

The Life Cycle Dynamics of Wealth Mobility

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Disclaimer: The views below are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York, the Federal Reserve System, the European Central Bank or the Eurosystem.

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- Mobility is a key measure for contextualizing inequality (research + 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

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 - Top 20% and Bottom 40% rarely fall/rise while remaining 40% Rise and Fall in the middle
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 - Find 4 "typical" trajectories by clustering individuals revealing segmented mobility
 - Top 20% and Bottom 40% rarely fall/rise while remaining 40% Rise and Fall in the middle
 - Relationship to portfolio, income, education, etc.
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

Norwegian Wealth Data

Data: Norwegian Tax Registry 1993 – 2017

▶ Context

- No top-coding + Limited misreporting or measurement error (third-party reporting)
 - Focus on tradable wealth (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

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

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

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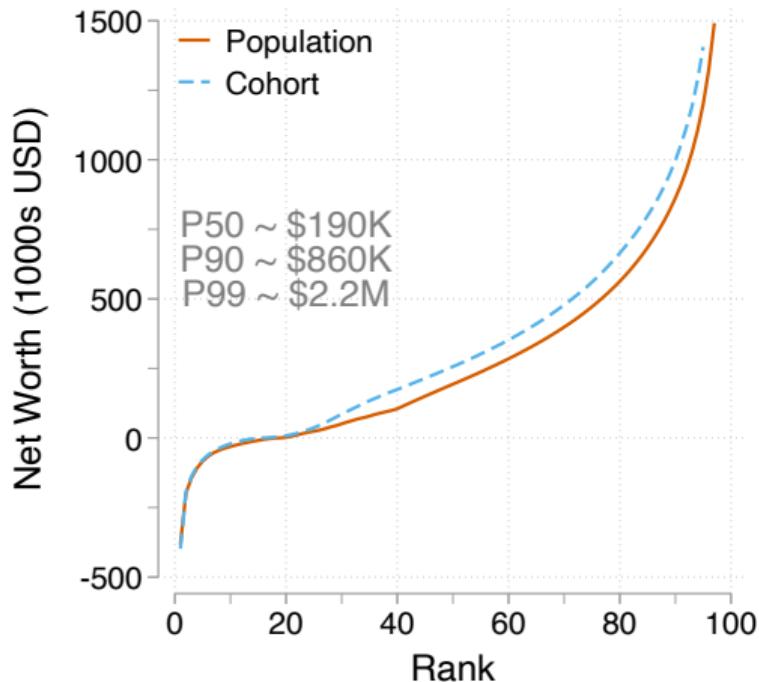
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- Compare with household and population ranks
- **Trajectories:** Histories of ranks

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

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)



- Meaningful differences in wealth levels across ranks
- Substantial wealth inequality in Norway
- Changes in wealth levels at each rank as the cohort ages

► BC vs Pop Ranks

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

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

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

► AR(1) ► Income

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- Conditional moments, $E [y_{i,t+h}|y_{i,t}]$, and quantiles, $Q_{y_{i,t+h}|y_{i,t}}(\tau)$
 - 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)

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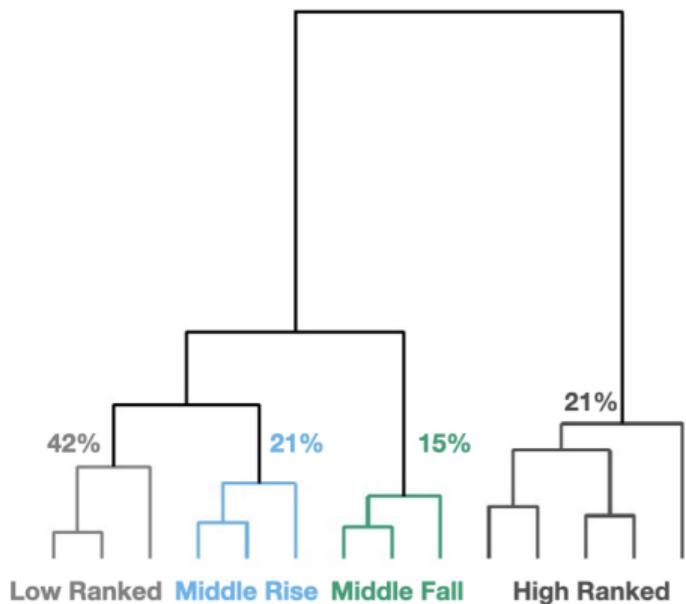
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Result: Hierarchy of partitions ranging from $G = N$ to $G = 1$.

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

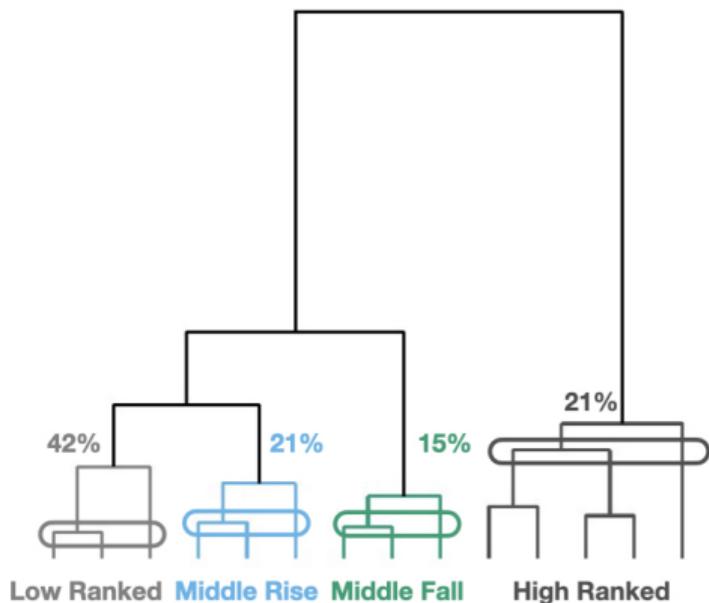
Two Levels of Clustering

Clustering Tree

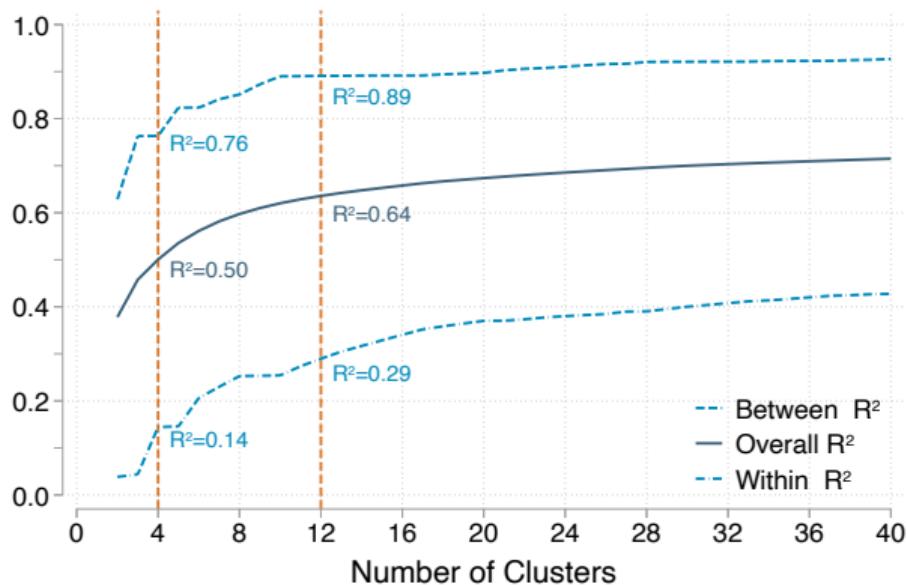


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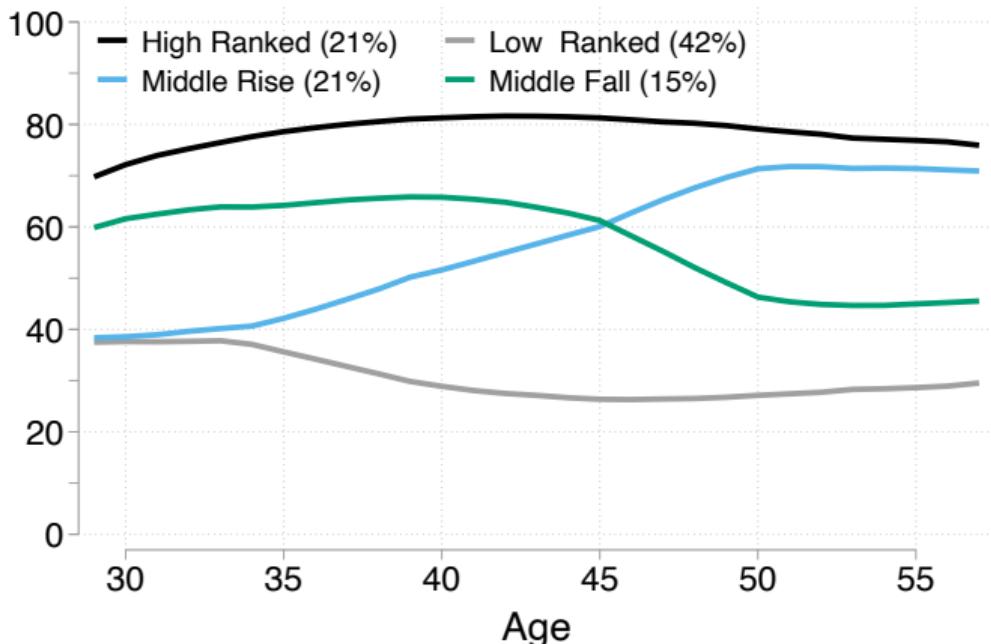


Variation Explained



Typical Rank Histories

Cohort Ranks

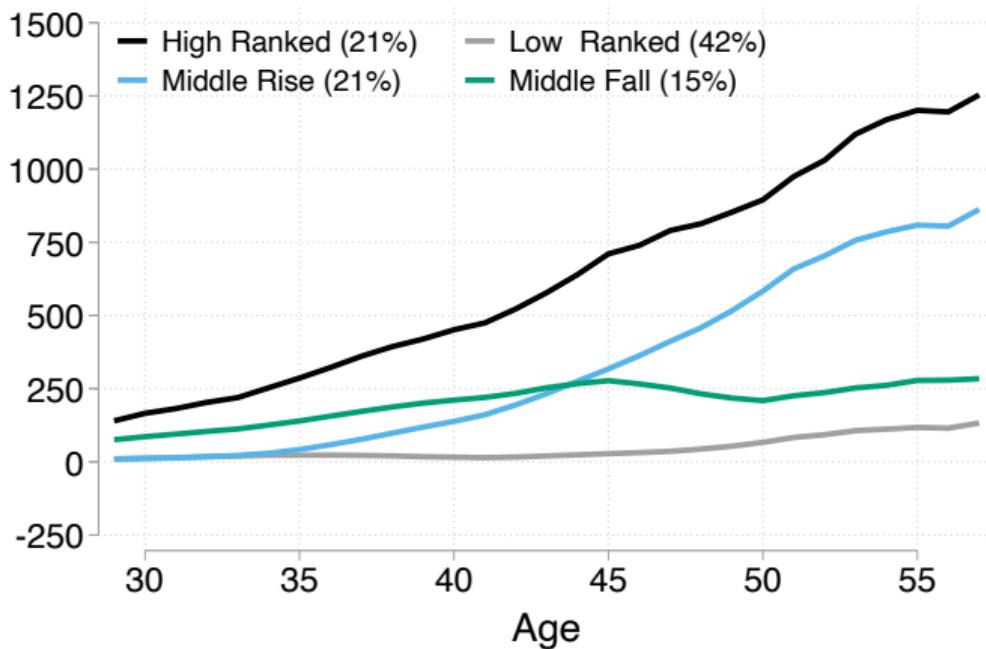


Segmented mobility

- 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%

Wealth Histories Across Segments of the Distribution

Net Worth (\$1000s)

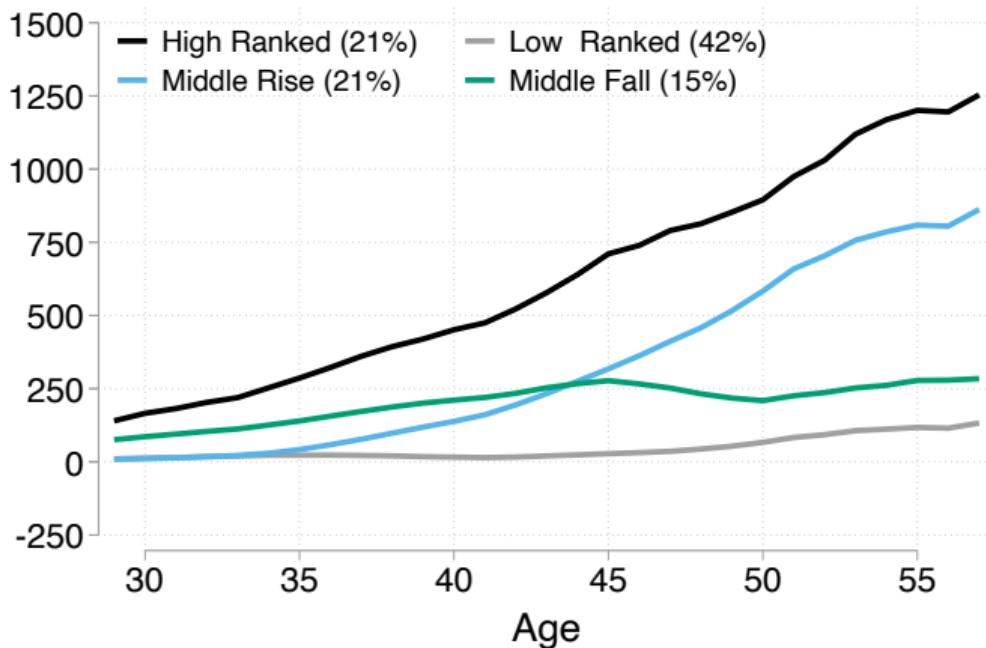


Significant diff. in wealth profiles

- Top: Maintaining rank means level growth (8-10%)
- Bottom: Grow in 50s (housing)

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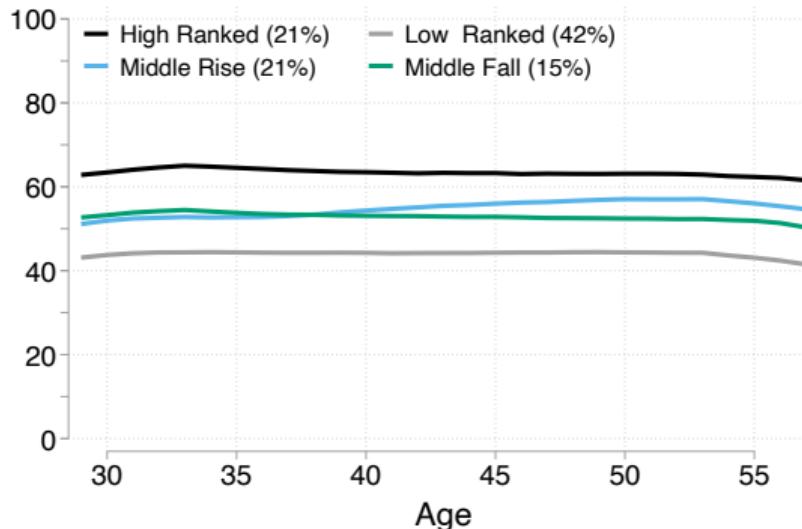


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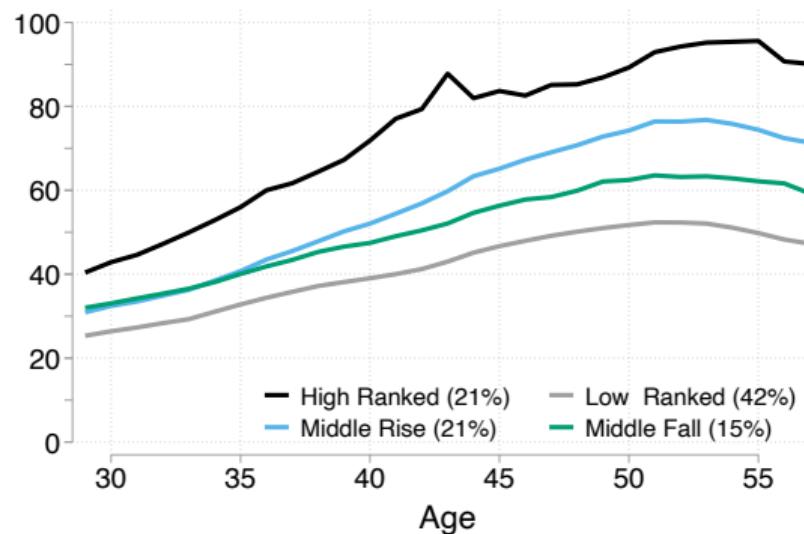
- Top: Maintaining rank means level growth (8-10%)
- Bottom: Grow in 50s (housing)
- Risers: Grow on avg. 18%/y
- Fallers: ahead in 30s + low growth (5%) + great recession

Income Histories Across Segments of the Distribution

Income Cohort Ranks



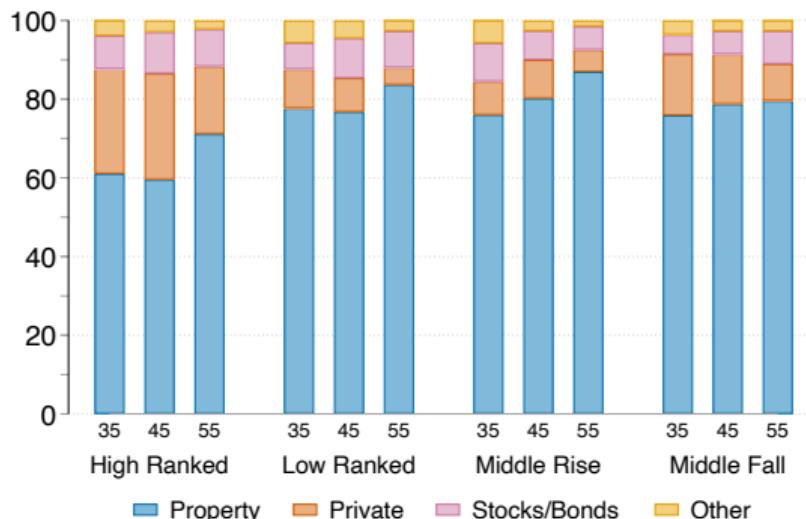
Income (\$1000s)



- 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

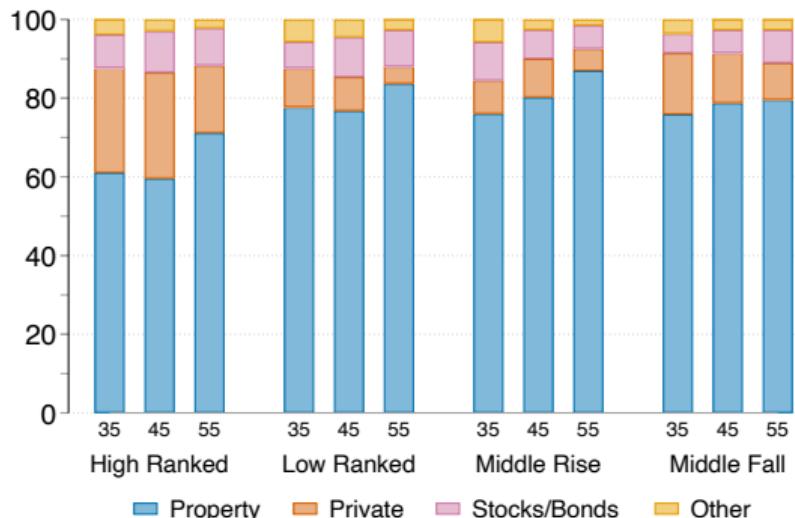


- Asset differences across clusters in **Private Equity** and **Property**

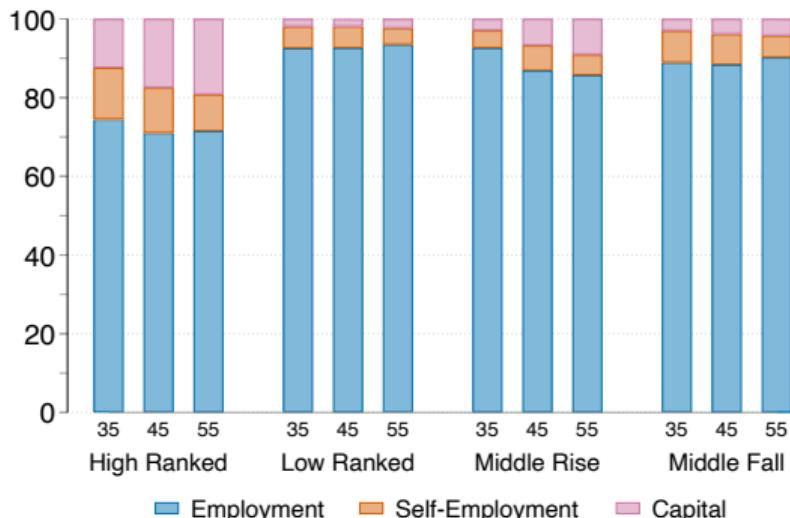
▶ Home-ownership

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Income Sources



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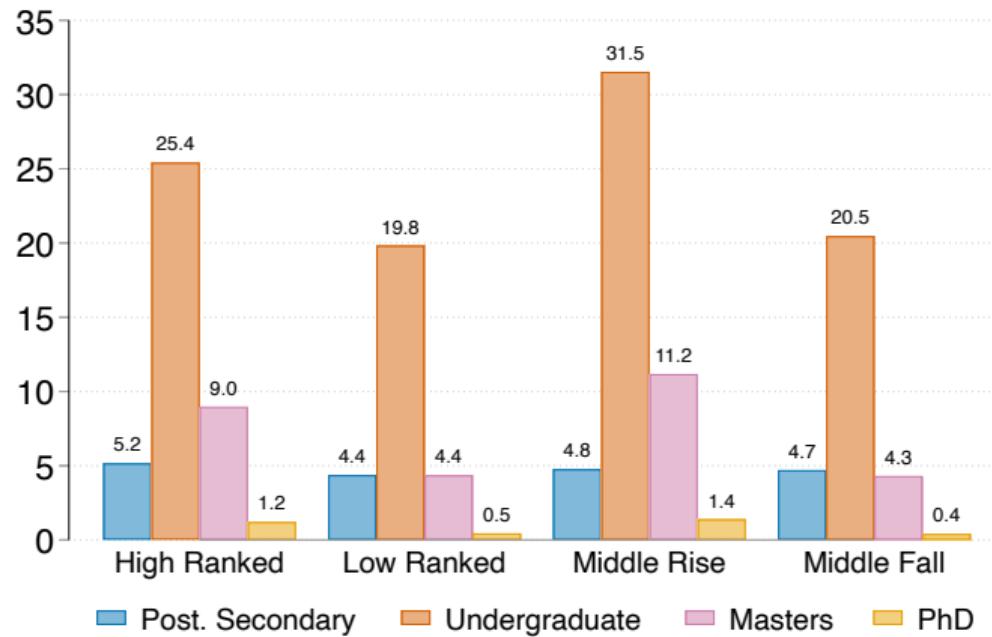
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- Income differences in **Self-Employment** and **Capital**

▶ SE ▶ Transfers ▶ Gifts

Education: Highest among risers

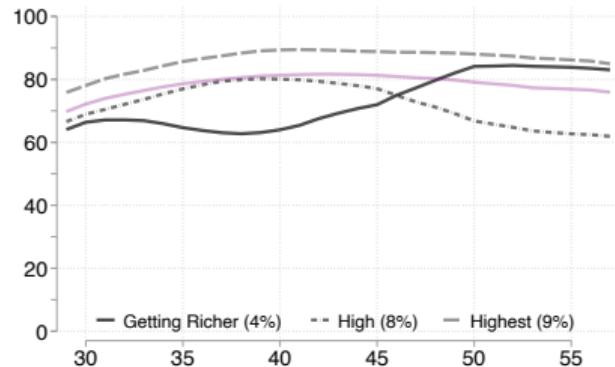
Highest Education Level Shares (%)



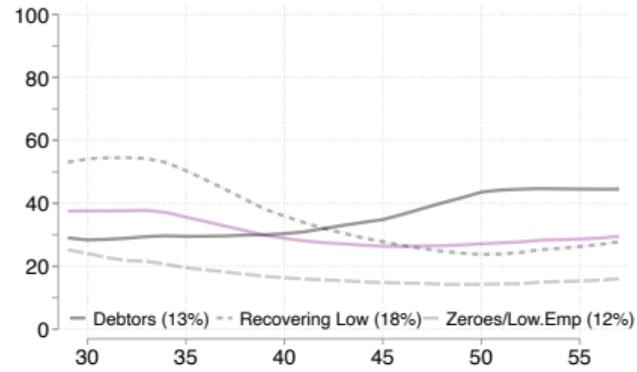
Heterogeneity: Levels vs Timing

► Details ► Wealth ► Portfolio ► Inc. ► SE ► Edu.

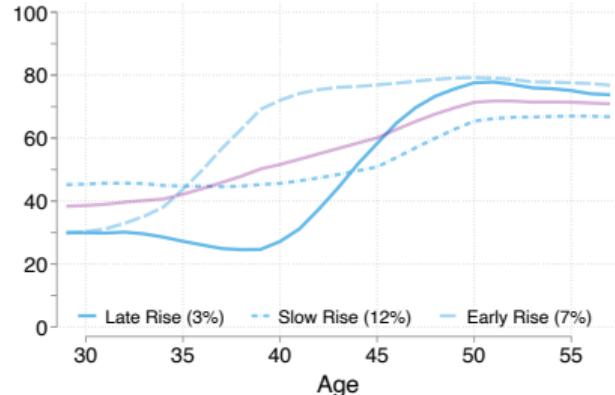
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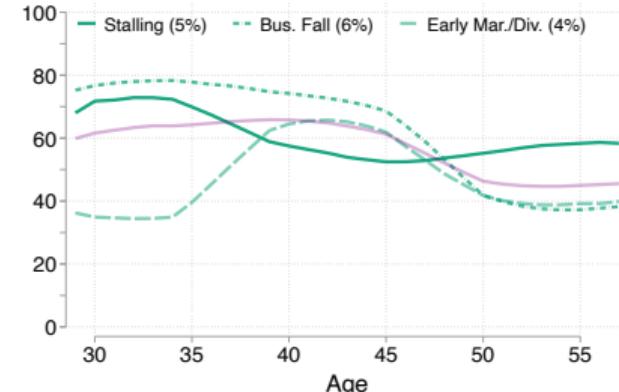
Low Ranked



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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- $\alpha_{q(i)}^j$: Indicators for 1993 parental wealth (cohort rank by ventile)

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- $\lambda_{bcounty(i)}^j$: Indicator for birth location ▶ Location APE

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▶ Sex APE

▶ Location APE

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

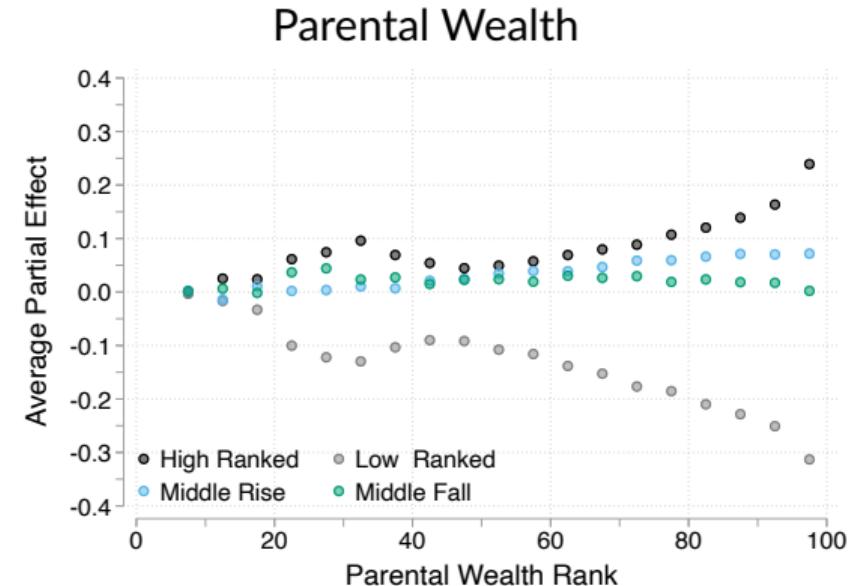
▶ Results

Non-Linear Effects of Parental Wealth and Education

PW Cls

ED Cls

ED Field



- Parental wealth's explanatory power: High for top/bottom, limited for middle groups

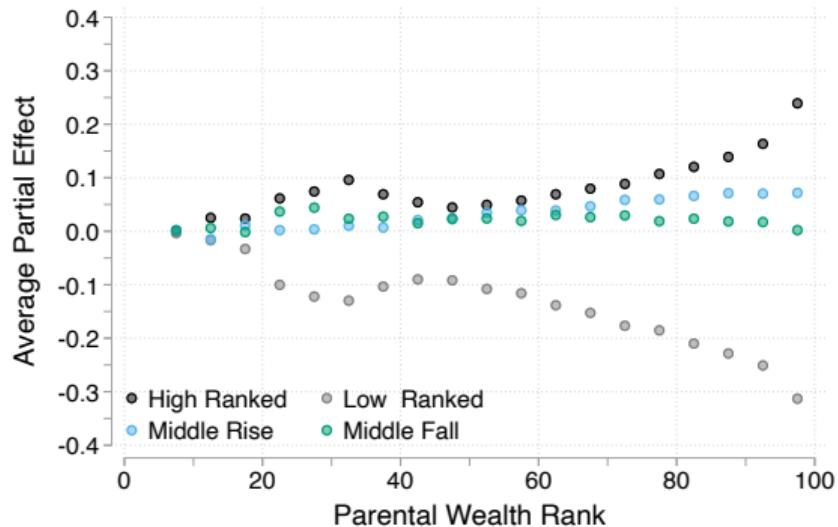
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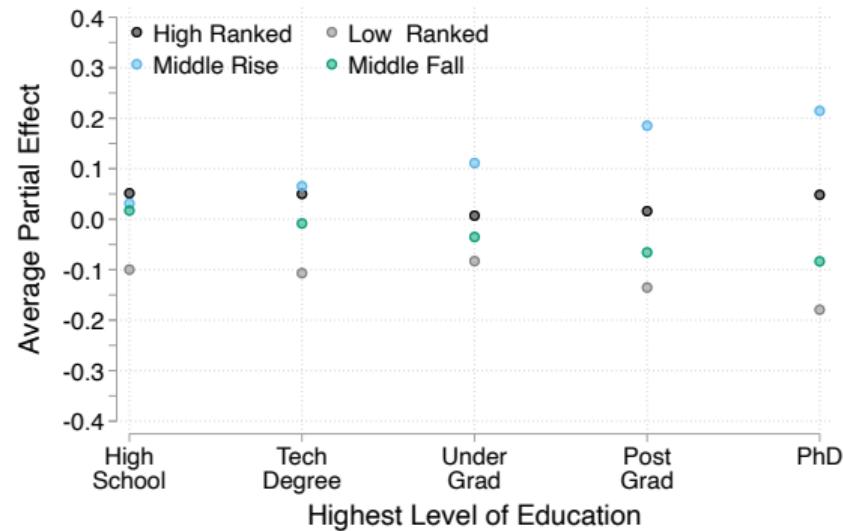
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Parental Wealth



Education



- 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

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

▶ High Ranked

▶ Low Ranked

▶ Middle Rise

▶ Middle Fall

Heterogeneity and Robustness

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▶ High Ranked ▶ Low Ranked ▶ Middle Rise ▶ Middle Fall

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

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)

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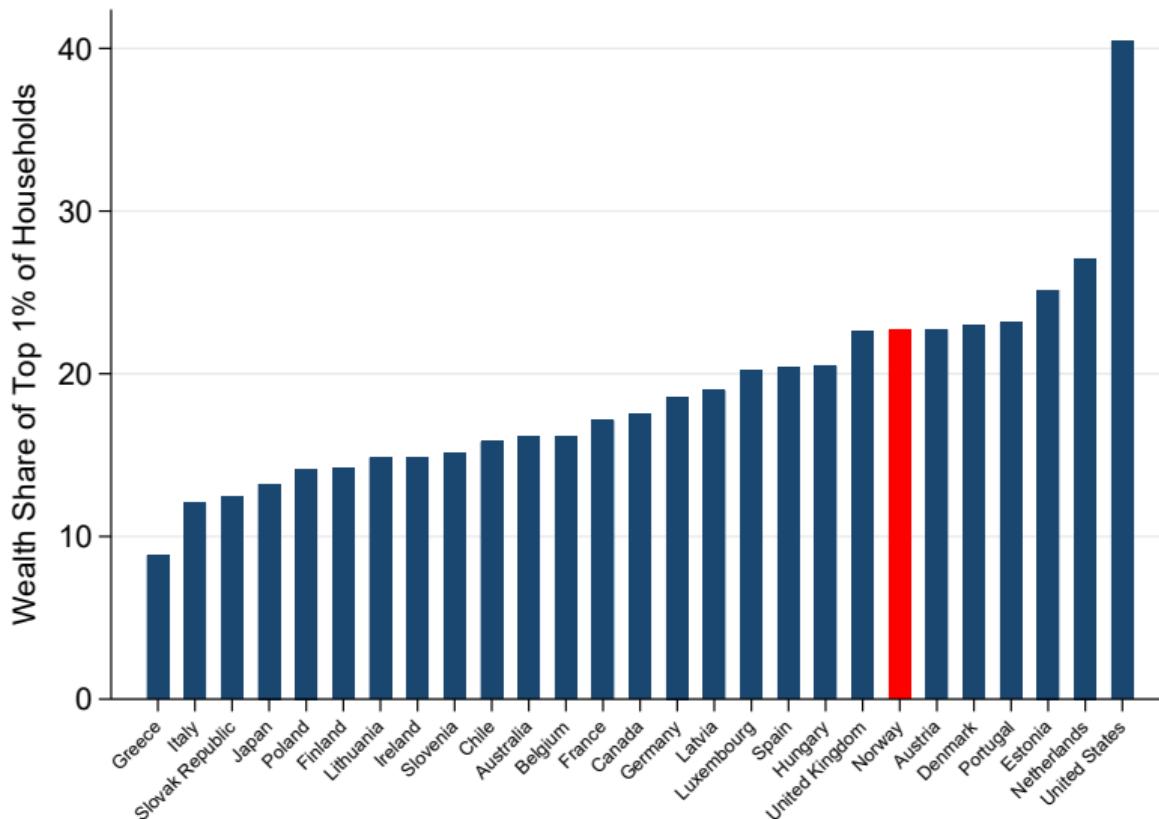
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4. Dimension reduction methods in economics & applications to labor markets
 - K-Means (Bonhome, Lamadon, Manresa; Gregory, Menzio, Wiczer), Sequence Analysis (Humphries), Hidden Markov (Ahn, Hobijn, Şahin), Finite Mixture

Extra

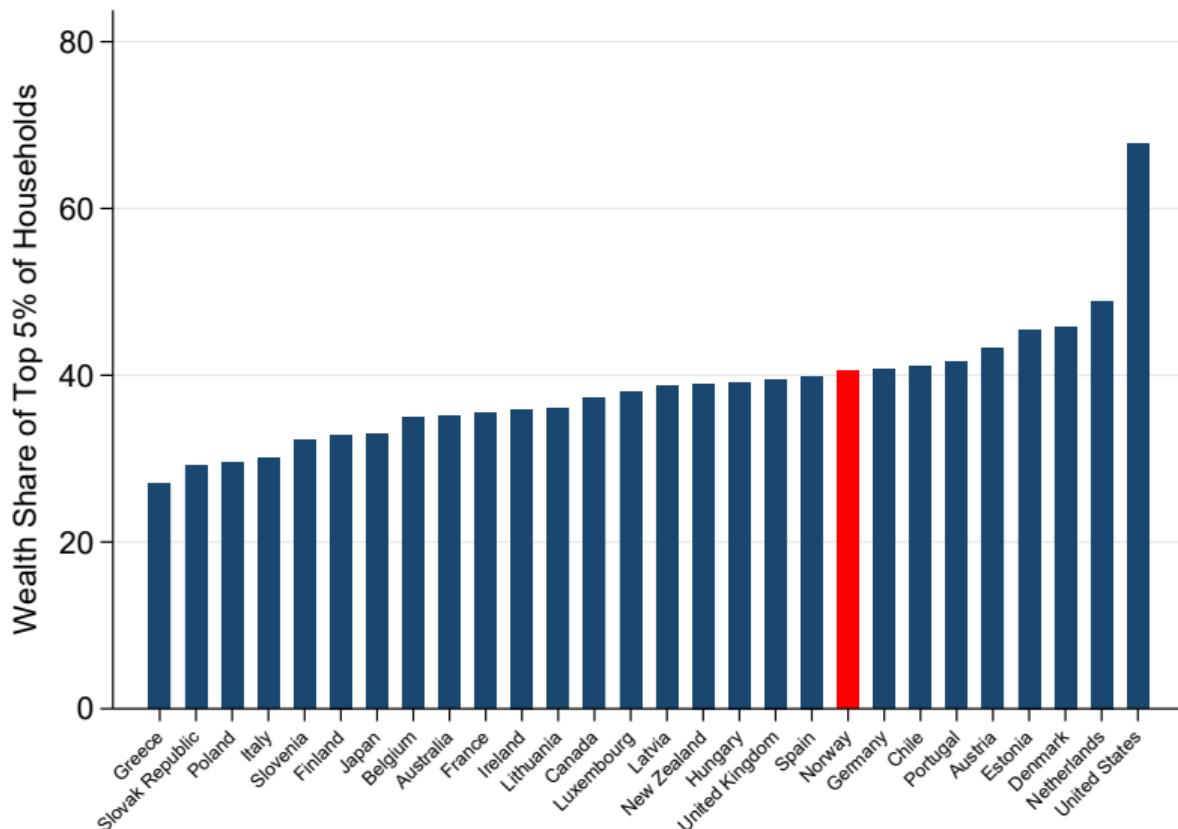
Norway in Context

◀ Back



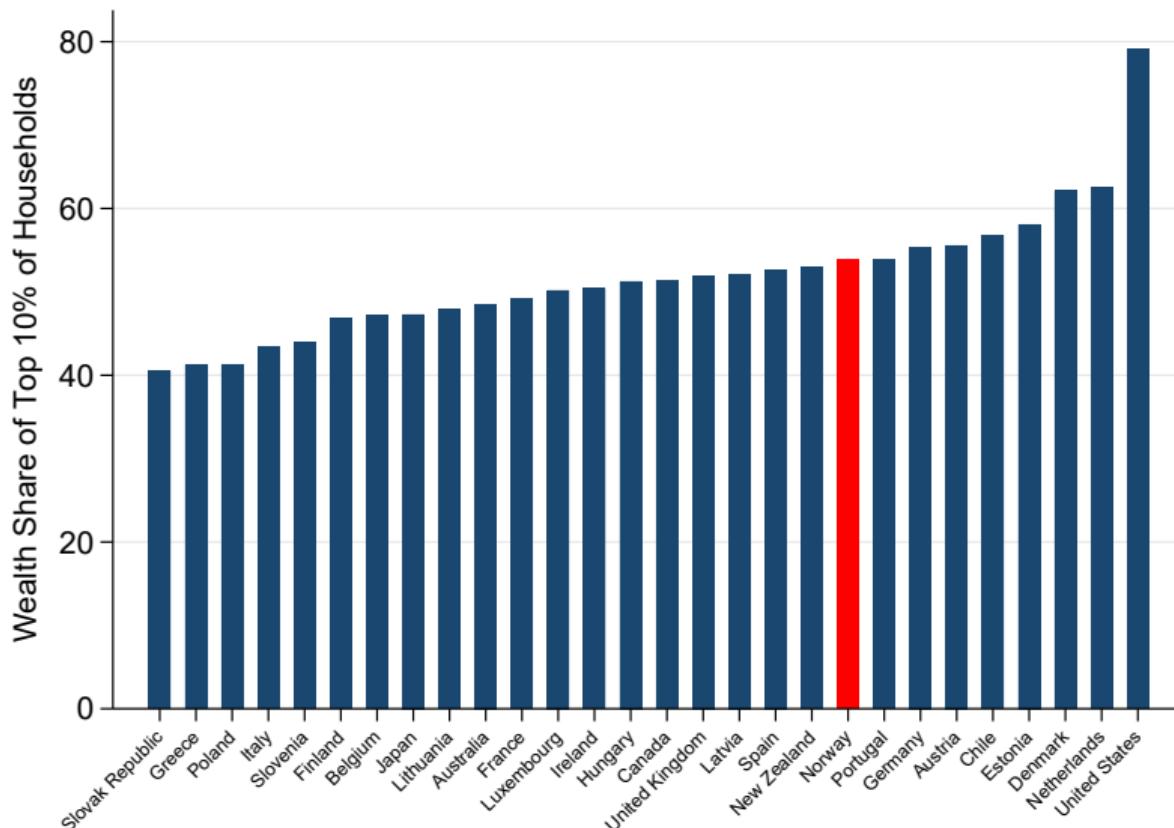
Norway in Context: Top 5% Share

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Norway in Context: Top 10% Share

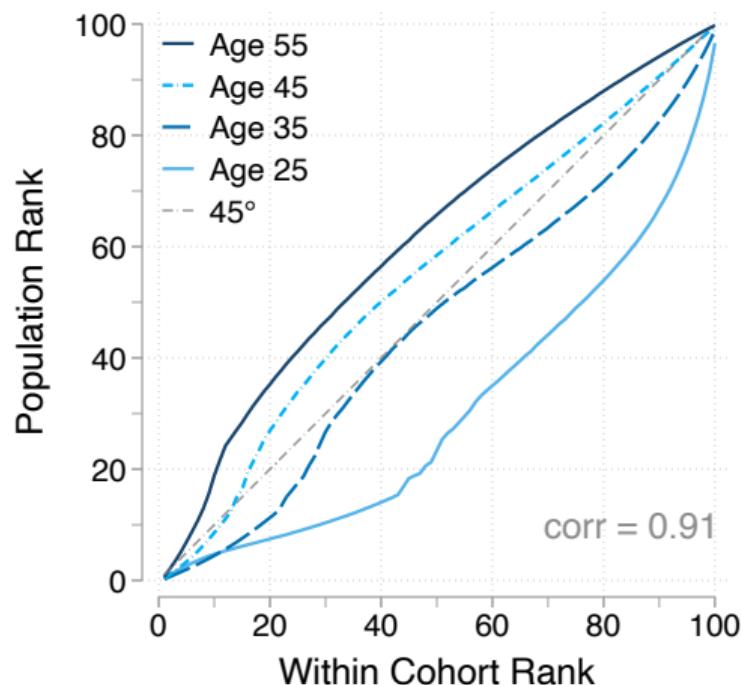
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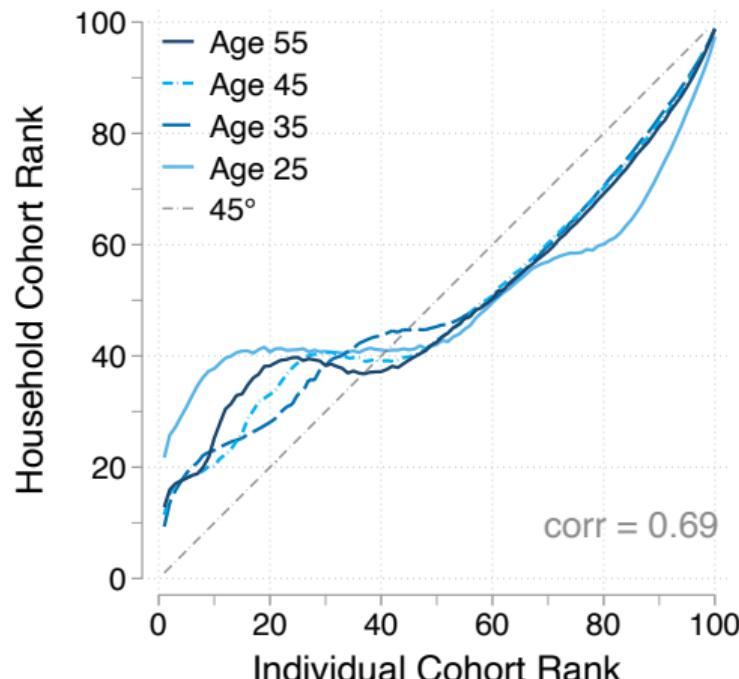
Birth Cohort Ranks vs Population Ranks and Household Ranks

◀ back

BC Ranks vs Pop Ranks



BC Individual Ranks vs Household Ranks

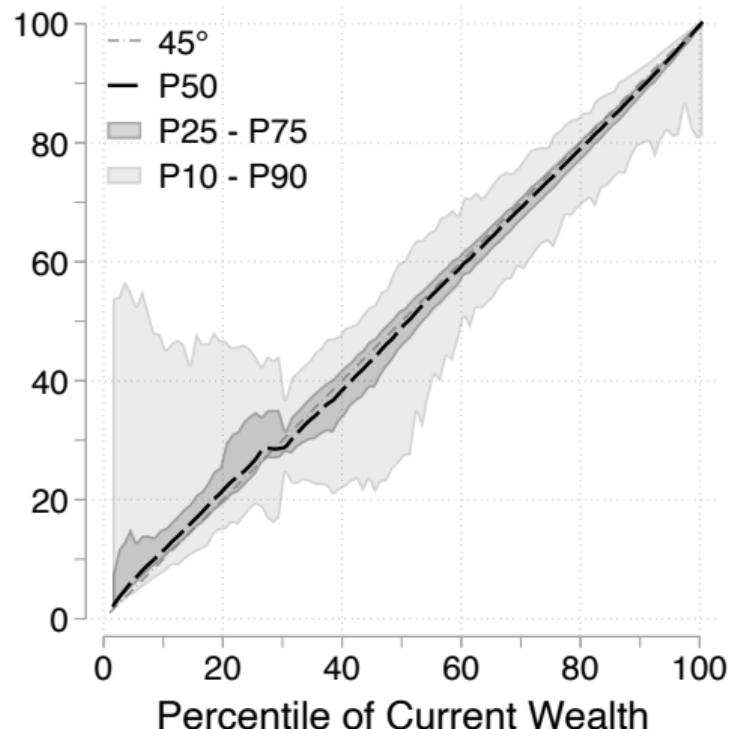


Conditional Distribution of Rank Changes

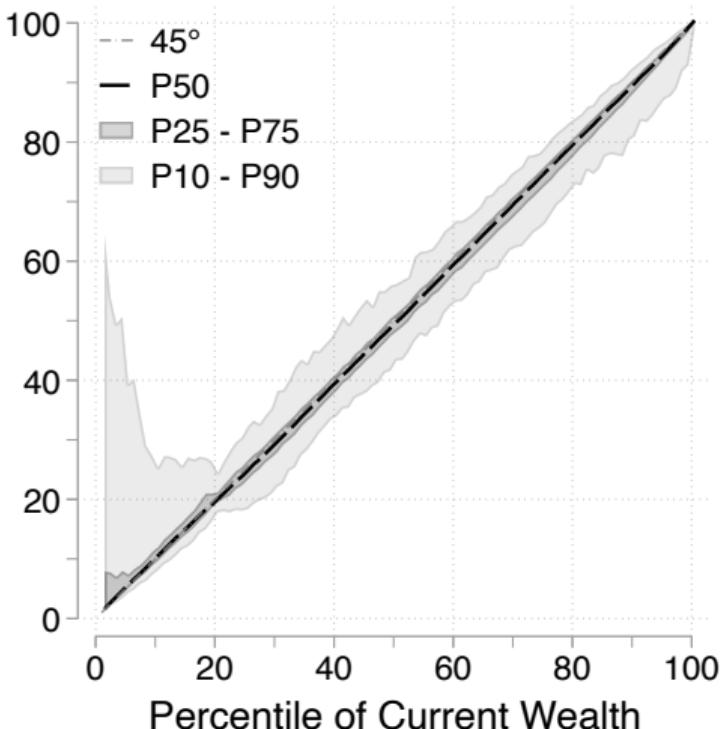
The Distribution of Rank Changes (1-year)

◀ Back

Age 35 – Cond. pct



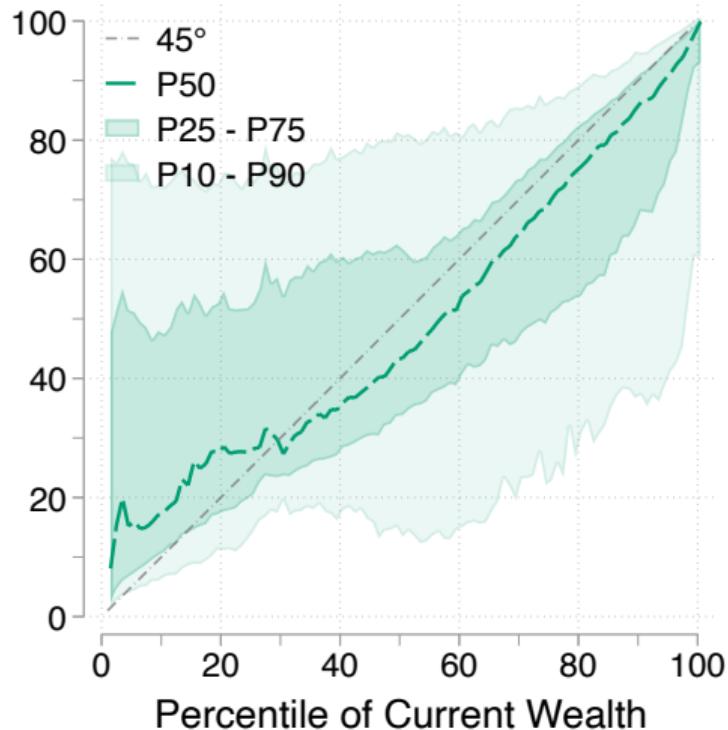
Age 45 – Cond. pct



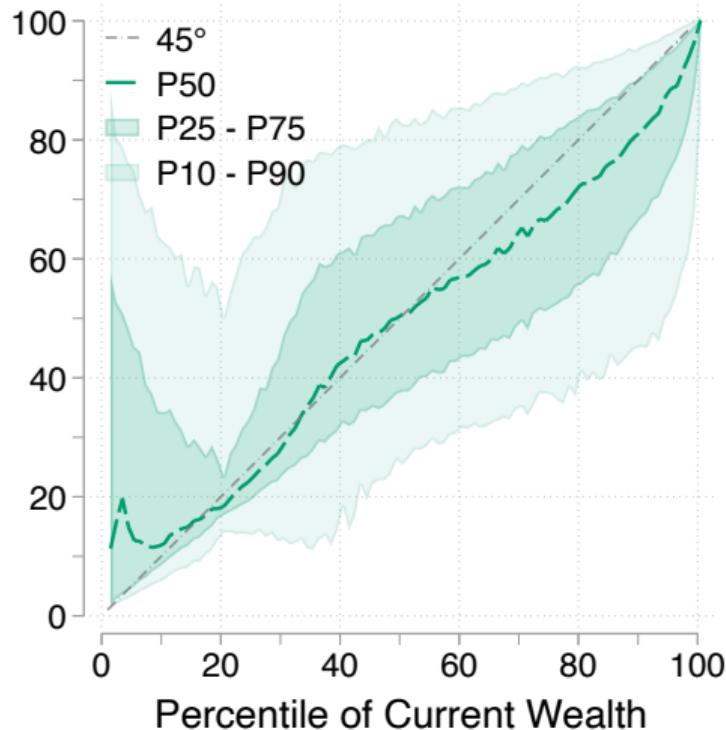
The Distribution of Rank Changes (5-year)

Back

Age 35



Age 45

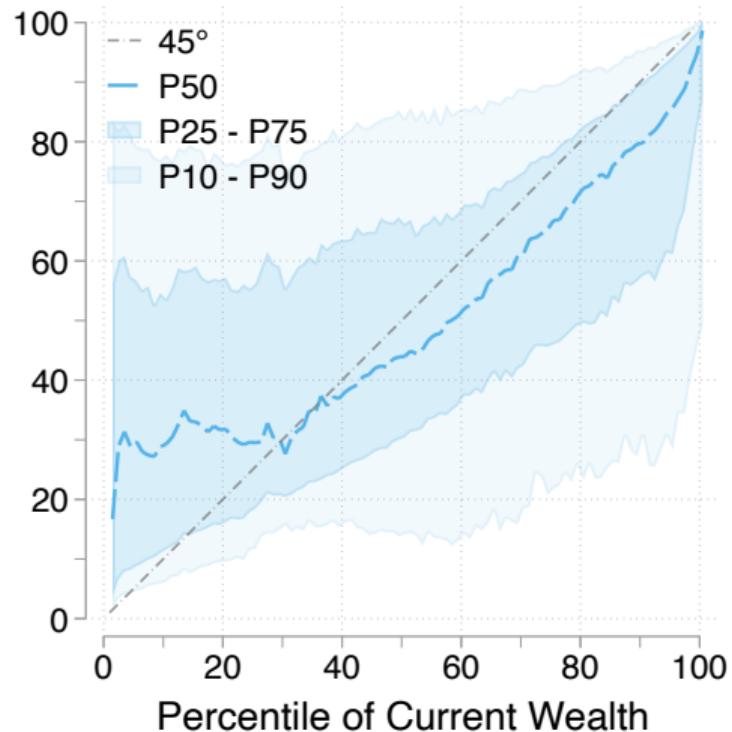


At the top few fall, but cushioned Middle class rarely climb, but some fall

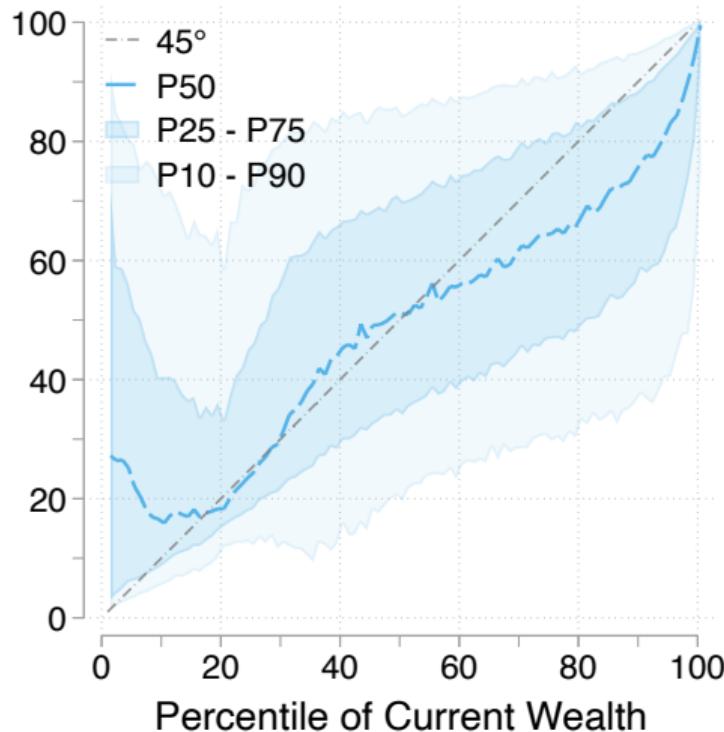
The Distribution of Rank Changes (10-year)

◀ Back

Age 35



Age 45



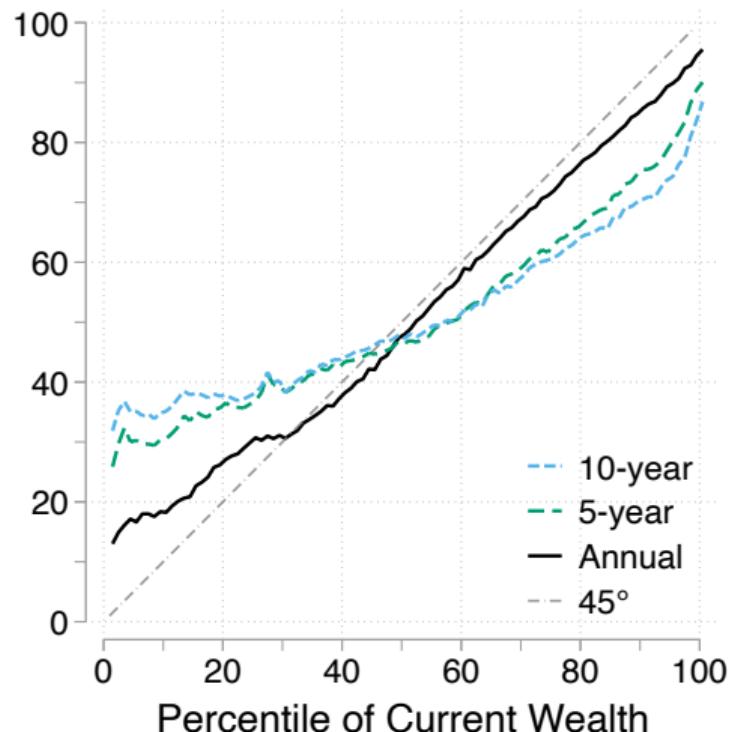
Over longer horizons more evenly spread and dispersion growing

Conditional Moments of Rank Changes

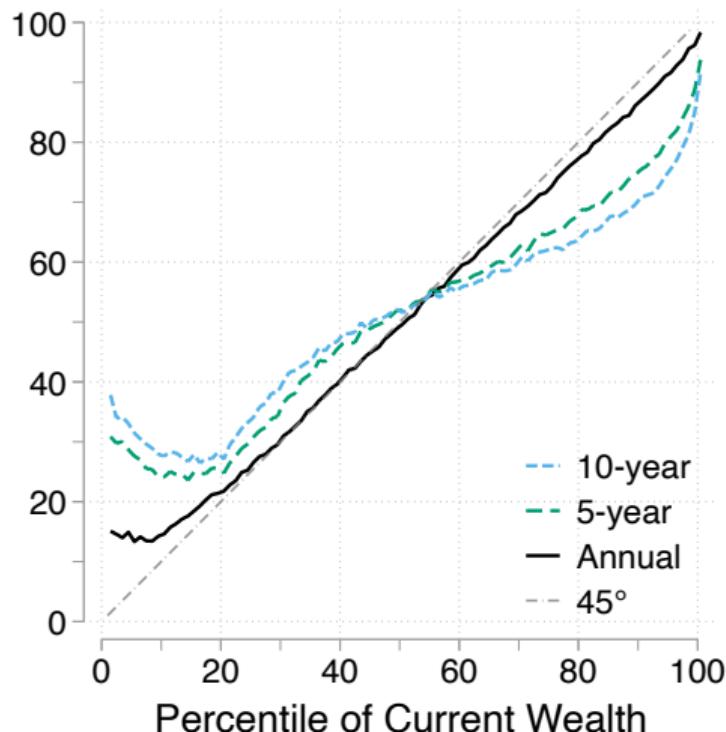
Rank Changes: Average

◀ Back

Age 35 – Cond. Mean

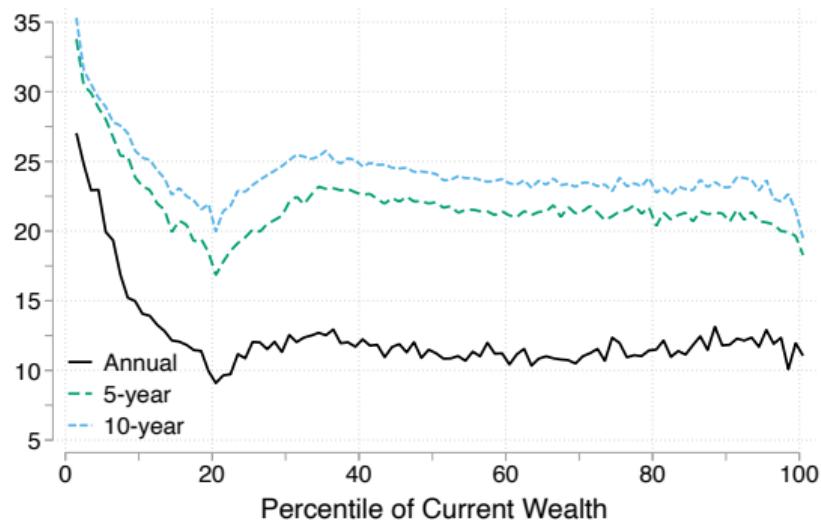
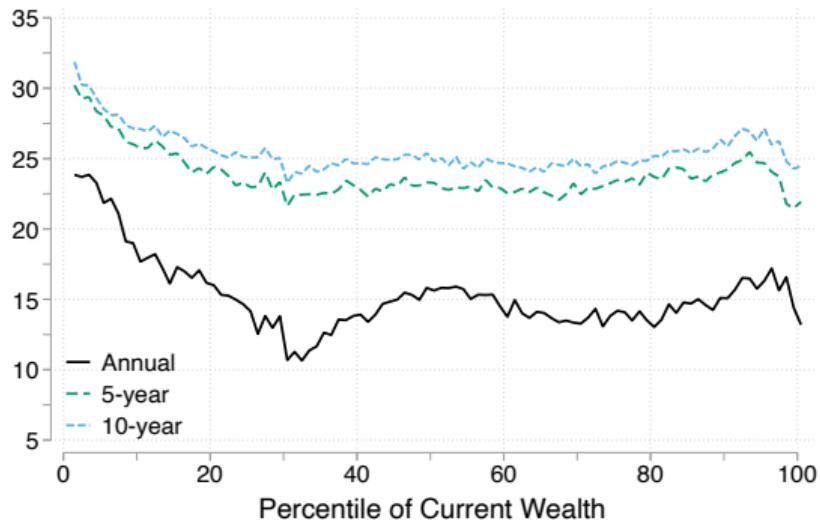


Age 45 – Cond. Mean



Rank Changes: Standard Deviation

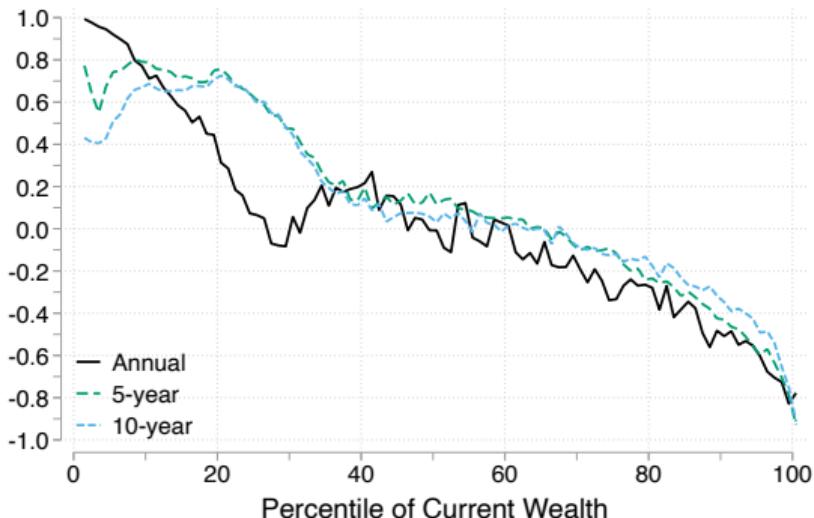
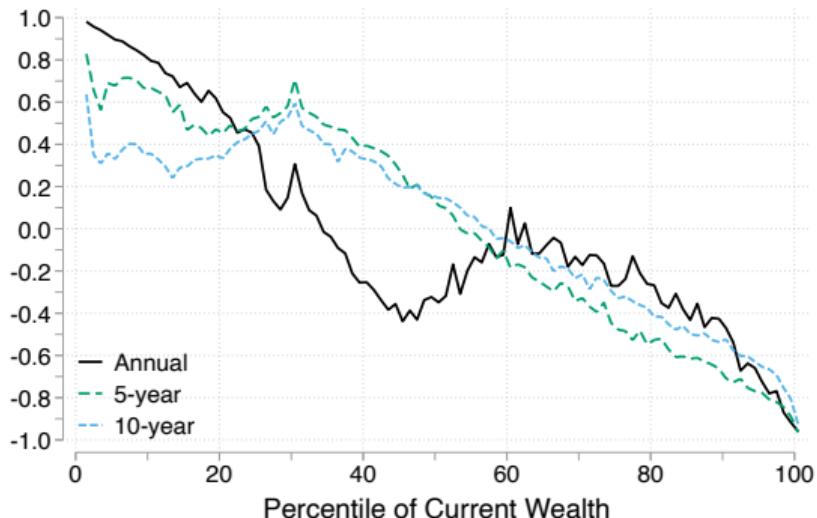
◀ Back



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

Rank Changes: Skewness

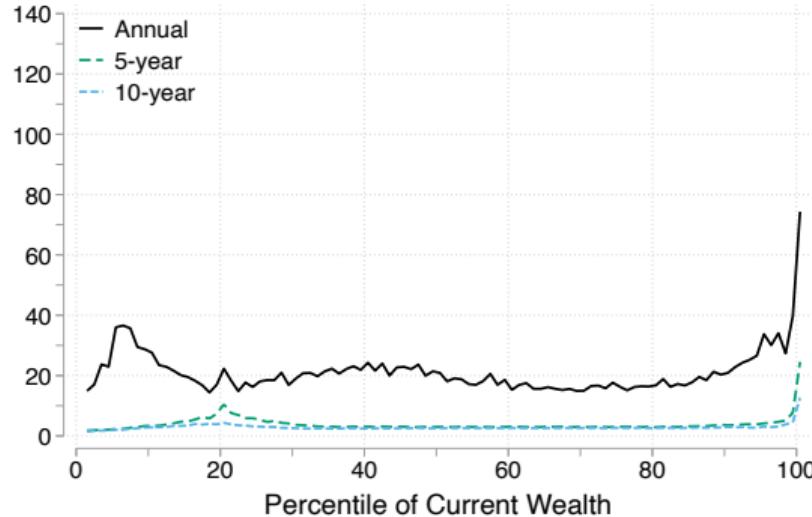
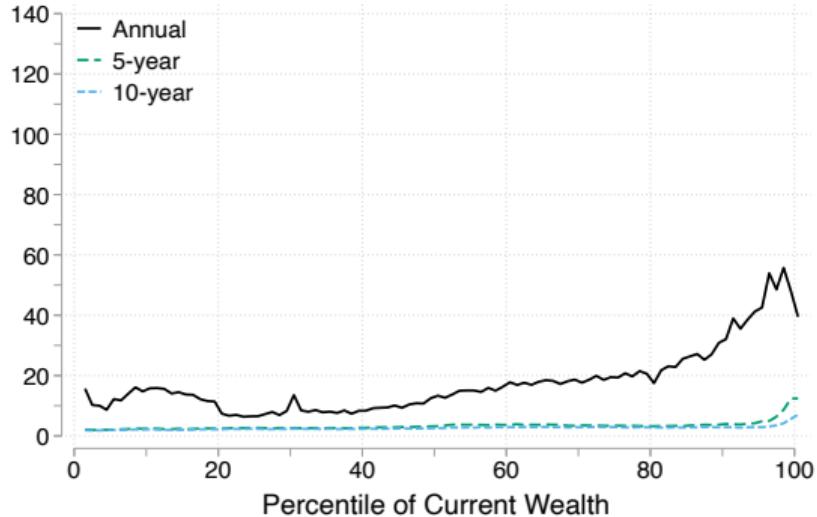
◀ Back



- 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

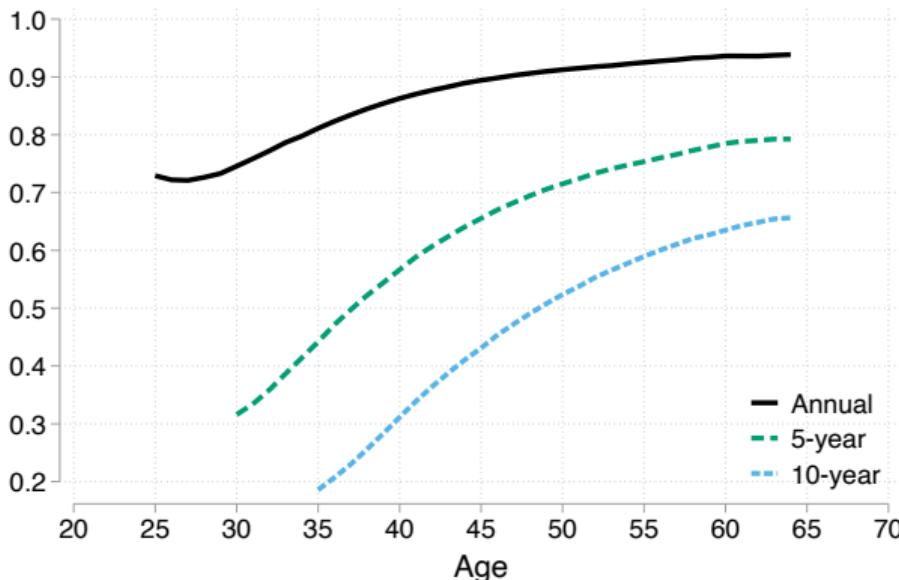
Persistence of Ranks

Persistence in Wealth Rank: Higher at long-run

▶ 1960bc

◀ Back

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

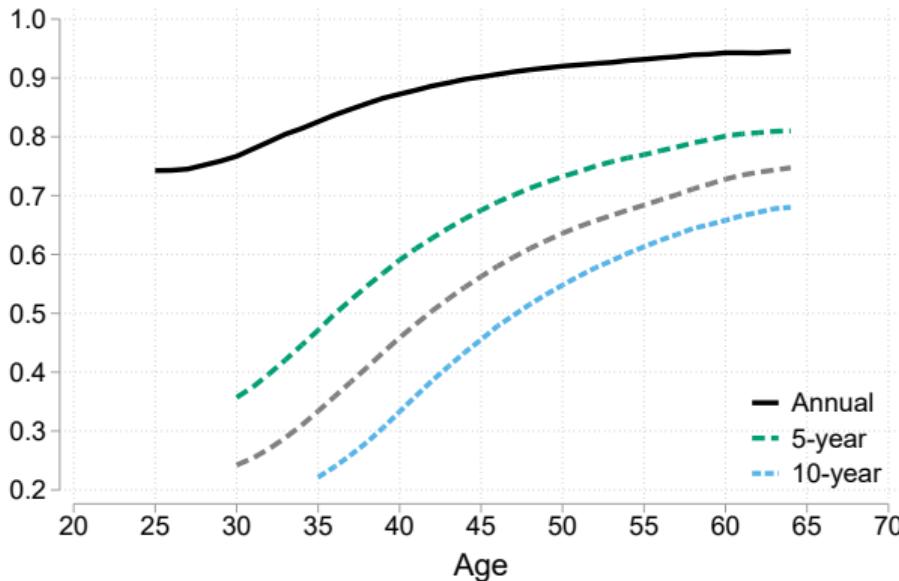


- Annual persistence is slow to stabilize, but eventually high ($\rho_t(1) \approx 0.95$)

Persistence in Wealth Rank: Higher at long-run

[1960bc](#)[Back](#)

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

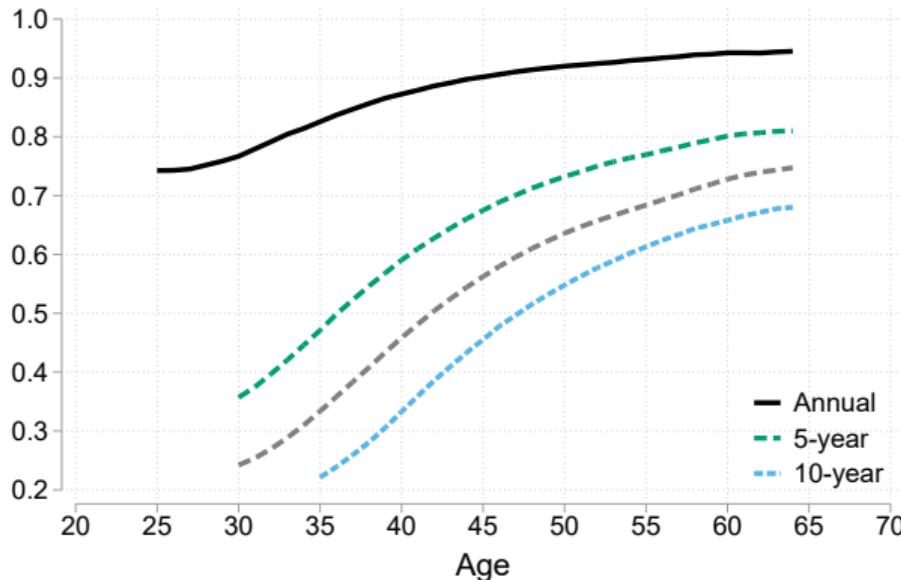


- **5y Iteration bias:** 5y Persistence higher than implied by annual ρ

Persistence in Wealth Rank: Higher at long-run

[1960bc](#)[Back](#)

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

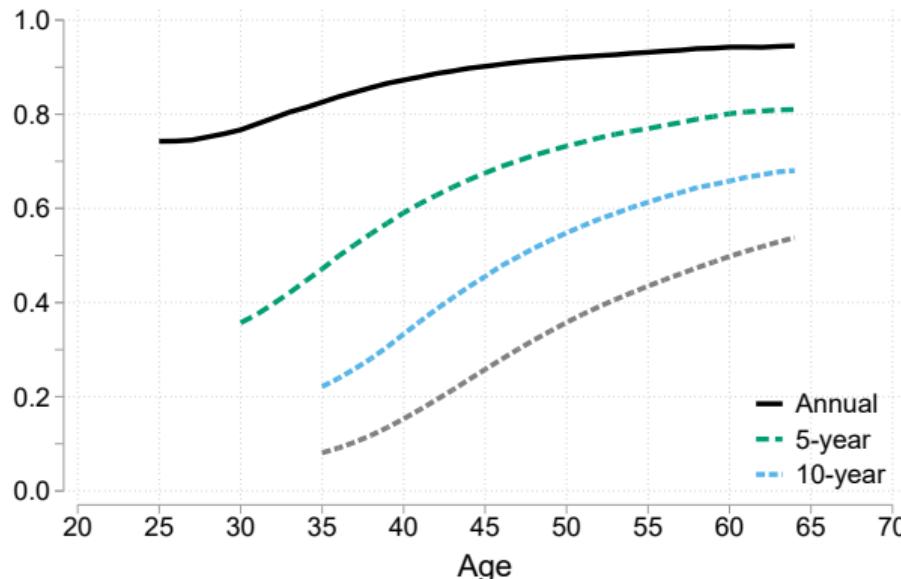


- **5y Iteration bias:** 5y Persistence higher than implied by annual ρ
- Life cycle snapshots can be misleading! Short-run mobility \gg Long-run mobility

Persistence in Wealth Rank: Higher at long-run

[1960bc](#)[Back](#)

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

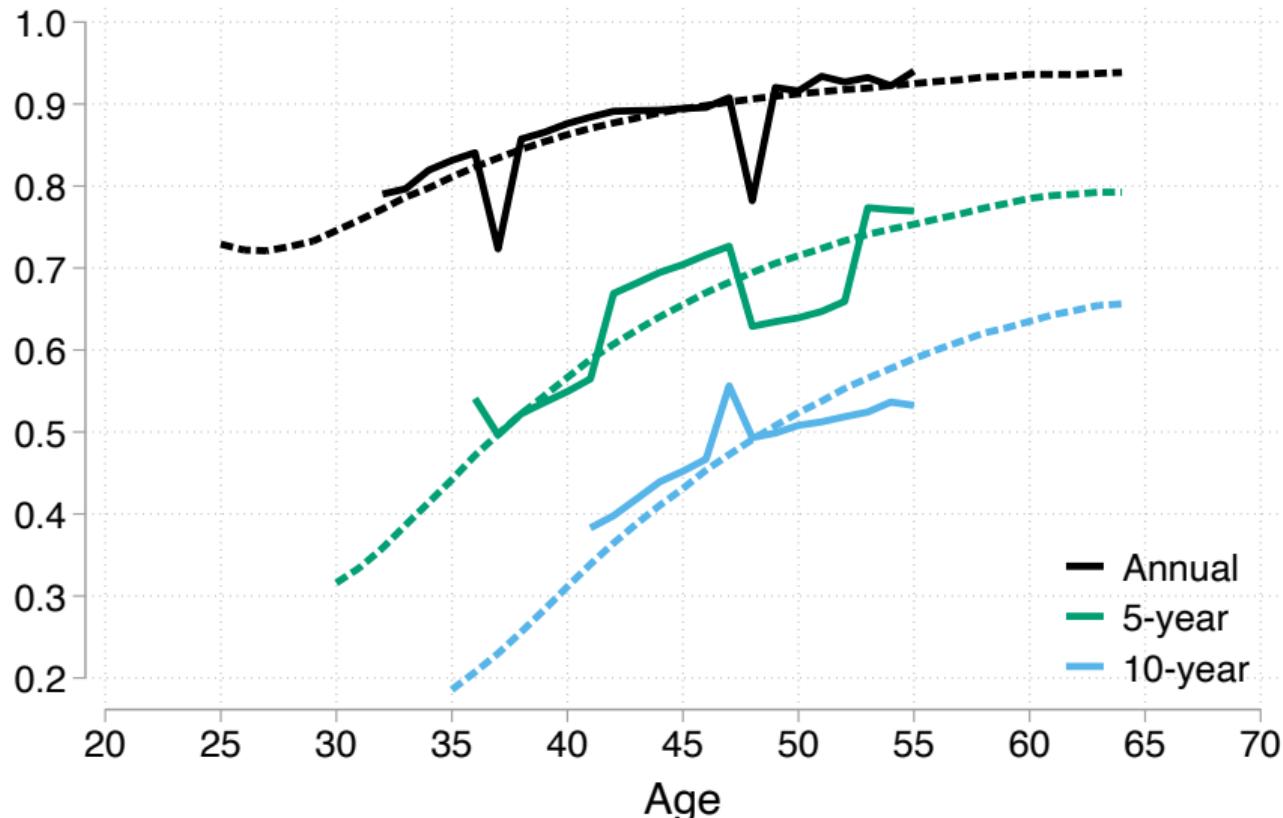


- **10y Iteration bias:** Dramatic bias! Actual $\rho(10)$ is 50-250% implied persistence
- Life cycle snapshots can be misleading! Short-run mobility \gg Long-run mobility

Persistence in Wealth Rank: Within Cohort

◀ Back

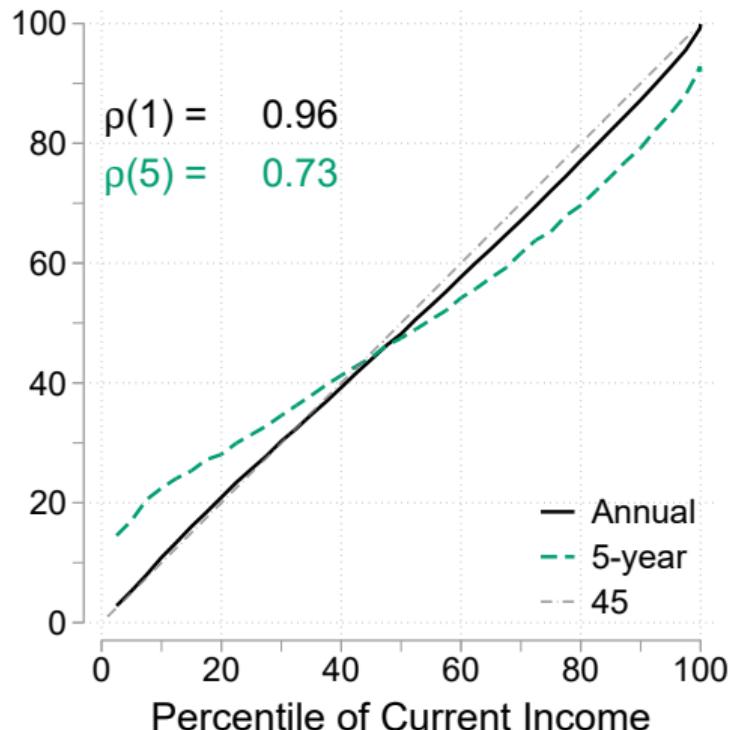
All Cohorts vs 1960-1964 Birth Cohort



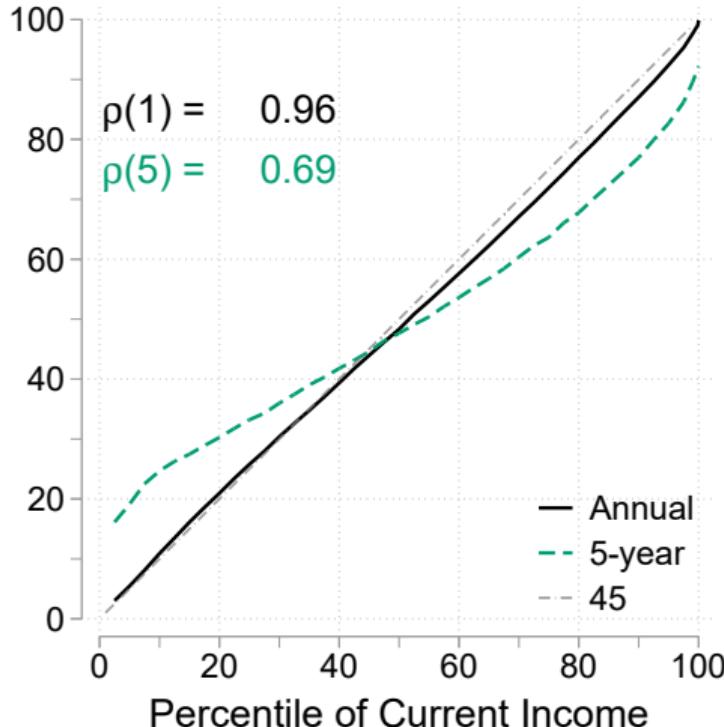
How Non-Linear is Income Mobility in Norway?

[◀ Back](#)[▶ USA](#)

Age 35-44



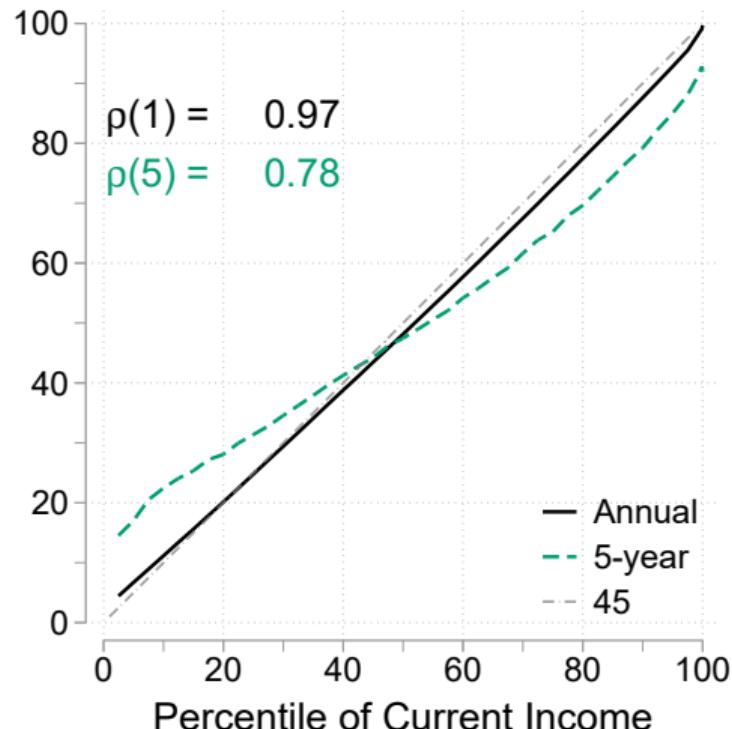
All



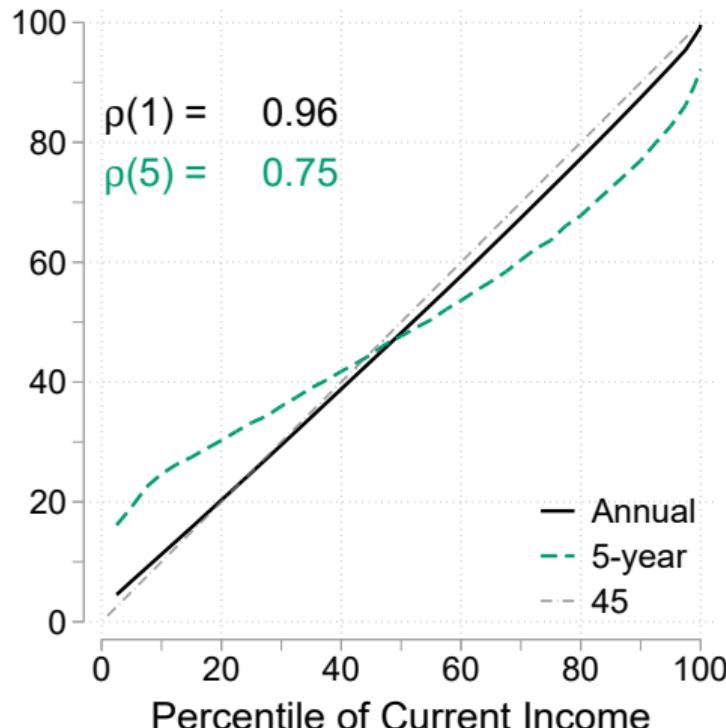
Source: GRID database for 2005

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

Age 35-44



All



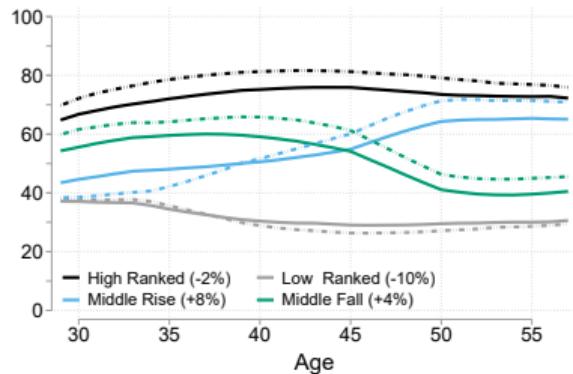
Source: GRID database for 2005

Characteristics of Main Clusters

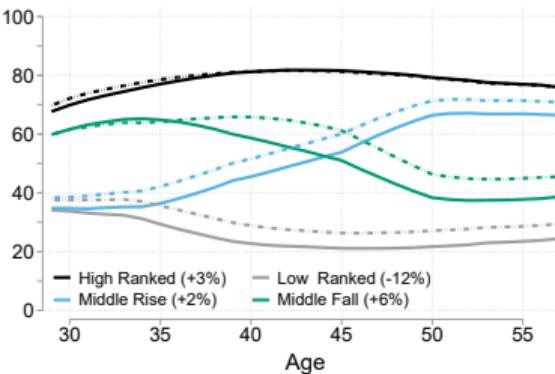
Alternative Clustering

◀ Back

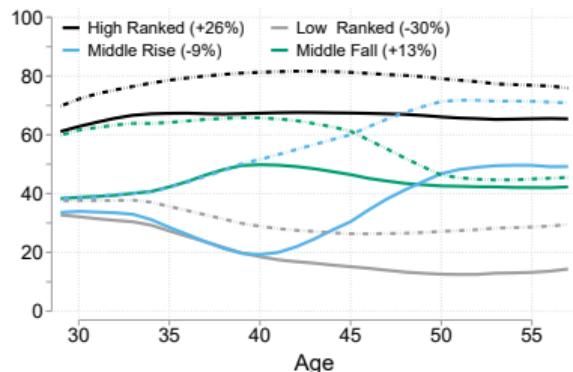
Household Cohort Ranks



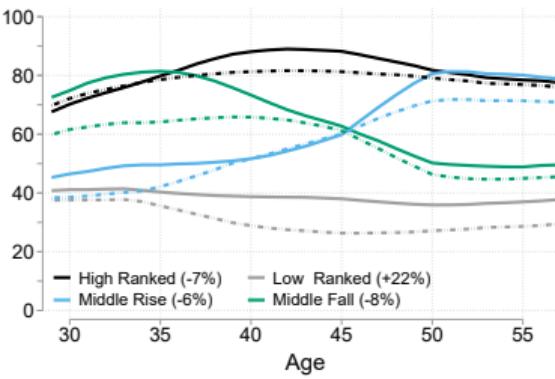
K Means on Ind. Cohort Ranks



Log Net Worth



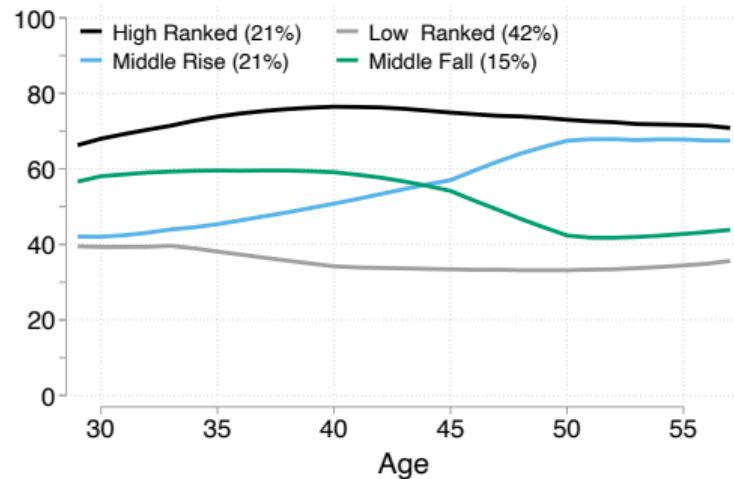
"Lorenz" Ordinates



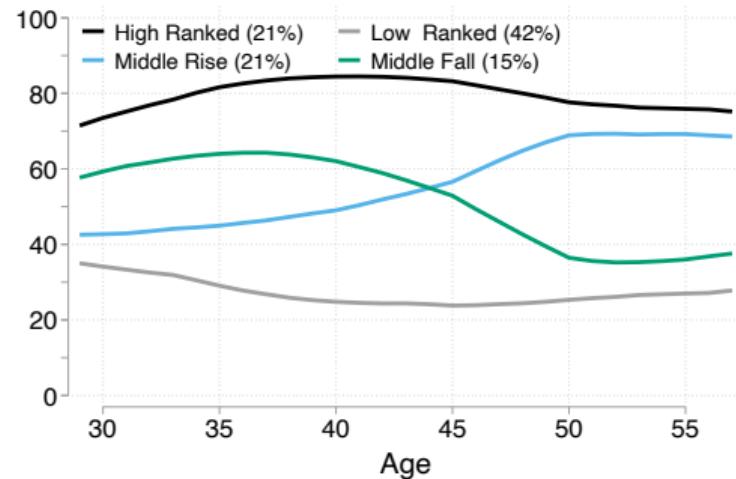
Household Wealth Ranks

◀ Back

Household Cohort Ranks (Ind. CI)



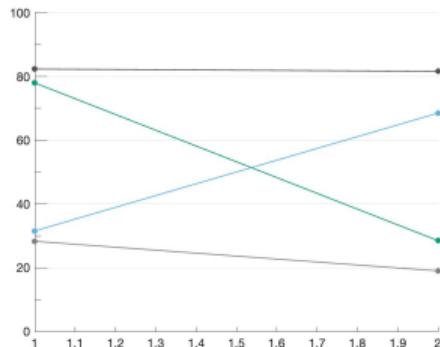
Household Cohort Ranks (HH. CI)



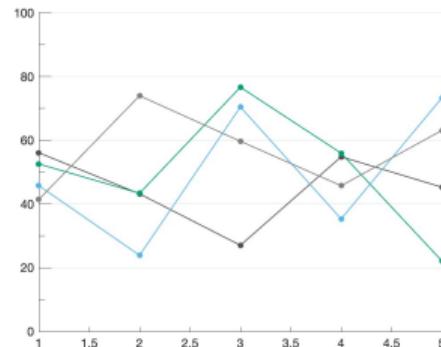
Clustering Random Ranks

◀ Back

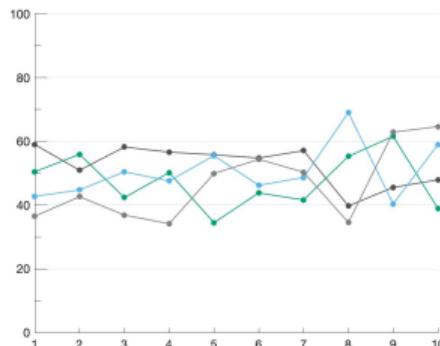
2 Periods



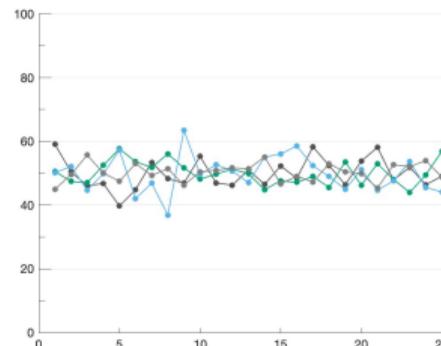
5 Periods



10 Periods



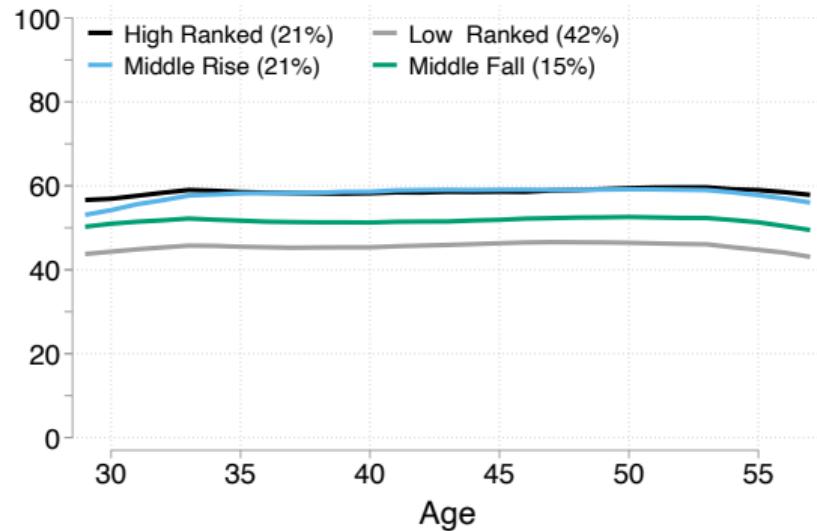
25 Periods



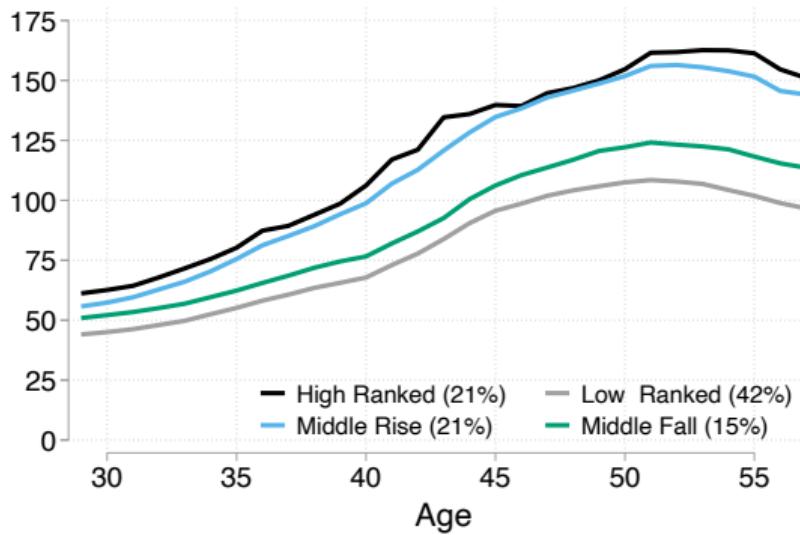
Household Income

Back

Household Income Cohort Ranks



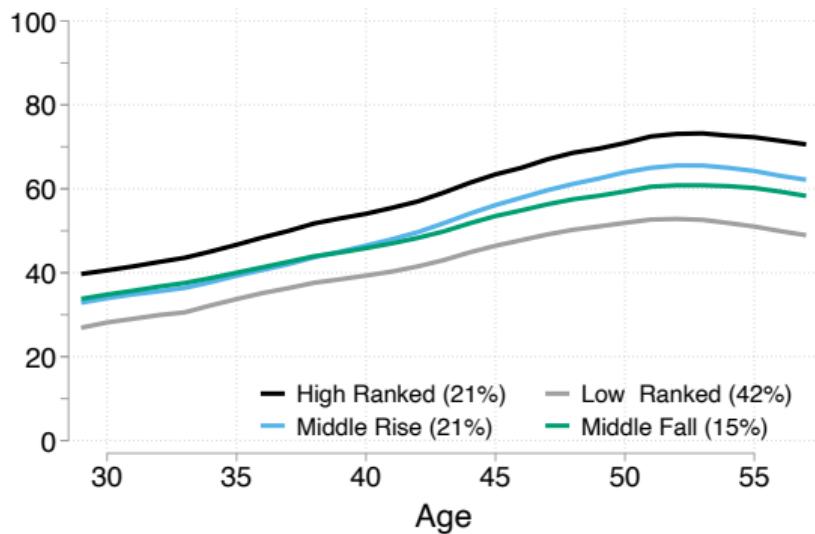
Household Income (\$1000s)



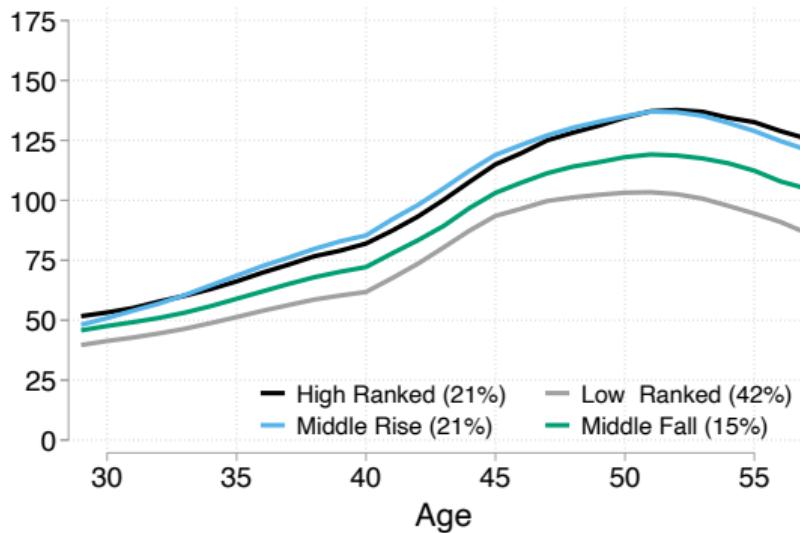
Median Income Histories

◀ Back

Median Income

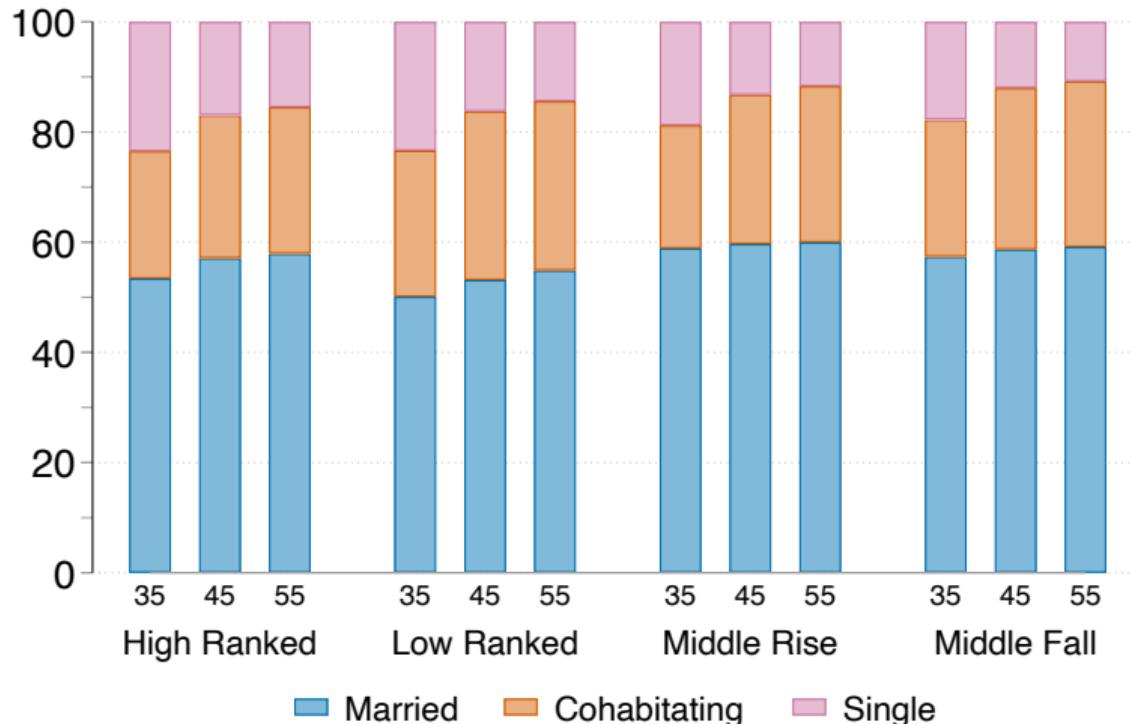


Household Median Income (\$1000s)



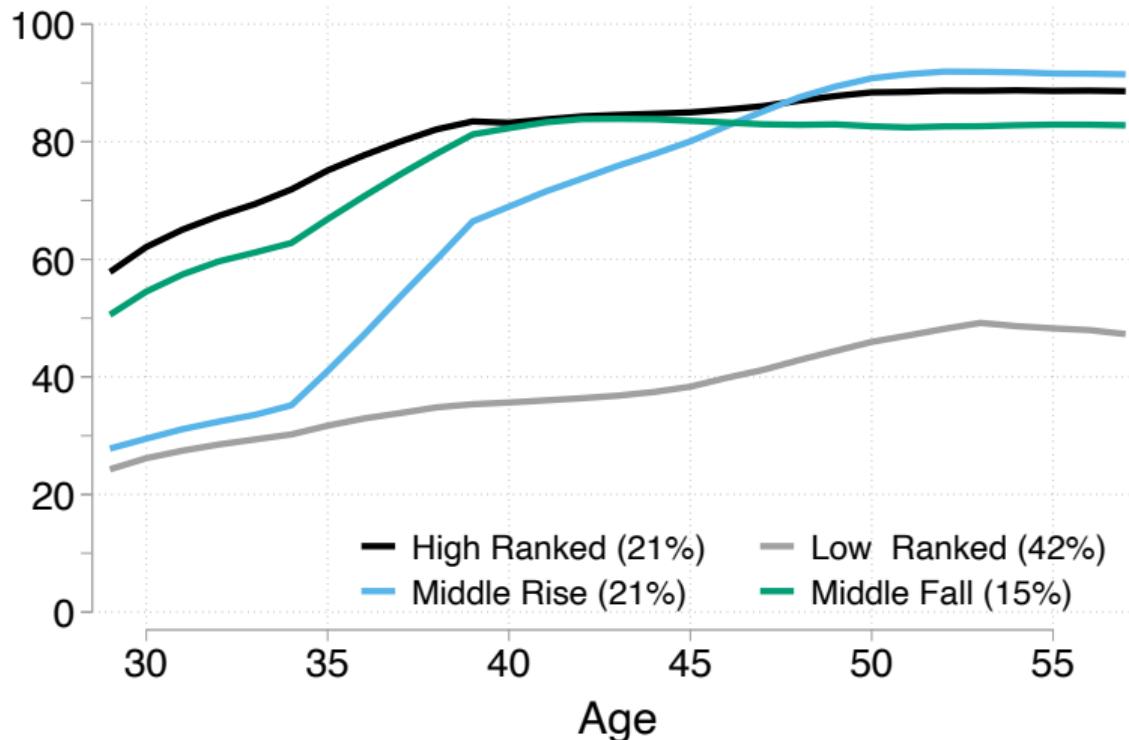
Civil Status

◀ Back



Home-ownership Rates by Cluster

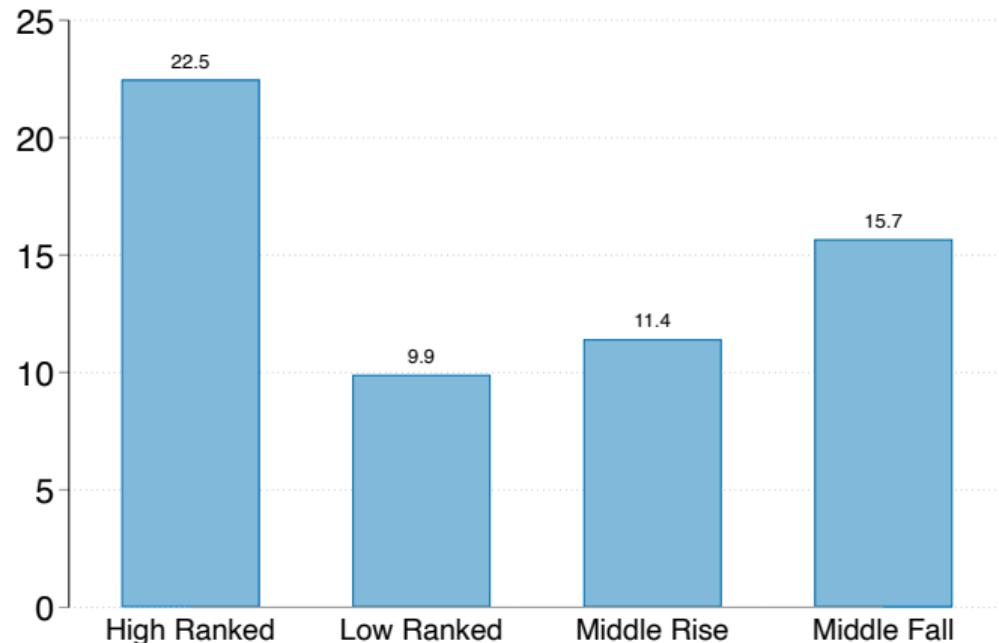
◀ Back



Self-Employment Rates, Age 45

◀ Back

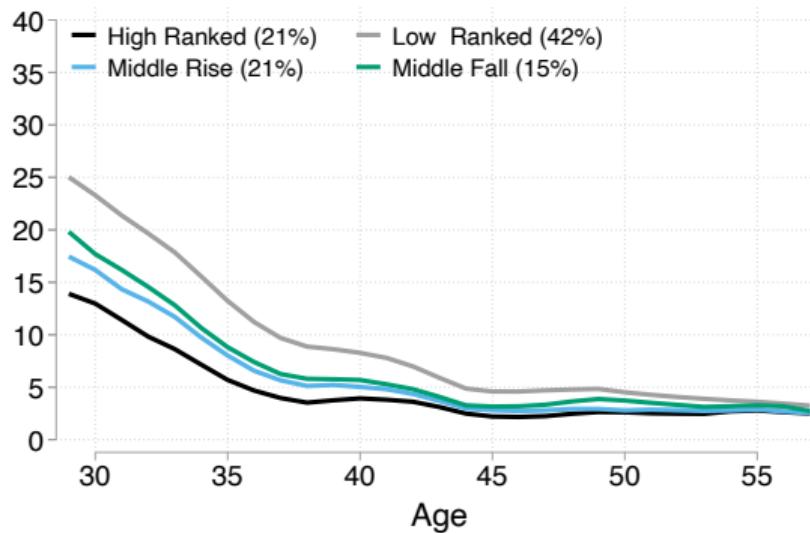
Share with Self-Employment Income (%)



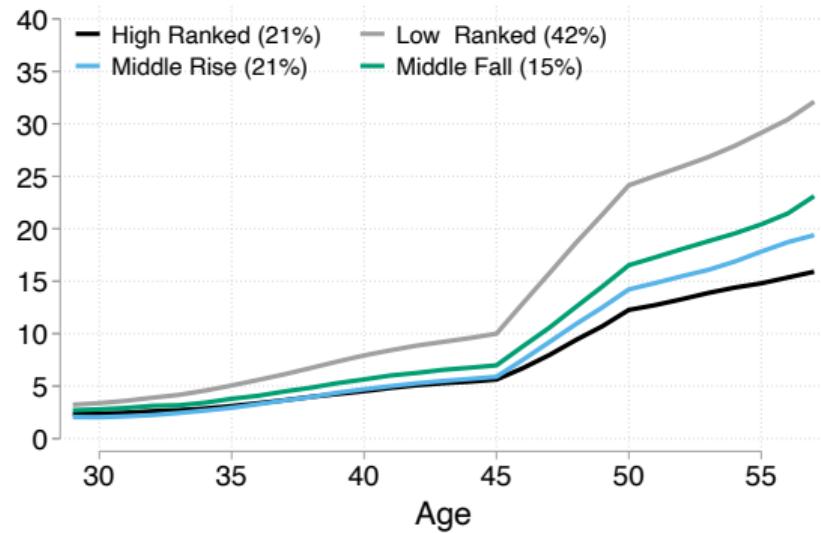
Transfers: Unemployment, Disability, Sick Leave, Nursing

◀ Back

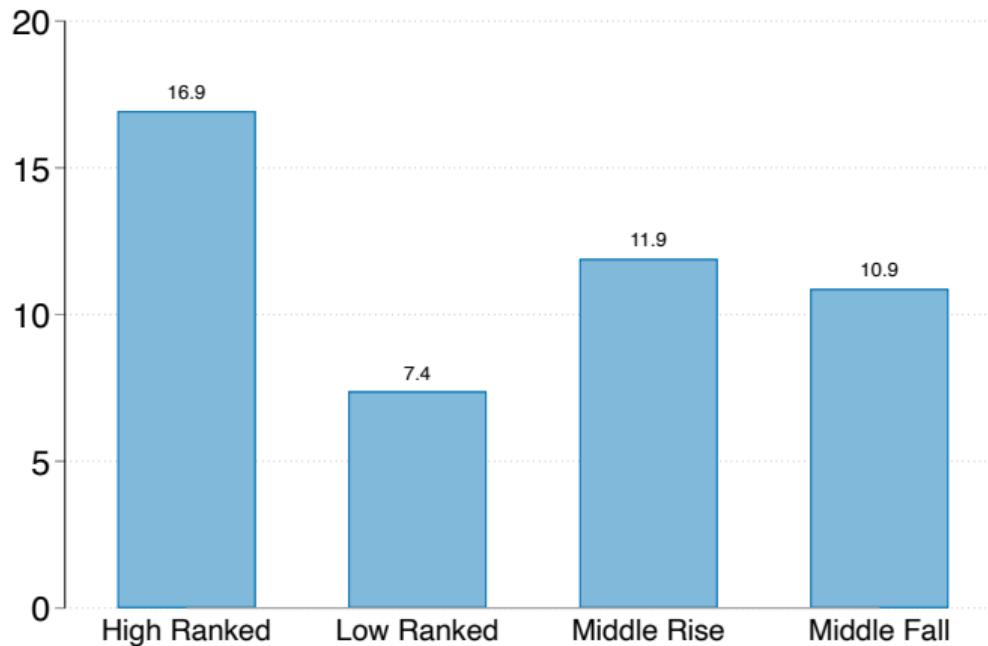
Share with Unemployment Benefits (%)



Share with Health-Related Transfers (%)



Share Received Gifts by 2014 (%)



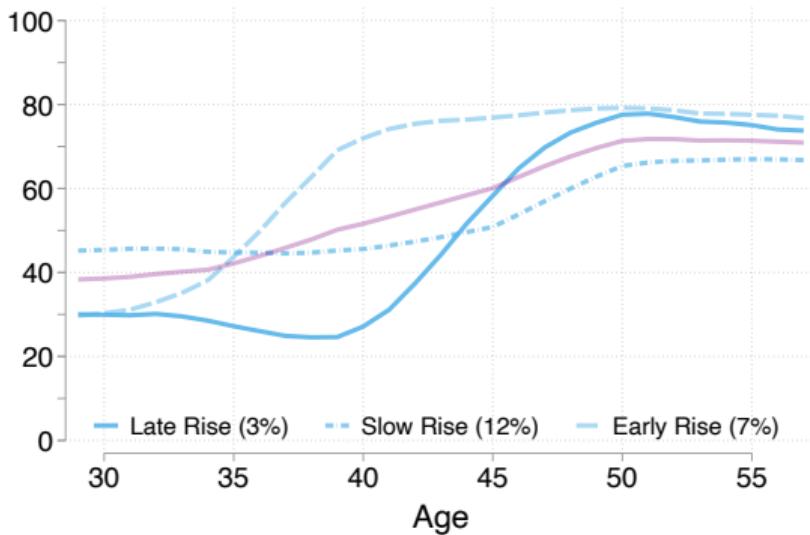
Notes: Total received > NOK 470K ($\approx \$47K$) before 2014

Characteristics of Sub-Clusters

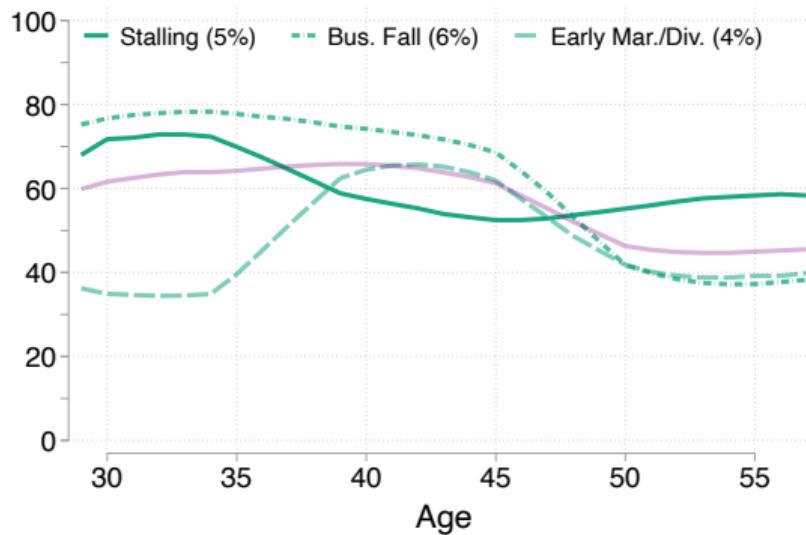
Heterogeneity in Trajectories: Levels vs Timing

◀ Back

Middle Risers



Middle Fallers

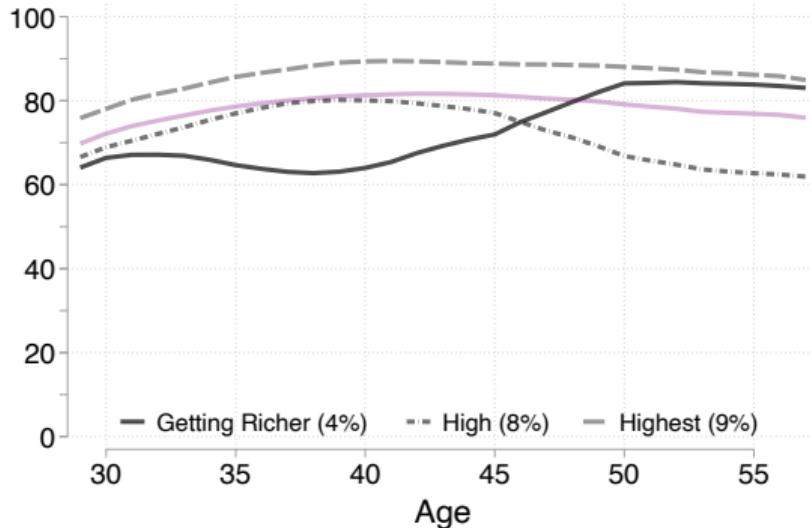


- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)

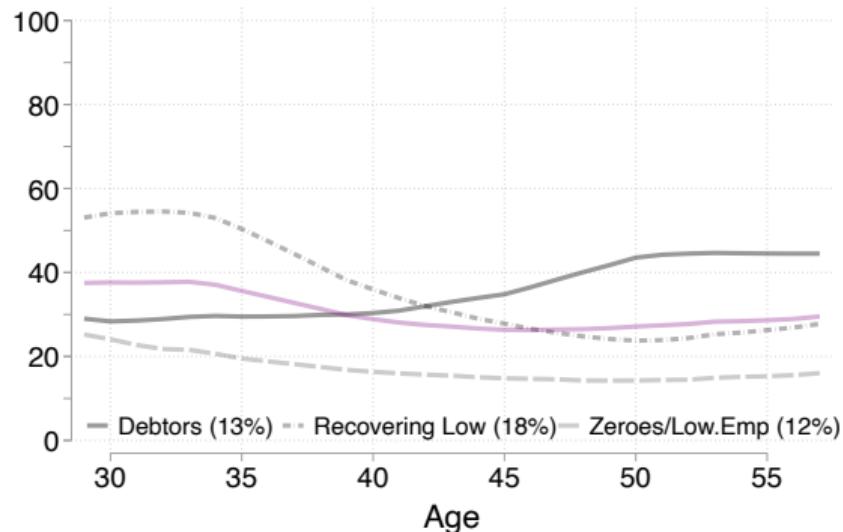
Heterogeneity in Trajectories: Levels vs Timing

[Back](#)

Top of the Distribution



Bottom of the Distribution

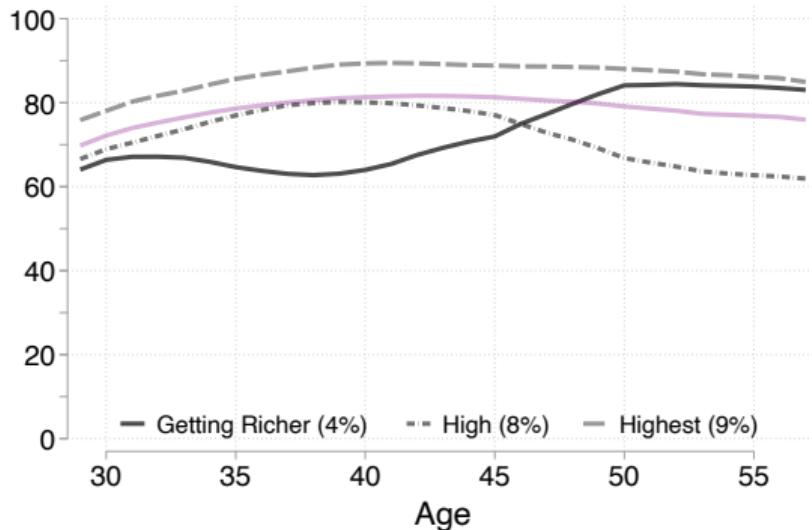


- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)
- Top and bottom groups differ mainly in avg. levels (with a rising sub-group in each)

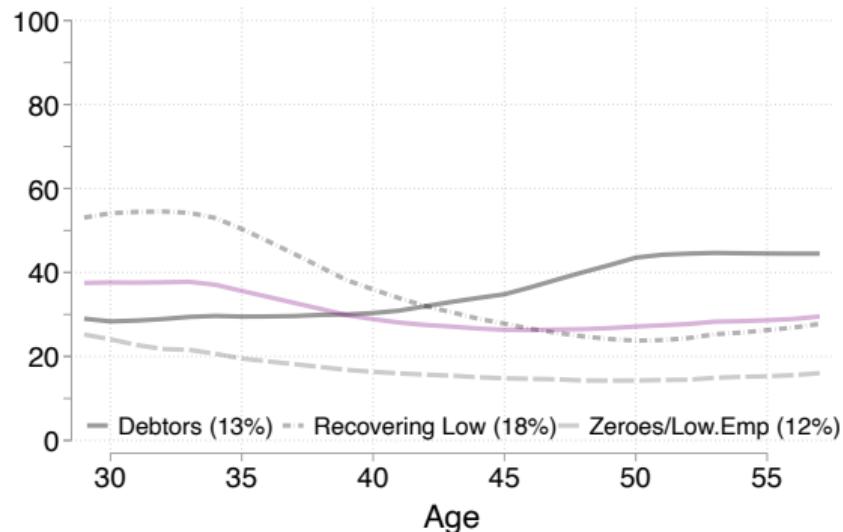
Heterogeneity in Trajectories: Levels vs Timing

[◀ Back](#)

Top of the Distribution



Bottom of the Distribution

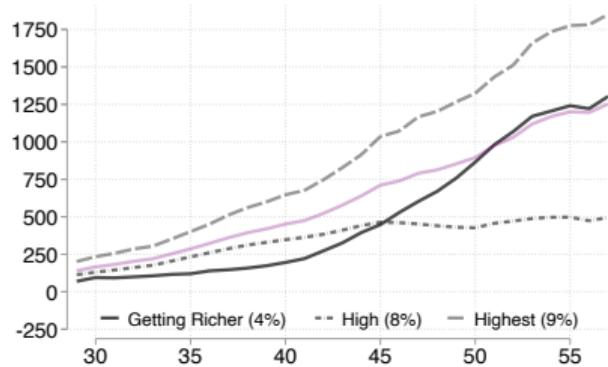


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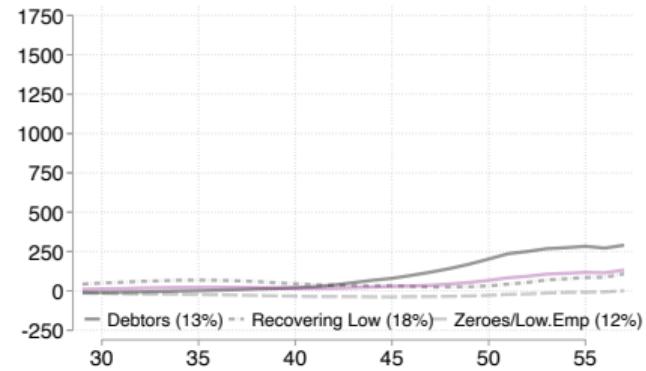
Sub-Clusters: Wealth Levels

◀ Back

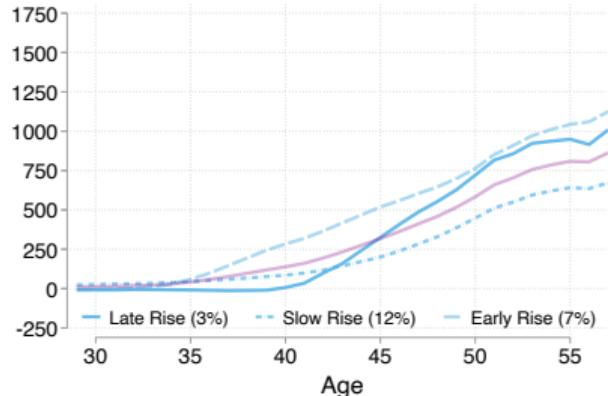
High Ranked



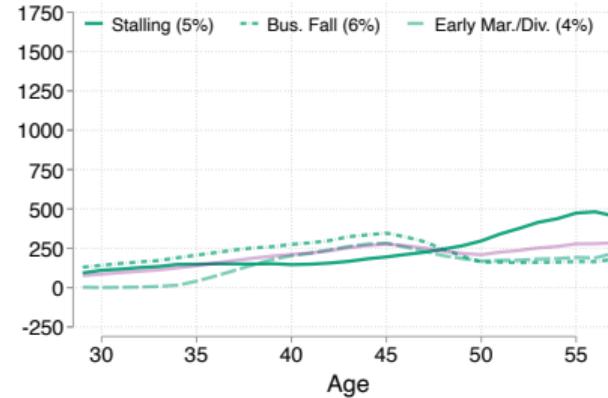
Low Ranked



Middle Risers



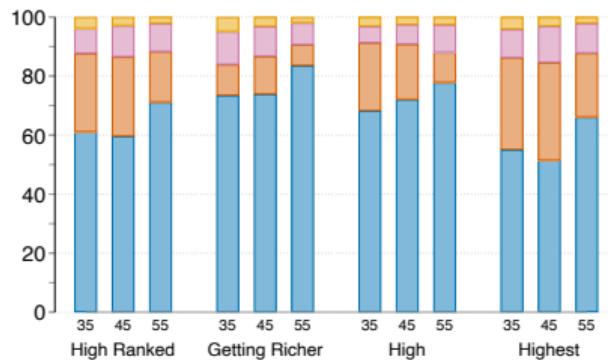
Middle Fallers



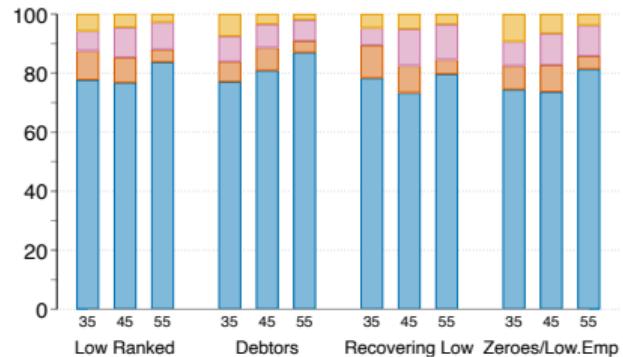
Sub-Clusters: Portfolio

◀ Back

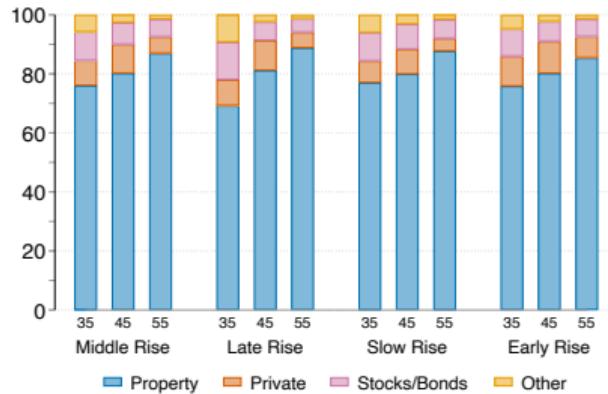
High Ranked



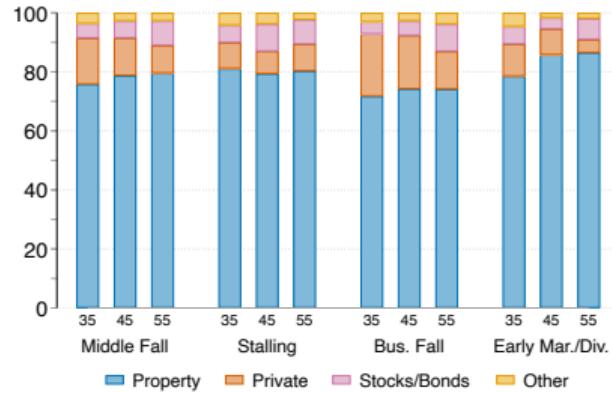
Low Ranked



Middle Risers



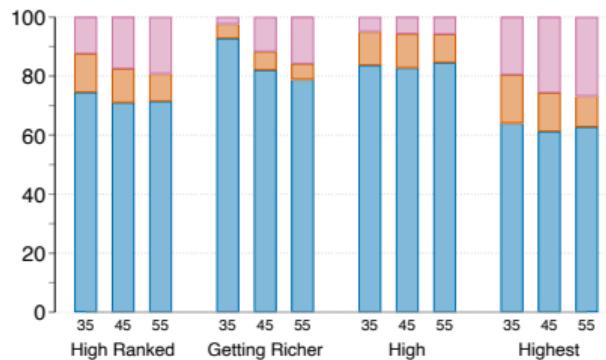
Middle Fallers



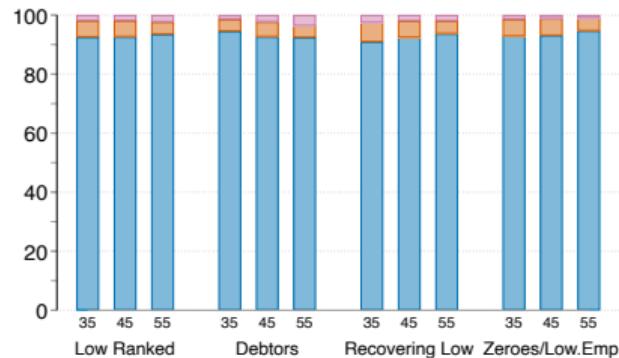
Sub-Clusters: Income Composition

◀ Back

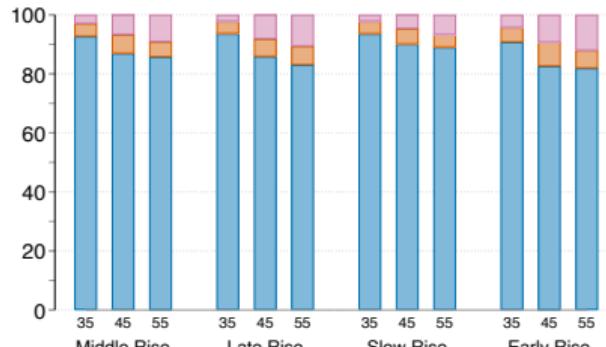
High Ranked



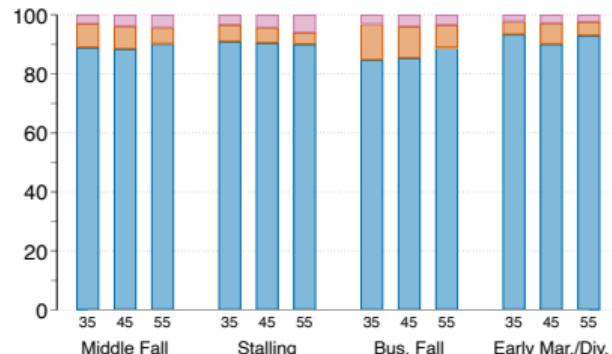
Low Ranked



Middle Risers



Middle Fallers



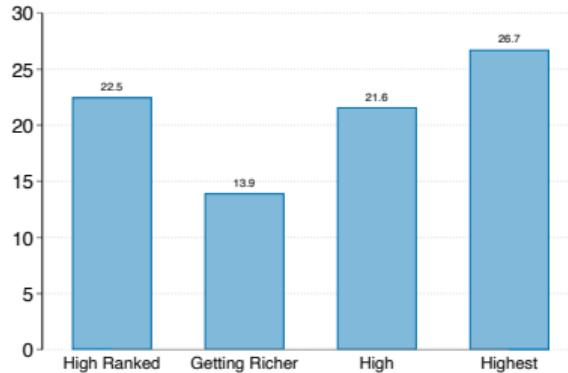
■ Employment ■ Self-Employment ■ Capital

■ Employment ■ Self-Employment ■ Capital

Sub-Clusters: Self-Employment

◀ Back

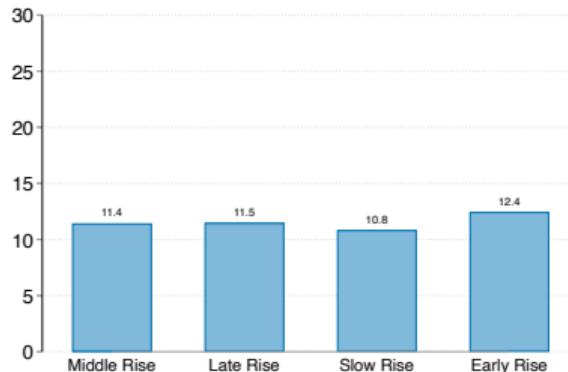
High Ranked



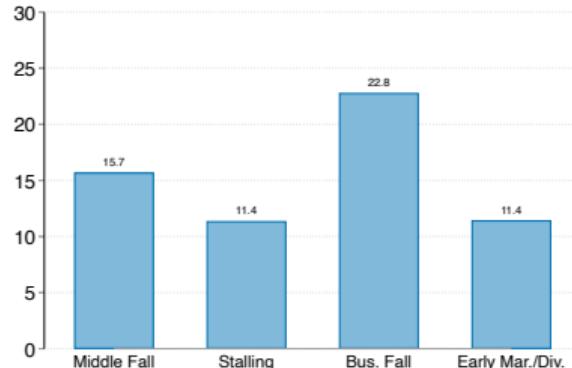
Low Ranked



Middle Risers



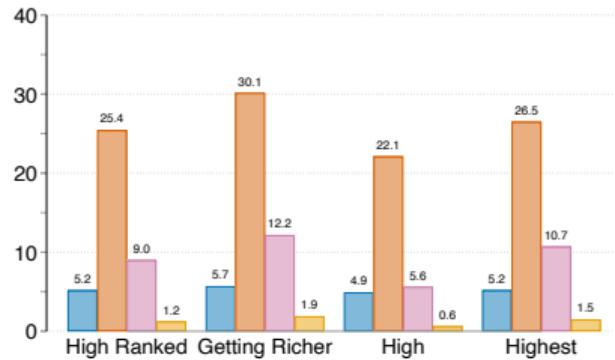
Middle Fallers



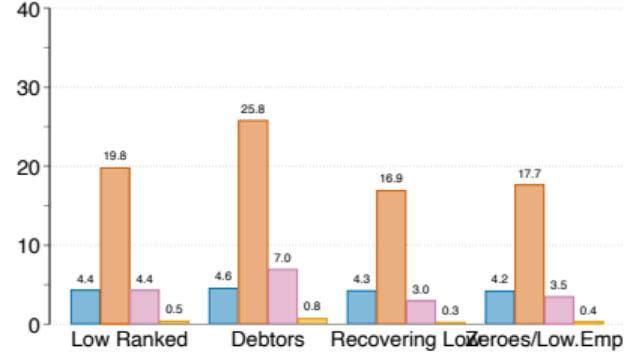
Sub-Clusters: Education

◀ Back

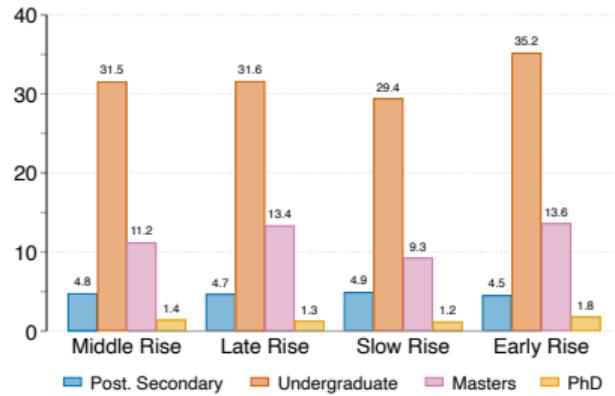
High Ranked



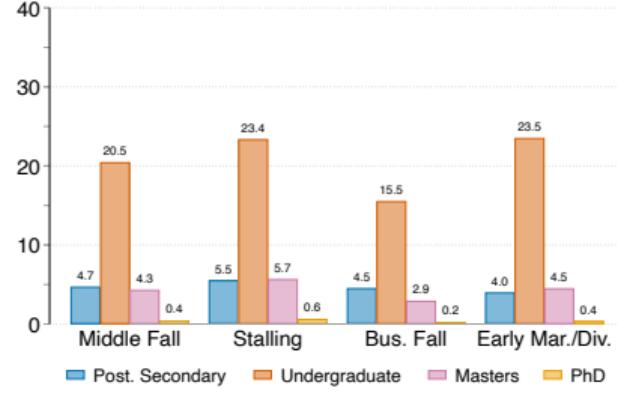
Low Ranked



Middle Risers



Middle Fallers



Shapley-Owen Decomposition

How Important Are Ex-Ante Explanations? ◀ Back

Two measures:

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

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

How Important Are Ex-Ante Explanations? ◀ Back

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

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

How Important Are Ex-Ante Explanations? ◀ Back

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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
<hr/> Share of Individuals Correctly Classified (pp)				
3.1	1.1	1.3	0.6	1.2

*Contribution relative to random classification using population shares.

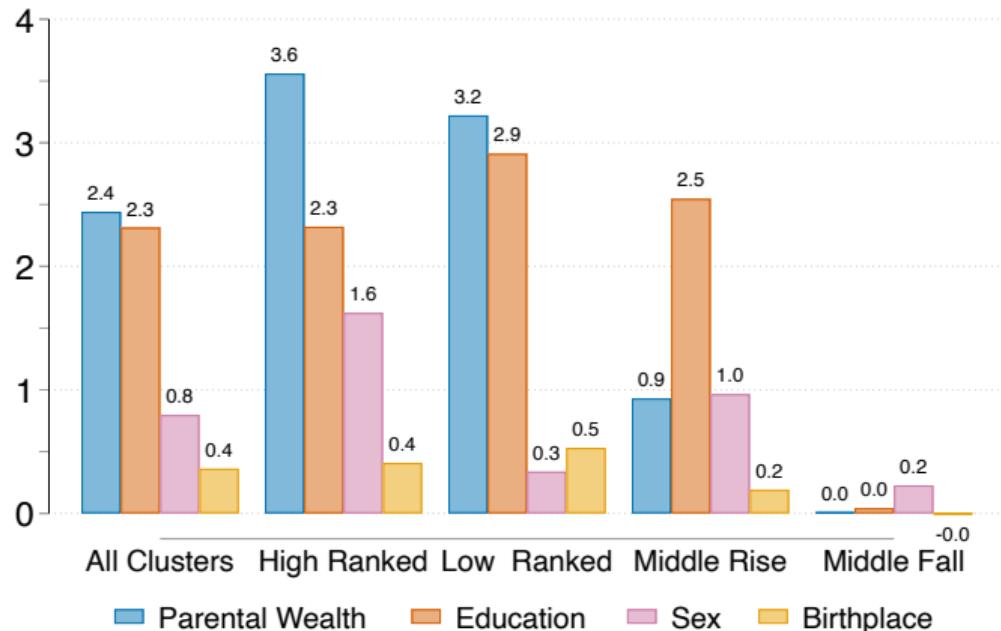
Share of individuals correctly classified by random classification 29.3% vs 32.5% with full model.

▶ D by Cluster

▶ C by Cluster

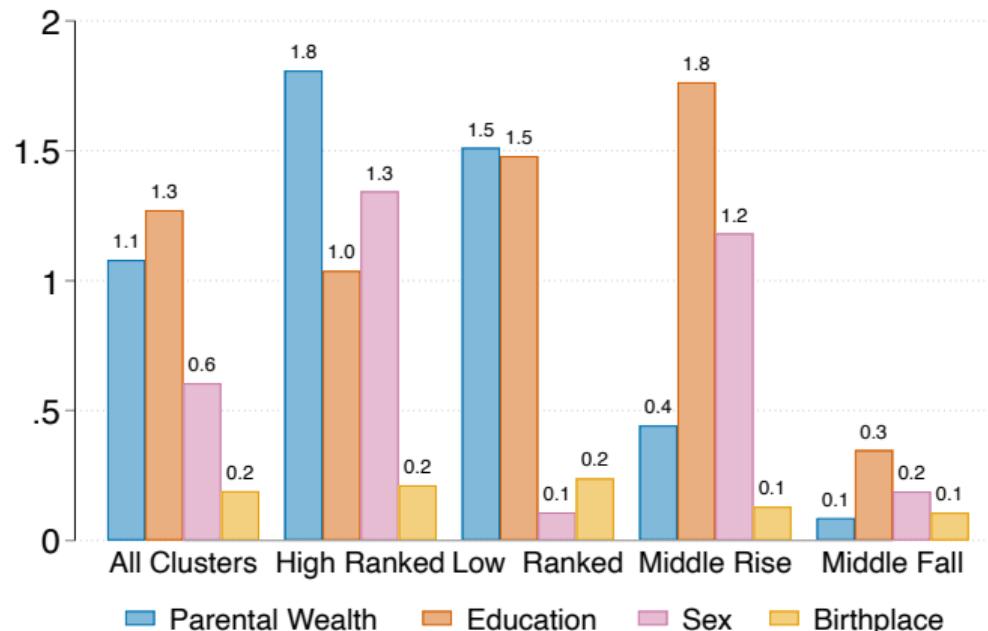
How Important Are Ex-Ante Explanations? [◀ back](#)

Share of Cross-Group Variation Explained by Variable



How Important Are Ex-Ante Explanations? [◀ back](#)

Share of Individuals Correctly Classified



* 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.

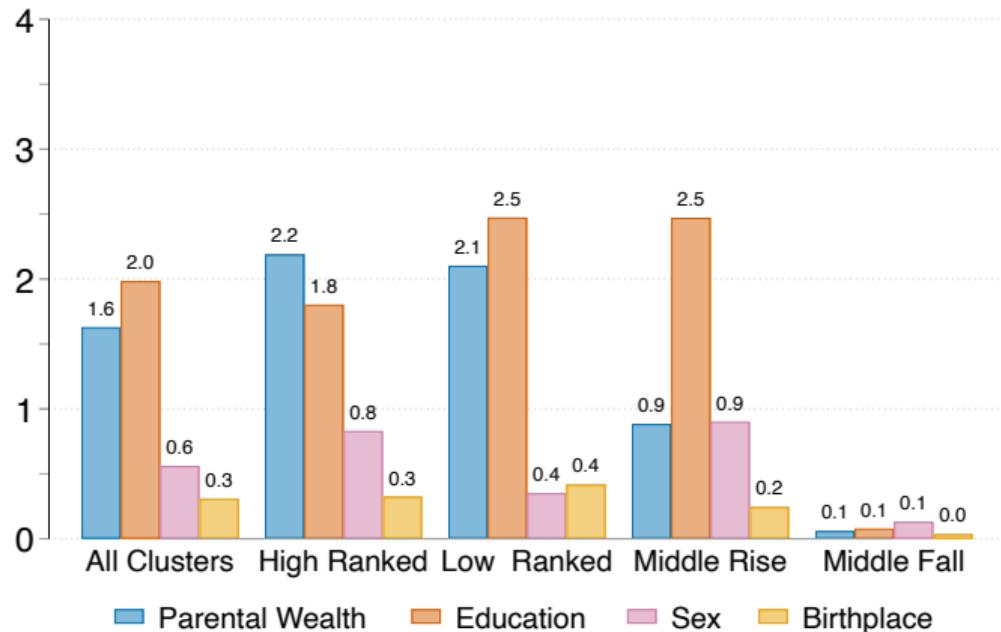
Share of individuals correctly classified by random classification 29.3% vs 40.0% with full model.

▶ D by Cluster

▶ C by Cluster

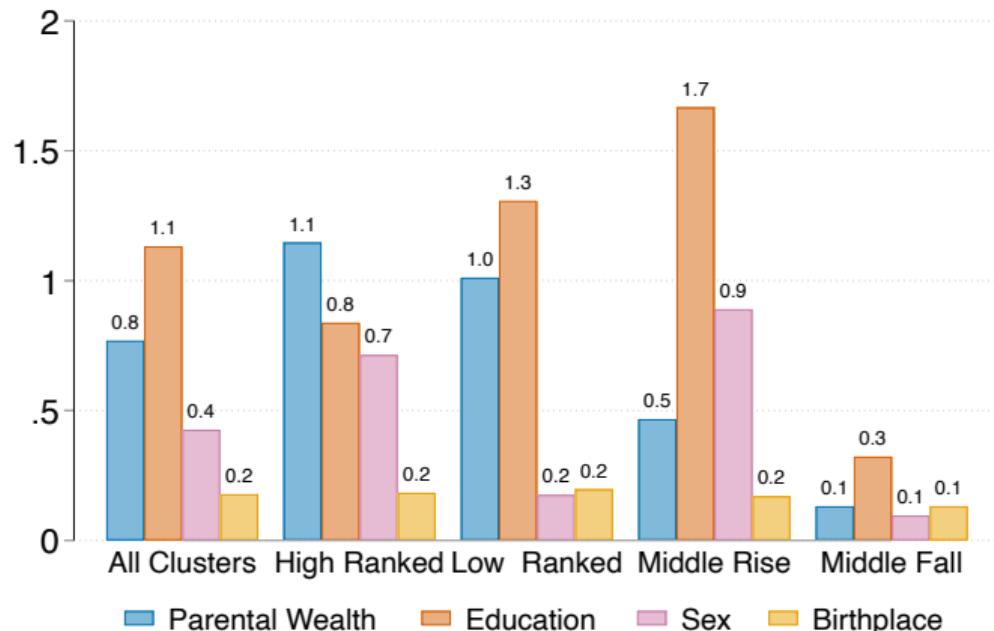
How Important Are Ex-Ante Explanations? [◀ back](#)

Share of Cross-Group Variation Explained by Variable



How Important Are Ex-Ante Explanations? [◀ back](#)

Share of Individuals Correctly Classified

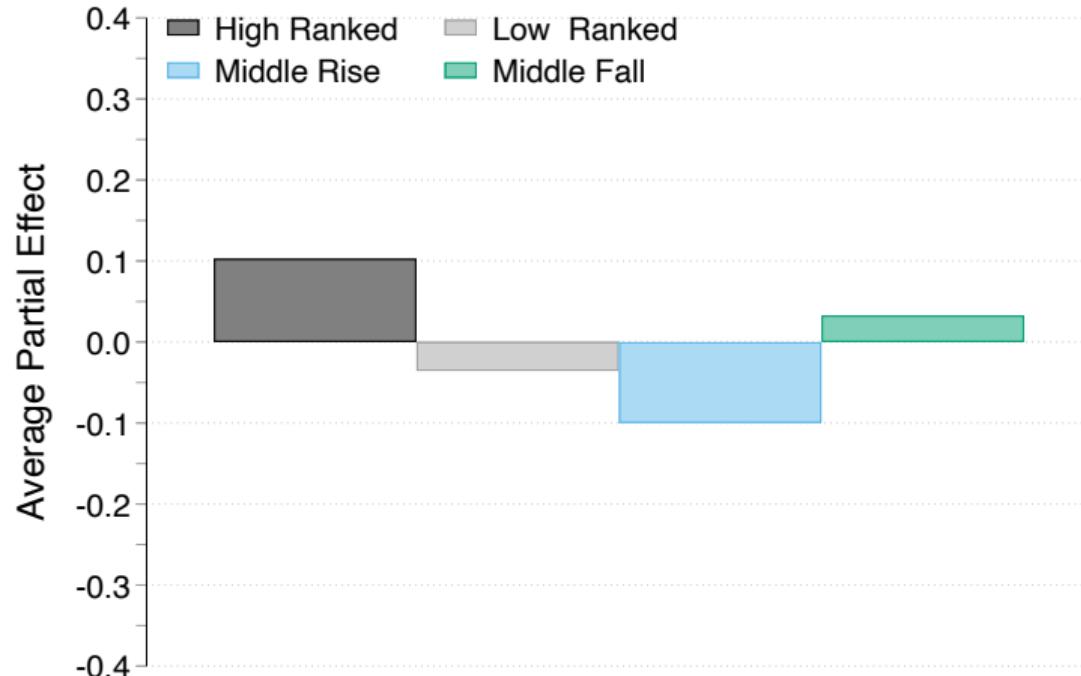


* Contribution relative to random classification using population shares.

Classification Results for Main Clusters

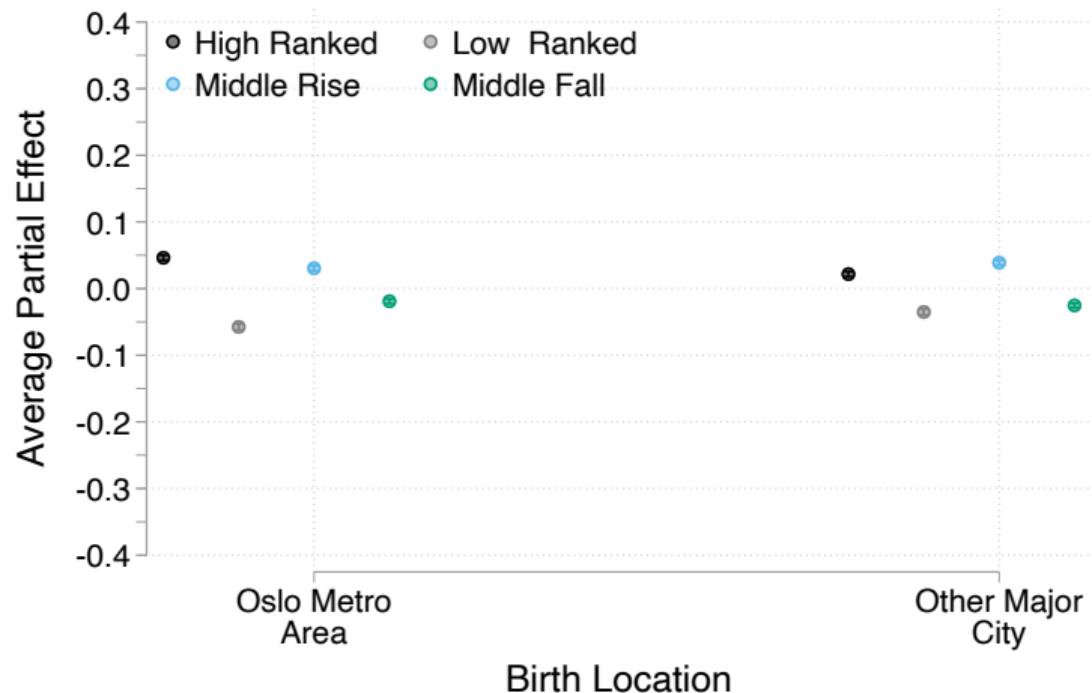
Sex Average Partial Effect

◀ back



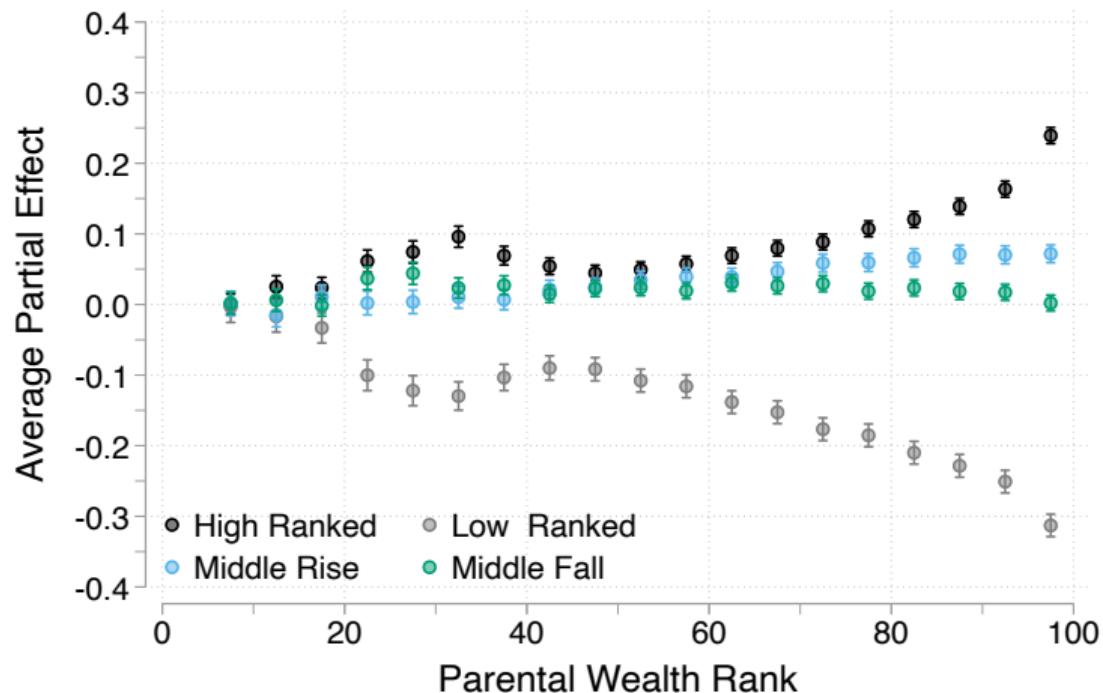
Where Is The Land of Opportunity? Norway

◀ back



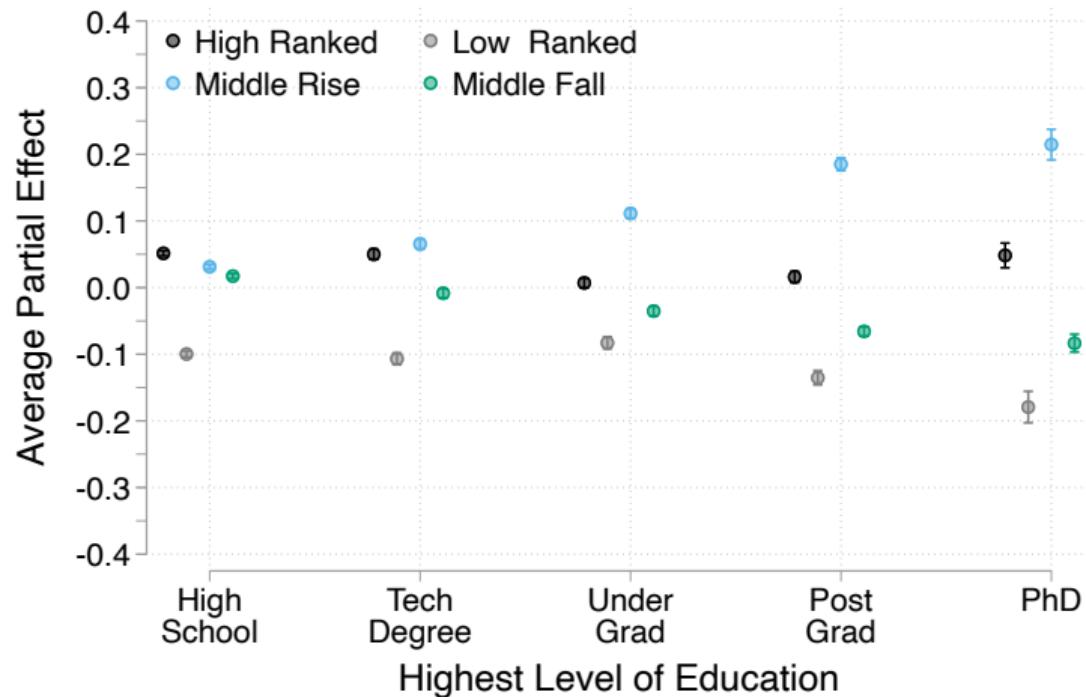
The Non-Linear Effect of Parental Wealth: CI

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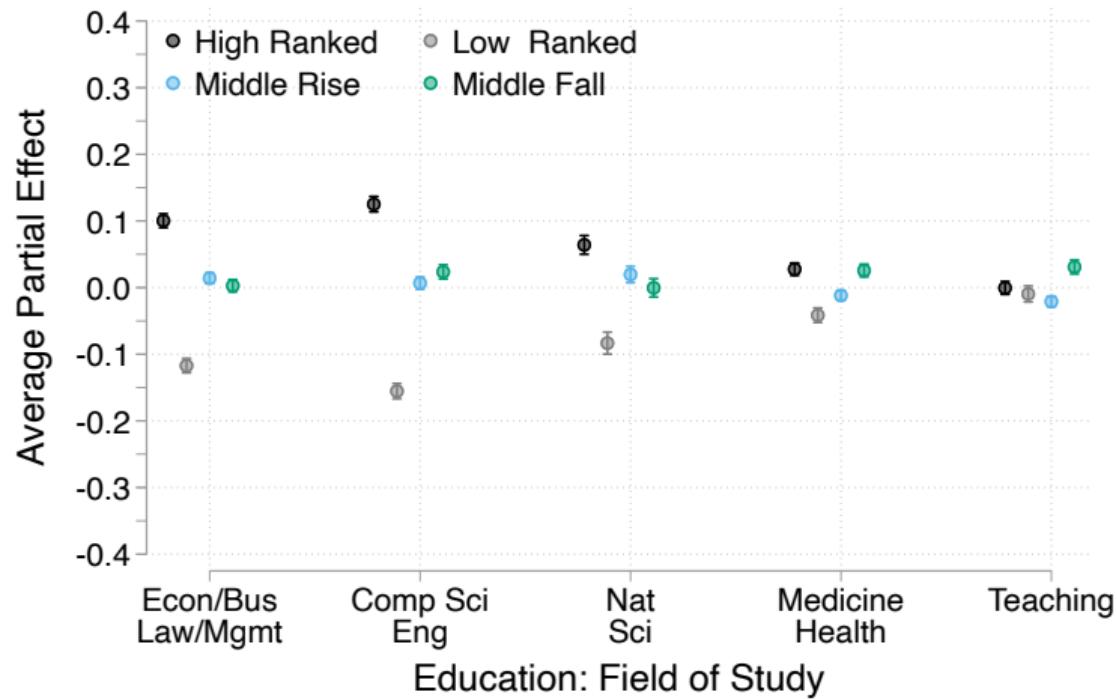
Learn & Rise?: CI

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Education: Fields

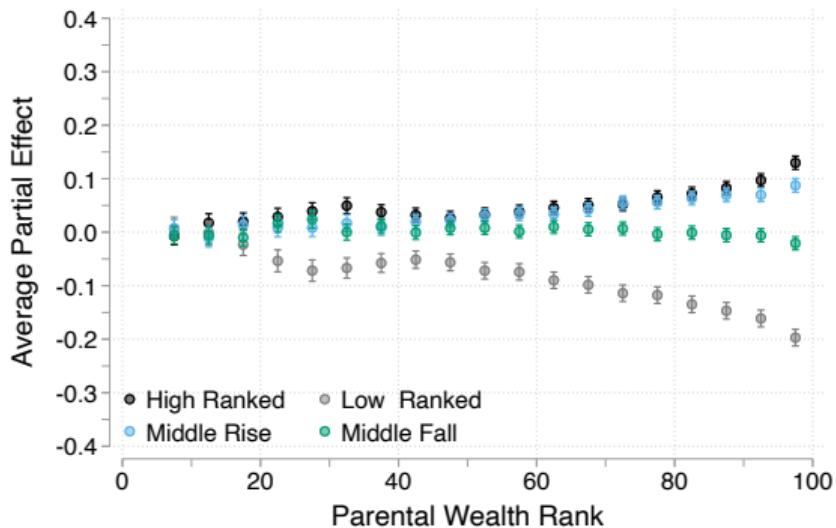
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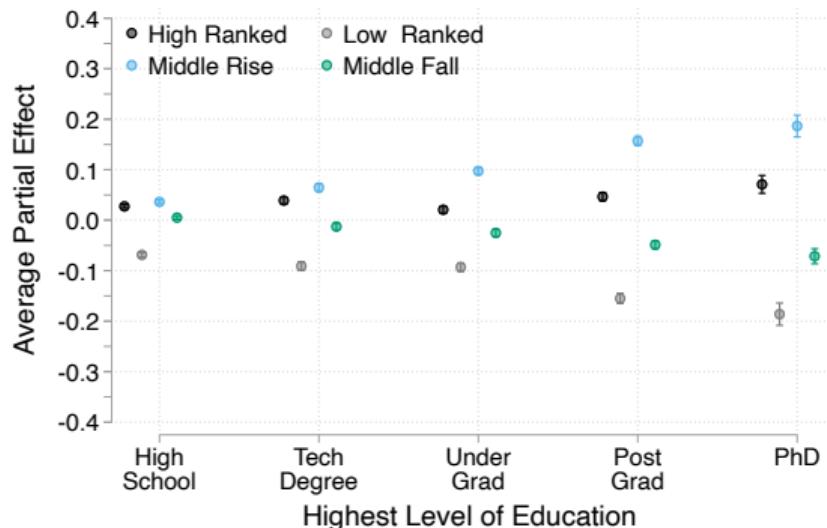
Effects of Parental Wealth and Education with Extra Controls

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Parental Wealth



Education

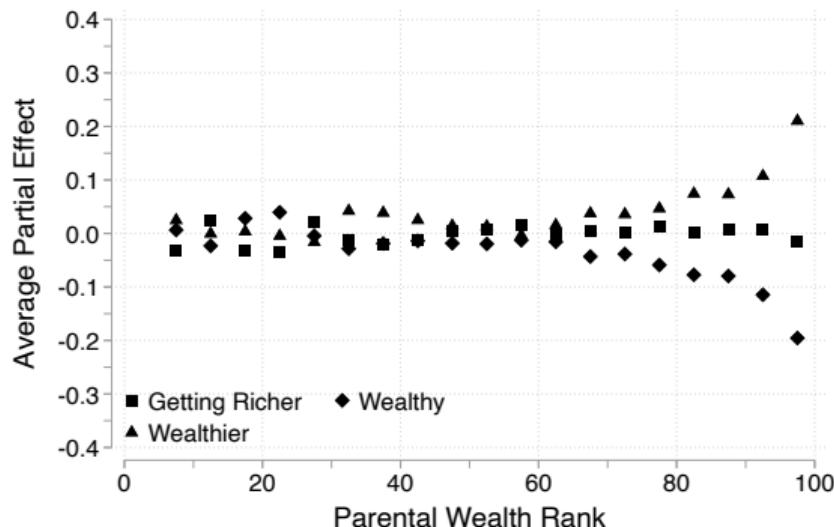


Classification Results for Sub-Clusters

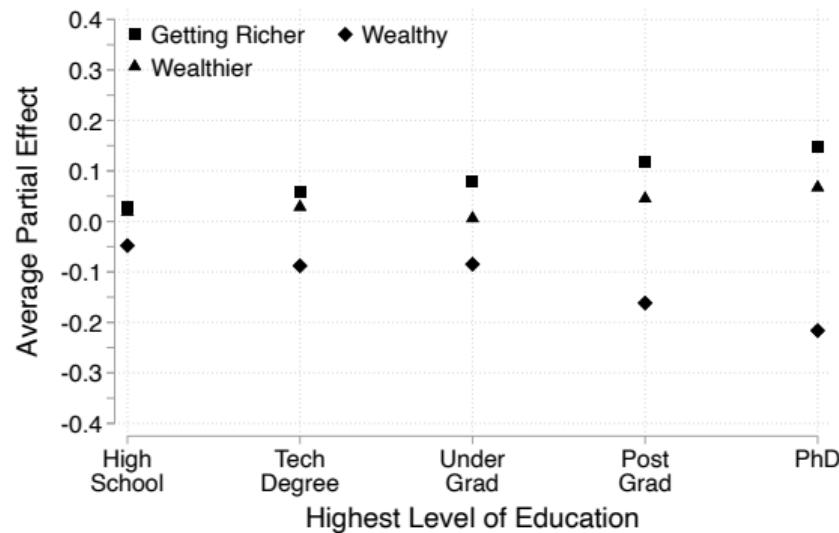
What about heterogeneity within clusters? Top Group

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Parental Wealth



Education

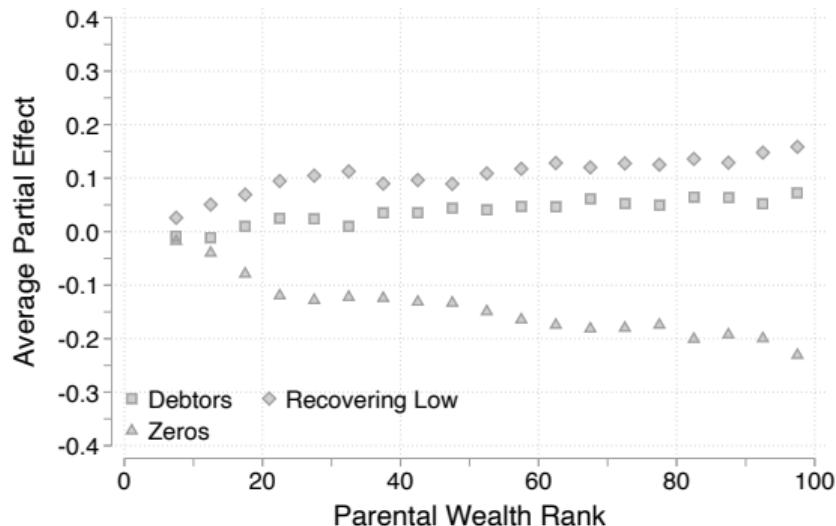


- Even within the groups, movers are hard to predict with parental wealth PW CI
- Education predicts dynamics within groups (e.g., getting richer vs already wealthy) ED CI

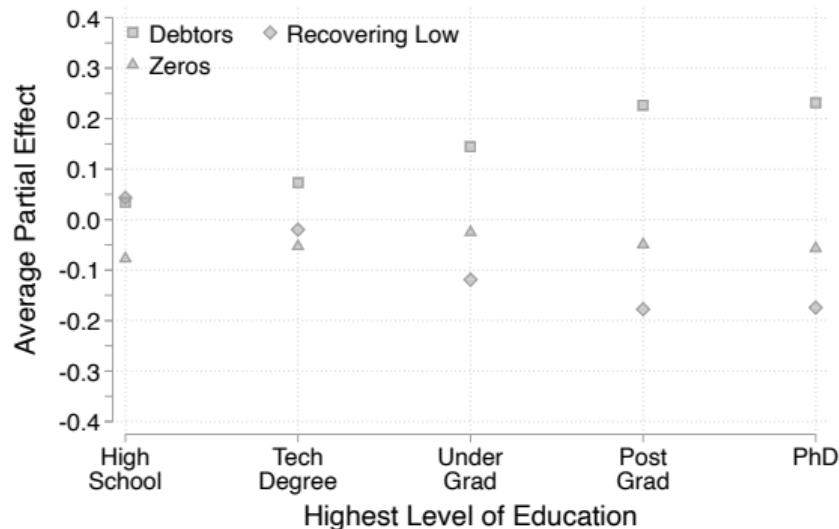
What about heterogeneity within clusters? Bottom Group

Back

Parental Wealth



Education

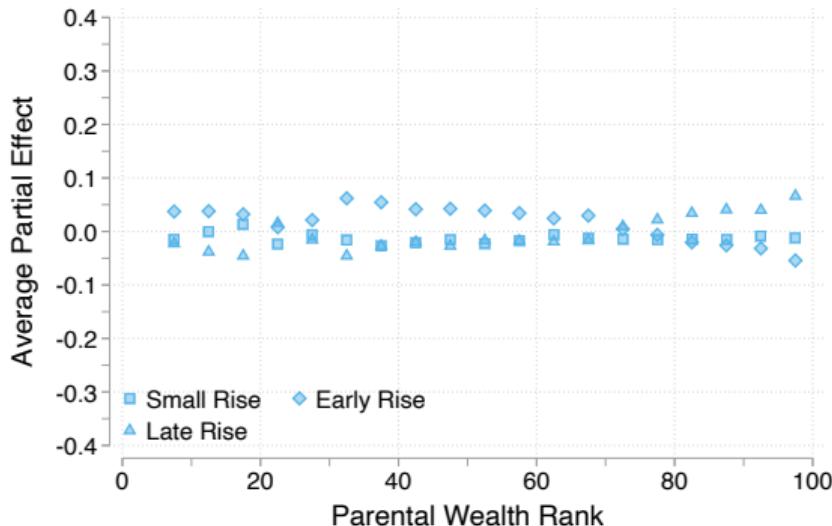


- Among poor, parental wealth does not predict movements
- Education predicts recovery

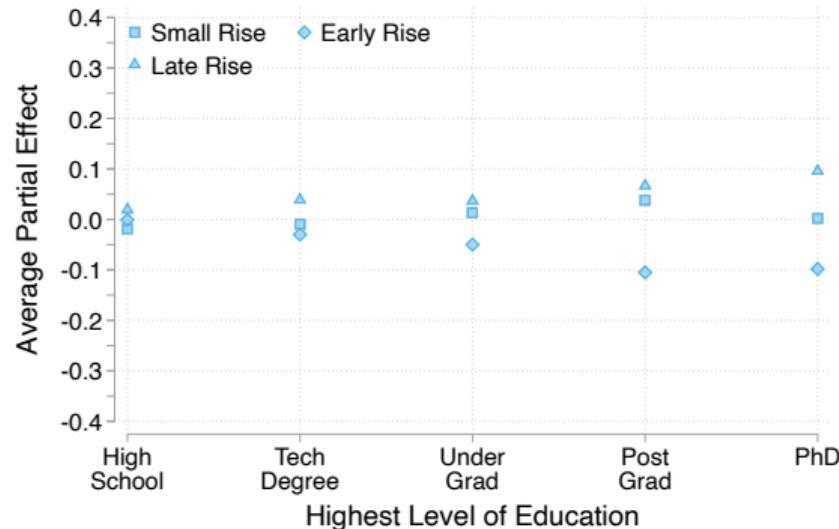
What about heterogeneity within clusters? Middle Risers

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Parental Wealth



Education



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

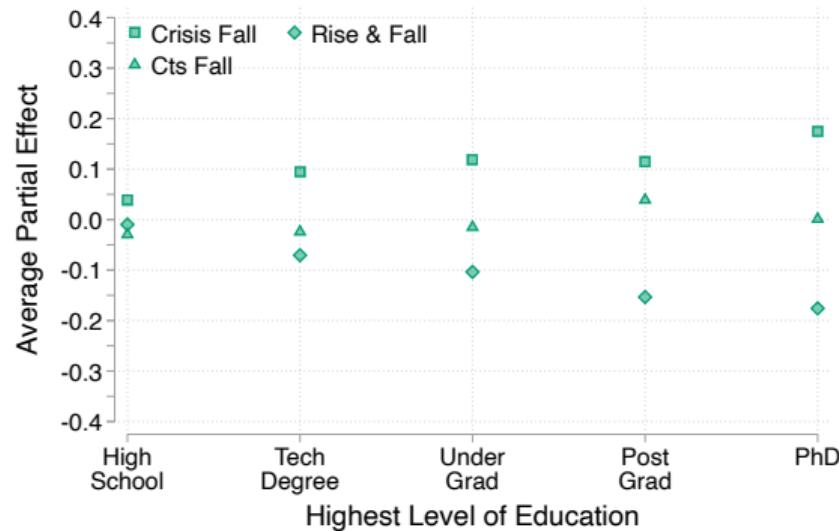
What about heterogeneity within clusters? Middle Fallers

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Parental Wealth



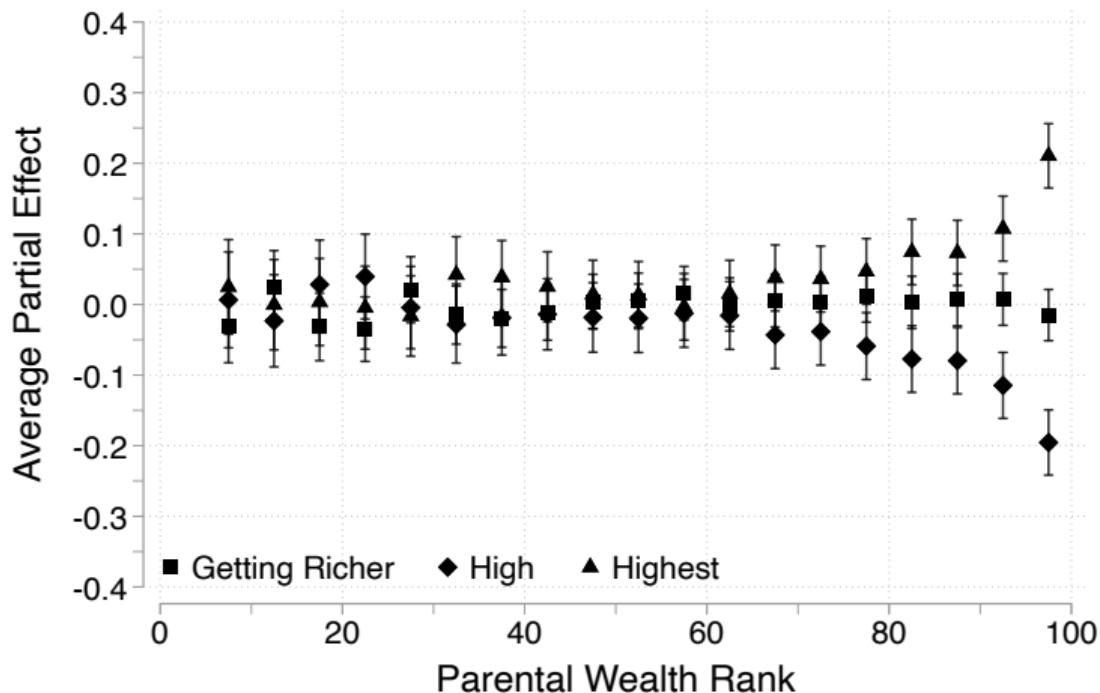
Education



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

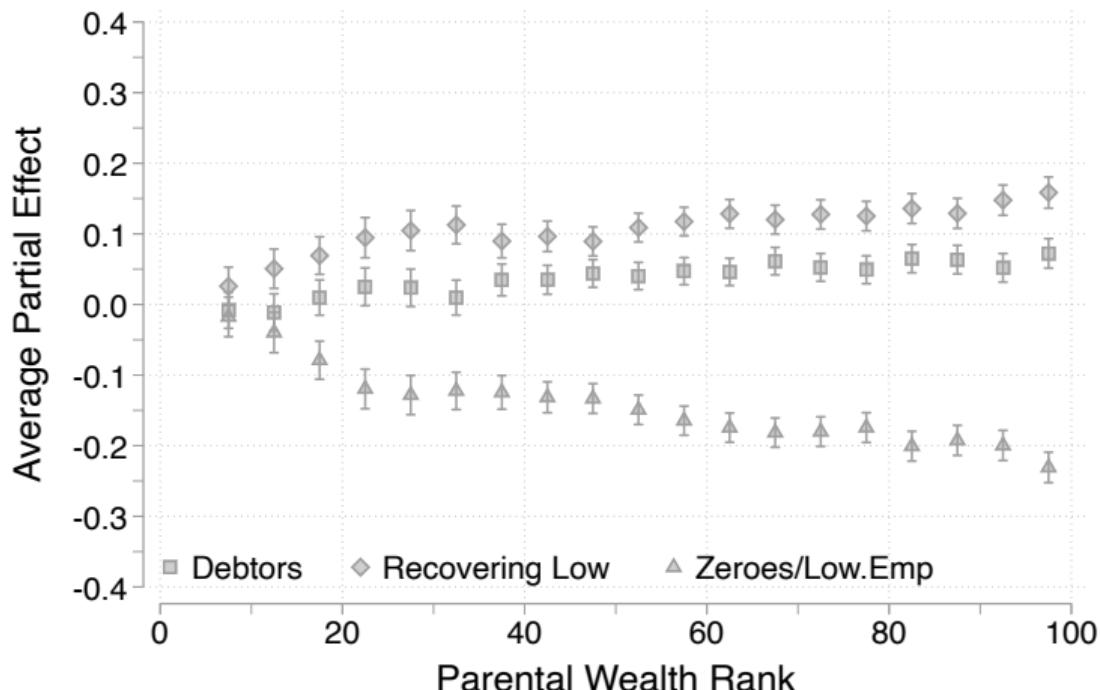
The Non-Linear Effect of Parental Wealth: CI

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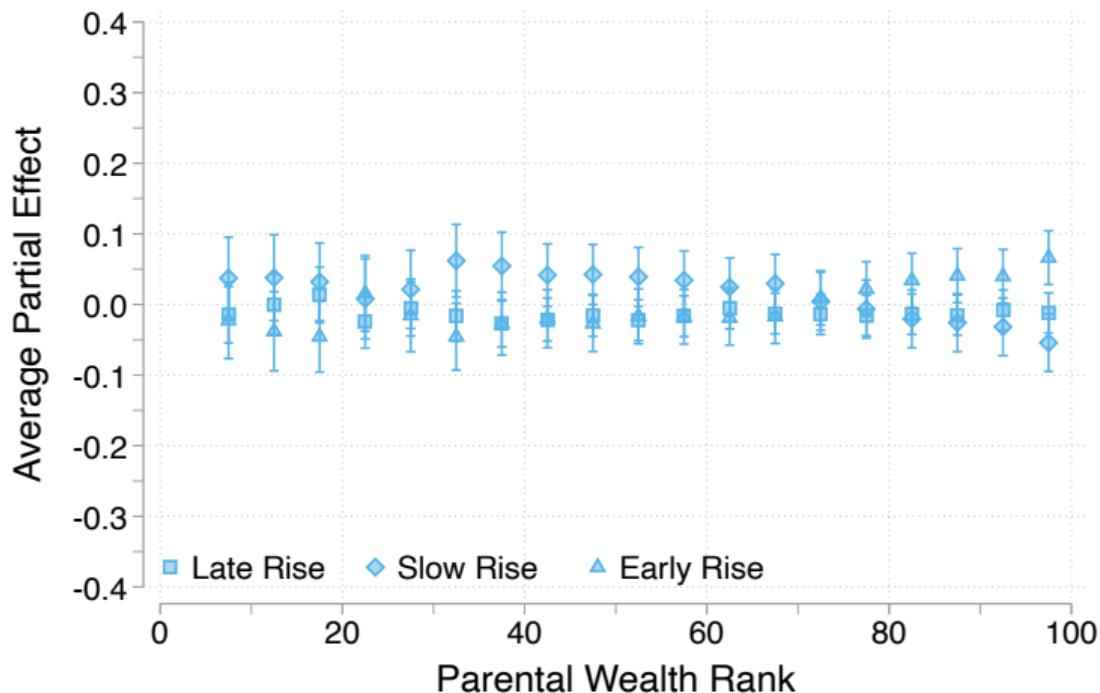
The Non-Linear Effect of Parental Wealth: CI

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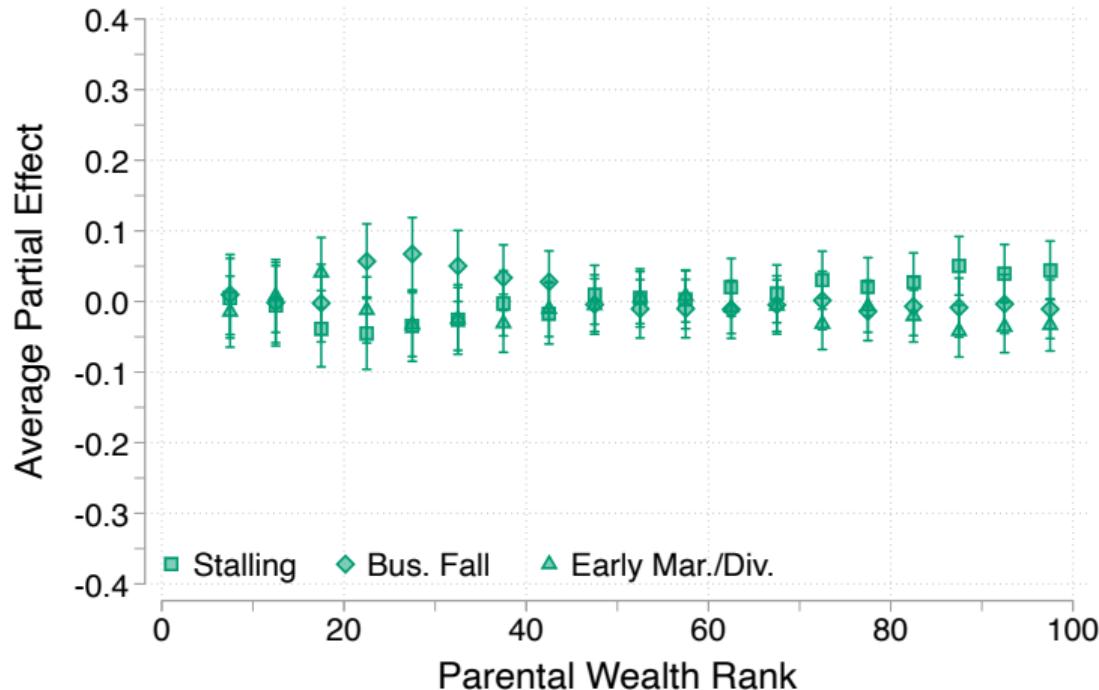
The Non-Linear Effect of Parental Wealth: CI

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The Non-Linear Effect of Parental Wealth: CI

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Learn & Rise for Wealthy: CI

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