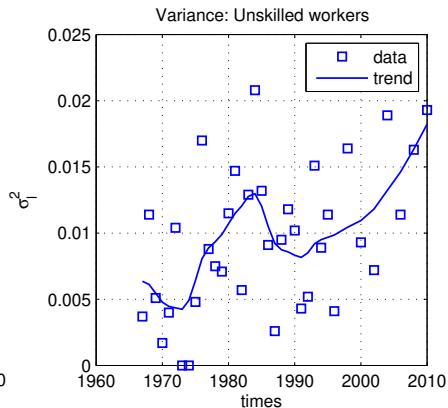
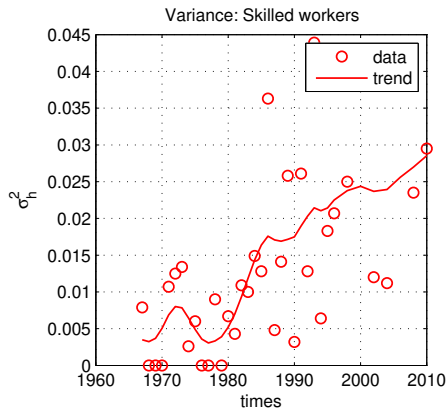
④ Growth, r-g mechanism

- Between inequality: Wage and wealth premium increase, although...
 - the model overestimates the increase in wealth premium (2.82 pp vs 3.34 pp)
 - while it slightly underestimates the increase in wage premium (0.38 pp vs 0.91 pp)
- Within inequality increases by 0.05 points for skilled and 0.02 points for unskilled, close to 0.04 point increase observed in data
- Conclusions: The growth shock is the only one that can explain both between and within inequality

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Income risk has increased since 1989



Source: Hong et al. 2019

Empirical data VS model results, 1989-2010

	Wage premium Between ineq.↑	Wealth premium Between ineq.↓	Wealth top 25% skilled Within ineq.↓	Wealth top 25% unskilled Within ineq.↓	Gini ↓
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Model 1989	2.44	3.33	0.80	0.86	0.69
Data 2010	3.34	5.11	0.86	0.87	0.85
Model 2010	3.33	5.34	0.67	0.59	0.64
Income risk	2.50	2.68	0.68	0.60	0.54

Conclusions & policy recommendations

- Between inequality is due to differences in educational attainment, within inequality is due to low productivity growth and differences in productivity across firms

Workers in more successful firms are paid more than their peers with the same level of education and skills in less successful firms (see Barth et al. 2016; Furman and Orszag 2018; Bloom et al. 2018)

Policies

- Equal access to quality education and progressive taxes to reduce inequality *between* groups
- How to reduce *within-groups* inequality? Policy package: regulation & taxation
 - Superstar firms are an extreme phenomenon of market concentration, dominating their markets almost as monopolies. Regulators should avoid market concentration
 - Property rights on data (Posner and Weyl et al. 2018)
 - New taxes to ensure that gains from digitalization can be shared equally throughout the economy, e.g. digital tax, minimum tax on multinational profits
 - Tax on capital income (Piketty 2014)

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감사합니다 Natick
Danke Ευχαριστίες Dalu
Grazie Thank You Köszönöm
Tack
Спасибо Dank Gracias
谢谢 Merci Seé
obligado ありがとう