Population Aging, Cohort Replacement, and the Evolution of Income Inequality in the United States

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* The views expressed in this paper are solely those of the authors and should not be interpreted as reflecting those of the Organisation for Economic Co-operation and Development (OECD).

Motivation

Household income inequality in the US is higher today than in the past:

	1970	1994	2018
Gini coefficient	.43	.52	.55
Top 5% income share	.21	.28	.33

Source: Survey of Consumer Finances

Motivation

Large literature emphasizes changes in the technological and institutional environment (skill-biased technical change, de-unionization, etc.)

At the same time, the characteristics of the population also changed

The population is older and newer generations...

- are generally better educated
- tend to marry partners with similar education levels
- are selected differently for higher education and professional careers
- ...

This paper

What is the *compositional* effect of *demographic change* on aggregate inequality?

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1. population aging
    - Inequality tends to increase within cohorts as they age $\rightarrow$ population aging leads to higher inequality
2. cohort replacement

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What is the *compositional* effect of *demographic change* on aggregate inequality?

Demographic change = change in the composition of the population via

1. population aging
   - Inequality tends to increase within cohorts as they age → population aging leads to higher inequality
2. cohort replacement
   - Recent cohorts are more unequal in their characteristics → cohort replacement leads to higher inequality

Thought experiment

How would income inequality evolve if the economic environment is held fixed and only demographic change is allowed to take place?

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Economic environment

- determines income distribution for given characteristics
- shapes the characteristics of newly entering cohorts

Preview of results

We find that demographic change accounts for much of the increase in income inequality over the past two decades (but not earlier)

We also project that future demographic change will increase inequality over the next decades

Data sources and sample definition

Income data from:

- Current Population Survey (CPS): 1968-2020
- Survey of Consumer Finances (SCF+): 1949-2019

Population projections from:

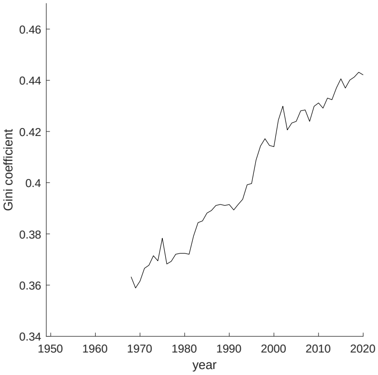
- US Census Bureau

We mainly focus on income inequality among bottom 99%

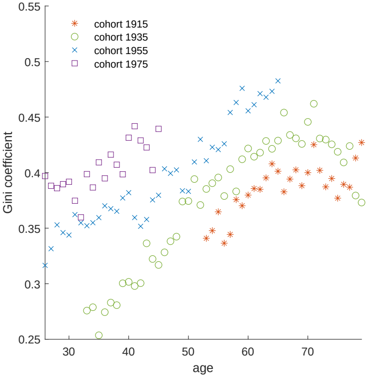
We assign household-level characteristics (age, education) based on the characteristics of the household head

We restrict our sample to households aged 26-79

Evolution of inequality



(a) aggregate inequality (CPS)



(b) inequality within cohorts (CPS)

Implementing the thought experiment

We need to know

- how income distributions change along the life cycle
- how income distributions differ between cohorts

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Assumption: logarithms of *mean income* and the *Gini coefficient* can be described by additive age, period, and cohort effects

Implementing the thought experiment

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- how income distributions change along the life cycle
- how income distributions differ between cohorts

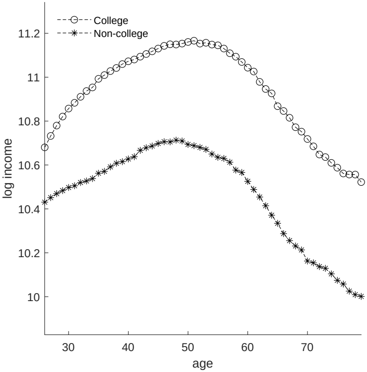
Assumption: logarithms of *mean income* and the *Gini coefficient* can be described by additive age, period, and cohort effects

$\rightarrow$ Estimate age profiles and cohort differences using an additive age-period-cohort model:

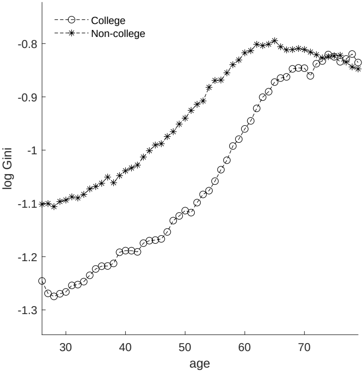
$$M_{a,p,c} = \mu + \alpha_a + \pi_p + \kappa_c + \varepsilon_{apc}$$

⏩ apc identification problem ⏩ income process

Age profiles (CPS data)



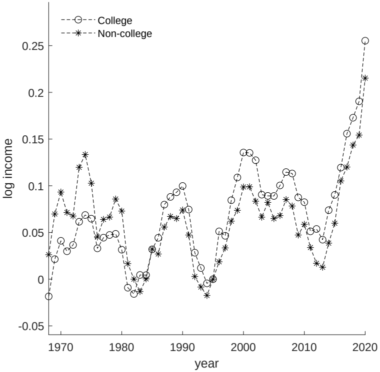
(a) log mean income



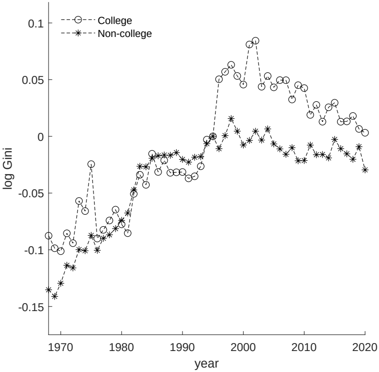
(b) log Gini

SCF+
Normalization

Period profiles (CPS data)



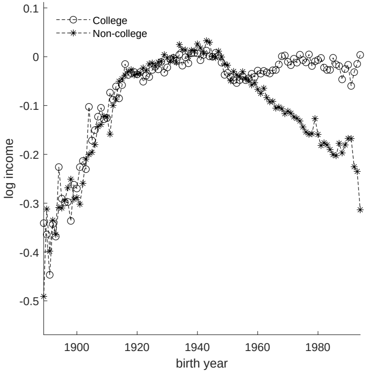
(a) log mean income



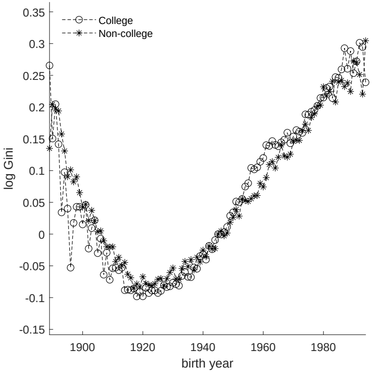
(b) log Gini

⏩ SCF+ ⏩ Normalization

Cohort profiles (CPS data)



(a) log mean income



(b) log Gini

▸▸ SCF+ ▸▸ Normalization ▸▸ NLSY re-weighting ▸▸ Regression table ▸▸ Model fit: example

Implementing the thought experiment

We use the estimated age and cohort profiles to construct counterfactual subgroup moments:

⏩ Implementation details

Implementing the thought experiment

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- maintain period effect at the level of base year

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We use the estimated age and cohort profiles to construct counterfactual subgroup moments:

- maintain period effect at the level of base year
- update age effects as cohorts grow older

▶▶ Implementation details

Implementing the thought experiment

We use the estimated age and cohort profiles to construct counterfactual subgroup moments:

- maintain period effect at the level of base year
- update age effects as cohorts grow older
- maintain cohort effects for cohorts present in the base year

▸▸ Implementation details

Implementing the thought experiment

We use the estimated age and cohort profiles to construct counterfactual subgroup moments:

- maintain period effect at the level of base year
- update age effects as cohorts grow older
- maintain cohort effects for cohorts present in the base year
- assign fixed effect of the youngest cohort to all cohorts entering the economy after base year

⏩ Implementation details

Implementing the thought experiment

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- maintain period effect at the level of base year
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We construct counterfactual population shares:

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Implementation details

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We construct counterfactual population shares:

- update population shares as cohorts grow older
- maintain college share for cohorts present in the base year

▸▸ Implementation details

Implementing the thought experiment

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We construct counterfactual population shares:

- update population shares as cohorts grow older
- maintain college share for cohorts present in the base year
- assign new cohorts the college share of the youngest cohort in the base year

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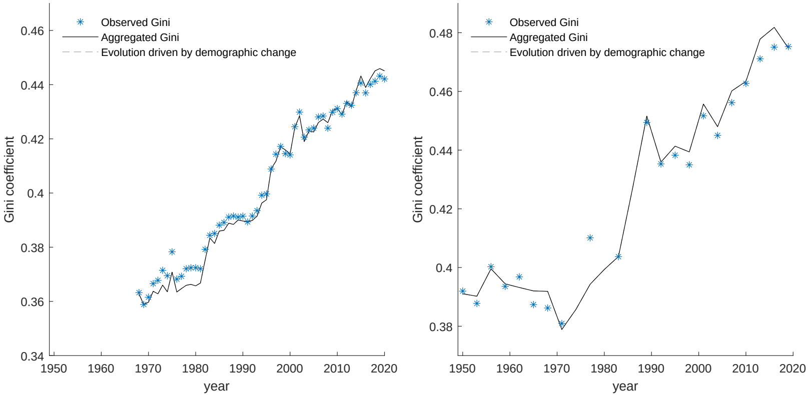
We compute aggregate Gini coefficient ⏩ Overcoming aggregation problem

⏩ Implementation details

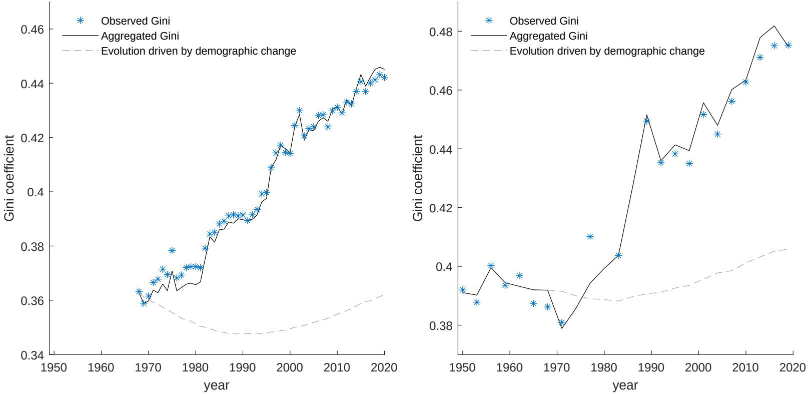
Results

The role of demographic change in the past



(a) CPS **(b)** SCF+

The role of demographic change in the past



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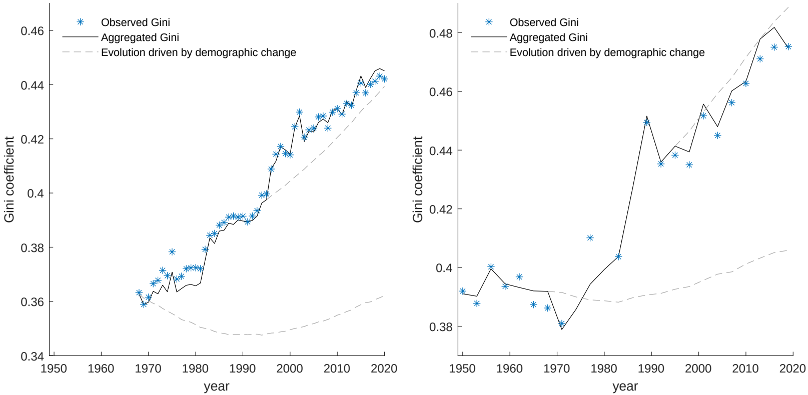

(a) CPS

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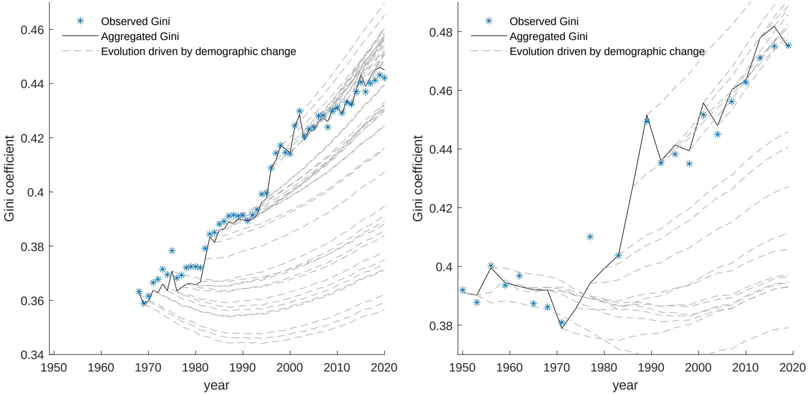

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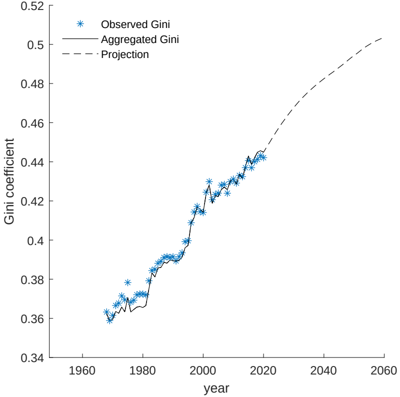
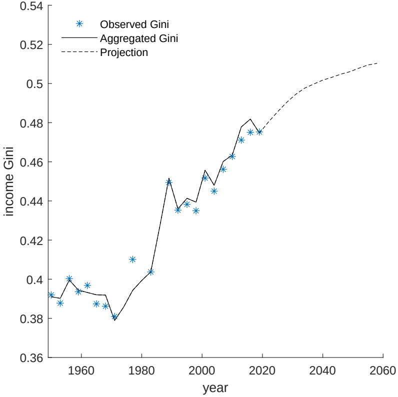
▶▶ Different normalizations ▶▶ Robustness (vintage predictions) ▶▶ Top 5 share ▶▶ Re-weighting analysis

The role of demographic change in the future



(a) CPS



(b) SCF+

Different normalizations Re-weighting analysis

Summary

We study how demographic change affects the evolution of household income inequality in the US

We document important cohort differences in income distributions

We argue that population aging and cohort replacement have increased inequality in the past, and we project further increases in inequality

Key insight: Changes in aggregate inequality are not always indicative of contemporaneous changes in economic environment

$\rightarrow$ Factors that engendered higher inequality among cohorts born in the late 20th century now drive aggregate inequality in the 21st century

Appendix

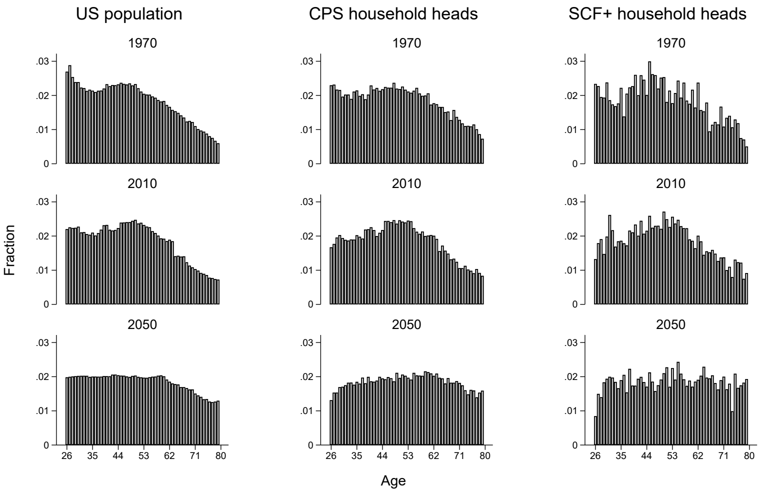
- ⏩ Decomposition of aging and cohort replacement
- ⏩ Benchmark: a re-weighting analysis
- ⏩ Aggregation strategy
- ⏩ Results under different normalizations
- ⏩ Robustness (Vintage predictions)
- ⏩ Robustness (NLSY re-weighting)

Evolution of the US age structure

Source: US Census Bureau

⏩ Age structure of household heads

Evolution of the US age structure



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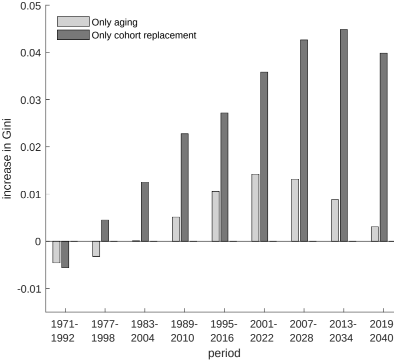
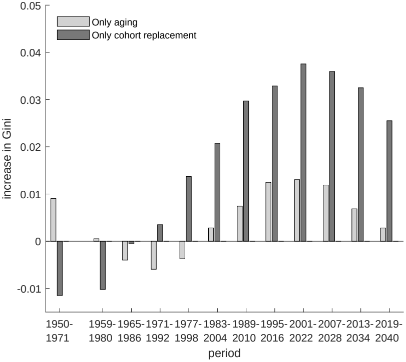
Population aging vs. cohort replacement



(a) CPS



(b) SCF+

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Estimating life cycle profiles and cohort differences

We estimate the following specification (Deaton and Paxson, 1994), separately for college and non-college educated households:

$$M_{a,p,c} = \mu + \alpha\, a + \pi\, p + \kappa\, c + \tilde{\alpha}_a + \tilde{\pi}_p + \tilde{\kappa}_c + \varepsilon_{apc}$$

$M \in \{\text{log of mean, log of Gini coefficient}\}$

$$\sum_a \tilde{\alpha}_a = \sum_p \tilde{\pi}_p = \sum_c \tilde{\kappa}_c = 0$$
$$\sum_a \tilde{\alpha}_a\, a = \sum_p \tilde{\pi}_p\, p = \sum_c \tilde{\kappa}_c\, c = 0$$

Trends in the age, period, and cohort profiles are unidentified, but deviations from trends can be estimated from the data!

Back R^2 and Shapley decomposition

Estimating life cycle profiles and cohort differences

We derive our results under three different normalizations:

- no linear trend in period effects (Deaton and Paxson, 1994)
- no linear trend in cohort effects (Heathcote et al., 2005)
- **equal linear trends (Lagakos et al., 2018)**

Provide support for equal trends assumption using additional data from the *National Longitudinal Survey of Youth* (NLSY)

Back interpretation

A simple income process

In each period, households with observed characteristics $X = \{age, education\}$ experience an income shock that has two components:

$$\text{Level shock:} \qquad y_{t+1} = (1+\beta) y_t, \qquad \beta \geq -1$$

$$\text{Inequality shock:} \qquad y_{t+1} = y_t + \gamma\big(y_t - \mathbb{E}[y_t | X_t]\big), \qquad \gamma \geq -1$$

Income shocks are separable in age and period

$$1 + \beta(e, a, t) = \big(1 + \beta_a(e, a)\big)\big(1 + \beta_t(e, t)\big)$$
$$1 + \gamma(e, a, t) = \big(1 + \gamma_a(e, a)\big)\big(1 + \gamma_t(e, t)\big)$$

We allow for arbitrary difference between birth cohorts in initial income distributions (to capture cohort differences in quality and distribution of education, sorting into occupations, degree assortative mating, etc.)

A simple income process

The income of household i with education e at age a in time t is given by

$$y^e_{i,a,t} = \prod_{k=1}^{a} \Big(1 + \beta_a(e,k)\Big) \prod_{k=t-a+1}^{t} \Big(1 + \beta_t(e,k)\Big)$$

$$\times \left[y^e_{i,0,t-a} + \left(\prod_{k=1}^{a} \Big(1 + \gamma_a(e,k)\Big) \prod_{k=t-a+1}^{t} \Big(1 + \gamma_t(e,k)\Big) - 1 \right) \big(y^e_{i,0,t-a} - \mathbb{E}[y^e_{0,t-a}] \big) \right]$$

A simple income process

Computing log mean income and the log Gini coefficient for a given demographic subgroup, we get

$$\ln\left(\mathbb{E}[y^e_{a,t,c}]\right) =$$

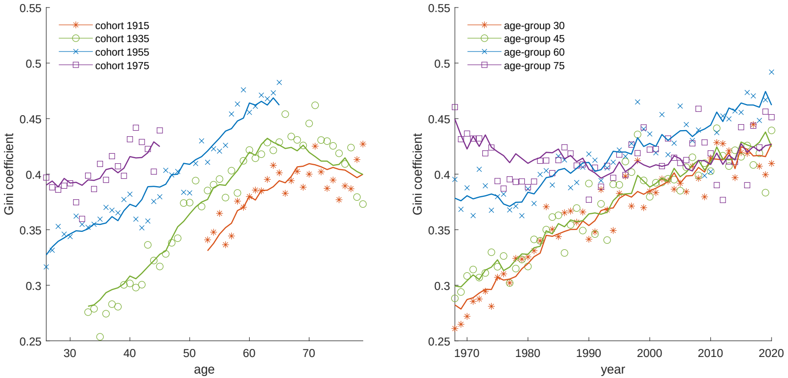
$$\underbrace{\sum_{k=1}^{a} \ln\left(1+\beta_a(e,k)\right)}_{\text{age effect}} + \underbrace{\sum_{k=1-a^{\max}+1}^{t} \ln\left(1+\beta_t(e,k)\right)}_{\text{period effect}} + \underbrace{\ln \mu_0^{e,c} - \sum_{k=1}^{c} \ln\left(1+\beta_t(e,k)\right)}_{\text{cohort effect}}$$

$$\ln\left(G(y^e_{a,t,c})\right) =$$

$$\underbrace{\sum_{k=1}^{a} \ln\left(1+\gamma_a(e,k)\right)}_{\text{age effect}} + \underbrace{\sum_{k=1-a^{\max}+1}^{t} \ln\left(1+\gamma_t(e,k)\right)}_{\text{period effect}} + \underbrace{\ln G_0^{e,c} - \sum_{k=1}^{c} \ln\left(1+\gamma_t(e,k)\right)}_{\text{cohort effect}}$$

→ Additive age, period, and cohort effects Back

Evolution of inequality within demographic subgroups revisited



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Are the estimated cohort differences credible?

We use data from the NLSY79 and NLSY97 to check the plausibility of the results from the age-period-cohort-model

In these data we observe more characteristics of selected cohorts including:

- parental education
- education of all household members
- cognitive test scores
- born in the US vs abroad

Are the estimated cohort differences credible?

We check how much the Gini coefficient of cohort 1959 increases if we impose on them the distribution of characteristics from cohort 1982

→ The increase corresponds to the difference in cohort effects between these cohorts

Difference in log Gini coefficients:

	college	non-college
NLSY	0.08	0.12
apc-model (CPS, baseline)	0.12	0.14
apc-model (SCF+, baseline)	0.08	0.10

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Final step: Aggregation

Subgroup average incomes, Gini coefficients, and population shares do not uniquely determine the aggregate Gini coefficient

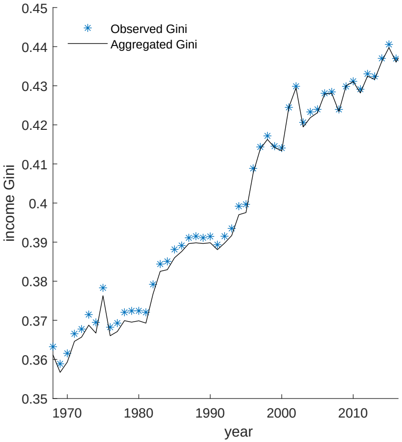
We need to model the entire income distribution for each subgroup:

- follow the principle of maximum entropy (Jaynes, 1957)
- model household income using a distribution that maximizes entropy for given mean and Gini coefficient (Eliazar and Sokolov, 2010)

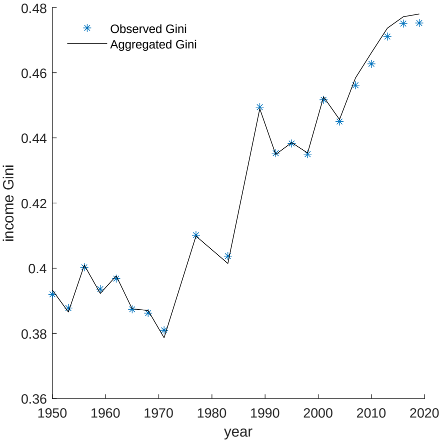
→ Use fitted subgroup income distributions together with population shares to construct an aggregate income distribution

▸▸ details

Aggregation



(a) CPS



(b) SCF+

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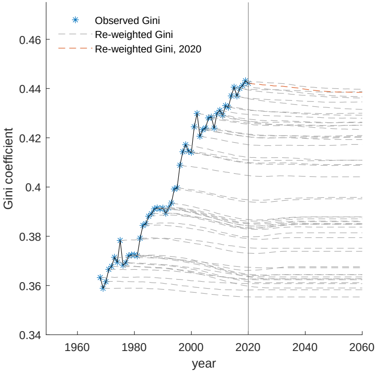
Results of the re-weighting analysis



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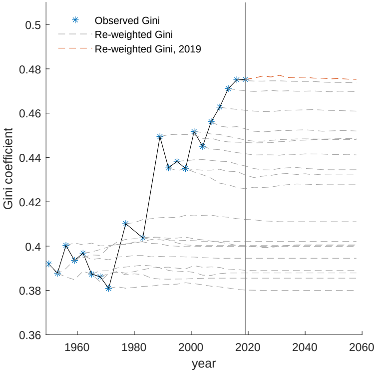

(b) SCF+

Implementation | Back | Appendix

Re-weighting analysis

For a given base year, we re-weigh the observations in that year so that

- the age structure of the population matches that of subsequent years
- the share of college graduates in each birth cohort remains as in the base year
  - e.g. for base year 1980 and target year 2000, the college share among households heads aged 50 in the re-weighted data equals the college share among households heads aged 30 in the base year
  - for any birth cohort not observed in the base year, we set their college share to that of the youngest households in the base year

We then compute the Gini coefficient on the re-weighted data

⏩ details ⏩ Back

Re-weighting analysis

For each base and target year pair $(\bar{p}, \hat{p})$ we construct two sets of age-specific re-weighting factors:

$$\phi_{\bar{p},\hat{p}}(a) = \frac{dF_{A,\hat{p}}(a)}{dF_{A,\bar{p}}(a)}$$

and

$$\psi_{\bar{p},\hat{p}}(e,a) = \begin{cases} \frac{dF_{E,\bar{p}}(e|a-(\hat{p}-\bar{p}))}{dF_{E,\bar{p}}(e|a)} & \text{for } a \geq \underline{a} + \hat{p} - \bar{p} \\ \frac{dF_{E,\bar{p}}(e|\underline{a})}{dF_{E,\bar{p}}(e|a)} & \text{for } a < \underline{a} + \hat{p} - \bar{p} \end{cases},$$

where a is age, e education and $\underline{a}$ is the youngest age in the sample

R^2 and Shapley decomposition

Panel A: CPS	(Log) mean income		(Log) income Gini	
	College	Non-college	College	Non-college
N	2,862	2,862	2,862	2,862
R^2	0.95	0.97	0.92	0.90
Shapley decomposition of R^2				
Linear trends	0.23	0.32	0.80	0.74
Nonlinear age effects	0.55	0.43	0.05	0.07
Nonlinear period effects	0.03	0.03	0.03	0.02
Nonlinear cohort effects	0.19	0.22	0.11	0.17

Panel B: SCF+	(Log) mean income		(Log) income Gini	
	College	Non-college	College	Non-college
N	399	399	399	399
R^2	0.94	0.97	0.90	0.91
Shapley decomposition of R^2				
Linear trends	0.15	0.36	0.54	0.46
Nonlinear age effects	0.41	0.23	0.03	0.09
Nonlinear period effects	0.24	0.17	0.19	0.15
Nonlinear cohort effects	0.21	0.24	0.25	0.30

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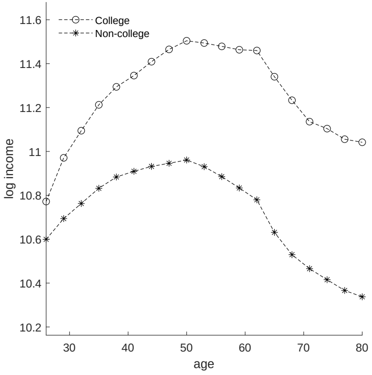
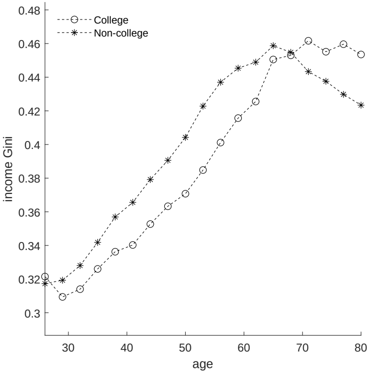
Age profiles (SCF+ data)



(a) log mean income



(b) log Gini

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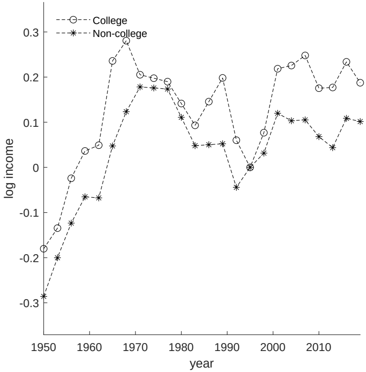
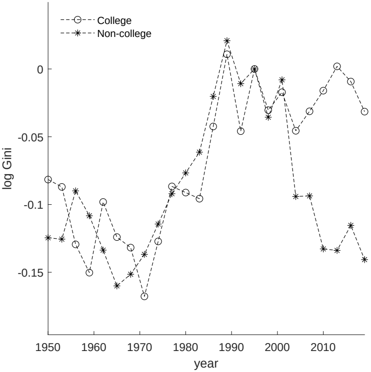
Period profiles (SCF+ data)



(a) log mean income



(b) log Gini

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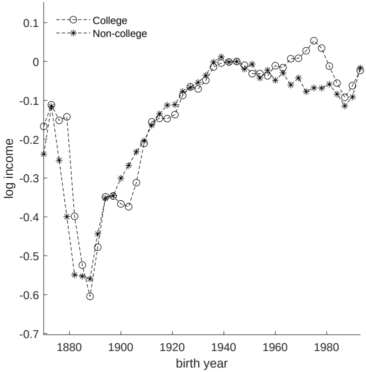
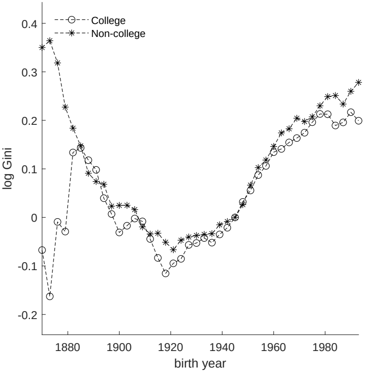
Cohort profiles (SCF+ data)



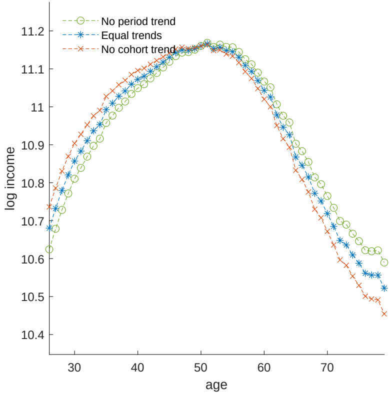
(a) log mean income



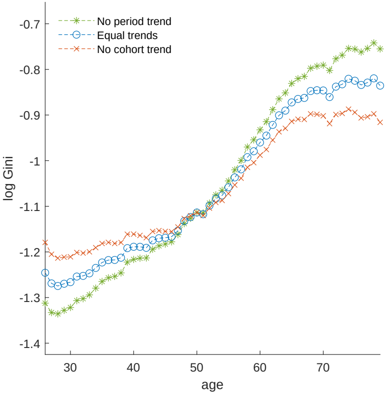
(b) log Gini

▸▸ Normalization ▸▸ Back

Age profiles under different normalizations (CPS data, college)



(a) log mean income



(b) log Gini

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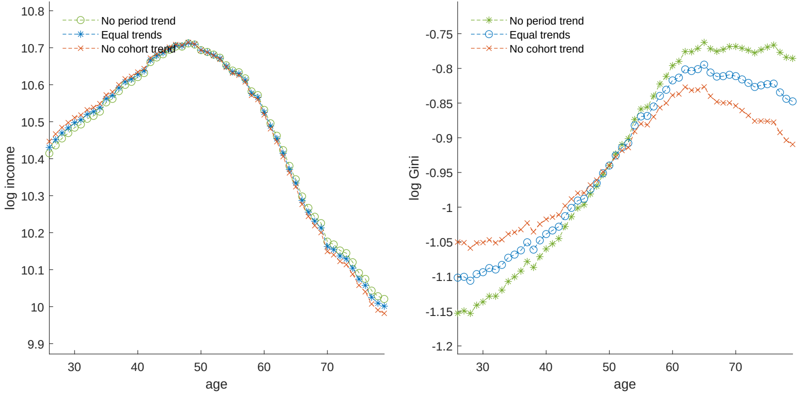
Age profiles under different normalizations (CPS data, non-college)



(a) log mean income **(b)** log Gini

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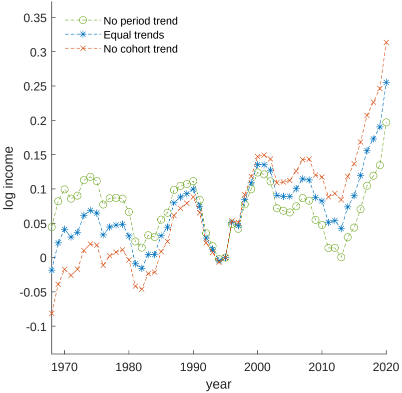
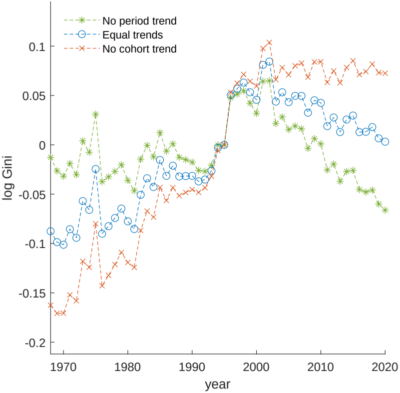
Period profiles under different normalizations (CPS data, college)



(a) log mean income



(b) log Gini

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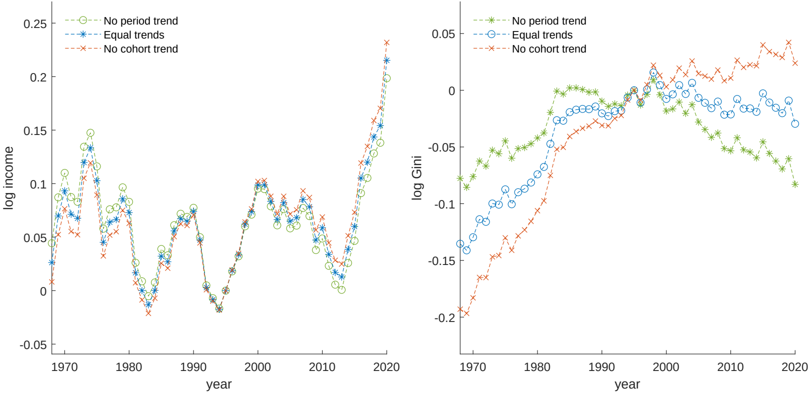
Period profiles under different normalizations (CPS data, non-college)



(a) log mean income **(b)** log Gini

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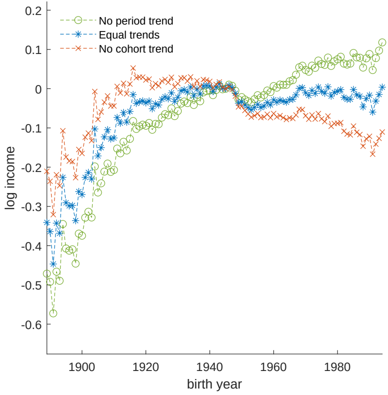
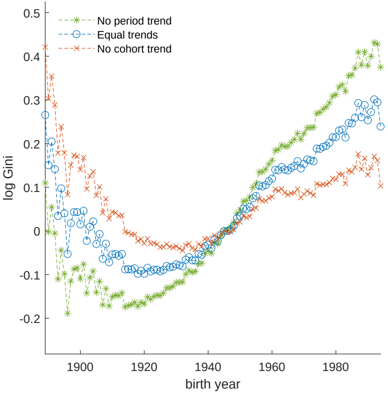
Cohort profiles under different normalizations (CPS data, college)



(a) log mean income



(b) log Gini

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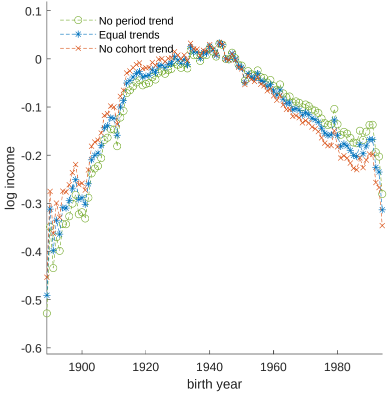
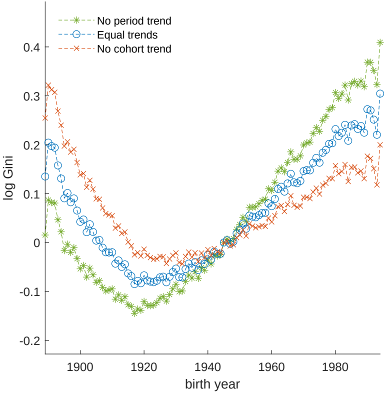
Cohort profiles under different normalizations (CPS data, non-college)



(a) log mean income



(b) log Gini

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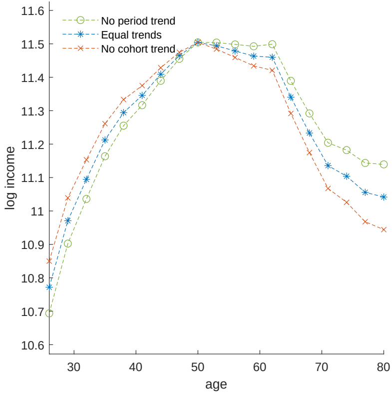
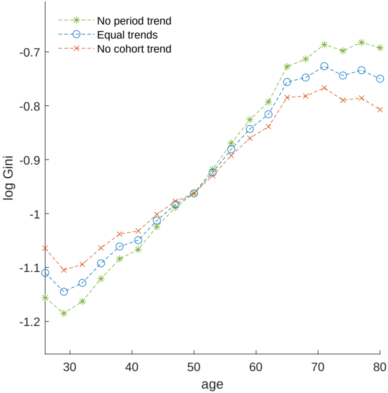
Age profiles under different normalizations (SCF+ data, college)



(a) log mean income



(b) log Gini

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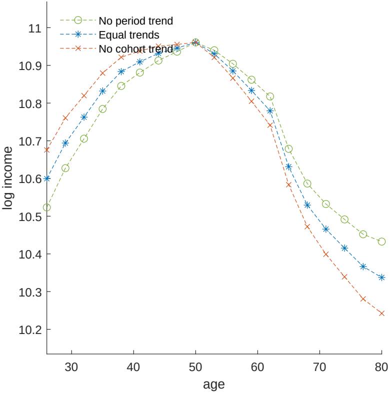
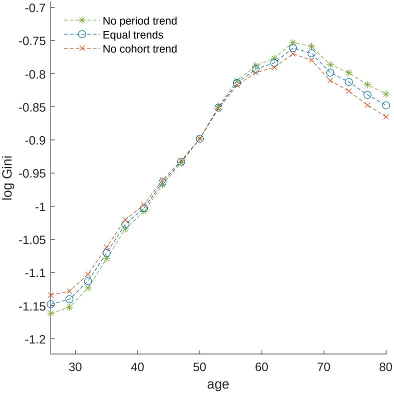
Age profiles under different normalizations (SCF+ data, non-college)



(a) log mean income



(b) log Gini

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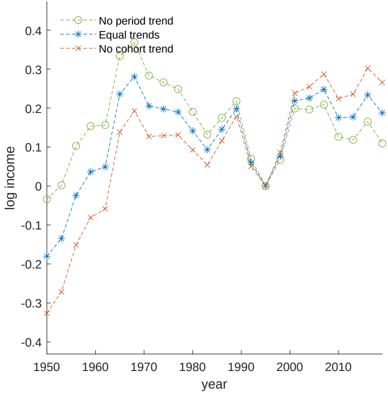
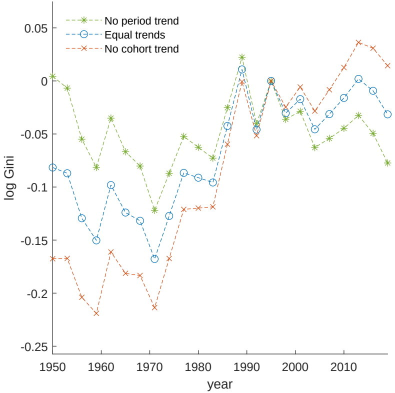
Period profiles under different normalizations (SCF+ data, college)



(a) log mean income



(b) log Gini

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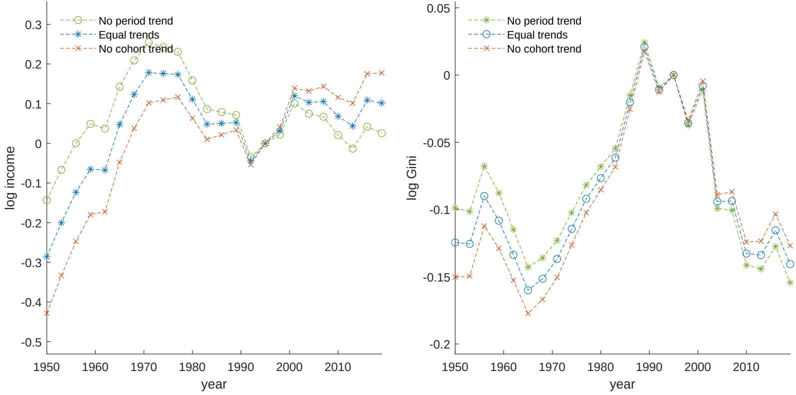
Period profiles under different normalizations (SCF+ data, non-college)



(a) log mean income

(b) log Gini

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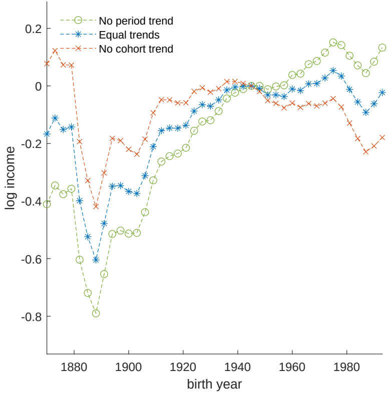
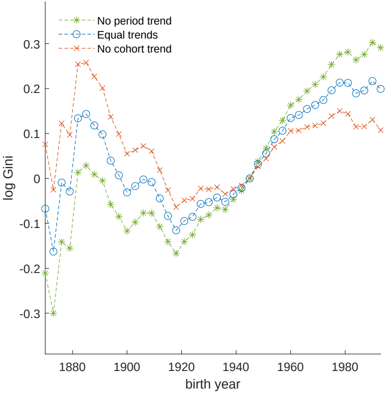
Cohort profiles under different normalizations (SCF+ data, college)



(a) log mean income



(b) log Gini

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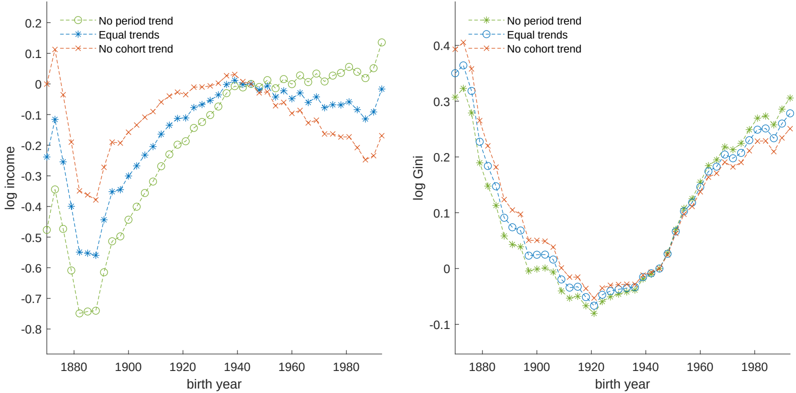
Cohort profiles under different normalizations (SCF+ data, non-college)



(a) log mean income **(b)** log Gini

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Interpretation of the normalizations

(Log) mean income

- Technological progress constitutes a trend in period effects
- Improving quality of education constitutes a trend in cohort effects
- Improvements in efficiency can be both period and cohort effects

(Log) Gini coefficient

- Globalization constitutes a period trend
- Secular changes in the distribution of human capital, sorting to education, or assortative mating constitute a trend in cohort effects

→ We consider the intermediate normalization of equal period and cohort trends a sensible baseline normalization

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Implementation of the thought experiment

Counterfactual moments:

$$\tilde{\mu}_{a,p',c,e} = \begin{cases} \exp\left(\theta^{\mu}_{e} + \alpha^{\mu}_{a,e} + \pi^{\mu}_{\bar{p},e} + \kappa^{\mu}_{c,e} + \frac{\sigma^2_{e,\mu}}{2}\right) & \text{if } \ c < \bar{c}_0 \\ \exp\left(\theta^{\mu}_{e} + \alpha^{\mu}_{a,e} + \pi^{\mu}_{\bar{p},e} + \kappa^{\mu}_{\bar{c}_0,e} + \frac{\sigma^2_{e,\mu}}{2}\right) & \text{if } \ c \geq \bar{c}_0, \end{cases}$$

$$\tilde{g}_{a,p',c,e} = \begin{cases} \exp\left(\theta^{g}_{e} + \alpha^{g}_{a,e} + \pi^{g}_{\bar{p},e} + \kappa^{g}_{c,e} + \frac{\sigma^2_{e,g}}{2}\right) & \text{if } \ c < \bar{c}_0 \\ \exp\left(\theta^{g}_{e} + \alpha^{g}_{a,e} + \pi^{g}_{\bar{p},e} + \kappa^{g}_{\bar{c}_0,e} + \frac{\sigma^2_{e,g}}{2}\right) & \text{if } \ c \geq \bar{c}_0, \end{cases}$$

Counterfactual population shares:

$$\tilde{s}_{a,p',c,e} = \begin{cases} \phi_{a,p'}\,\psi_c & \text{if } \ c < \bar{c}_0 \\ \phi_{a,p'}\,\psi_{\bar{c}_0} & \text{if } \ c \geq \bar{c}_0, \end{cases}$$

$\phi_{a,p}$: population share of age-group a in year p

ψ_c: college share in cohort c

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A novel method for the aggregation of Gini coefficients

CDF of the Maximum Entropy distribution for given mean μ and Gini γ is given

$$F_{a,p,c}(y;\sigma,\rho) = 1 - \frac{1}{\sigma \exp(\rho y) + (1-\sigma)}, \quad y \geq 0$$

where

$$\mu_{a,p,c} = \frac{\log \sigma}{(\sigma - 1)\rho}$$

$$\gamma_{a,p,c} = 1 + \frac{1}{\sigma - 1} - \frac{1}{\log \sigma}$$

A novel method for the aggregation of Gini coefficients

We can construct population-level CDF as

$$\Phi_p = \sum_{a=a_1}^{a_n} s_{a,p} F_{a,p,c},$$

where $s_{a,p}$ is the population share of age-group a in period p.

We can then compute the population-level Gini coefficient in period p using

$$G_p = \Gamma(\Phi_p) = 1 - \frac{1}{\mu_p} \int_0^\infty \big(1 - \Phi_p(y)\big)^2 dy,$$

$$\mu_p = \int_0^\infty \big(1 - \Phi_p(y)\big) dy$$

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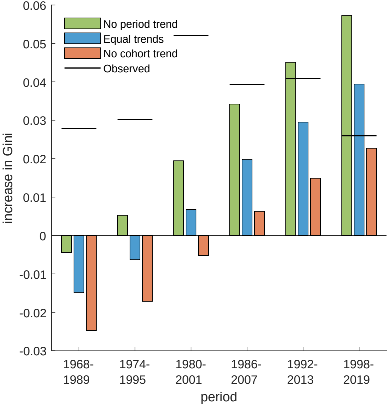
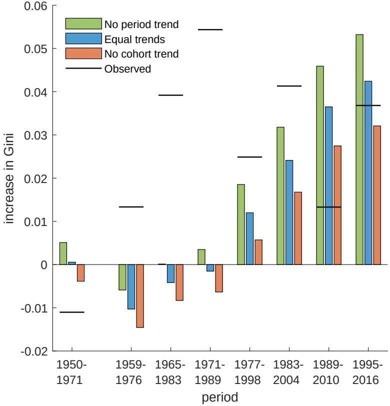
Demographic change and inequality in the past



(a) CPS



(b) SCF+

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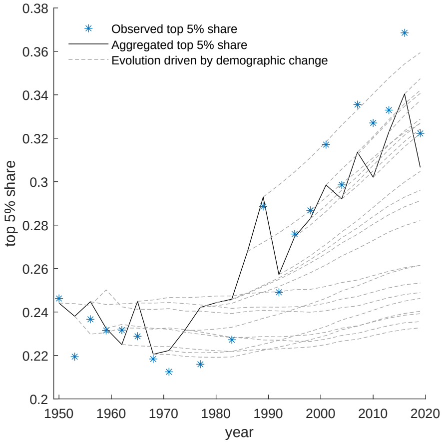
Top 5% income share



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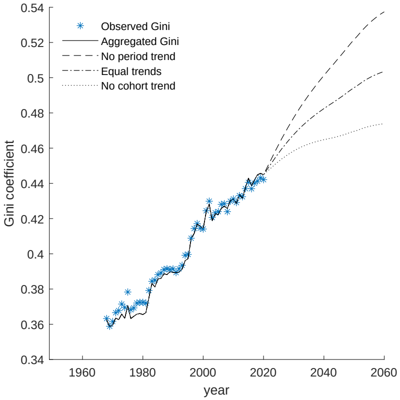
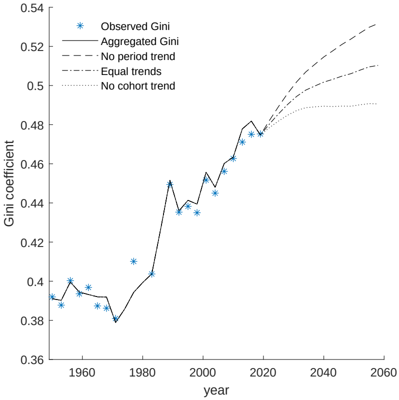
The role of demographic change in the future



(a) CPS



(b) SCF+

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Vintage predictions

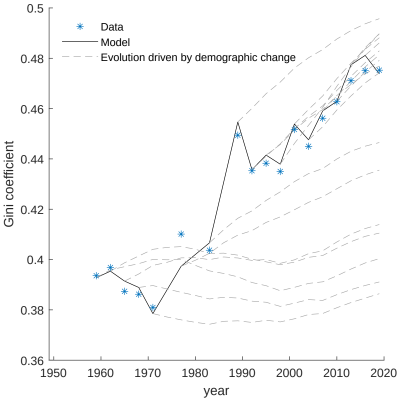

Figure 31: SCF+ data

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