The Life Cycle Dynamics of Wealth Mobility

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Today: Document patterns of wealth mobility across life cycle

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

Three Main Exercises

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3. To which extent do individual characteristics at age 30 predict trajectories?
   - Parental background: key determinant of Top/Bottom groups
   - Education: key determinant of Risers/Fallers

Contributions

1. New evidence on wealth mobility and wealth accumulation: Full life cycle trajectories
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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 with liquidity (e.g., don't include public pensions)
    - No transaction data (e.g., changing houses or selling stocks)
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Sample selection: Norwegian residents 1993–2017, born 1905–1990

- Drop emigrants and immigrants after 25 or 2011
- 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

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

  - Computed separately for each year and each cohort (uses unbalanced panel)
  - Compare with household and population ranks

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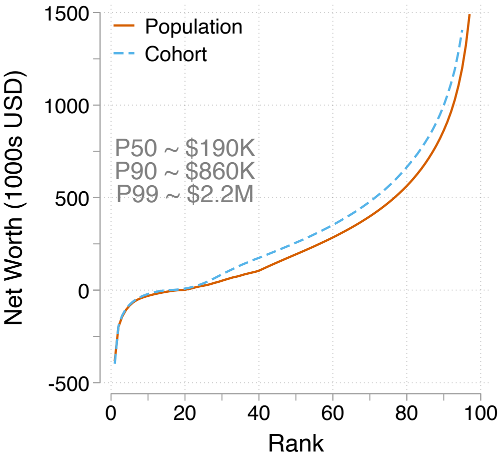
- Trajectories: Histories of ranks

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

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

Birth Cohort Ranks vs Population Ranks vs Wealth Levels

Net Worth CDF (2014)



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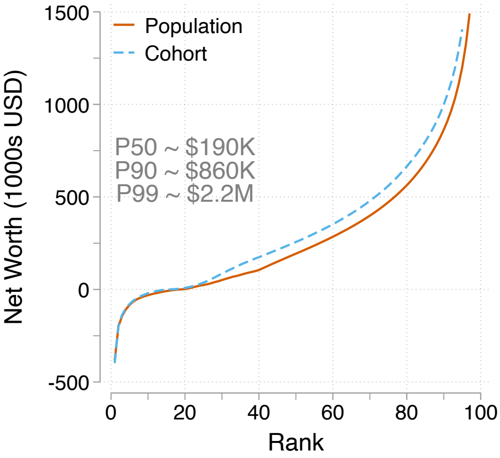
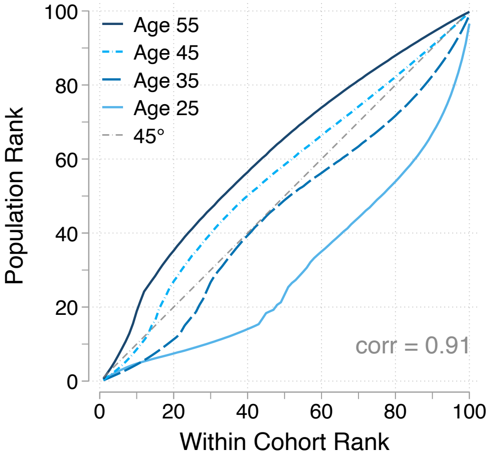


BC Ranks vs Pop Ranks



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▸ HH Ranks

How Non-Linear is Wealth Mobility?

- Conditional moments, $E\left[y_{i,t+h}|y_{i,t}\right]$, and quantiles, $Q_{y_{i,t+h}|y_{i,t}}(\tau)$ ▸ Moments ▸ Quantiles
    - Mean reversion in ranks weakens at the top
    - Dispersion $\downarrow$ with age (consistent with evidence on income) and initial rank
    - Distribution of 5y and 10y changes are similar (despite $\uparrow$ in dispersion from 1y to 5y)
- Linear persistence measures $y_{i,t} = \alpha_t(h) + \rho_t(h) y_{i,t-h} + u_{i,t}$ ▸ AR(1) ▸ Income
    - 5y, 10y persistence is much higher than implied by 1y persistence

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Comparing ranks at given ages gives an incomplete view of wealth mobility

Next Step: Analyze distribution of complete trajectories through the wealth distribution

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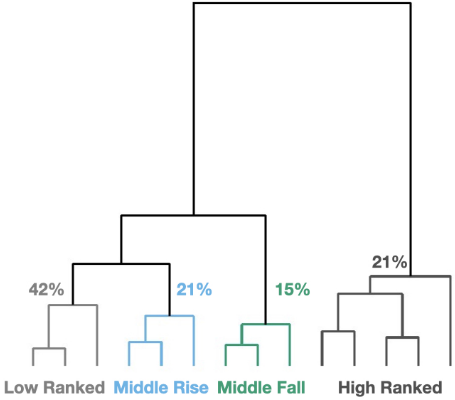
Result: Hierarchy of partitions ranging from $G = N$ to $G = 1$.

- 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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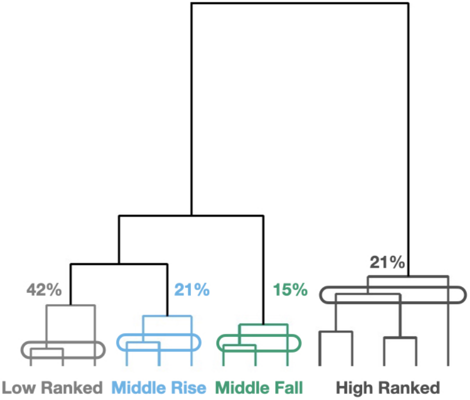
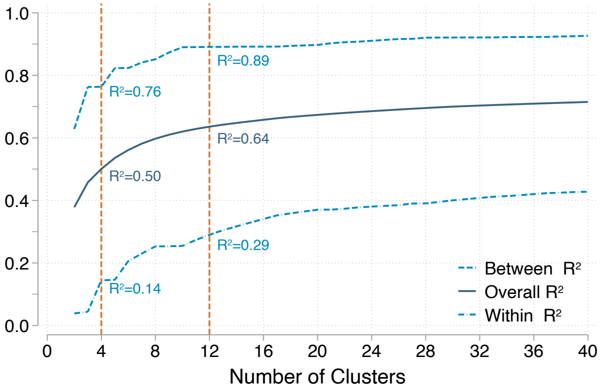
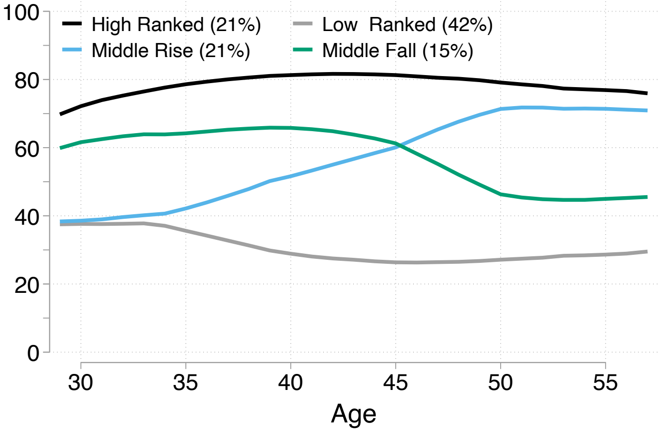


Variation Explained



Typical Rank Histories

Cohort Ranks



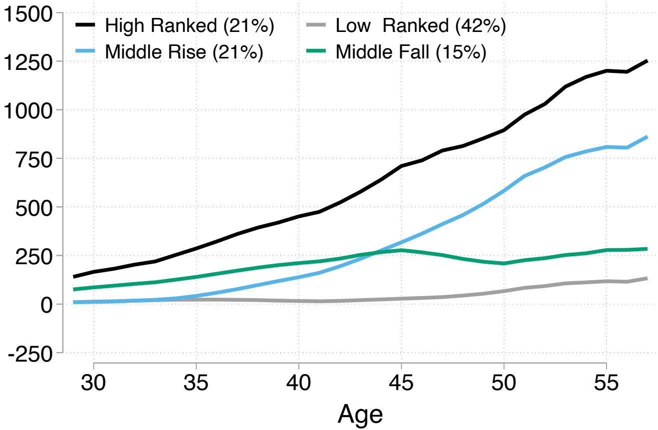
Segmented mobility

- 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%

▸ Alt. Clustering ▸ HH Ranks

Wealth Histories Across Segments of the Distribution

Net Worth ($1000s)

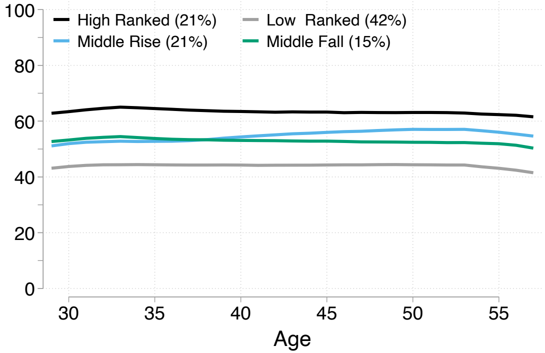


Significant diff. in wealth profiles

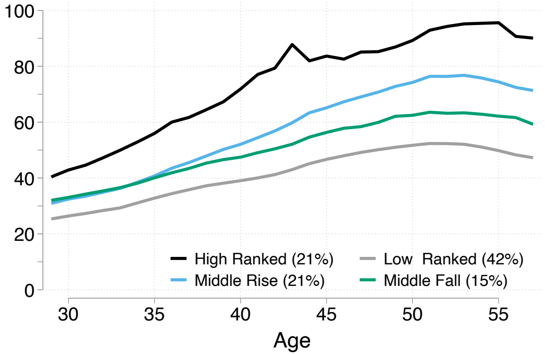
- Risers: start with no wealth + grow on ave. 18%/y
- Fallers: ahead in 30s + low growth (5%) + great recession
- Top: Maintaining rank means level growth (8-10%)
- Bottom: Low wealth + growth in 50s (housing)

Income Histories Across Segments of the Distribution

Income Cohort Ranks



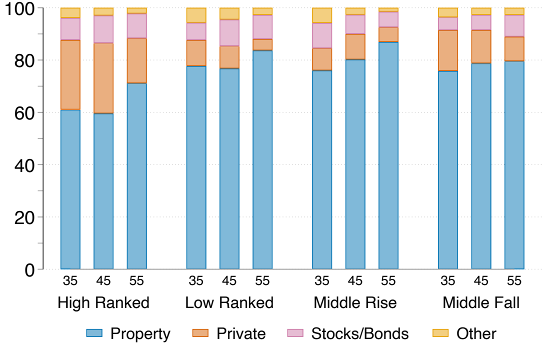
Income ($1000s)



- 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

Portfolio and Income Composition

Asset Portfolio



- Asset differences across clusters in Private Equity and Property

Home-ownership

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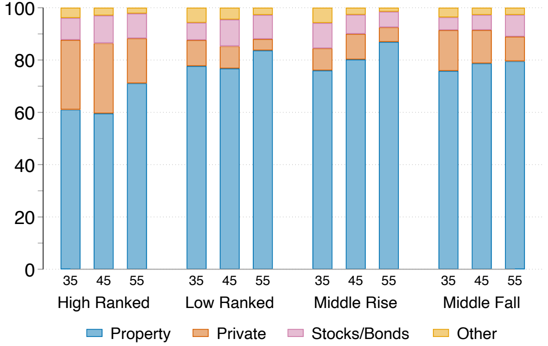
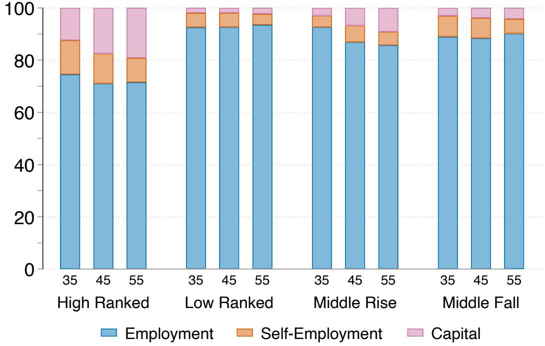


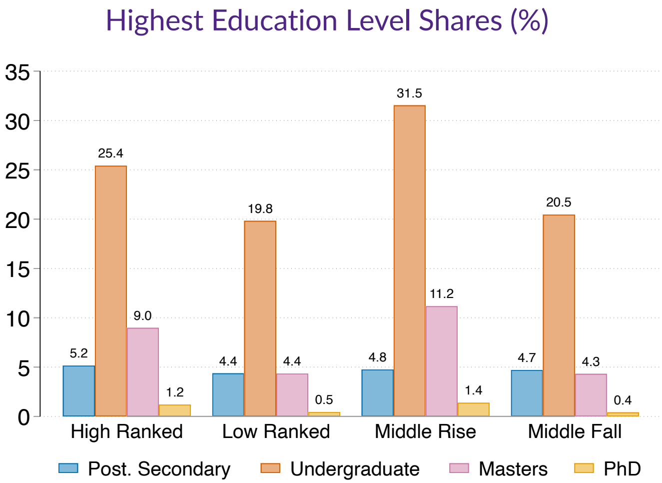
Income Sources



- Asset differences across clusters in Private Equity and Property ▸ Home-ownership

- Income differences in Self-Employment and Capital ▸ SE ▸ Transfers ▸ Gifts

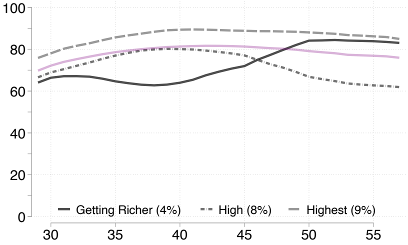
Education: Highest among risers



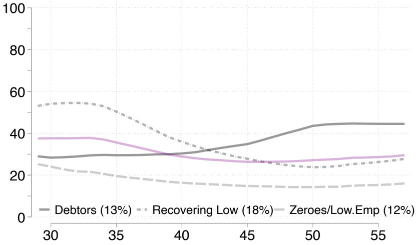
Heterogeneity: Levels vs Timing

▸ Details ▸ Wealth ▸ Portfolio ▸ Inc. ▸ SE ▸ Edu.

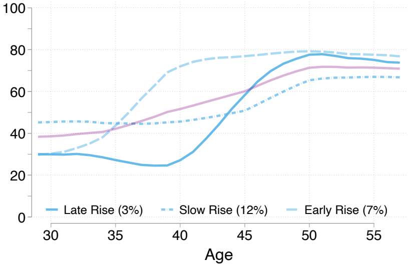
High Ranked



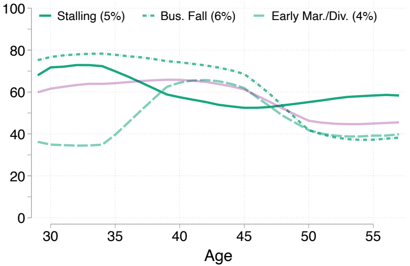
Low Ranked



Middle Risers



Middle Fallers



Towards Determinants of Trajectories

Hereditary Advantage vs Human Capital

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

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  ▸ Sex APE
- $\boldsymbol{\lambda_{bcounty(i)}^j}$: Fixed effect for birth location
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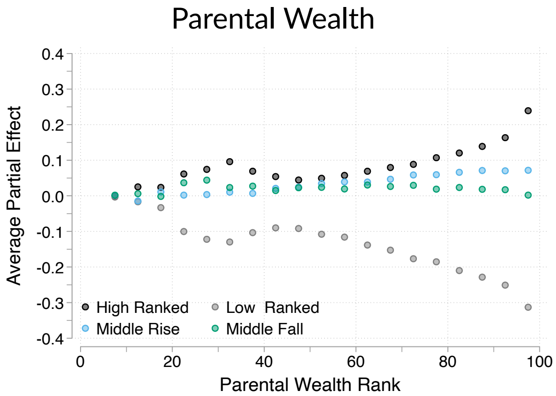
Predictors explain at most 6% of cross-group variation (same as rank-rank inter-gen reg) ▸ Results

Non-Linear Effects of Parental Wealth and Education

PW CIs ED CIs ED Field



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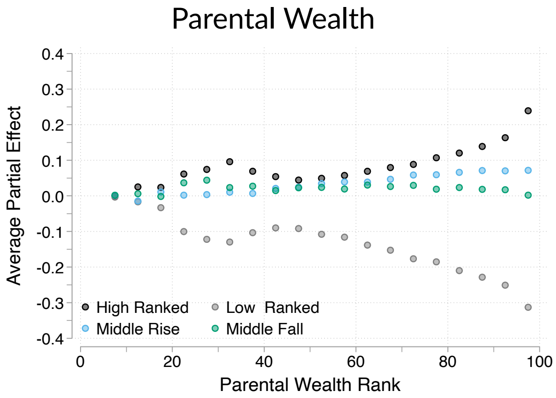

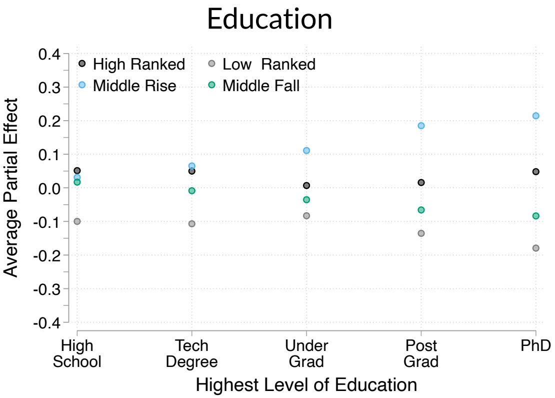

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- Education tells risers/fallers apart: Equalizing effect but doesn't overcome initial cond.

Heterogeneity and Robustness

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

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

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

▸ APE ▸ Shapley-Owen

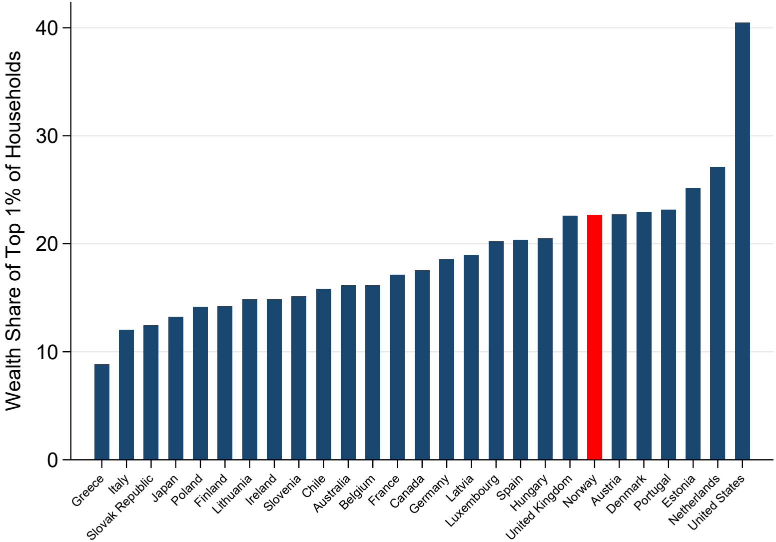
Conclusions

Conclusions

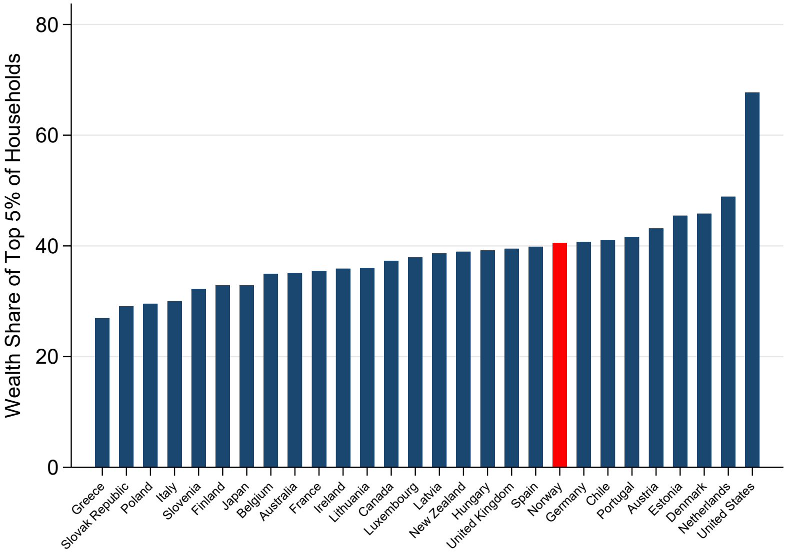
- Document persistence of wealth over the life cycle
- Characterise non-linear persistence and mobility
  - Top of the distribution cushioned against falls
- Uncover typical trajectories of individuals through the wealth distribution
- Intergenerational background an important predictor of **whole**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

Extra

Norway in Context ◂ Back

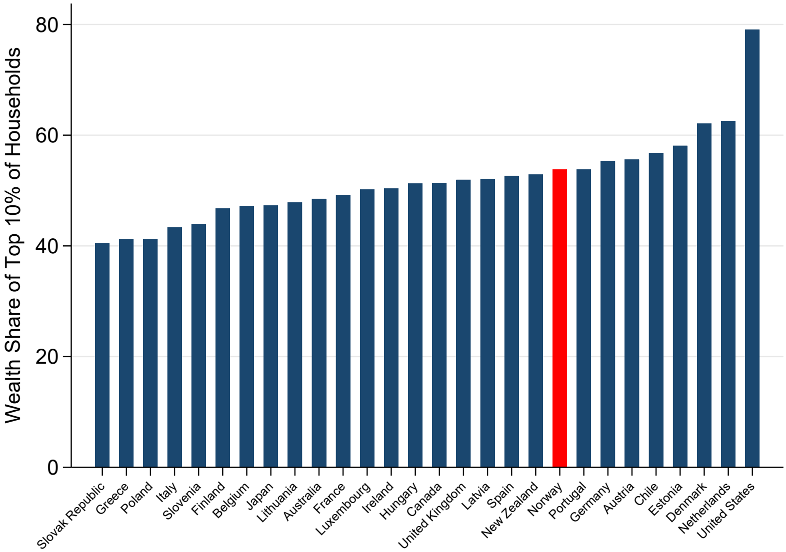


Norway in Context: Top 5% Share ◂ Back



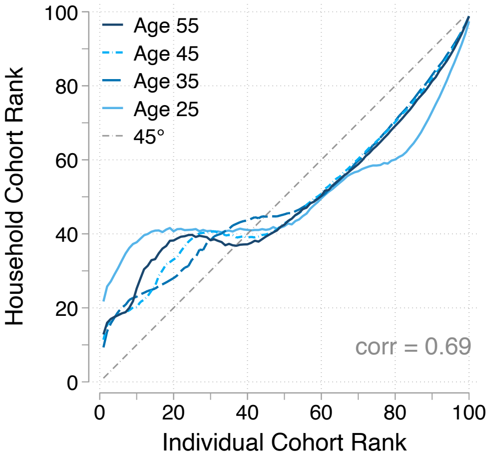
Norway in Context: Top 10% Share

Back



Birth Cohort Individual Ranks vs Household Ranks

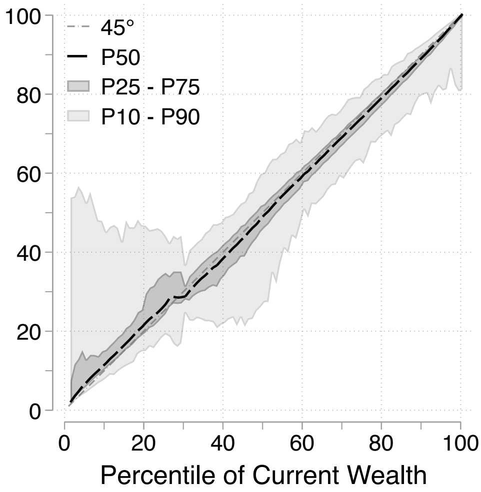
◂ back



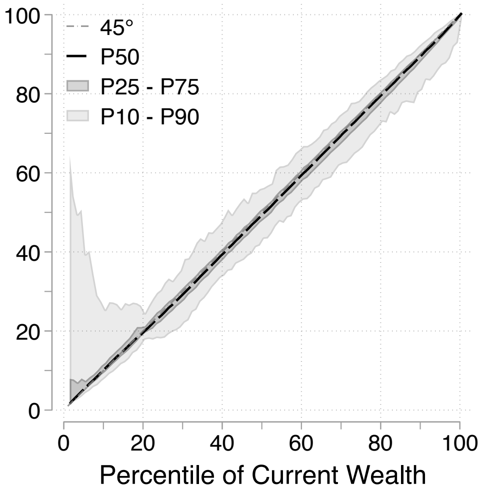
Conditional Distribution of Rank Changes

The Distribution of Rank Changes (1-year) ◂ Back

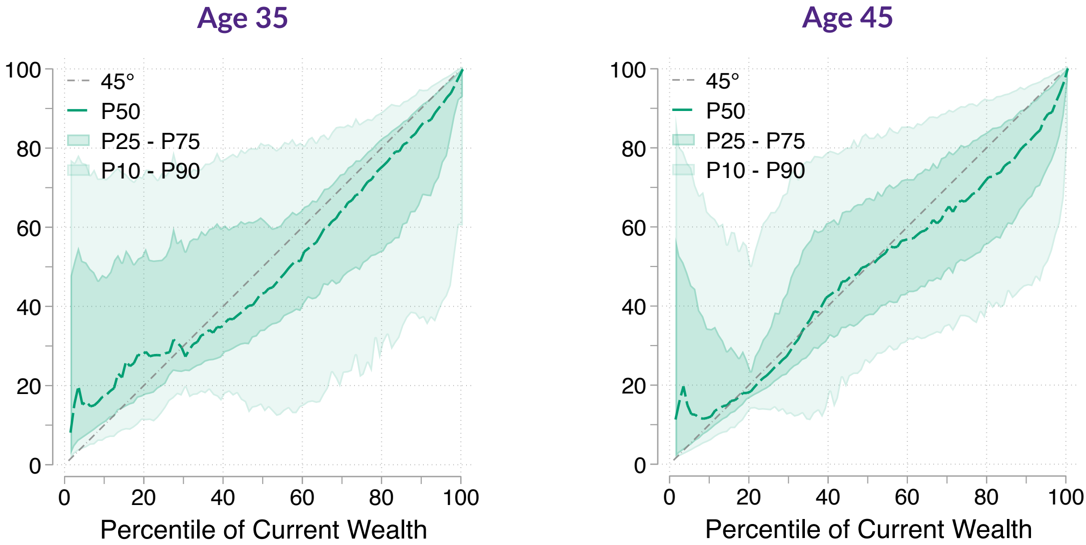
Age 35 – Cond. pct



Age 45 – Cond. pct

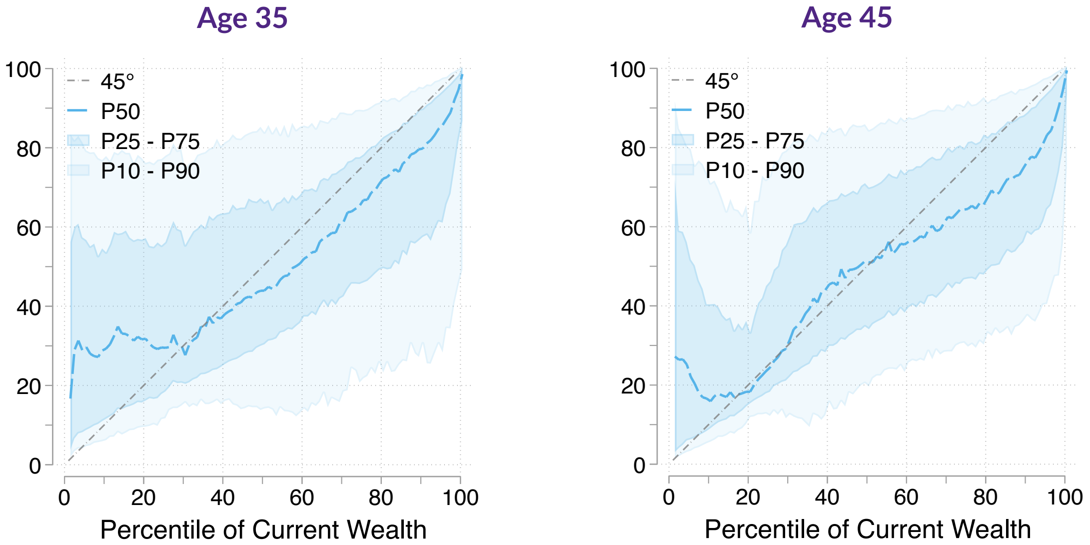


The Distribution of Rank Changes (5-year) Back



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

The Distribution of Rank Changes (10-year) Back

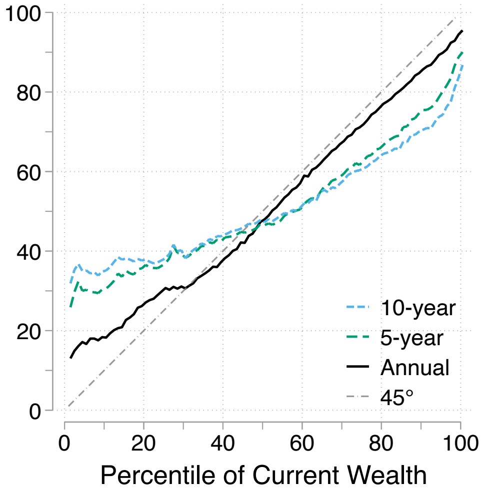


Over longer horizons more evenly spread and dispersion growing

Conditional Moments of Rank Changes

Rank Changes: Average ◂ Back

Age 35 – Cond. Mean



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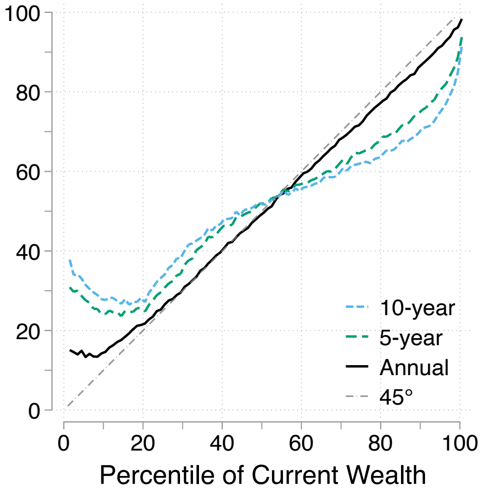
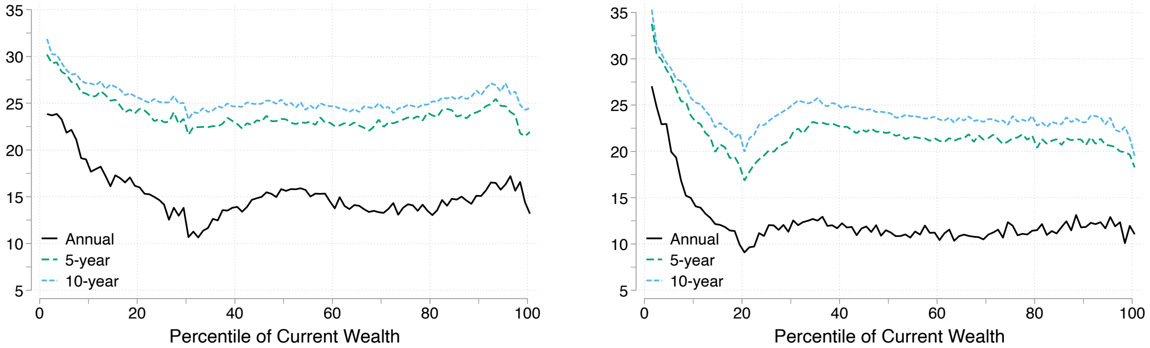


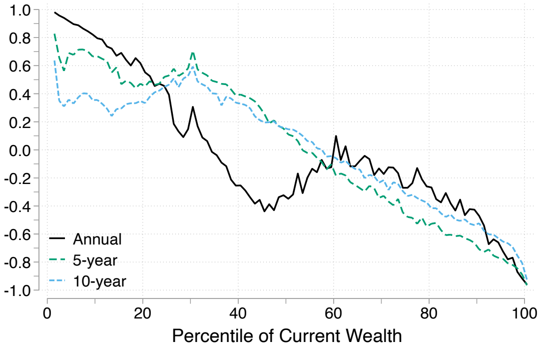
Rank Changes: Standard Deviation

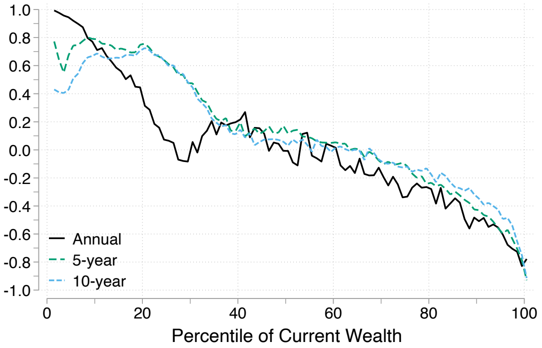
Back



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

Rank Changes: Skewness ◂ Back

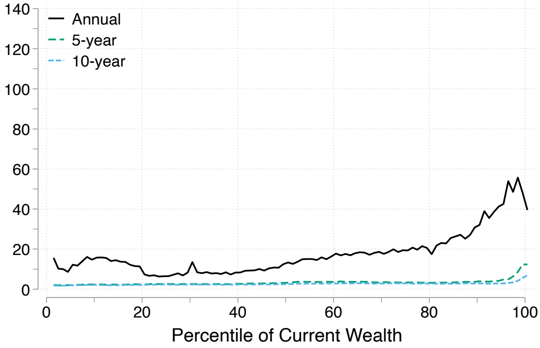


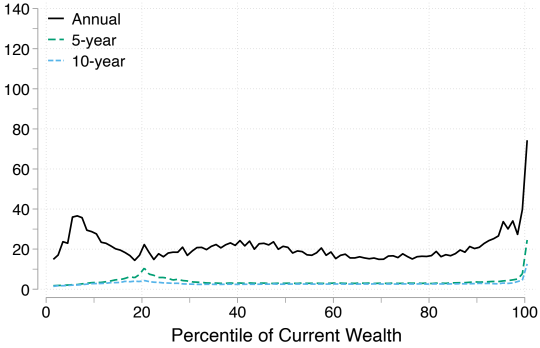


- Skewness decreases by construction
- Changes in ranks: No way to go but up/down for low/high ranks

Rank Changes: Kurtosis

Back



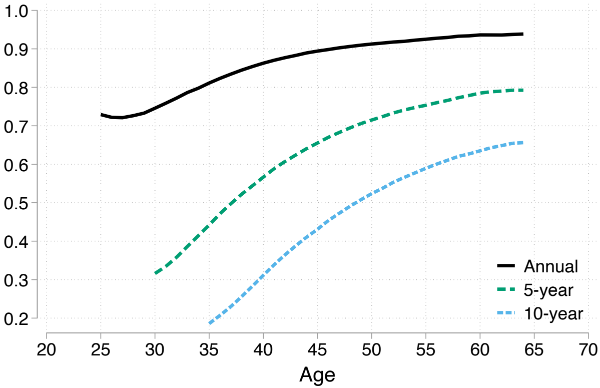


- Distribution of rank changes is *leptokurtic*
- Most individuals experience small changes with some individuals having large changes
- Holds across ranks but is particularly so at short horizon (1y) and upper tail

Persistence of Ranks

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

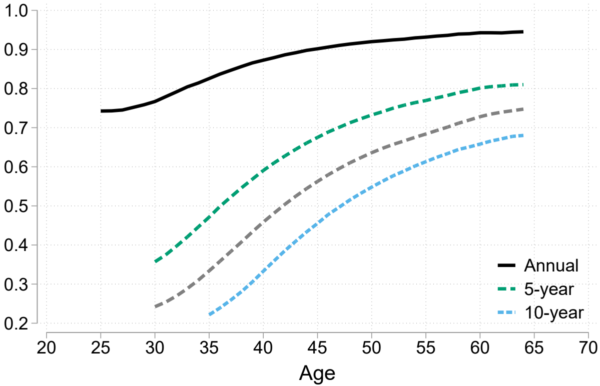
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



- 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

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

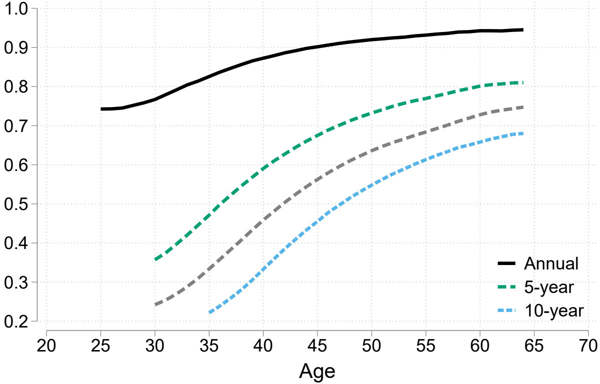


- **5y Iteration bias:** 5y Persistence higher than implied by annual ρ

Persistence in Wealth Rank: Higher at long-run

▸ 1960bc ◂ Back

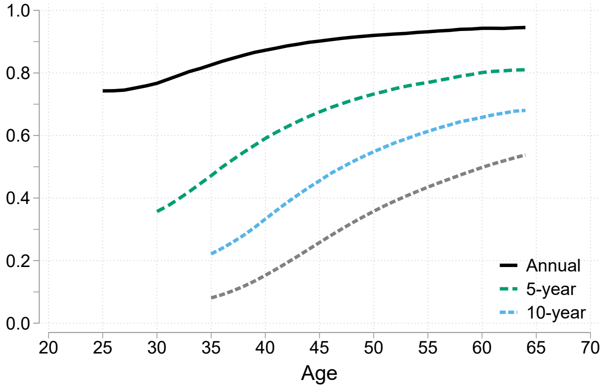
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



- **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

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

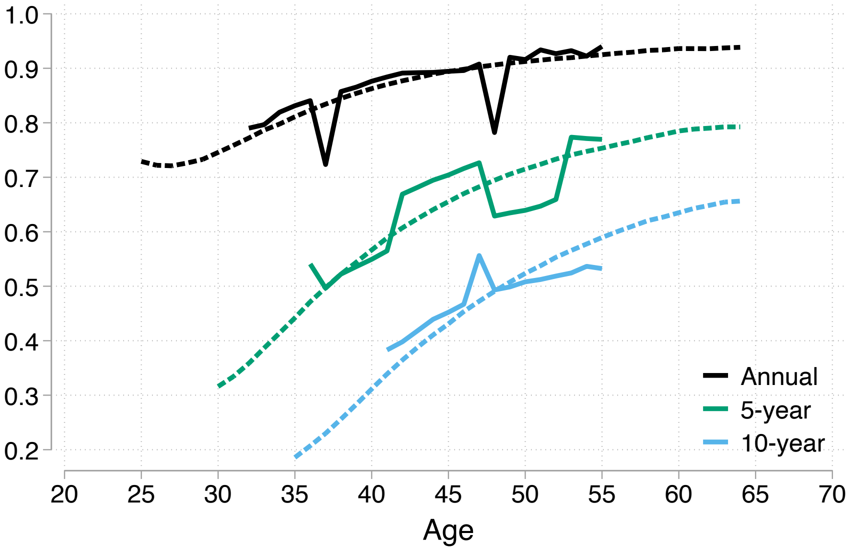


- **10y Iteration bias:** Dramatic bias! Actual $\rho(10)$ is 50-250% implied persistence
- Life cycle snapshots can be misleading! Short-run mobility $\gg$ Long-run mobility

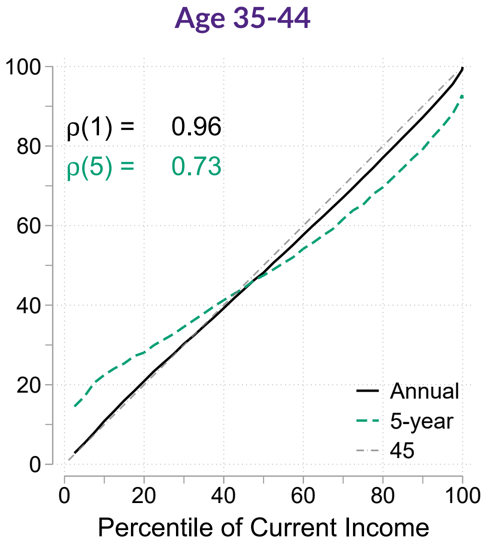
Persistence in Wealth Rank: Within Cohort

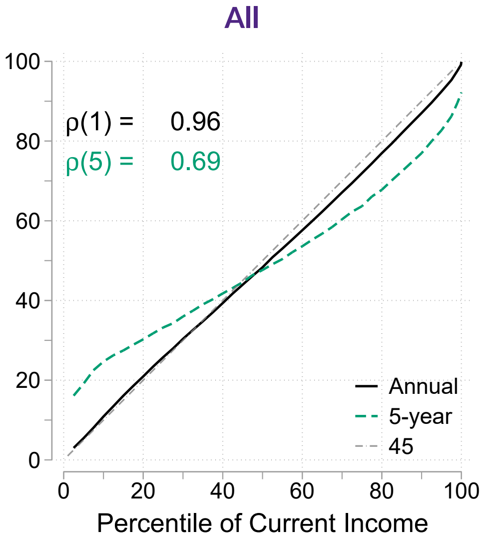
Back

All Cohorts vs 1960-1964 Birth Cohort



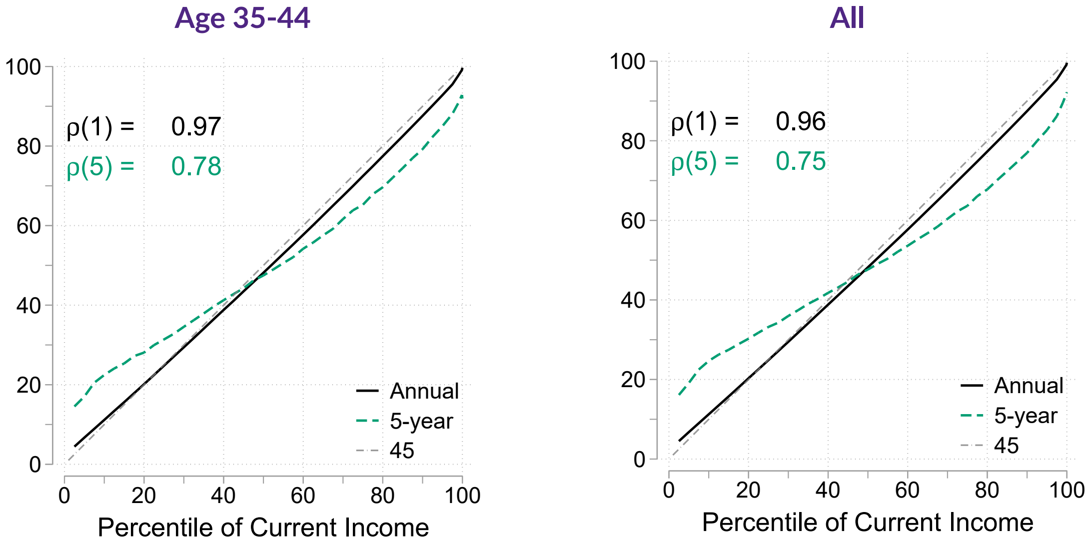
How Non-Linear is Income Mobility in Norway? ◂ Back ▸ USA





Source: GRID database for 2005

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

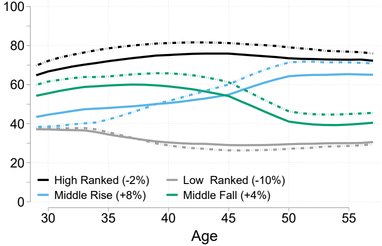


Source: GRID database for 2005

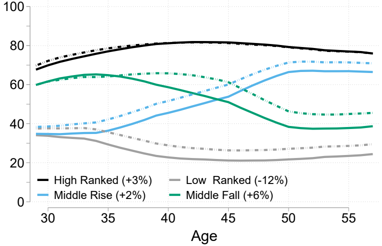
Characteristics of Main Clusters

Alternative Clustering ◂ Back

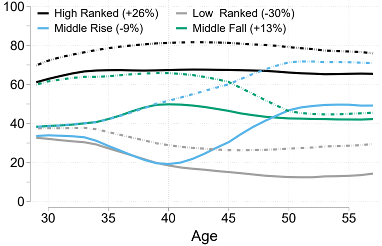
Household Cohort Ranks



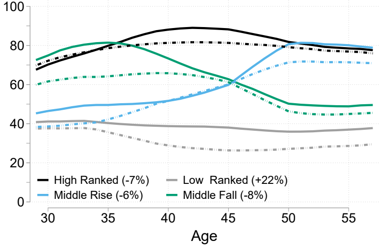
K Means on Ind. Cohort Ranks



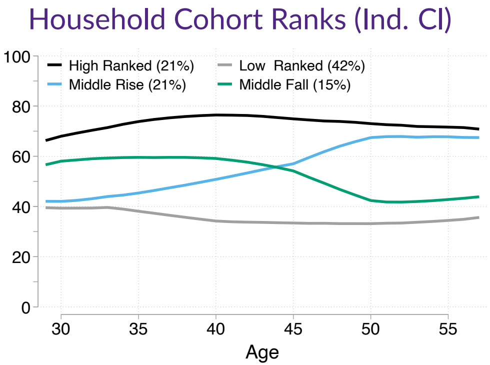
Log Net Worth

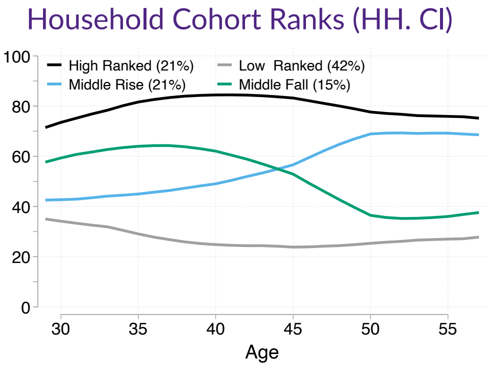


"Lorenz" Ordinates



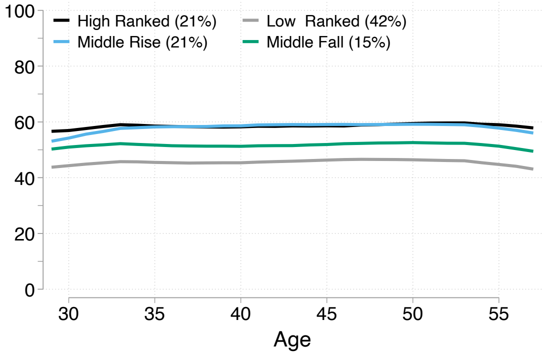
Household Wealth Ranks ◂ Back



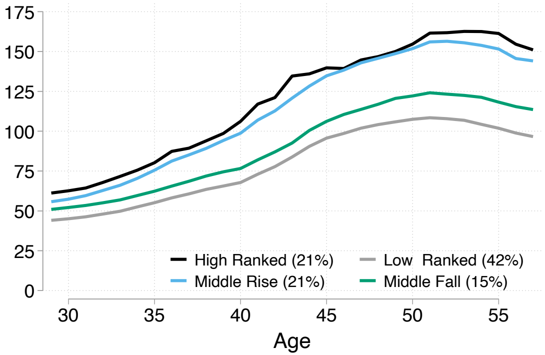


Household Income ◂ Back

Household Income Cohort Ranks



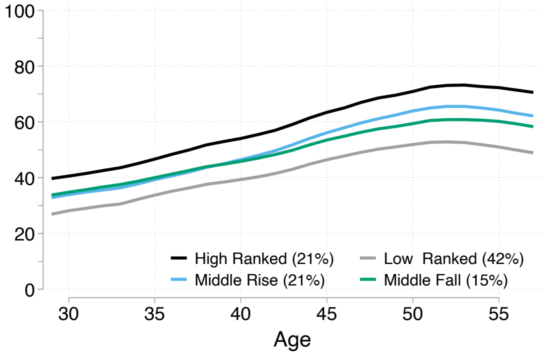
Household Income ($1000s)



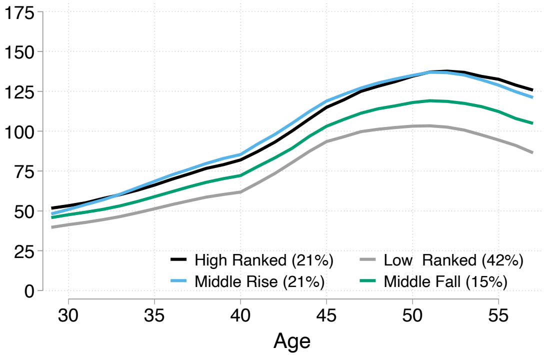
Median Income Histories

Back

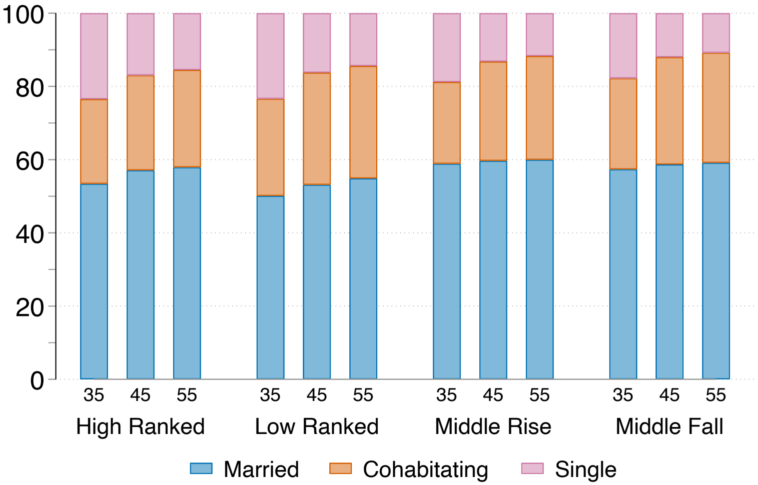
Median Income



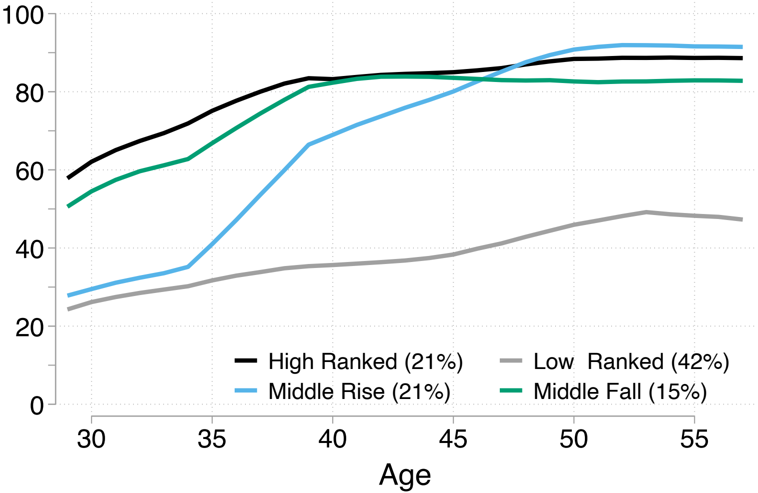
Household Median Income ($1000s)



Civil Status ◂ Back

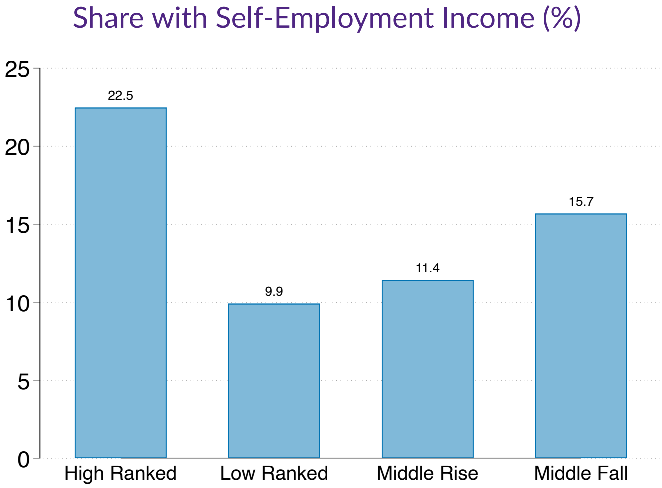


Home-ownership Rates by Cluster ◂ Back



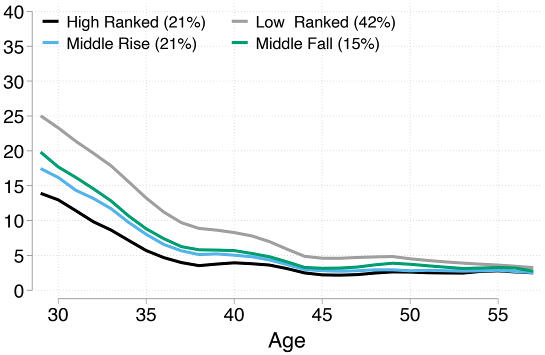
Self-Employment Rates, Age 45

Back

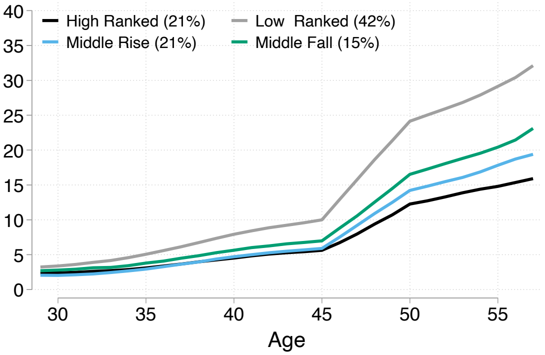


Transfers: Unemployment, Disability, Sick Leave, Nursing ◂ Back

Share with Unemployment Benefits (%)

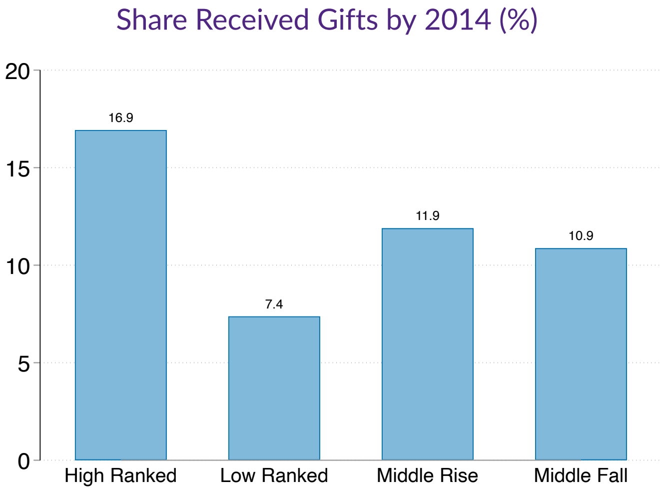


Share with Health-Related Transfers (%)



Lifetime Inheritances and Gifts

Back

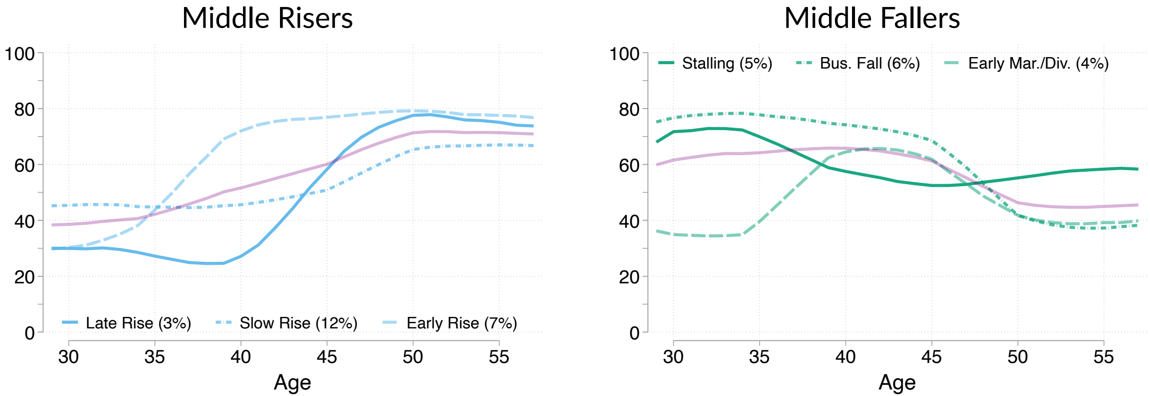


Notes: Total received $>$ NOK 470K ($\approx$ \$47K) before 2014

Characteristics of Sub-Clusters

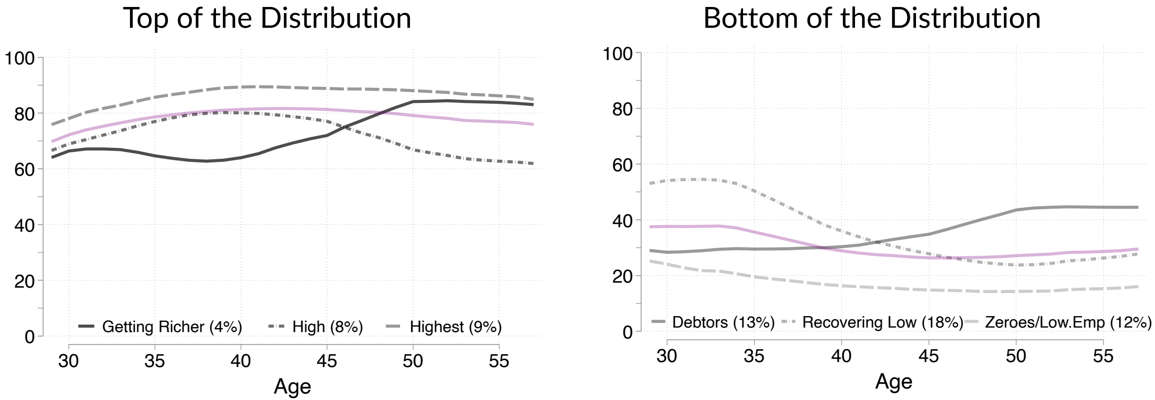
Heterogeneity in Trajectories: Levels vs Timing

Back



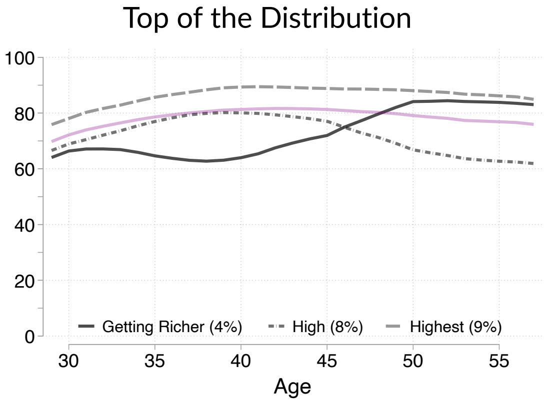
- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)

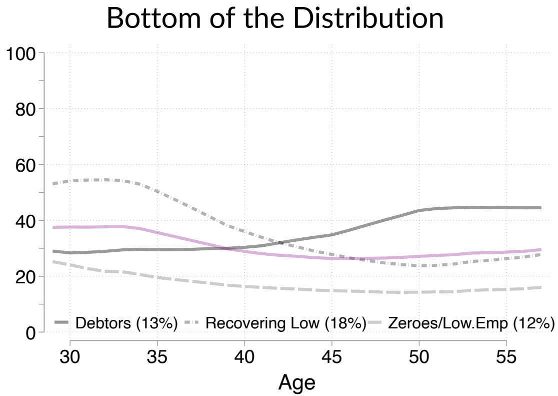
Heterogeneity in Trajectories: Levels vs Timing ◂ Back



- 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





- Risers differ mainly in timing of changes (similar initial conditions)
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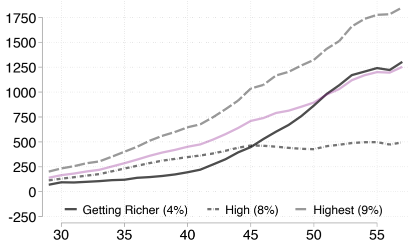
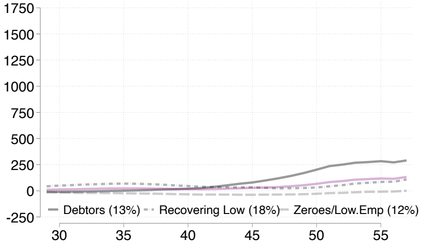
Sub-Clusters: Wealth Levels

Back

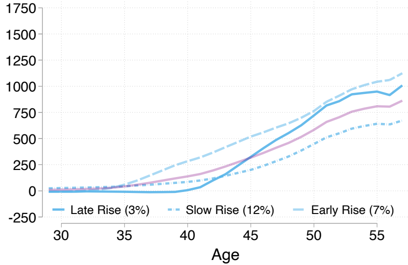
High Ranked



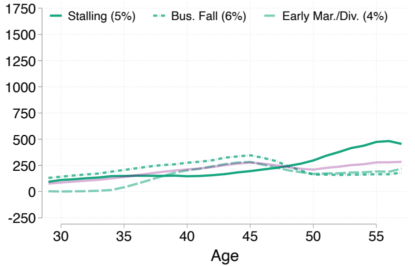
Low Ranked



Middle Risers

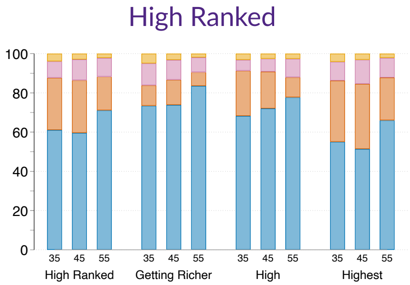


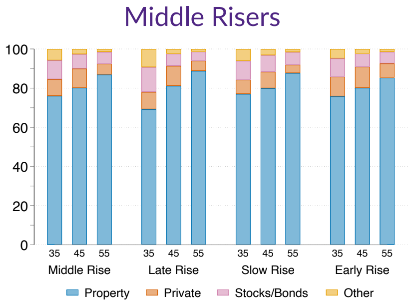
Middle Fallers

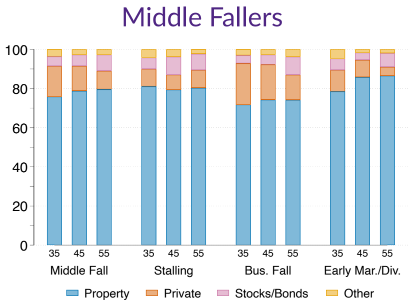


Sub-Clusters: Portfolio

Back



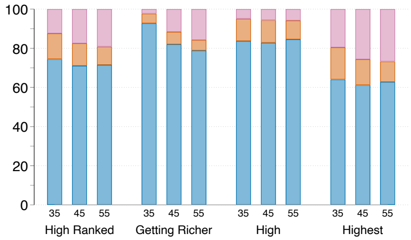




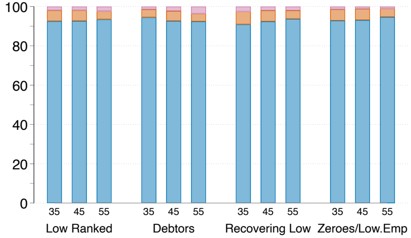
Sub-Clusters: Income Composition

Back

High Ranked



Low Ranked

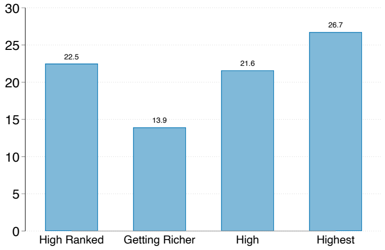


Middle Risers

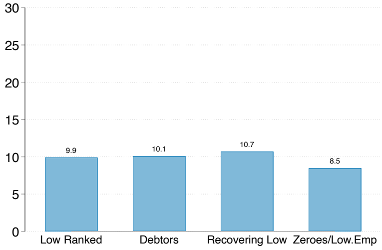
Middle Fallers

Sub-Clusters: Self-Employment ◂ Back

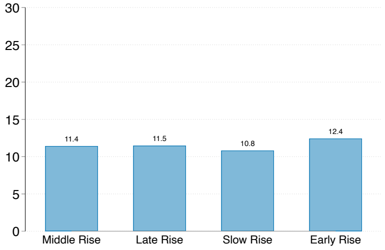
High Ranked



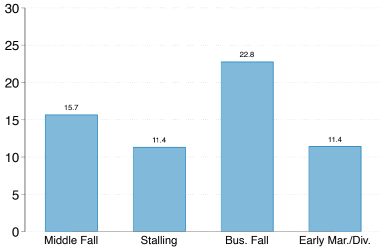
Low Ranked



Middle Risers



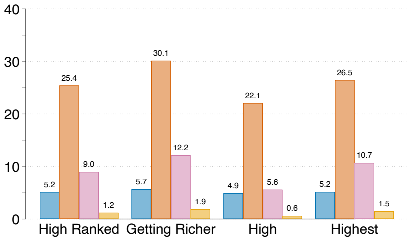
Middle Fallers



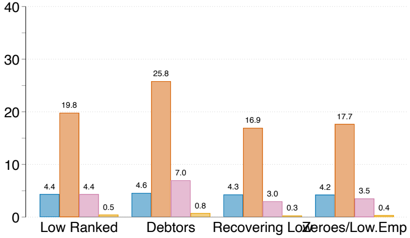
Sub-Clusters: Education

Back

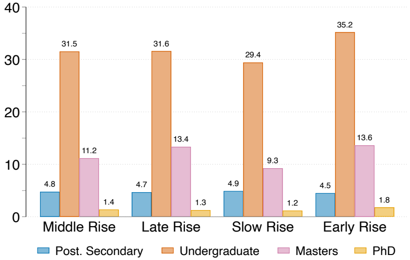
High Ranked



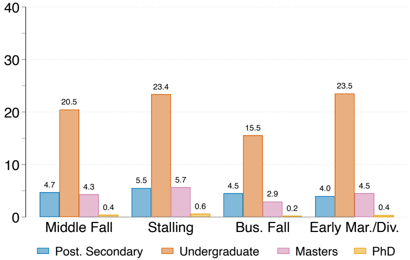
Low Ranked



Middle Risers



Middle Fallers



Shapley-Owen Decomposition

How Important Are Ex-Ante Explanations? Back

Two measures:

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

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

How Important Are Ex-Ante Explanations? Back

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

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

How Important Are Ex-Ante Explanations? ◂ Back

Two measures:

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

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

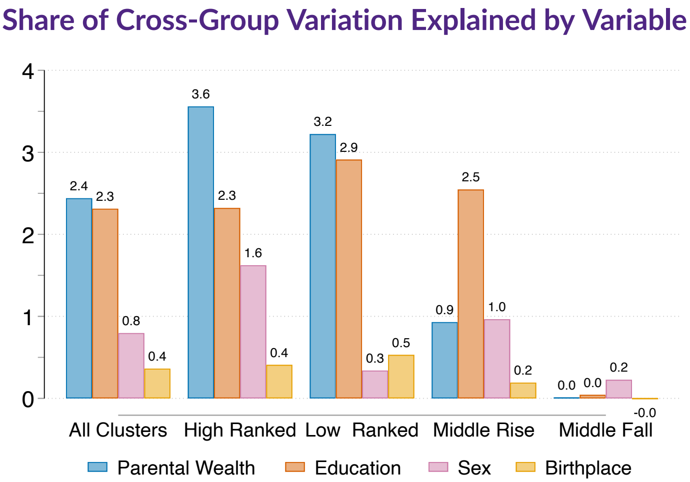
How Important Are Ex-Ante Explanations? Back

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

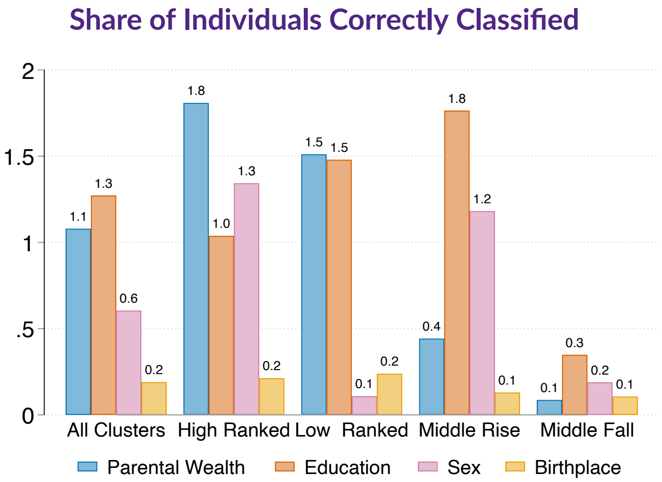
*Contribution relative to random classification using population shares.
Share of individuals correctly classified by random classification 29.3% vs 32.5% with full model.

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.

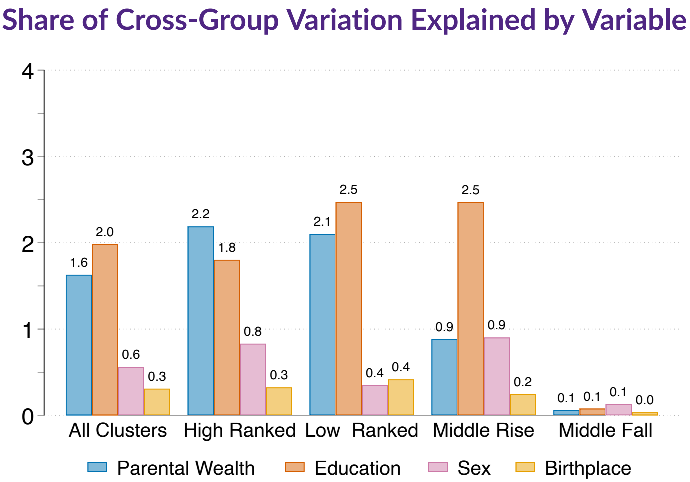
How Important Are Ex-Ante Explanations? Extra controls ◂ Back

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

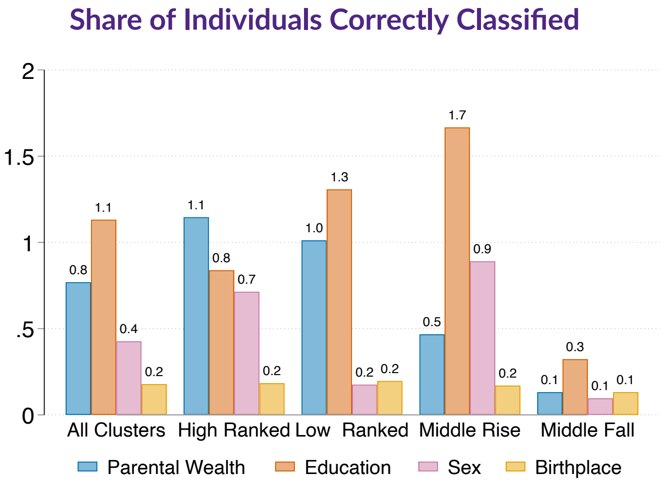
* Contribution relative to random classification using population shares.
Share of individuals correctly classified by random classification 29.3% vs 40.0% with full model.

▸ D by Cluster ▸ C by Cluster

How Important Are Ex-Ante Explanations? back



How Important Are Ex-Ante Explanations? ◂ back

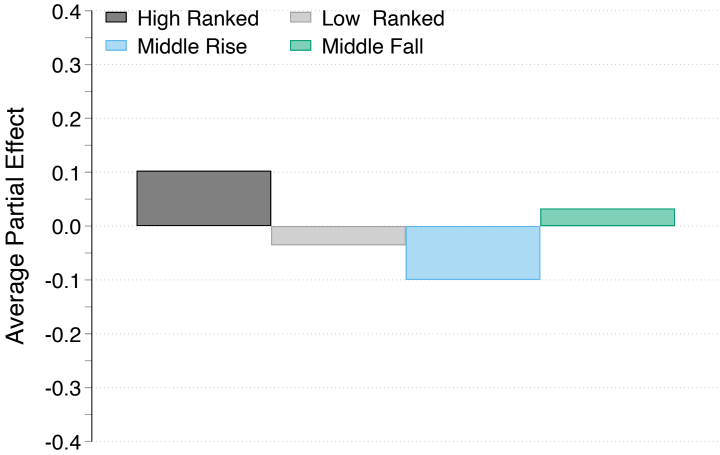


*Contribution relative to random classification using population shares.

Classification Results for Main Clusters

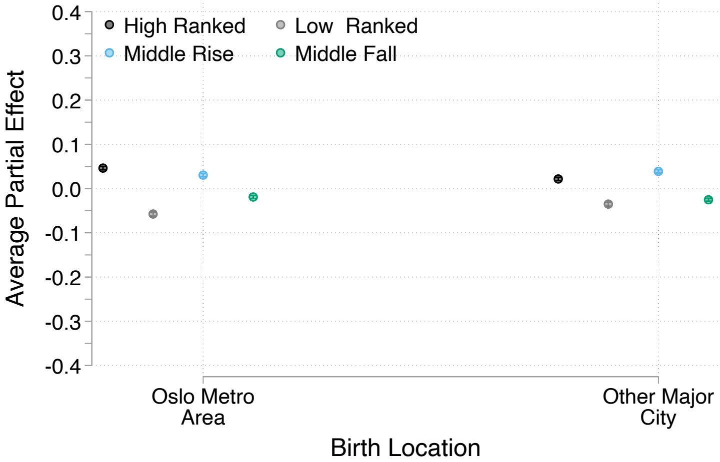
Sex Average Partial Effect

back



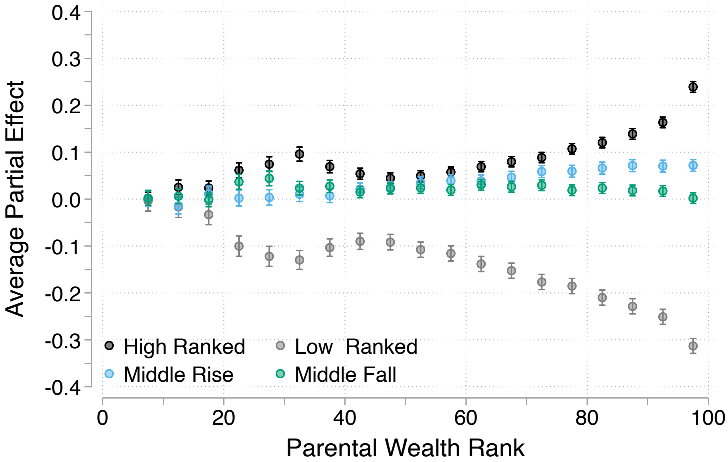
Where Is The Land of Opportunity? Norway

back



The Non-Linear Effect of Parental Wealth: CI

back



Learn & Rise?: CI

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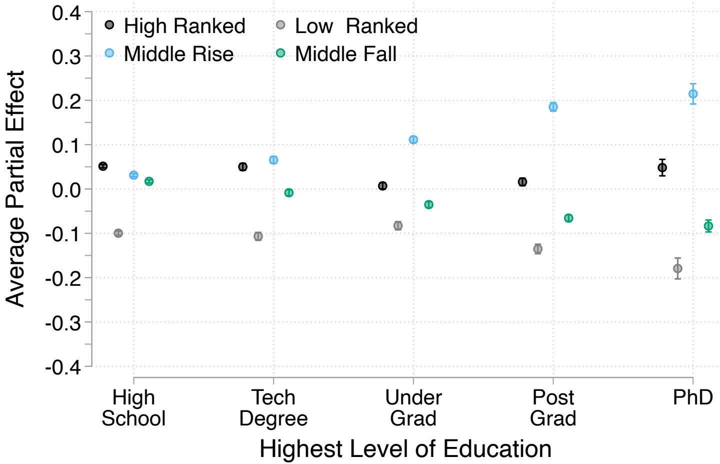
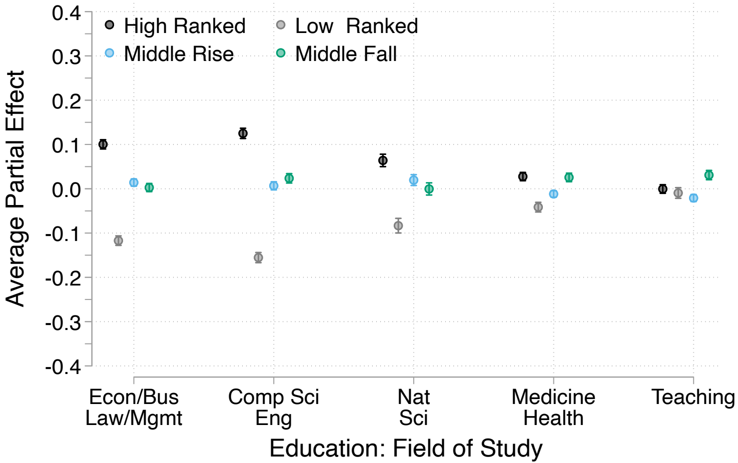


Education: Fields ◂ Back



Effects of Parental Wealth and Education with Extra Controls

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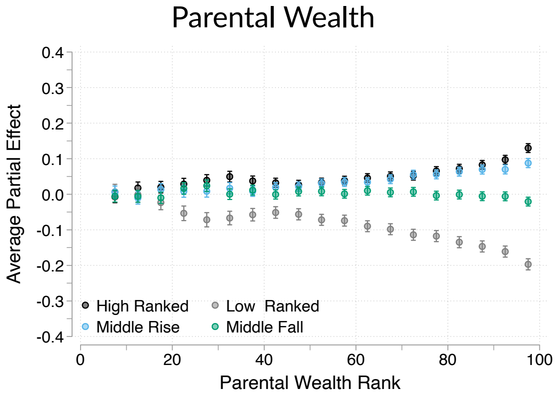
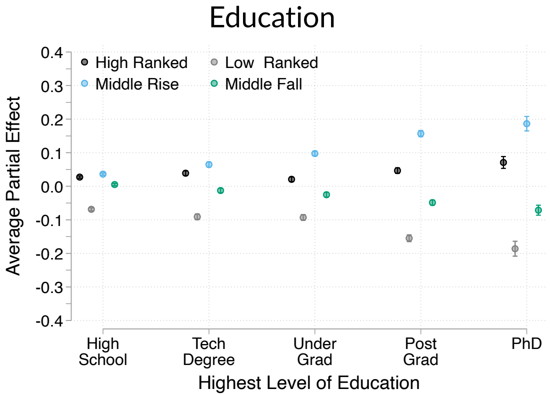
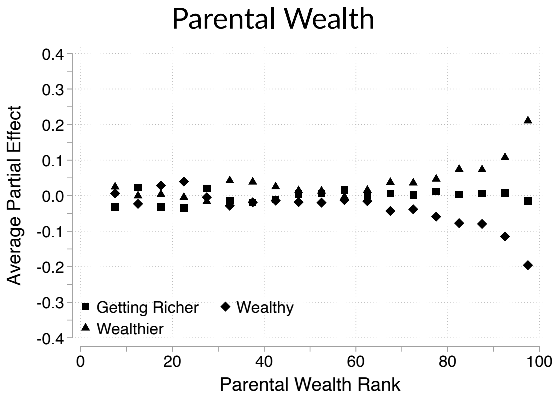
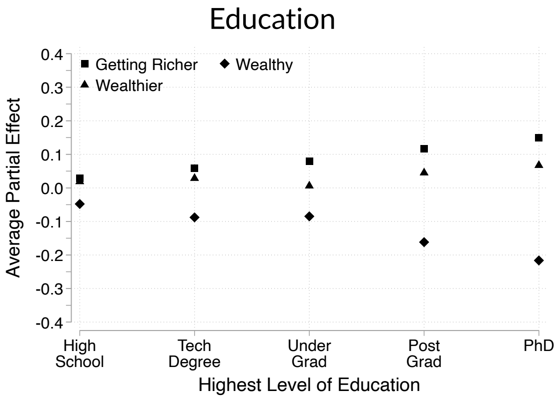




Classification Results for Sub-Clusters

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

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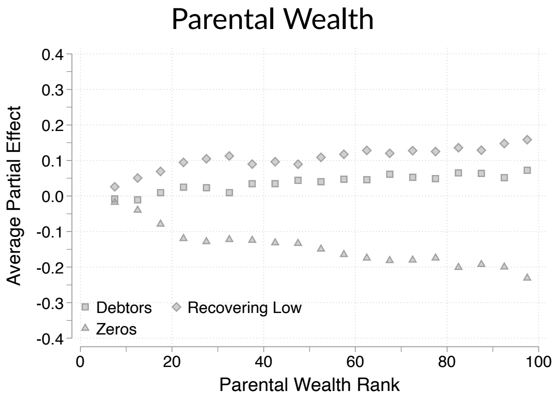
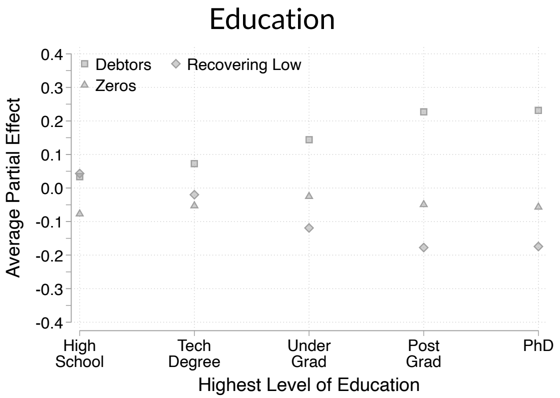
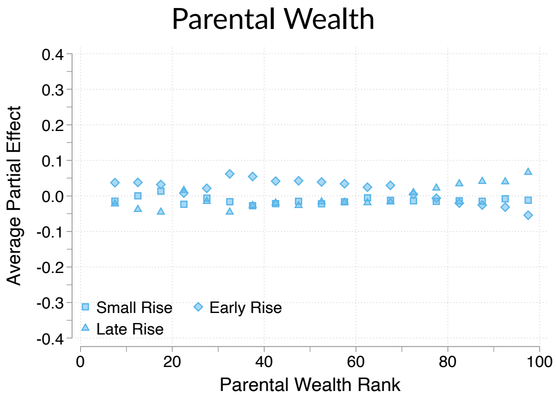
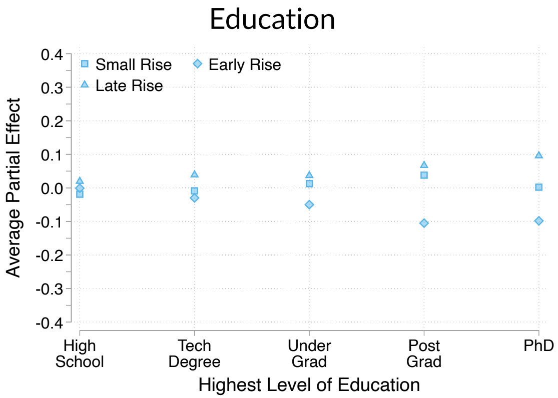




- Among poor, parental wealth does not predict movements
- Education predicts recovery

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

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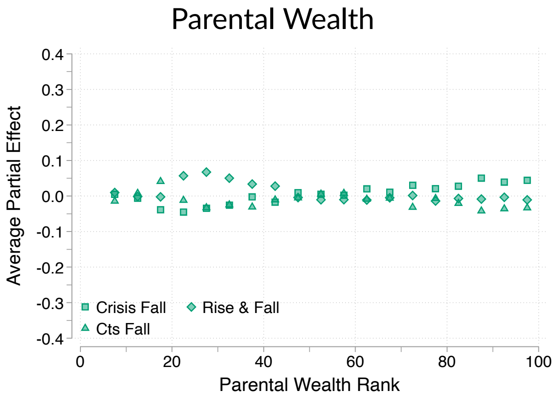

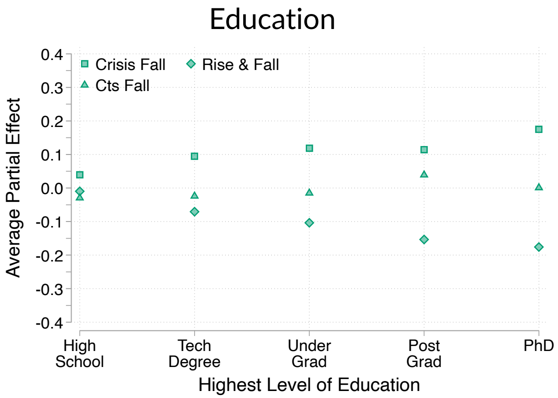

- Similar to Risers, little role for parental wealth
- But Education predicts dynamics

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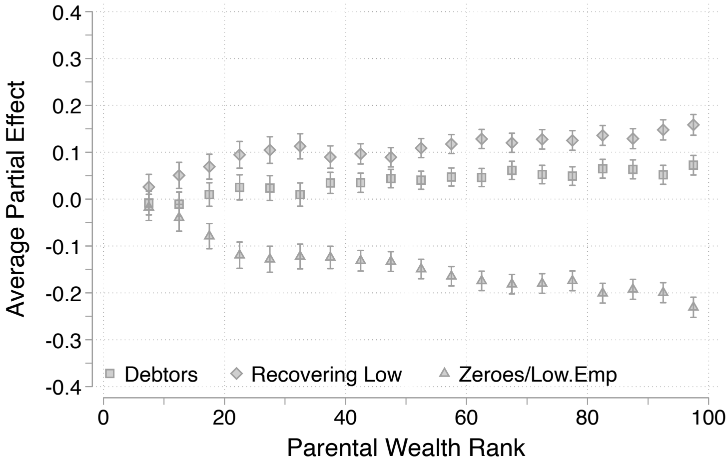

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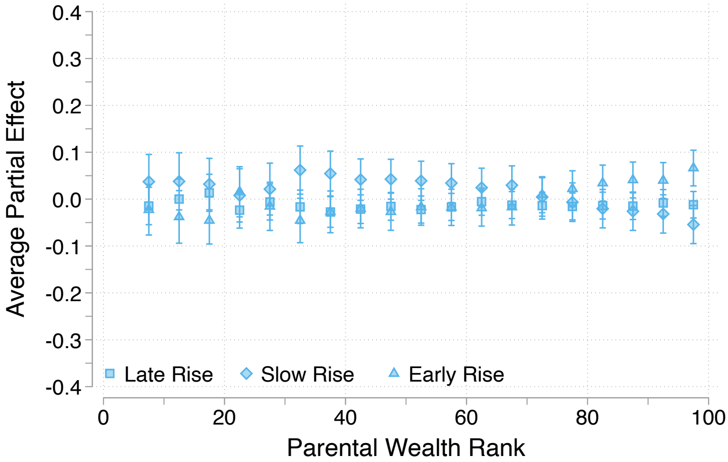

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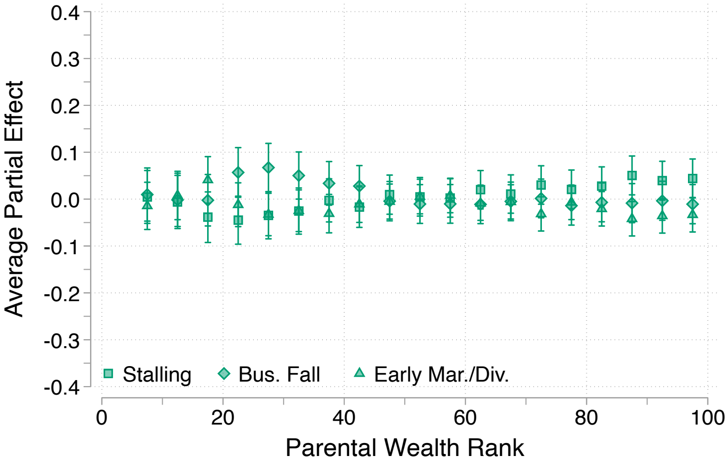

Learn & Rise for Wealthy: CI

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