The Life Cycle Dynamics of Wealth Mobility

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Wealth mobility over the life cycle

- Individual wealth histories result from many decisions and shocks
  - Human capital accumulation, homeownership, portfolio choices, entrepreneurship, etc.
- Wealth mobility matters:
  - Key to contextualize inequality. What makes some people rich and some poor?
  - Policy design (wealth tax, government insurance...) $+$ Public debate

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Today: Document patterns of wealth mobility across life cycle

Made possible by **Norwegian administrative data** on wealth+income 1993–2017

This paper

- Study individuals as they transition across the wealth distribution over their lives
  - Focus on individuals' (within-cohort) rank in wealth distribution
  - Look at persistence/change in wealth ranks
  - But: as many different histories as individuals
  - Use clustering techniques to find "typical" trajectories
- Study how our clusters relate to other observable characteristics
  - Housing, civil status, portfolio composition, etc.
  - To which extent do individual characteristics at age 30 predict future trajectories?

Main findings

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   - Wealthy, Poor, Middle Risers and Middle Fallers clusters $\rightarrow$ reveal segmented mobility
   - Income is higher for Wealthy and Risers, but not enough to explain wealth differences
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3. Individual circumstances help to predict trajectories
   - Parental background: key determinant of Wealthy/Poor
   - Education: key determinant of Risers/Fallers

Contributions

1. New evidence on wealth mobility and wealth accumulation: Full life cycle trajectories
   - Add to results for the super wealthy (Ozkan, Hubmer, Salgado, Halvorsen) and the role of individual factors like inheritances (Black, Devereux, Landaud, Salvanes).
2. New facts documenting the distribution of changes in wealth ranks
   - Extensive literature on income (Guvenen, Ozkan, Karahan, Song; Guvenen, Pistaferri, Violante; Arellano, Blundell, Bonhomme; De Nardi, Fella, Paz-Pardo)
3. Intergenerational links to full life cycle wealth dynamics
   - Complements "snapshot" links in income (Solon; Aaronson, Mazumder; Chetty, Hendren, Kline, Saez, Turner; Chetty, Grusky, Hendren, Hell, Manduca, Narang) & wealth (Charles, Hurst; Boserup, Kopczuk, Kreiner; Fagereng, Guiso, Malacrino, Pistaferri; Fagereng, Mogstad, Rønning)
4. Dimension reduction methods in economics & applications to labour markets
   - K-Means (Bonhome, Lamadon, Manresa; Gregory, Menzio, Wiczer),
     Sequence Analysis (Humphries), Hidden Markov (Ahn, Hobijn, Şahin), Finite Mixture

Norwegian Wealth Data

Data: Norwegian Tax Registry 1993 – 2017 ▸ Context

- No top-coding + Limited misreporting or measurement error (third-party reporting)
  - Focus on wealth (e.g., don't include public pensions)
  - No transaction data (e.g., changing houses or selling stocks)
- We adjust the tax value to reflect market values (Fagereng, Holm, Torstensen, 2023)
- We link to administrative records (Education, Family, Civil Status, Income)
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Sample selection: Norwegian residents 1993–2017 (no immigrants after 25/2011, no emigrants)

- Focus on birth cohort born between 1960 and 1965 (first observed in early 30s)
  - 292,222 individuals in this sample (279,002 after balancing)

Ranks and Histories

- Compute within cohort ranks as

$$y_{i,t} = 100 \times F_w\left(w_{i,t} \middle| t, i \in BC(i)\right)$$

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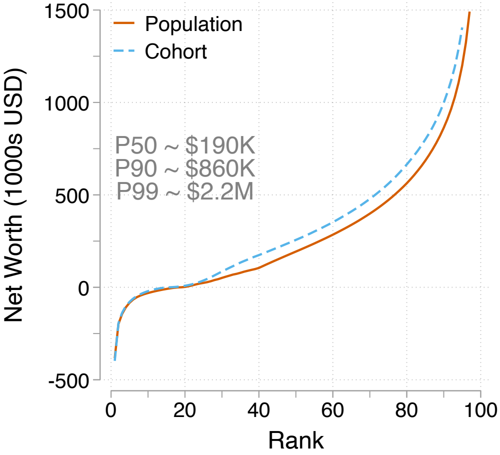
- Trajectories: Histories of ranks

$$\mathbf{Y}_i = \left(y_{i,1993}, y_{i,1994}, \ldots, y_{i,2016}, y_{i,2017} \right) \in [0, 100]^{25}$$

We are interested in the distribution of the trajectories $\mathbf{Y}_i$

Ranks vs Wealth Levels

Net Worth CDF (2014)

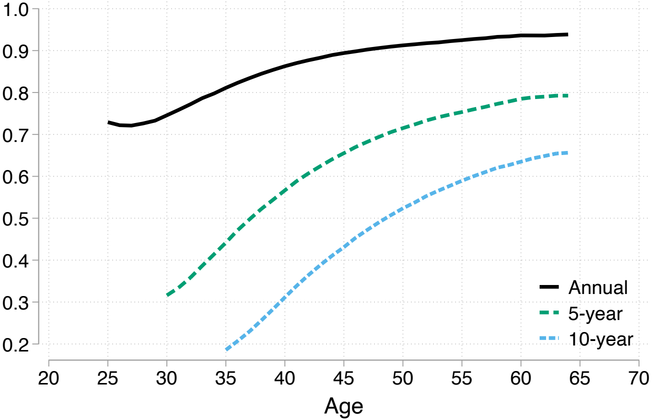


- Substantial wealth inequality in Norway
- Meaningful differences in wealth levels across ranks
- e.g. at the median, 10 ranks $\approx$ 60k USD

▸ BC vs Pop Ranks

- US: p90≈$620K, p99≈$3.5M (SZZ, 2022)

Persistence of Wealth Ranks

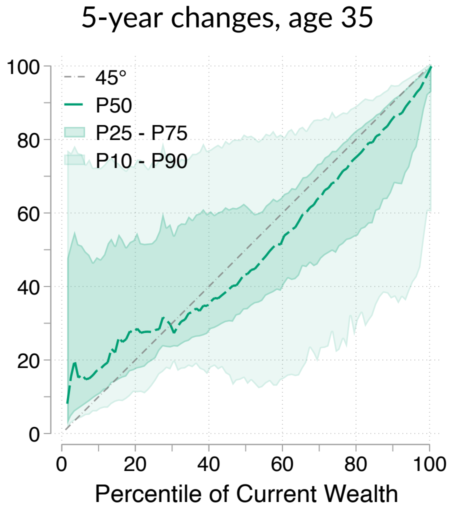


Linear persistence measures:
$$y_{i,t} = \alpha_t(h) + \rho_t(h) y_{i,t-h} + u_{i,t}$$

- 5y, 10y persistence much higher than implied by 1y persistence

AR(1) Income

How Non-Linear is Wealth Mobility?



Measure conditional moments, $E\left[y_{i,t+h} | y_{i,t}\right]$, and quantiles, $Q_{y_{i,t+h}|y_{i,t}}(\tau)$

- Substantial mobility at 5-year horizon
- Dispersion $\downarrow$ with age (consistent with evidence on income) and initial rank
- Mean reversion weakens at the top
- Dist. of 5y and 10y changes are similar (despite $\uparrow$ in dispersion from 1y to 5y)

Incomplete picture:
Move to study complete life-cycle histories

Moments Quantiles

Clustering Wealth Histories

Grouping Individuals Into Typical Histories

Goal: Identify patterns in (ex-post) life cycle paths without restricting to a single statistic

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Method: Agglomerative Hierarchical Clustering to group rank histories

- Start with $G = N$ groups (one for each individual)
- Recursively merge groups by selecting *similar* pairs: $\underset{g,g' \in G,\, g \neq g'}{\operatorname{argmin}} \; d(g, g')$.

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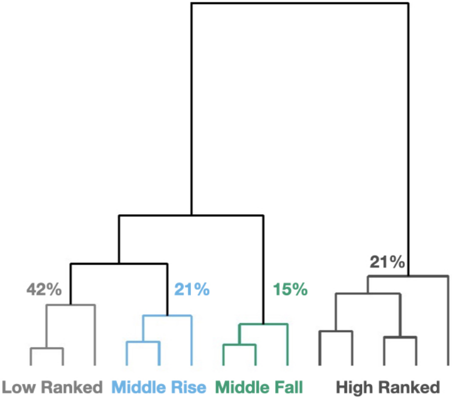
Result: Hierarchy of partitions ranging from $G = N$ to $G = 1$.

- Global result with nested clusters
- Similar results for alternative clustering (HH ranks, log-assets, "Lorenz" position, K means)

Two Levels of Clustering

Clustering Tree



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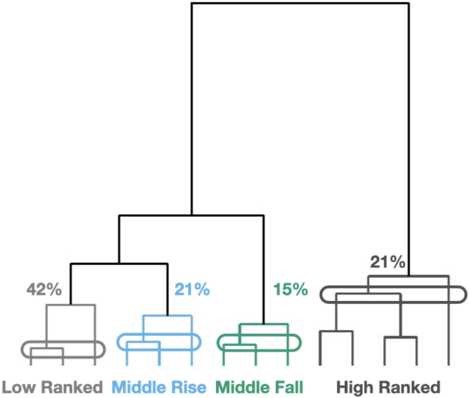
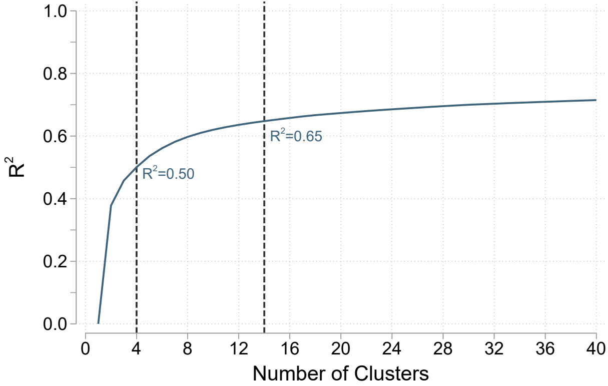
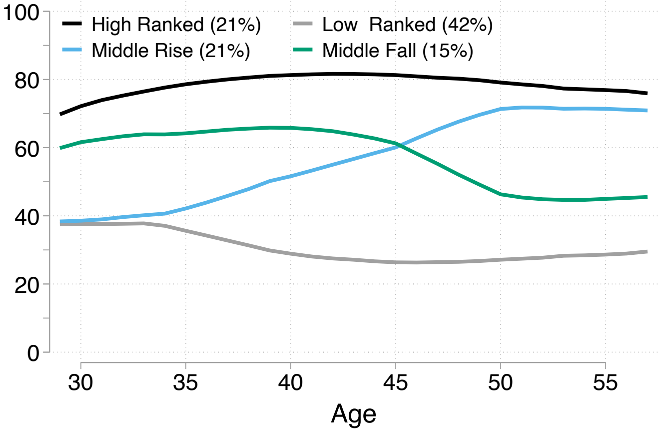


Variation Explained



Typical Rank Histories

Cohort Ranks



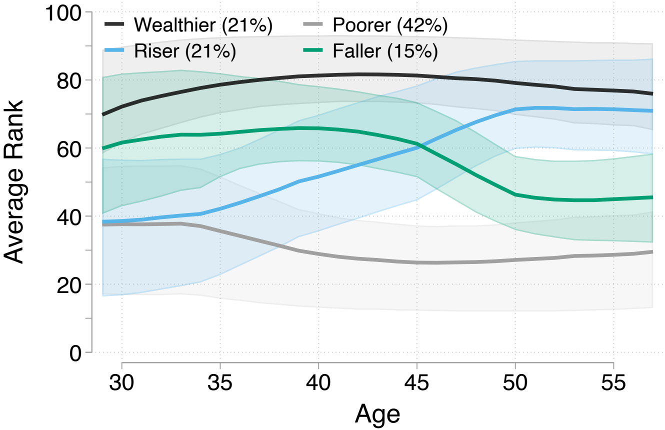
Four largest groups

- Wealthy/High Ranked: always at top of the distribution
- Poor/Low Ranked: always at the bottom of the distribution
- Middle class: one group of Risers and one group of Fallers

▸ Alt. Clustering ▸ HH Ranks ▸ Rnd Clustering ▸ Rank Dist.

Typical Rank Histories

Cohort Ranks, interquartile range

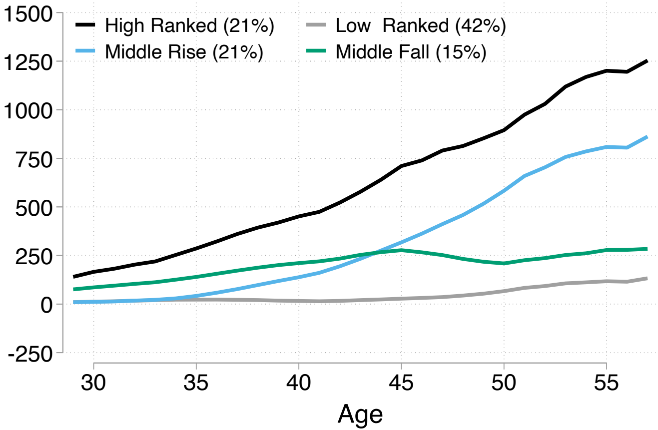


Segmented mobility

- Individuals move within segments of the distribution
- The mean trajectory of a group hides rank swaps within
    - Subclusters reveal patterns
- Segments overlap: Middle 60% Top & Bottom 40%

Wealth Histories Across Segments of the Distribution

Net Worth ($1000s)

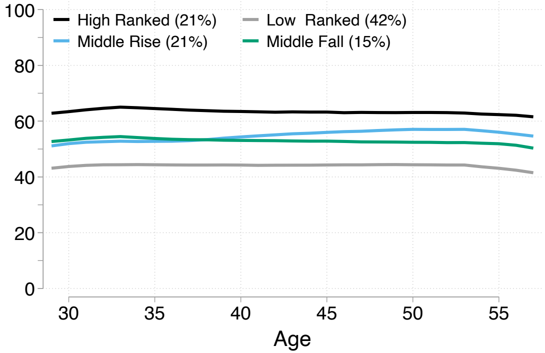


Significant diff. in wealth profiles

- Top: Maintaining rank means level growth (8-10%)
- Bottom: Stay very low
- Risers: Grow on avg. 18%/y
- Fallers: ahead in 30s + low growth (5%) + Great Recession

Income Histories Across Segments of the Distribution

Income Cohort Ranks



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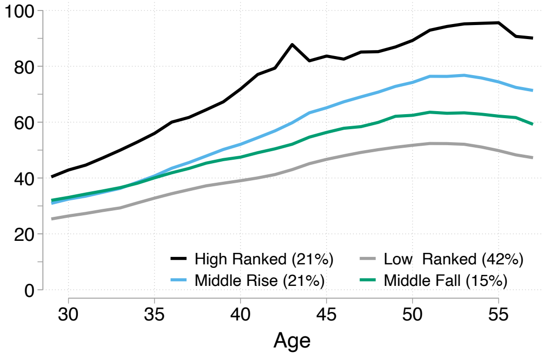
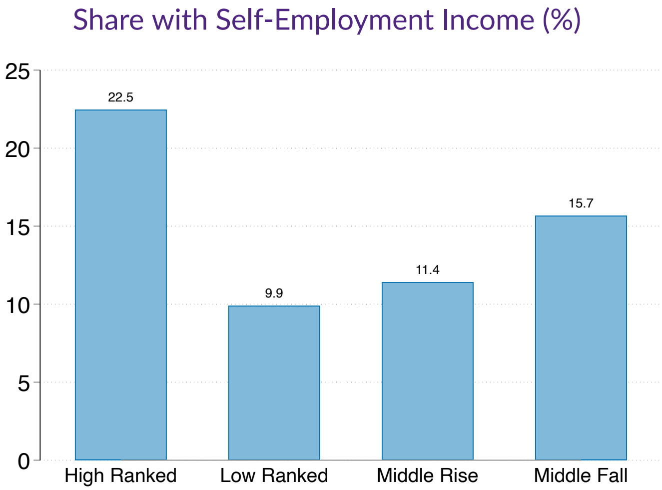


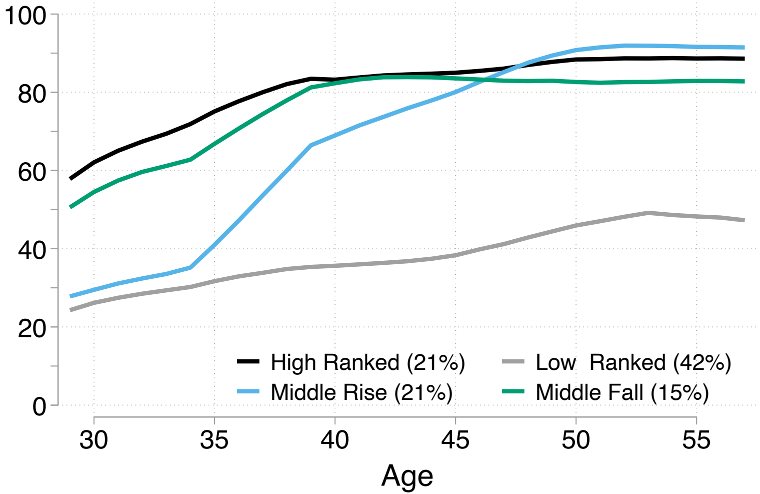
- Distribution of income across clusters compressed relative to wealth ▸ Median Income
- Similar patterns for HH income; Risers same inc. as high ranked on average ▸ HH Inc. CS

Self-Employment Rates, Age 45



▸ Income shares

Homeownership Rates by Cluster



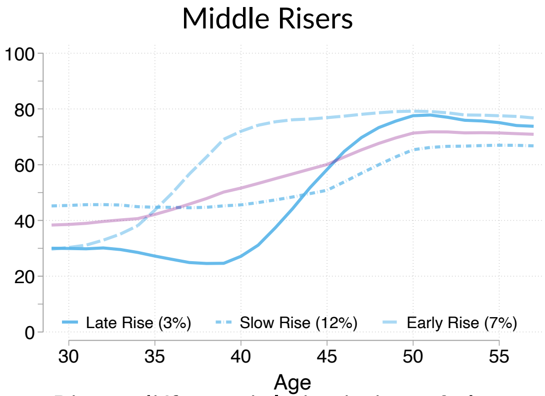
▸ Asset Portfolios

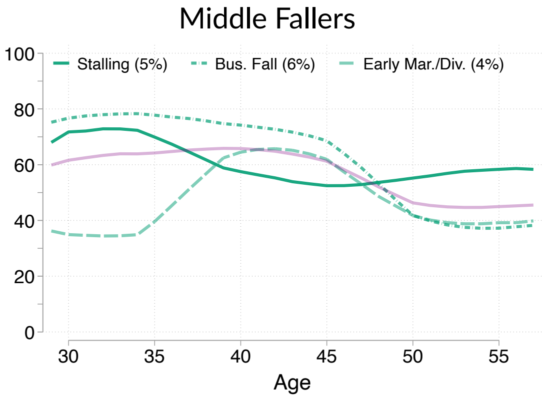
Taking stock: four largest clusters

- Wealthy - High Ranked
  - Stable at the top
  - Accumulate wealth fast
  - Homeowners, likely to own businesses
  - Largest labour market income
- Risers
  - Start out low
  - Accumulate wealth fast
  - Income similar to Wealthy
  - Become homeowners along the way
- Fallers
  - Start out relatively well off
  - Relatively lower labour market income
  - Likely to be self-employed
  - Usually own assets
- Poor - Low Ranked
  - Stuck at the bottom
  - Little rise at the end
  - Lowest incomes
  - Non-homeowners

Heterogeneity in Trajectories

▸ Wealth ▸ Portfolio ▸ Homeownership ▸ Inc. ▸ SE ▸ Edu.





- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)

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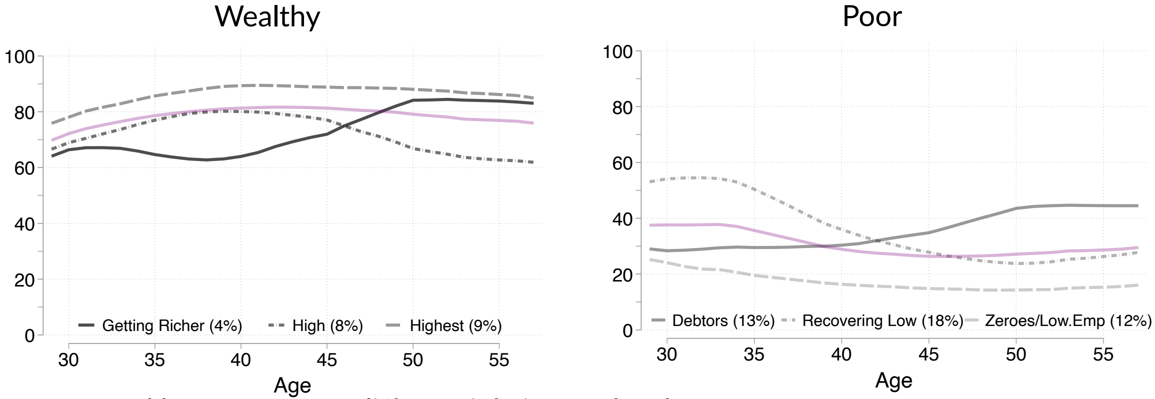

- Top and bottom groups differ mainly in avg. levels

- Zeros are quite different from debtors

Next Step: Relate differences in timing/level to individual circumstances

Towards Determinants of Trajectories

Hereditary Advantage vs Human Capital

Goal: Understand role of different circumstances/characteristics in determining trajectories

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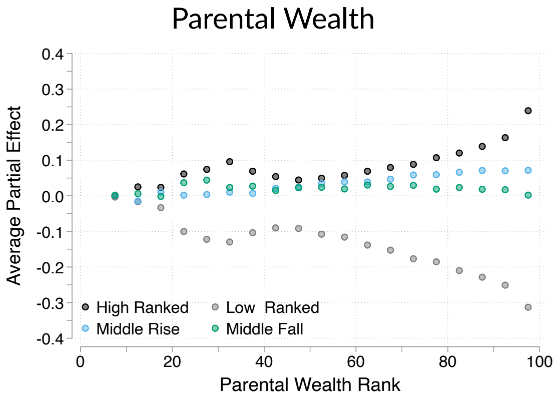
Predictors explain at most 6% of cross-group variation (same as rank-rank inter-gen reg) ▸ Results

Non-Linear Effects of Parental Wealth and Education

PW CIs ED CIs ED Field



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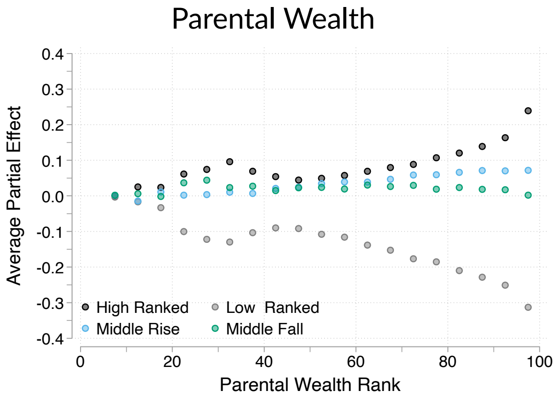

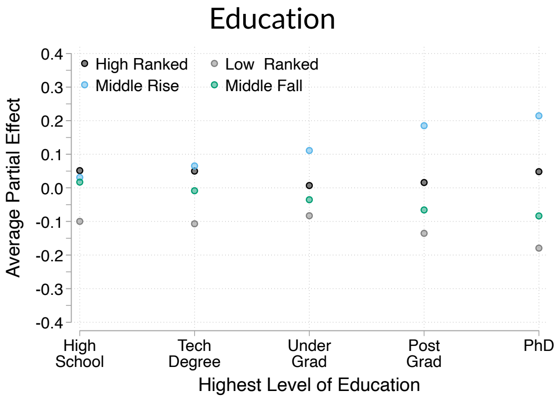

- Parental wealth's explanatory power: High for top/bottom, limited for middle groups
- Education tells risers/fallers apart: Equalizing effect but doesn't overcome initial cond.

Heterogeneity and Robustness

- Robust to controlling for individuals' initial wealth rank + parent portfolio (1993)
  - $\downarrow$ Effect sizes by 25-40% (+ explained variation)
  - $\uparrow$ Overall variation explained ($\times$4)
  - Driven by own initial wealth $\Rightarrow$ consistent w/ segmentation!

▸ APE ▸ Shapley-Owen

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- Patterns across sub-clusters:
  - Education and Parental Wealth explain risers and fallers within segments

▸ High Ranked ▸ Low Ranked ▸ Middle Rise ▸ Middle Fall

Conclusions

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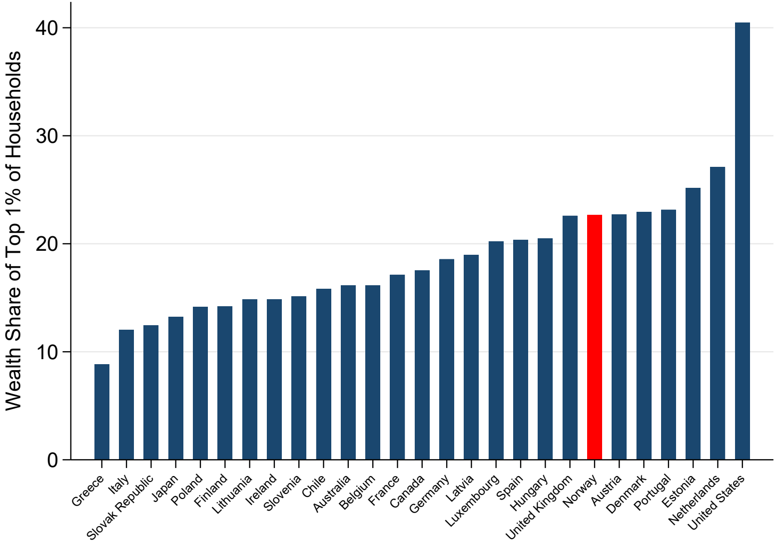
- Document persistence of wealth over the life cycle
- Characterise non-linear persistence and mobility
  - Top of the distribution cushioned against falls
- Uncover typical trajectories of individuals through the wealth distribution
- Intergenerational background an important predictor of whole history
- Education is key for movements through the wealth distribution

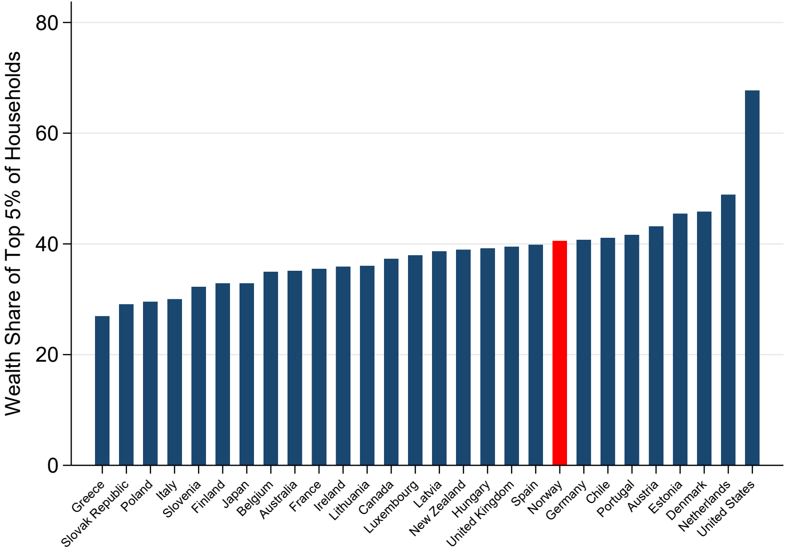
Extra

Norway in Context ◂ Back

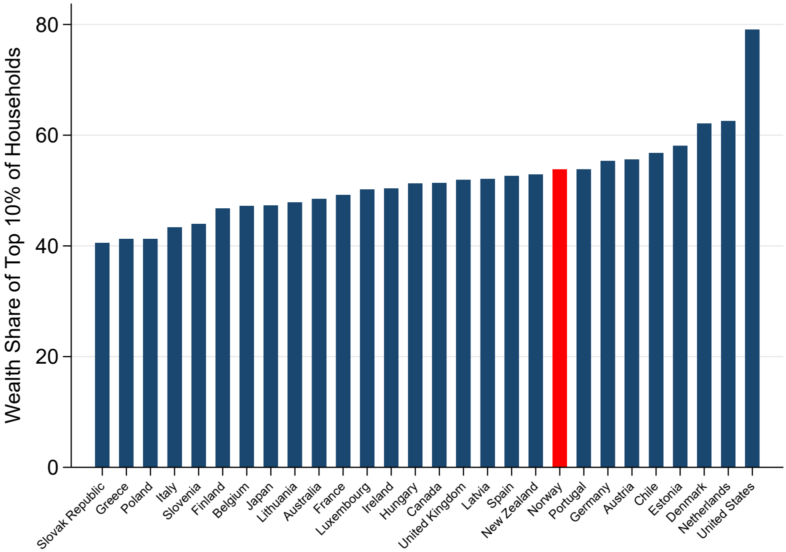


Norway in Context: Top 5% Share

Back

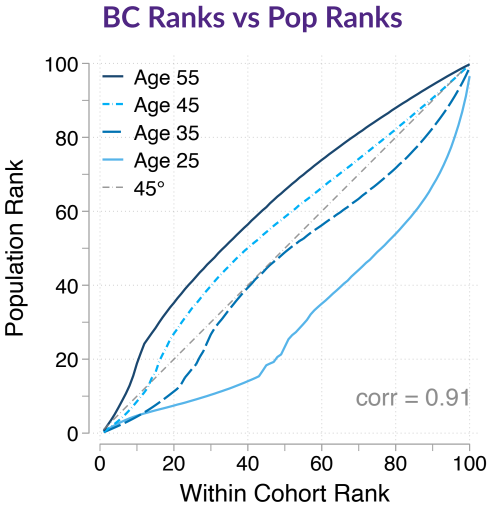


Norway in Context: Top 10% Share ◂ Back



Birth Cohort Ranks vs Population Ranks

back

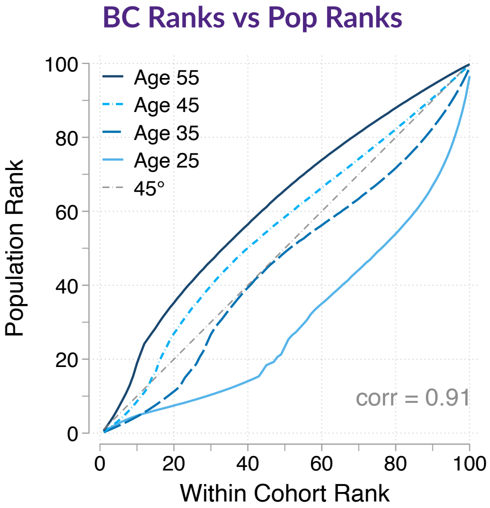


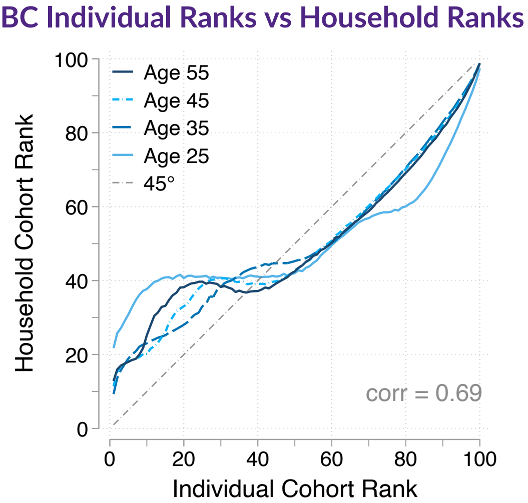
- Changes in wealth levels at each rank as the cohort ages
- 75 percent of age 25 individuals are below the median
- 35 percent of age 55 individuals are below the median

Household Ranks

Birth Cohort Individual Ranks vs Household Ranks

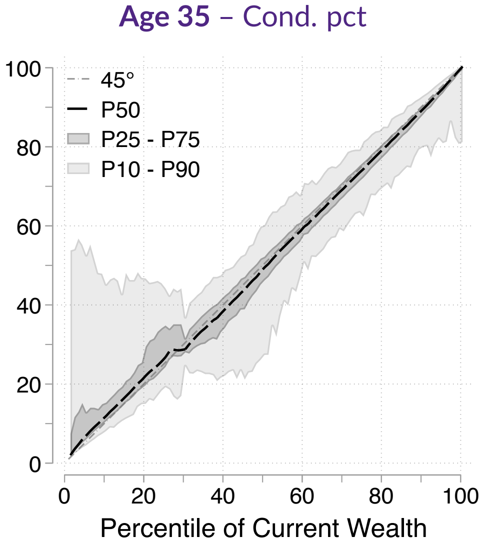
back

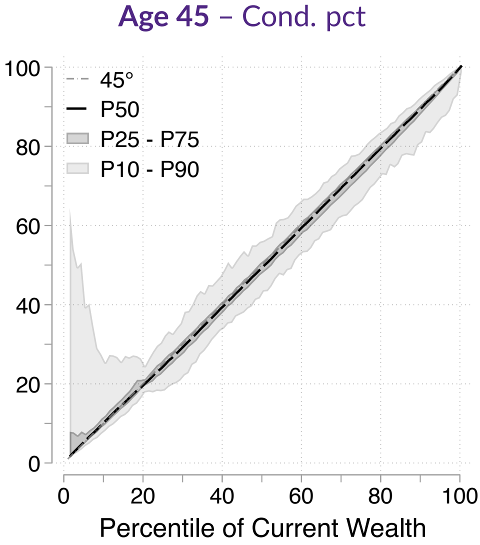




Conditional Distribution of Rank Changes

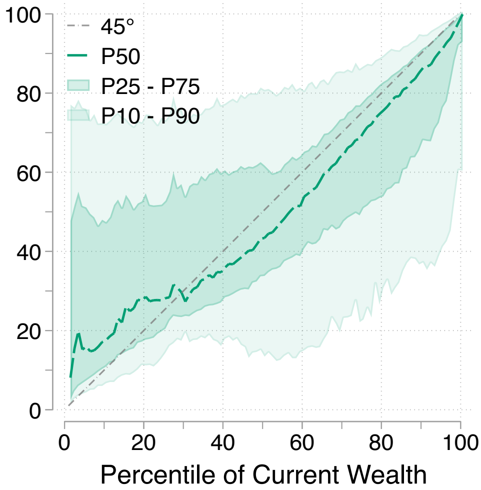
The Distribution of Rank Changes (1-year) Back



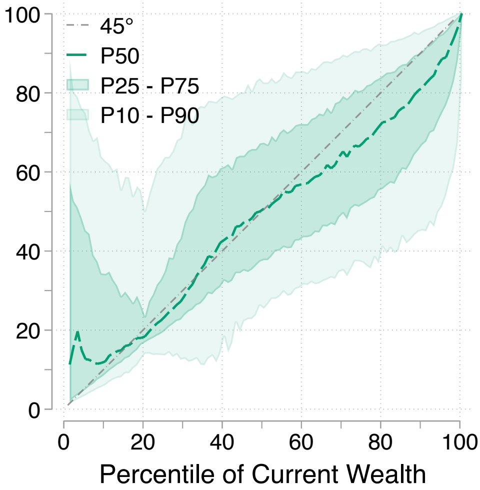


The Distribution of Rank Changes (5-year) ▸ Back

Age 35

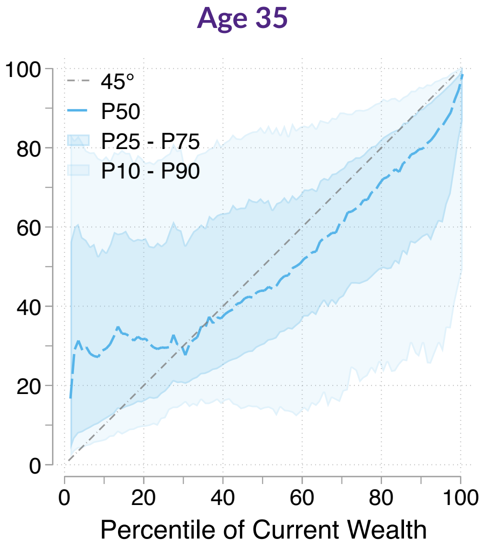


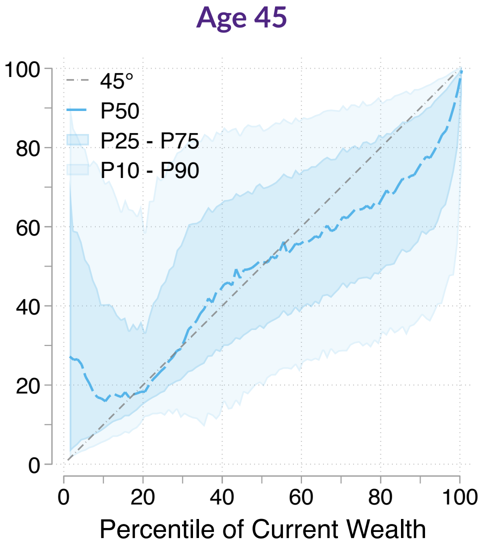
Age 45



At the top few fall, but cushioned Middle class rarely climb, but some fall

The Distribution of Rank Changes (10-year) ◂ Back

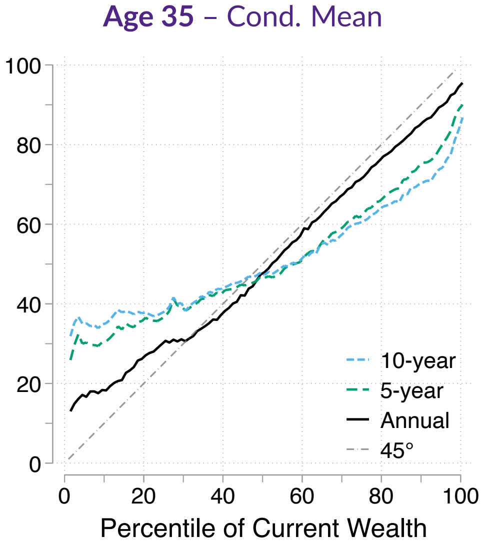


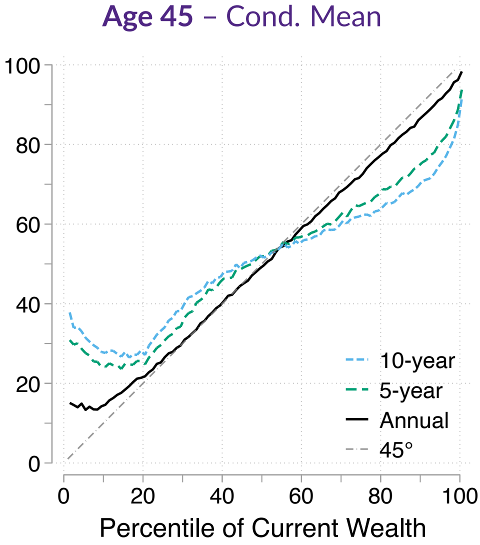


Over longer horizons more evenly spread and dispersion growing

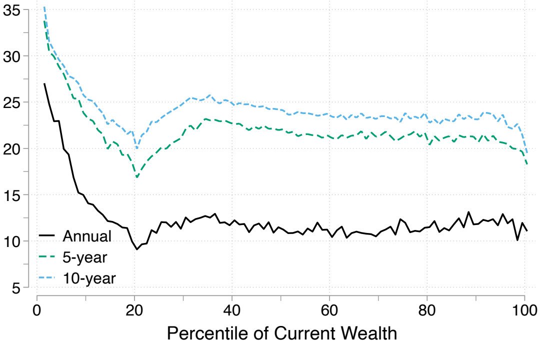
Conditional Moments of Rank Changes

Rank Changes: Average ◂ Back



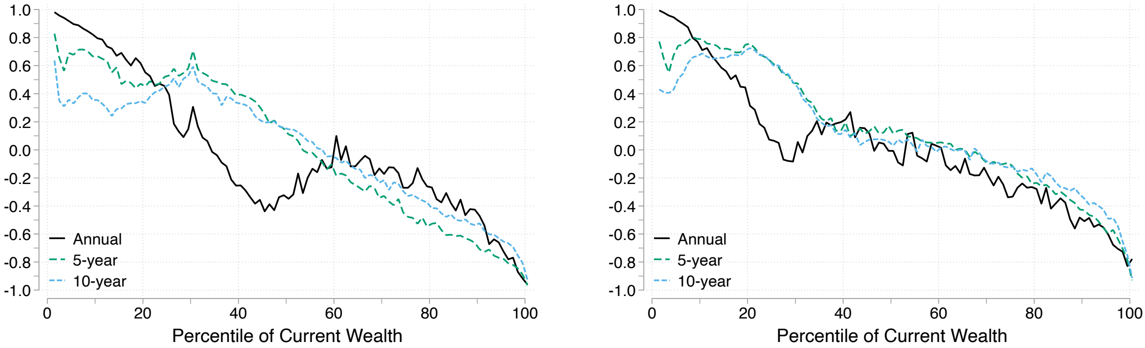


Rank Changes: Standard Deviation ◂ Back



- Dispersion grows slowly with time horizon
- Dispersion level depends (asymmetrically) on rank: Lower dispersion at the top!

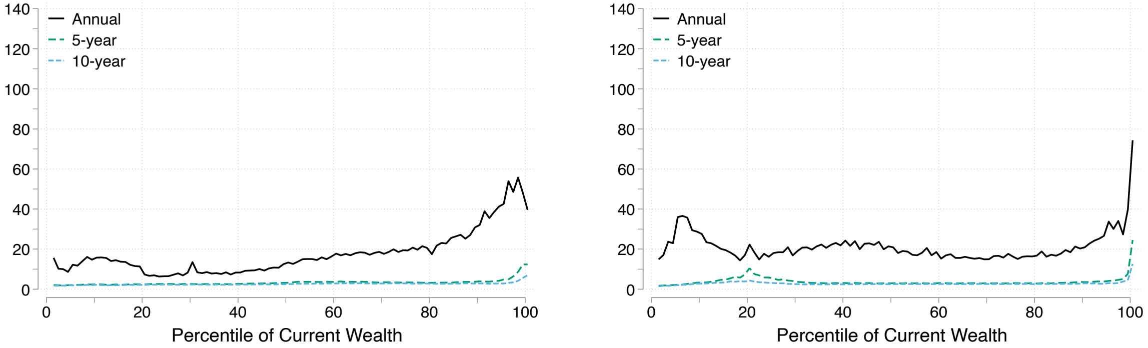
Rank Changes: Skewness ◂ Back



- Skewness decreases by construction

- Changes in ranks: No way to go but up/down for low/high ranks

Rank Changes: Kurtosis Back

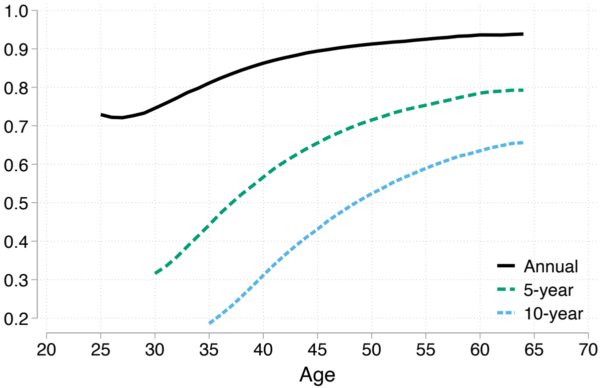


- Distribution of rank changes is *leptokurtic*
- Most individuals experience small changes with some individuals having large changes
- Holds across ranks but is particularly so at short horizon (1y) and upper tail

Persistence of Ranks

Persistence in Wealth Rank: Higher at long-run ▸ 1960bc ◂ Back

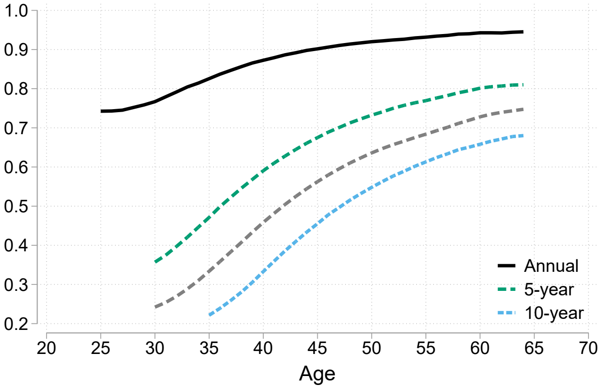
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



- Annual persistence is slow to stabilize, but eventually high ($\rho_t(1) \approx 0.95$)

Persistence in Wealth Rank: Higher at long-run ▸ 1960bc ◂ Back

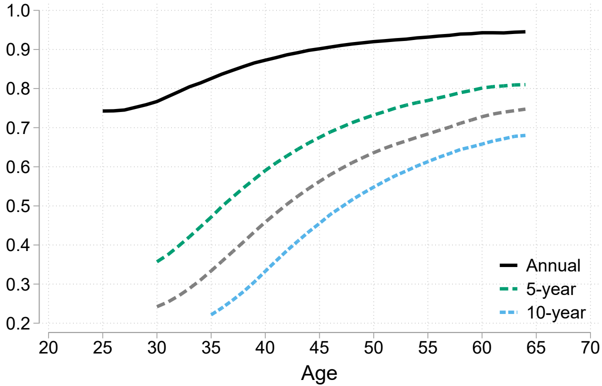
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



- **5y Iteration bias:** 5y Persistence higher than implied by annual ρ

Persistence in Wealth Rank: Higher at long-run ▸ 1960bc ◂ Back

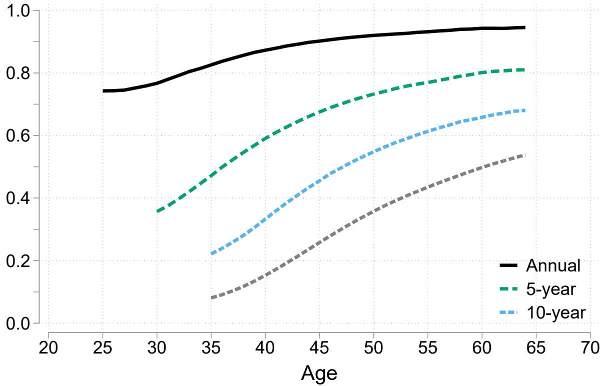
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



- **5y Iteration bias:** 5y Persistence higher than implied by annual ρ
- Life cycle snapshots can be misleading! Short-run mobility $\gg$ Long-run mobility

Persistence in Wealth Rank: Higher at long-run ▸ 1960bc ◂ Back

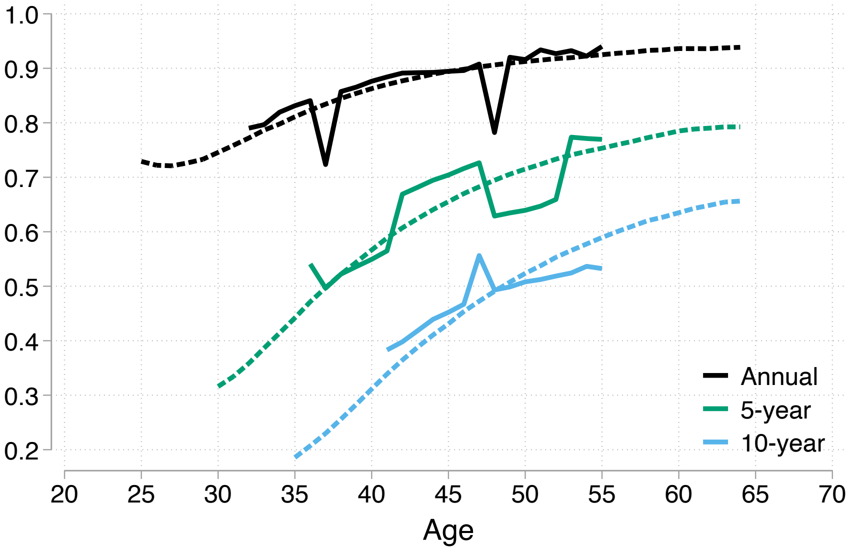
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



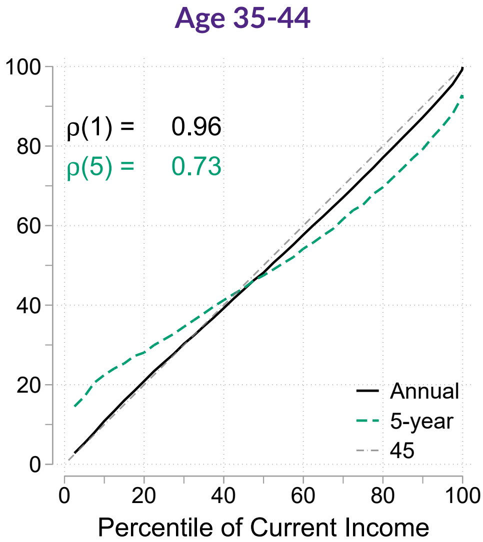
- **10y Iteration bias:** Dramatic bias! Actual $\rho(10)$ is 50-250% implied persistence
- Life cycle snapshots can be misleading! Short-run mobility $\gg$ Long-run mobility

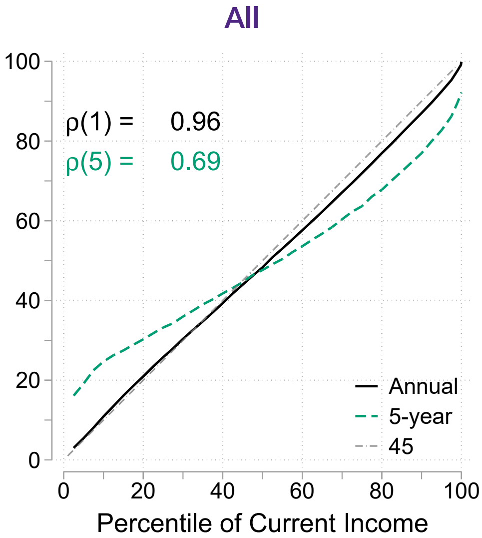
Persistence in Wealth Rank: Within Cohort ◂ Back

All Cohorts vs 1960-1964 Birth Cohort



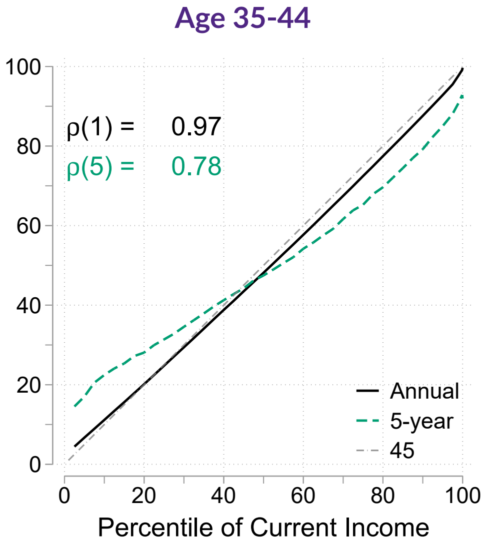
How Non-Linear is Income Mobility in Norway? Back USA

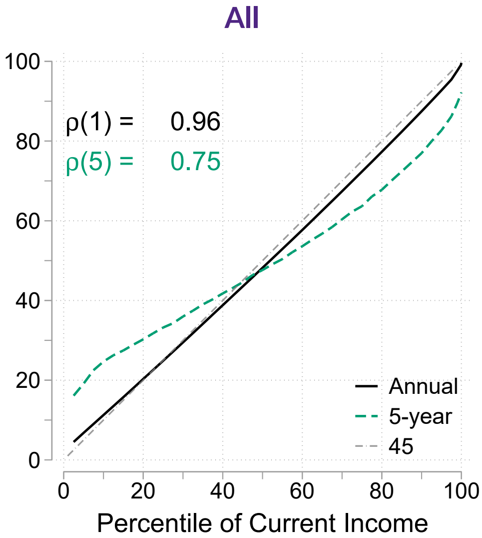




Source: GRID database for 2005

How Non-Linear is Income Mobility in the U.S.? Back





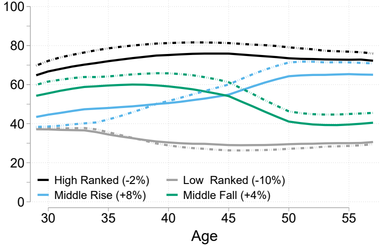
Source: GRID database for 2005

Characteristics of Main Clusters

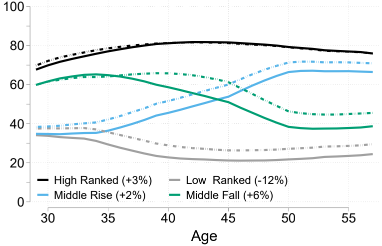
Alternative Clustering

Back

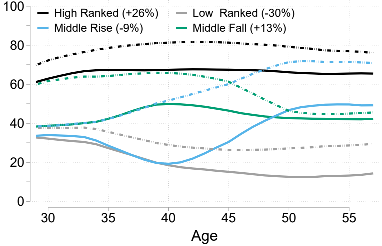
Household Cohort Ranks



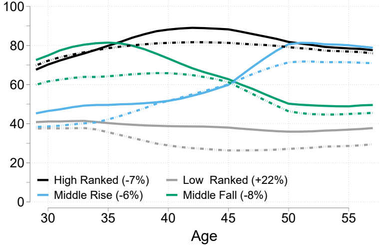
K Means on Ind. Cohort Ranks



Log Net Worth



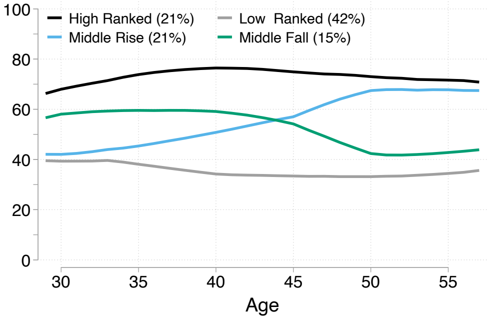
“Lorenz” Ordinates



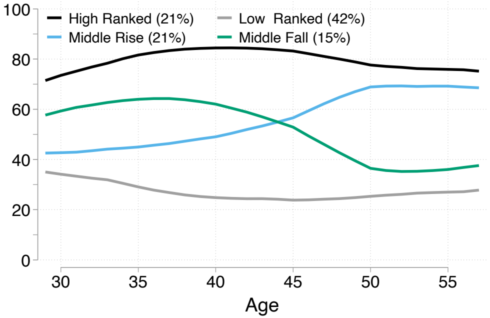
Household Wealth Ranks

Back

Household Cohort Ranks (Ind. CI)

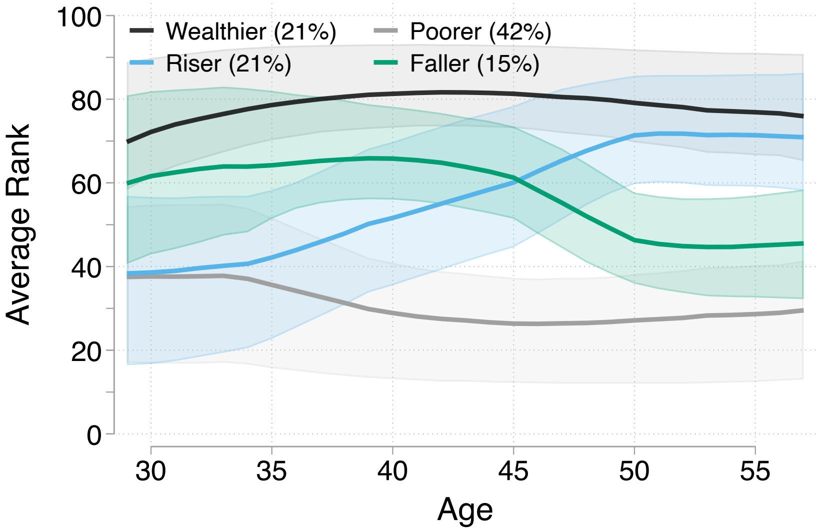


Household Cohort Ranks (HH. CI)



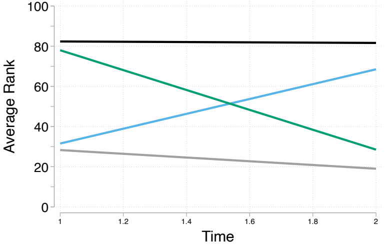
Distribution of Trajectories by Cluster

Back

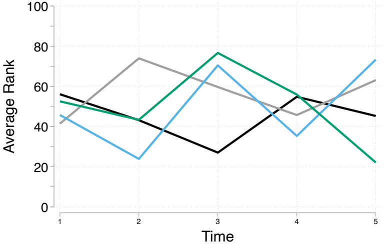


Clustering Random Ranks ◂ Back

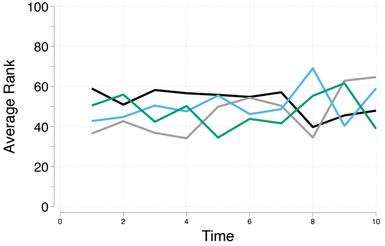
2 Periods



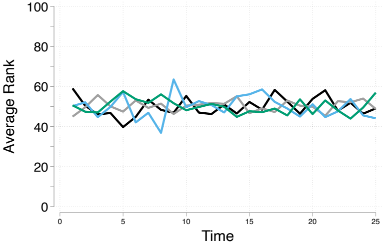
5 Periods



10 Periods

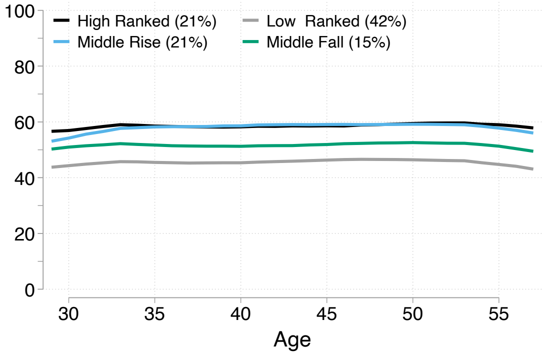


25 Periods

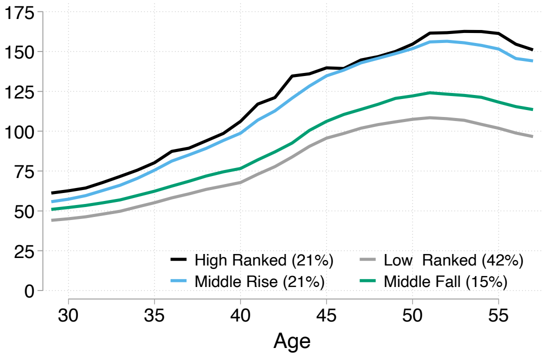


Household Income ◂ Back

Household Income Cohort Ranks



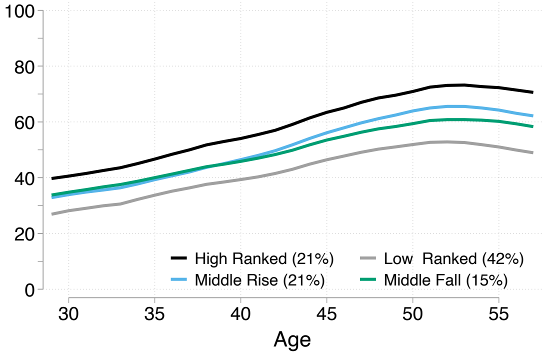
Household Income ($1000s)



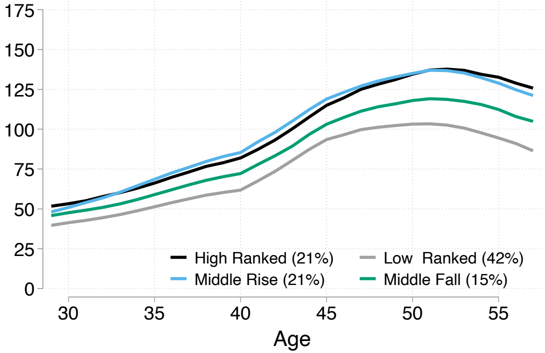
Median Income Histories

Back

Median Income

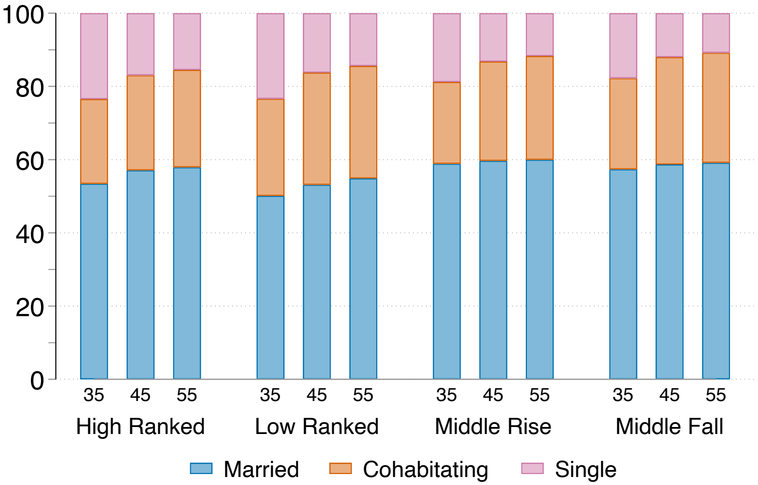


Household Median Income ($1000s)



Civil Status

Back



Portfolio and Income Composition
Back

Income Sources

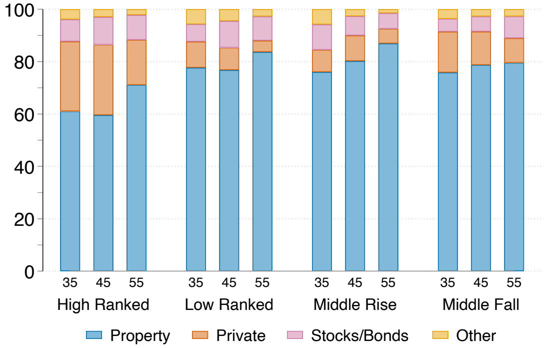
- Income differences in Self-Employment and Capital

SE Transfers Gifts

Portfolio and Income Composition ◂ Back

Income Sources

Asset Portfolio

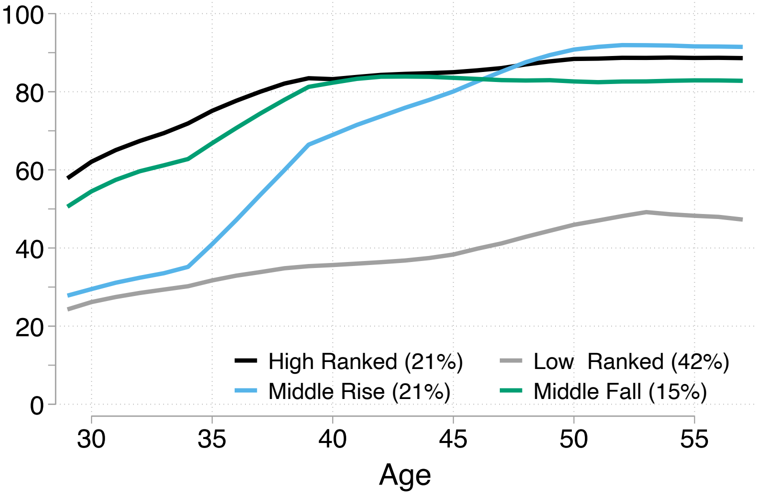


- Income differences in Self-Employment and Capital

▸ SE ▸ Transfers ▸ Gifts

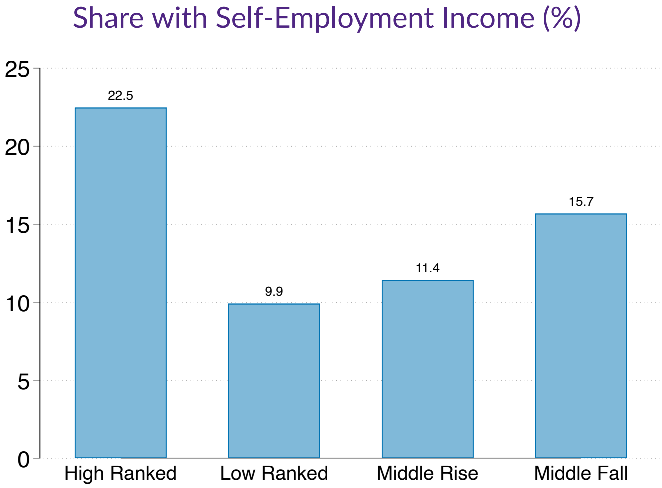
- Asset differences across clusters in Private Equity and Property

Home-ownership Rates by Cluster ◂ Back



Self-Employment Rates, Age 45

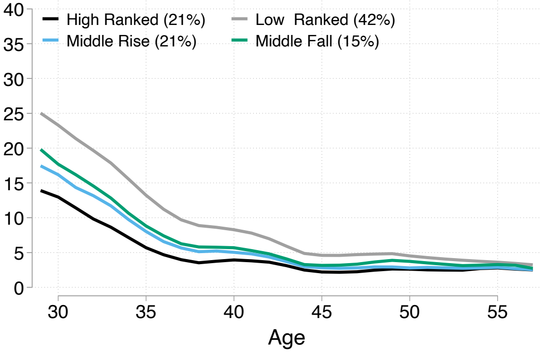
Back



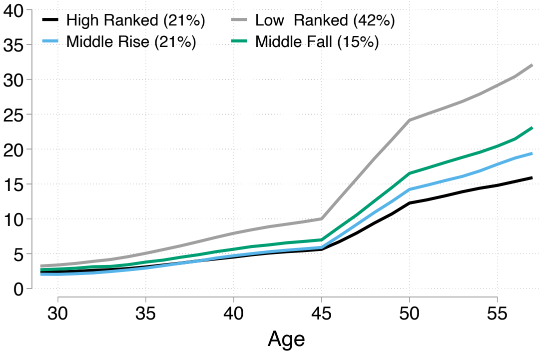
Transfers: Unemployment, Disability, Sick Leave, Nursing

Back

Share with Unemployment Benefits (%)

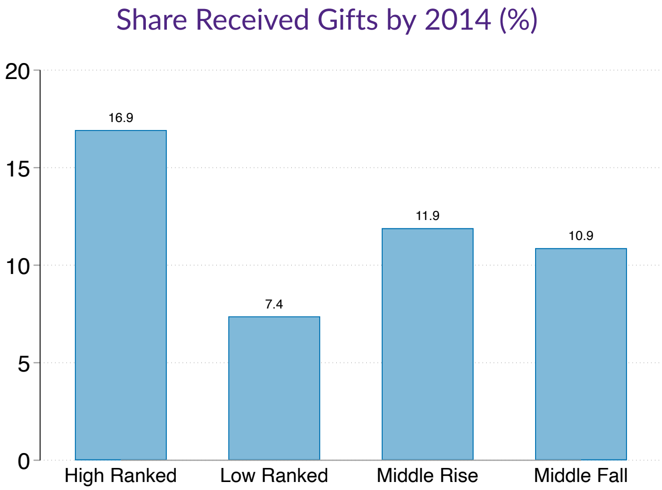


Share with Health-Related Transfers (%)



Lifetime Inheritances and Gifts

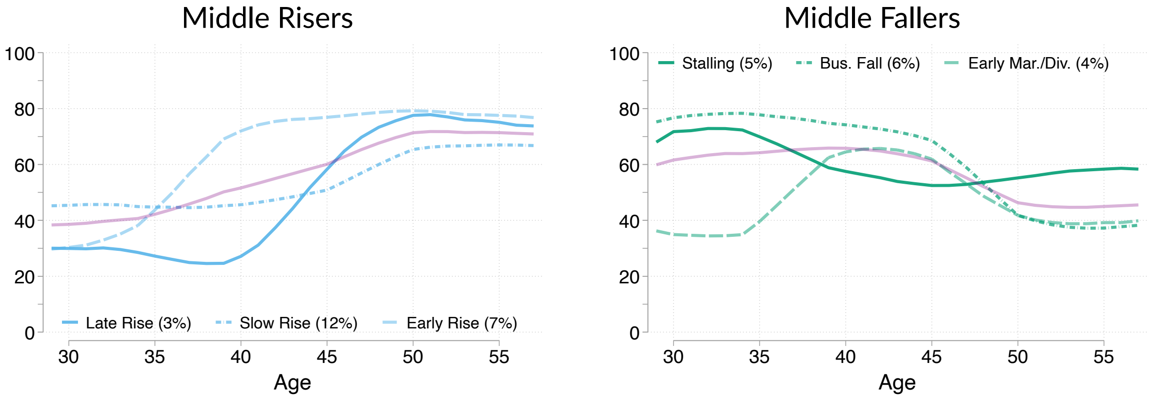
◂ Back



Notes: Total received $>$ NOK 470K ($\approx$ \$47K) before 2014

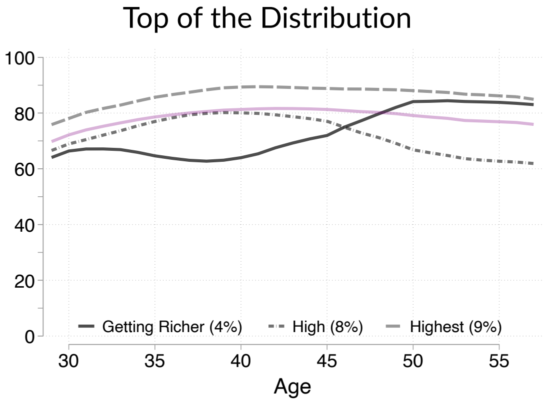
Characteristics of Sub-Clusters

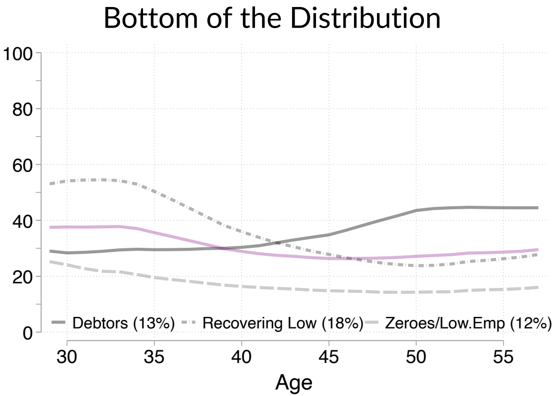
Heterogeneity in Trajectories: Levels vs Timing ◂ Back



- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)

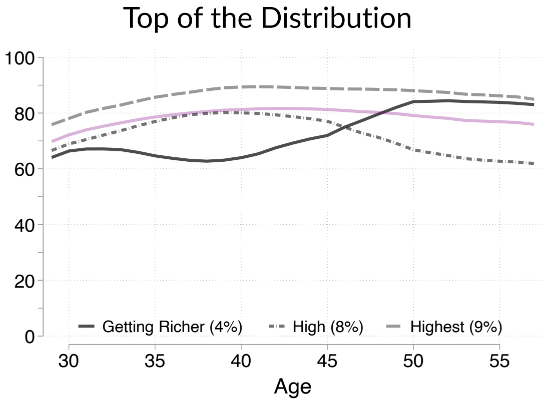
Heterogeneity in Trajectories: Levels vs Timing Back

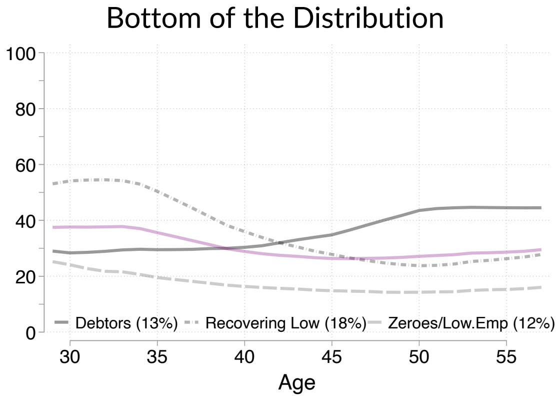




- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)
- Top and bottom groups differ mainly in avg. levels (with a rising sub-group in each)

Heterogeneity in Trajectories: Levels vs Timing ◂ Back





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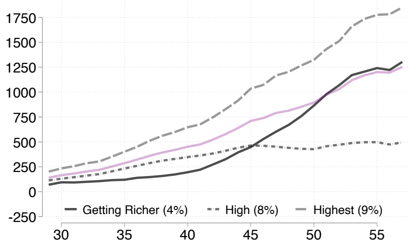
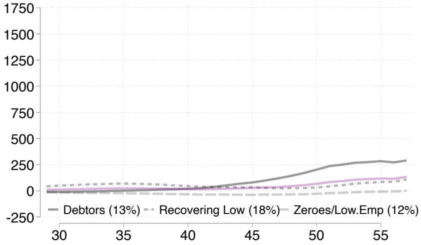
Sub-Clusters: Wealth Levels

Back

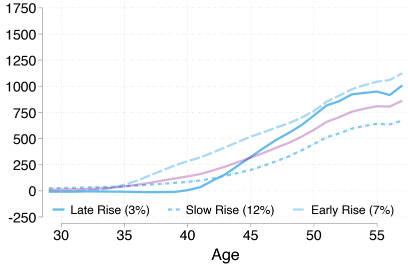
High Ranked



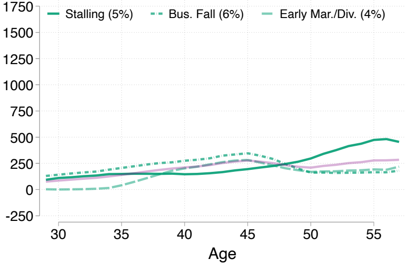
Low Ranked



Middle Risers



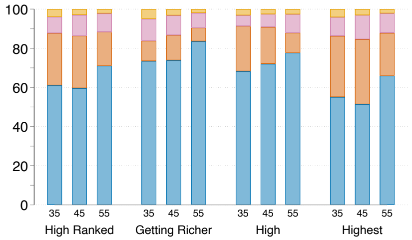
Middle Fallers



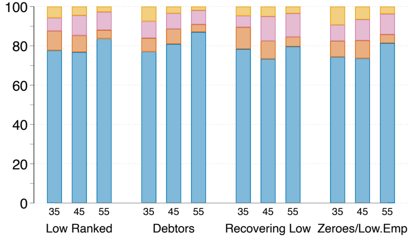
Sub-Clusters: Portfolio

Back

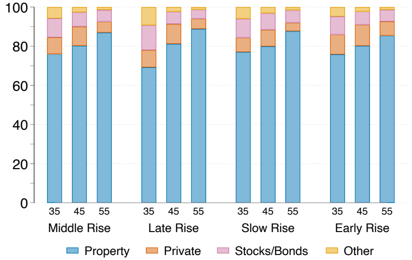
High Ranked



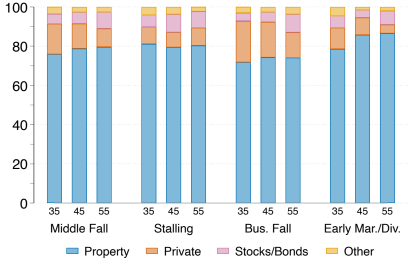
Low Ranked



Middle Risers



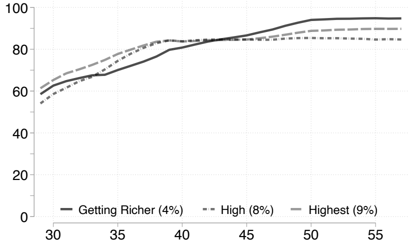
Middle Fallers



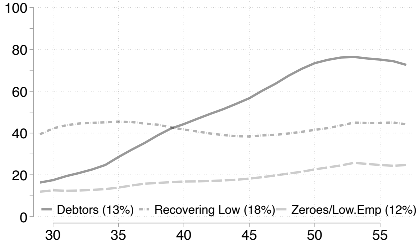
Sub-Clusters: Homeownership

Back

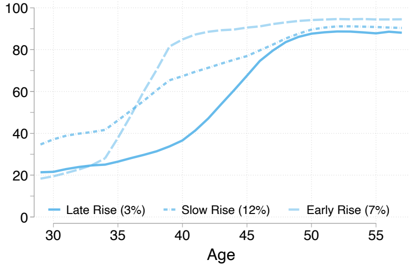
High Ranked



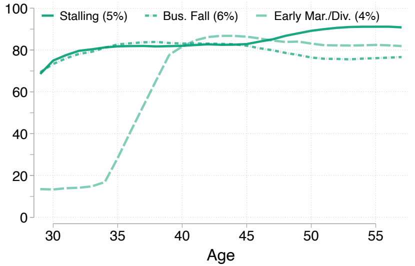
Low Ranked



Middle Risers



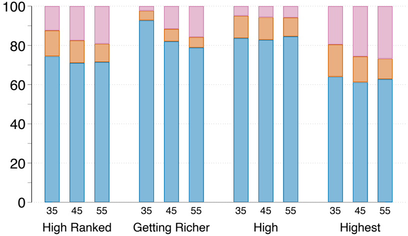
Middle Fallers



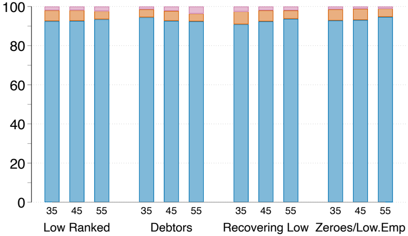
Sub-Clusters: Income Composition

Back

High Ranked



Low Ranked



Middle Risers

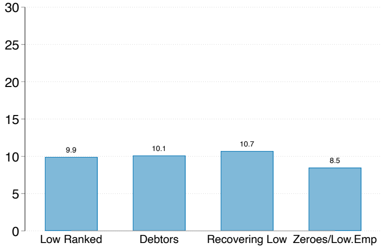
Middle Fallers

Sub-Clusters: Self-Employment

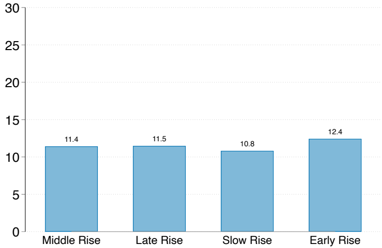
Back

High Ranked

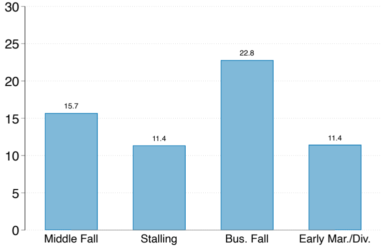
Low Ranked



Middle Risers



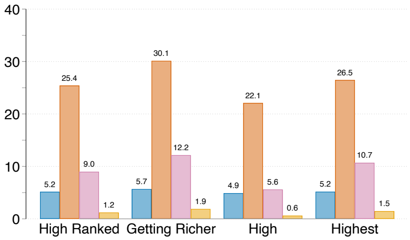
Middle Fallers



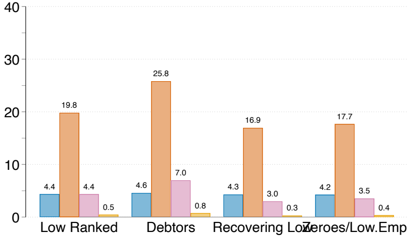
Sub-Clusters: Education

Back

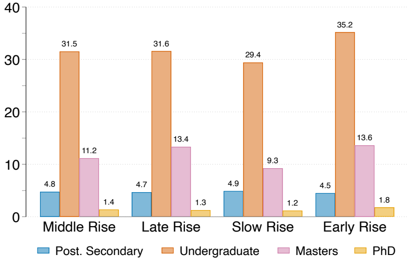
High Ranked



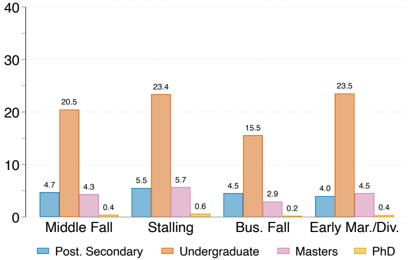
Low Ranked



Middle Risers



Middle Fallers



Shapley-Owen Decomposition

How Important Are Ex-Ante Explanations? Back

Two measures:

1. Distance Weighted Classification Rate $\in [0, 1]$

$$1 - \frac{\sum_{i=1}^{N} \sum_{k=1}^{G} \widehat{Pr}(g = k | X_i) D(g(i), k)}{\sum_{i=1}^{N} \sum_{k=1}^{G} \widehat{Pr}(g = k) D(g(i), k)} \qquad \left(\text{in spirit of } \frac{ESS}{TSS}\right)$$

How Important Are Ex-Ante Explanations? Back

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2. Correct Classification Rate $\in [0, 1]$

$$\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{G} \widehat{Pr}\,(g = k \mid X_i)\ \mathbb{1}[g(i) = k]$$

How Important Are Ex-Ante Explanations? Back

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$$\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{G} \widehat{Pr} \, (g = k \mid X_i) \; \mathbb{1}[g(i) = k]$$

- Report Shapley-Owen decomposition of covariates
  - Order invariant & sums to statistic + Single value per covariate category

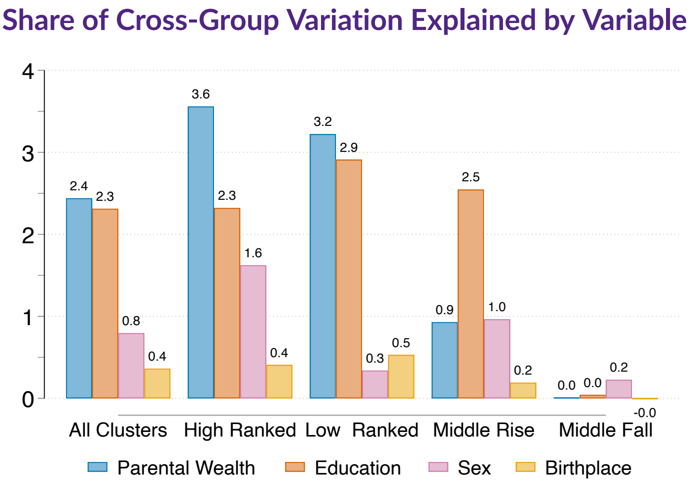
How Important Are Ex-Ante Explanations? Back

Total Contribution*	Partial Contribution			
	Parent	Education	Sex	Birth Place
Share of Distance Variation Explained by Variable (pp)				
5.9	2.4	2.3	0.8	0.4
Share of Individuals Correctly Classified (pp)				
3.1	1.1	1.3	0.6	1.2

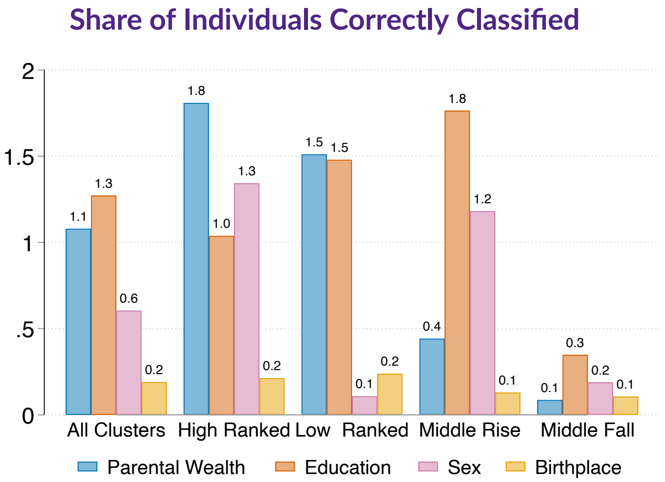
* Contribution relative to random classification using population shares.
Share of individuals correctly classified by random classification 29.3% vs 32.5% with full model.

D by Cluster C by Cluster

How Important Are Ex-Ante Explanations? back



How Important Are Ex-Ante Explanations? back



*Contribution relative to random classification using population shares.

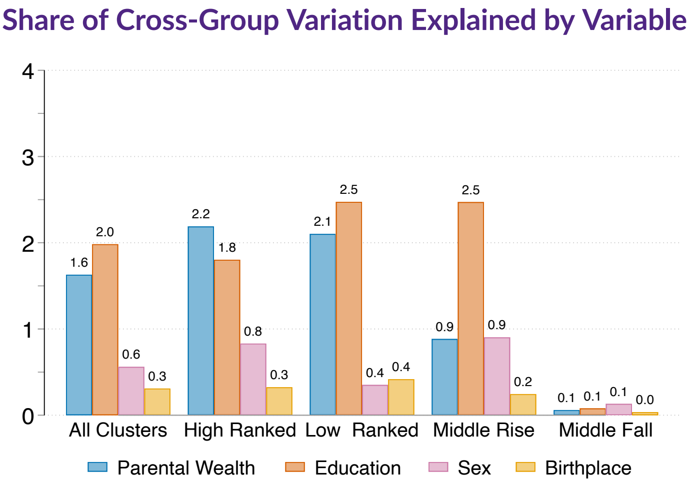
How Important Are Ex-Ante Explanations? Extra controls Back

Total Contribution*	Partial Contribution					
	Parent	Education	Sex	Birth Place	Par. Bus.	Own State
Share of Distance Variation Explained by Variable (pp)						
20.0	1.6	2.0	0.6	0.3	0.6	15.0
Share of Individuals Correctly Classified (pp)						
10.6	0.8	1.1	0.4	0.2	0.3	7.9

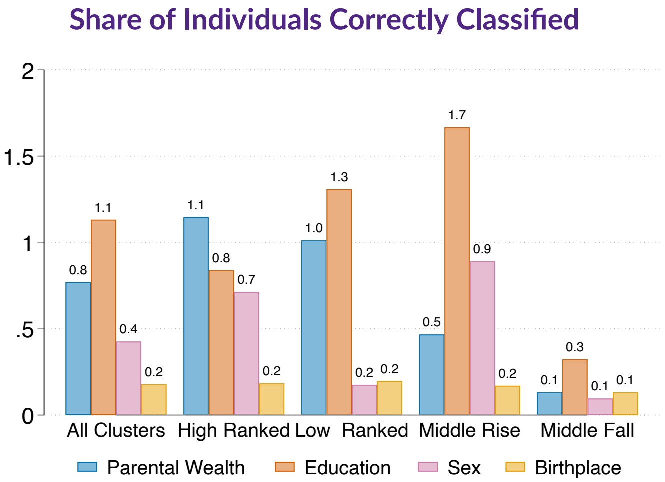
* Contribution relative to random classification using population shares.
Share of individuals correctly classified by random classification 29.3% vs 40.0% with full model.

D by Cluster C by Cluster

How Important Are Ex-Ante Explanations? back



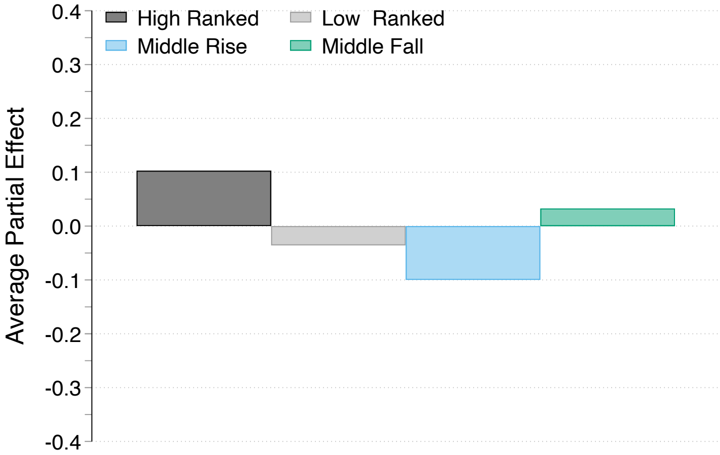
How Important Are Ex-Ante Explanations? back



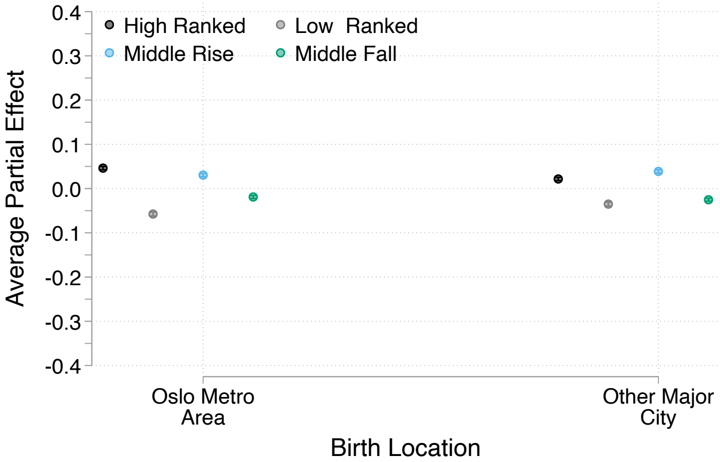
* Contribution relative to random classification using population shares.

Classification Results for Main Clusters

Sex Average Partial Effect ◂ back

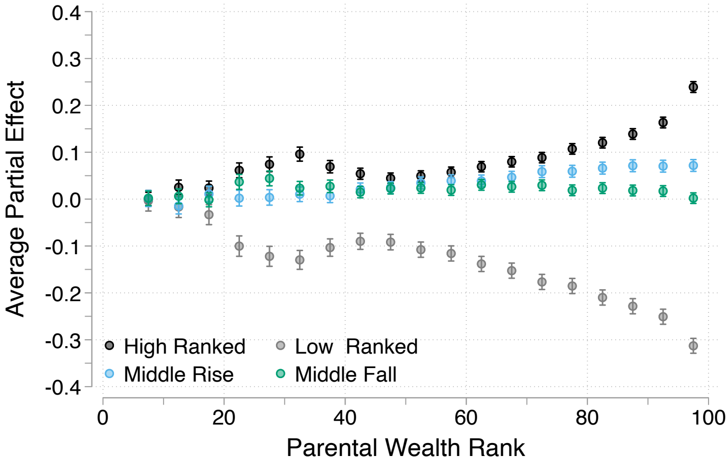


Where Is The Land of Opportunity? Norway back



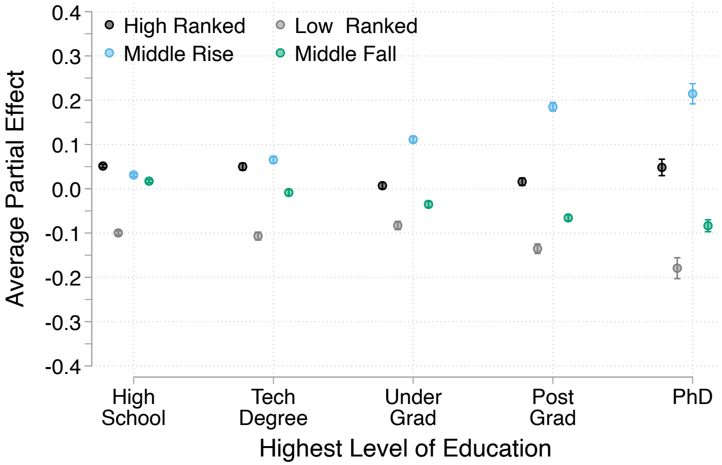
The Non-Linear Effect of Parental Wealth: CI

back



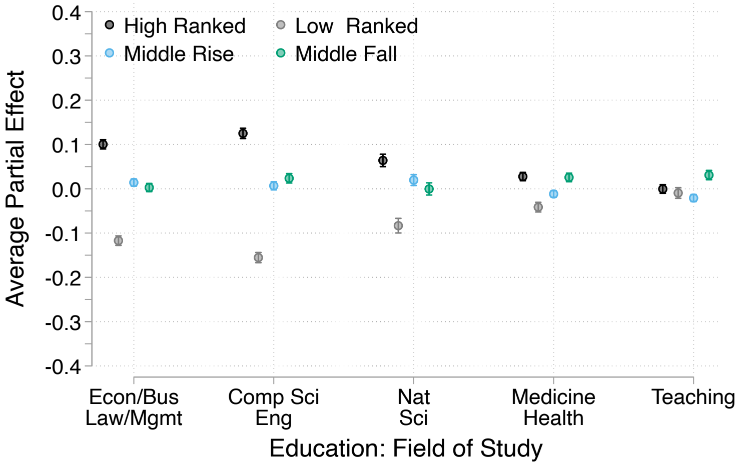
Learn & Rise?: CI

back

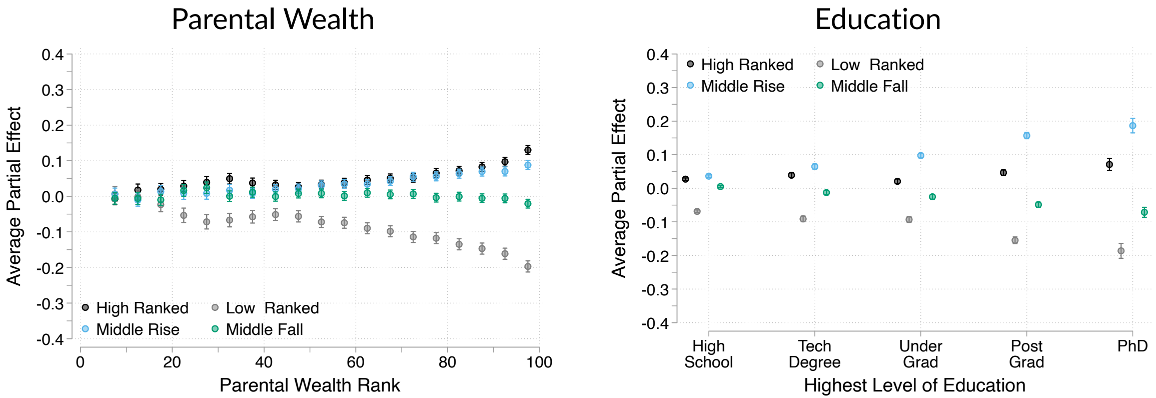


Education: Fields

◂ Back



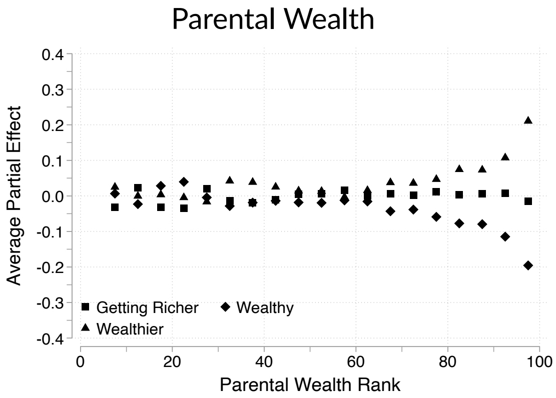
Patterns still present after conditioning on own initial wealth ◀ Back

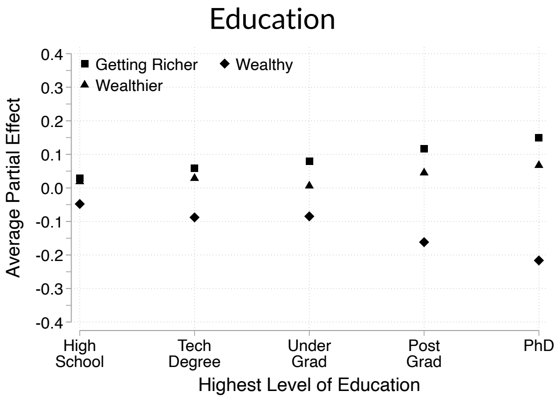


- Robust to controlling for individuals' initial wealth rank + parent portfolio (1993)
  - ↓ Effect sizes by 25-40% (+ explained variation)
  - ↑ Overall variation explained (×4)

Classification Results for Sub-Clusters

What about heterogeneity within clusters? Top Group ◂ Back

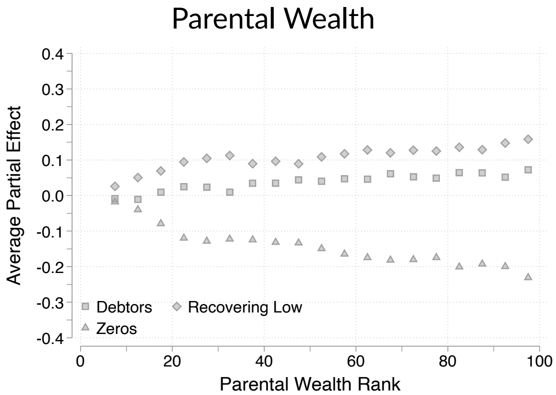


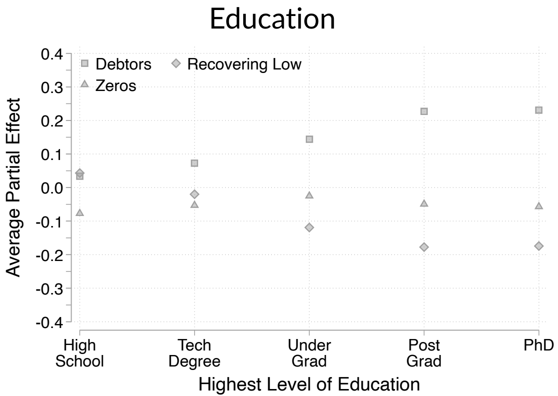


- Even within the groups, movers are hard to predict with parental wealth ▸ PW CI
- Education predicts dynamics within groups (e.g., getting richer vs already wealthy) ▸ ED CI

What about heterogeneity within clusters? Bottom Group

Back



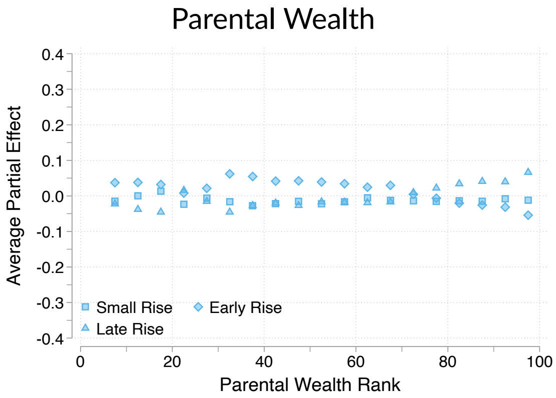


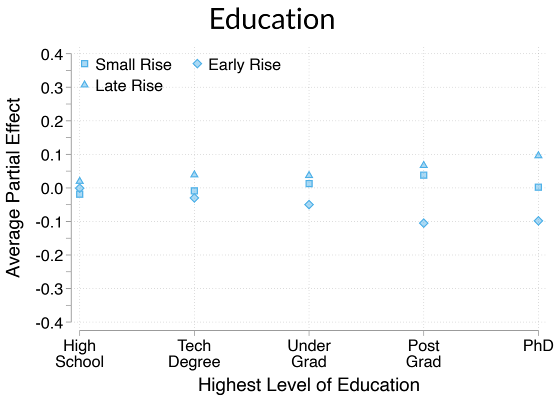
- Among poor, parental wealth does not predict movements
- Education predicts recovery

Middle Rise Middle Fall

What about heterogeneity within clusters? Middle Risers

Back

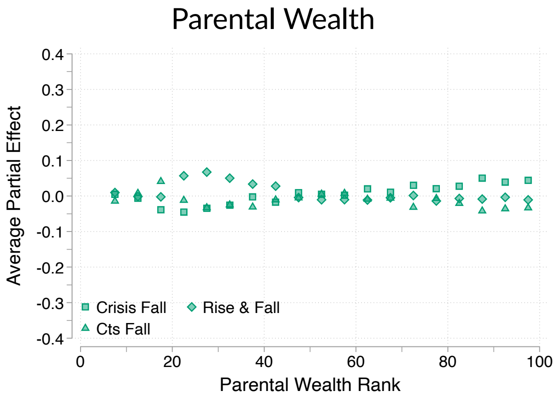


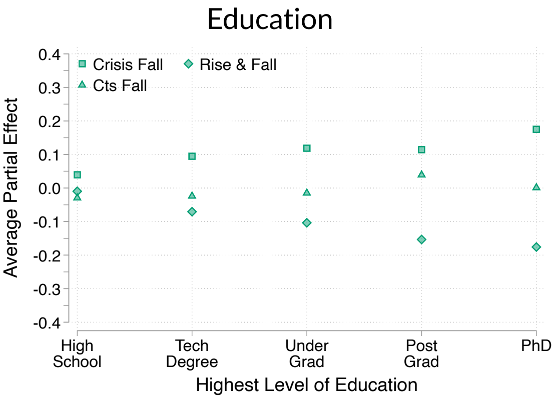


- Within Risers, movers not predicted by parental wealth
- Education predicts timing

What about heterogeneity within clusters? Middle Fallers

Back





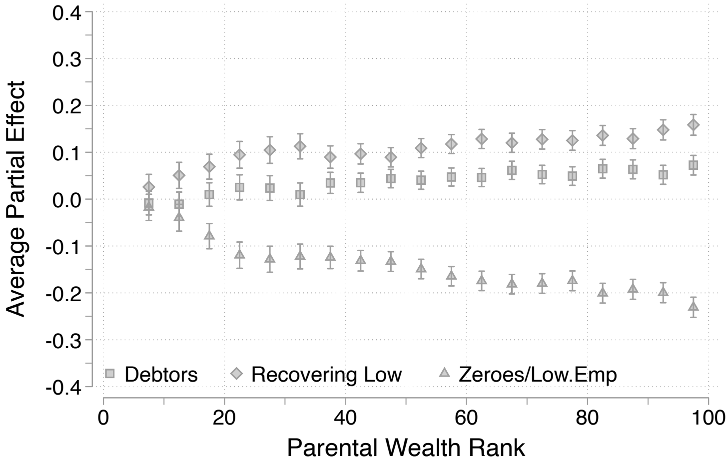
- Similar to Risers, little role for parental wealth
- But Education predicts dynamics

The Non-Linear Effect of Parental Wealth: CI

back

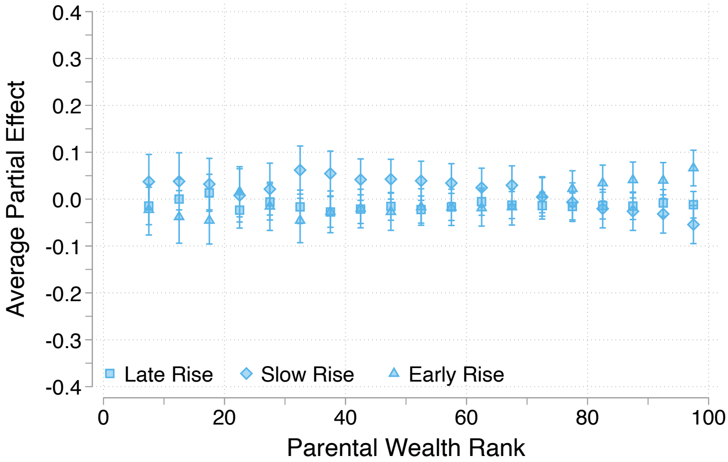
The Non-Linear Effect of Parental Wealth: CI

back



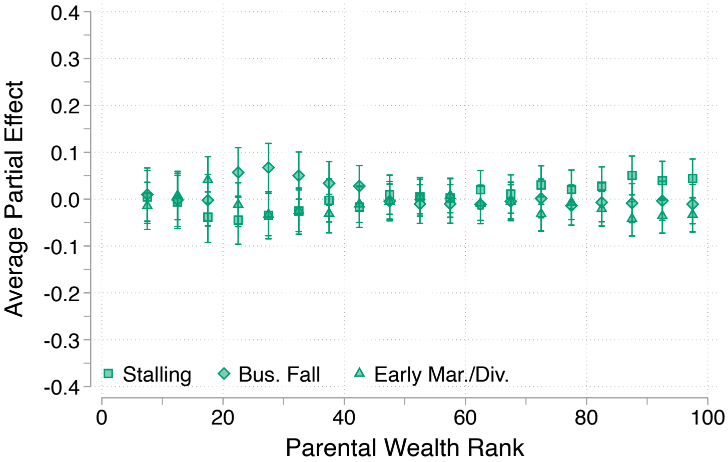
The Non-Linear Effect of Parental Wealth: CI

back



The Non-Linear Effect of Parental Wealth: CI

◂ back



Learn & Rise for Wealthy: CI

back