

The Life-Cycle Dynamics of Wealth Mobility

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April, 2023

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.

Wealth mobility over the life cycle

- Individual wealth histories result from many decisions and shocks
 - Human capital accumulation, homeownership, portfolio choices, entrepreneurship, etc.
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Today: Document patterns of relative wealth mobility across life cycle

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

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 - Measure intra- and inter-generational mobility
 - But: as many different histories as individuals
 - Use **clustering techniques** to find “typical” trajectories responsible for mobility
- Study how our clusters relate to other observable characteristics
 - Life cycle choices and events (Housing, civil status, portfolio composition, etc.)
 - To which extent do individual characteristics at age 30 predict future trajectories?

Main findings

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- Mobility driven by two groups experiencing a *reversal of fortune* in middle of distribution
- Pattern of **segmented mobility**:
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Mobility takes place only for some individuals and within a section of the distribution
3. Individual circumstances help to predict trajectories: Human capital is key
 - Parental background: key determinant of Wealthy/Poor
 - Education: key determinant of Risers/Fallers

Norwegian Wealth Data

Data: Norwegian Tax Registry 1993 – 2017

[▶ Context](#)[▶ Details](#)

- 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)
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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

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

- Computed separately for each year and each cohort

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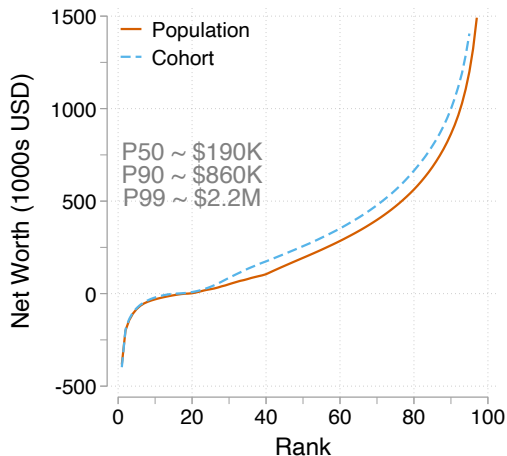
- Computed separately for each year and each cohort
- Trajectories: Histories of ranks

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

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

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

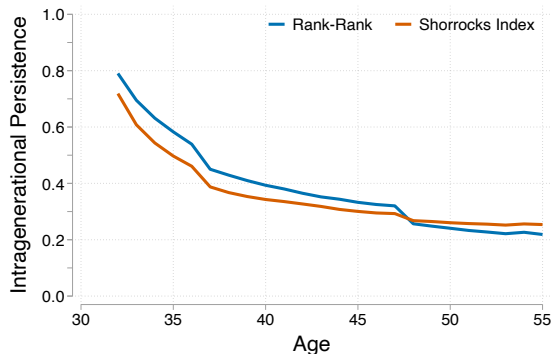
- US: p90 \approx \$620K, p99 \approx \$3.5M (SZZ, 2022)

Intra-Generational Wealth Mobility

- Linear rank-rank persistence: $y_{i,t} = \alpha_t + \rho_t y_{i,0} + u_{i,t}$
- Shorrocks Index: Share that remains in initial quintile of dist. (trace of transition matrix)

Intra-Generational Wealth Mobility

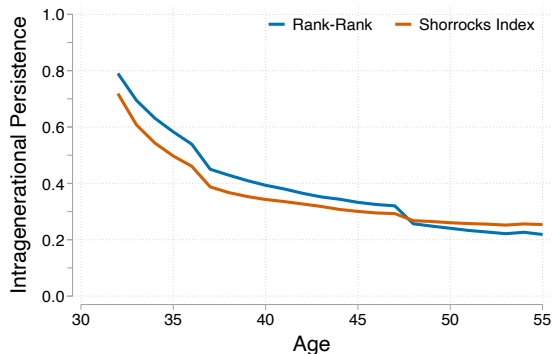
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→ Increased (cumulative) mobility
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- By age 55 only 25% of individuals remain in age 30 quintile (13% in decile)
- How broad-based is mobility?
What (who) drives patterns?
- Persistence collapses heterogeneous trajectories

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: $\operatorname{argmin}_{g, g' \in G, g \neq g'} d(g, g')$.

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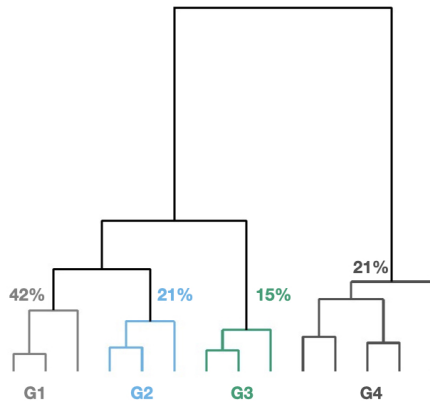
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Result: Hierarchy of partitions ranging from $G = N$ to $G = 1$.

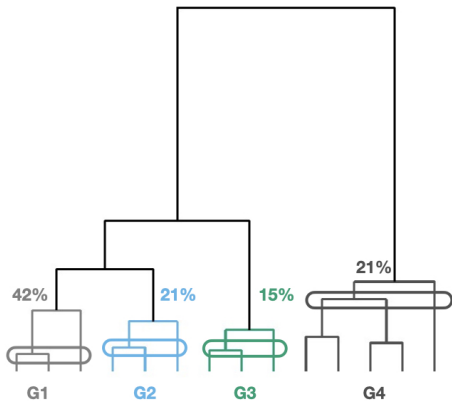
- Global result with nested clusters (feasible in large datasets)
- Asymptotically consistent as we observe longer trajectories, even for fixed N
(Borysov, Hannig, Marron, 2014; Egashira, Yata, Aoshima, 2024)

Clustering Tree

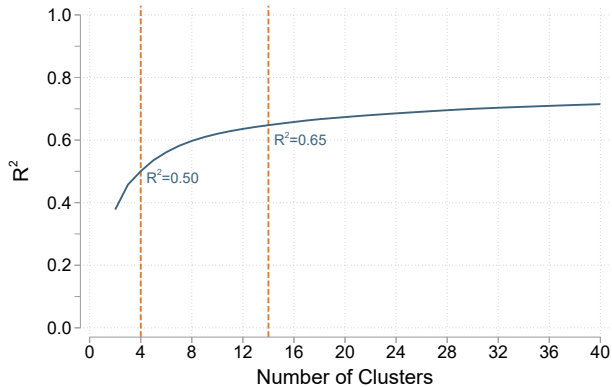


Two Levels of Clustering

Clustering Tree

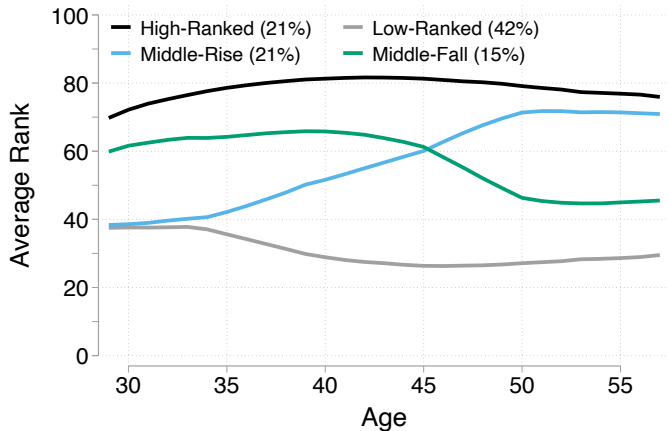


Variation Explained



Typical Rank Histories

Cohort Ranks

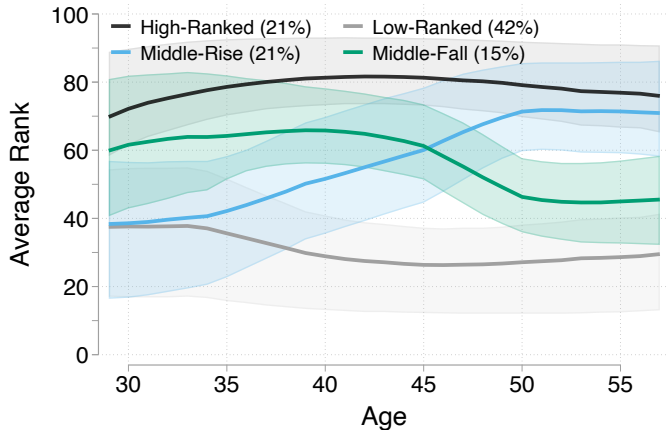


Four largest groups

- 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

Typical Rank Histories

Cohort Ranks, interquartile range

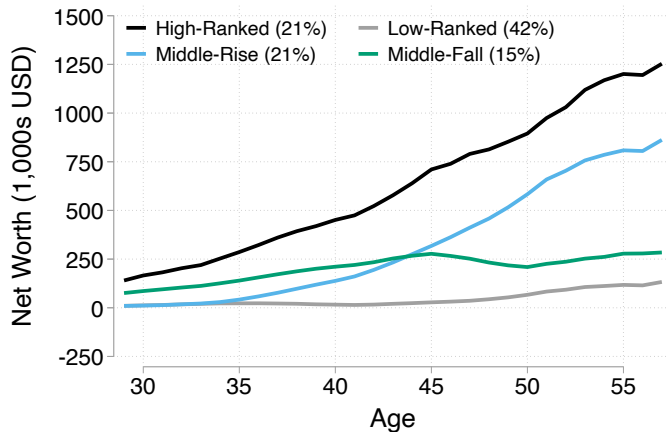


Segmented mobility

- 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)

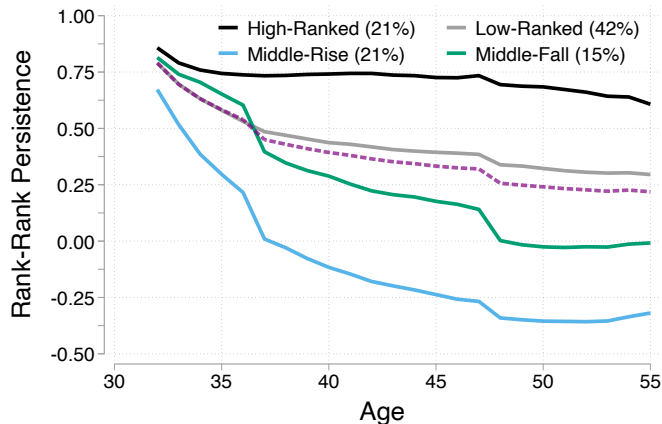


Significant diff. in wealth profiles

- **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

Intra-Generational Mobility

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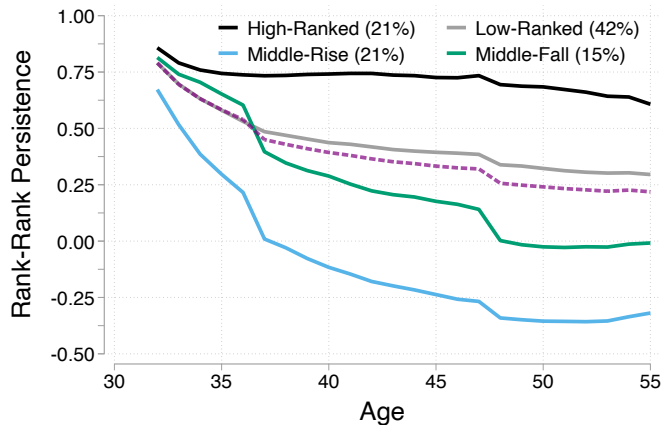


- **Top:** Immobile over 25y
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- Mobility in the middle drives population mobility patterns. Risers are key.

Heterogeneity Across and Within Groups

Link Tax Registry to Income and Demographic Data

► Group Characteristics

- Both income levels and composition of portfolio play a role.
- Self-emp. and business ownership relevant for High-Ranked and Fallers. Not Risers.

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Use Hierarchy of Clusters for Subgroups

► Subgroup Trajectories

- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)
- High- and Low-Ranked differ in levels within segments

Towards Determinants of Trajectories

Hereditary Advantage: Wealth vs Human Capital

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

► Results

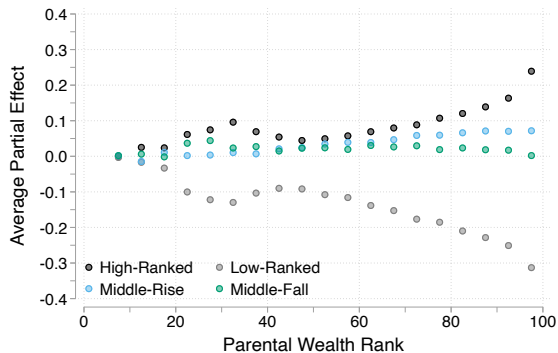
Non-Linear Effects of Parental Wealth and Education

PW CIs

ED CIs

ED Field

Parental Wealth



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

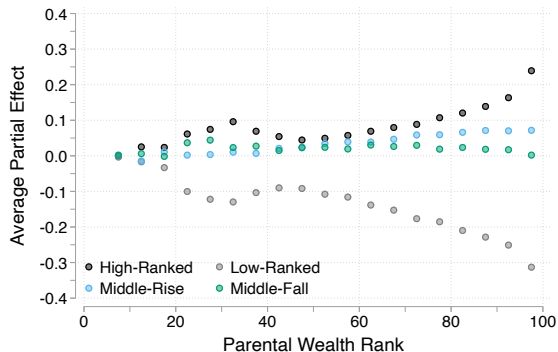
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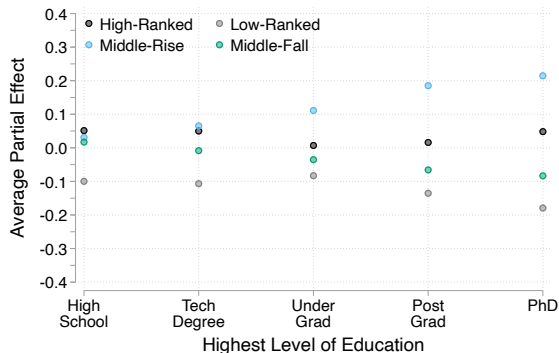
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Education



- 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 + Robustness + Intergenerational Mobility

- 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!

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▶ Low Ranked

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[▶ High Ranked](#) [▶ Low Ranked](#) [▶ Middle Rise](#) [▶ Middle Fall](#)
- Decreasing intergenerational mobility:
 - Correlation between parents' and own wealth ranks increases over age
 - Reversal of fortune increases inter-generational persistence [▶ details](#)

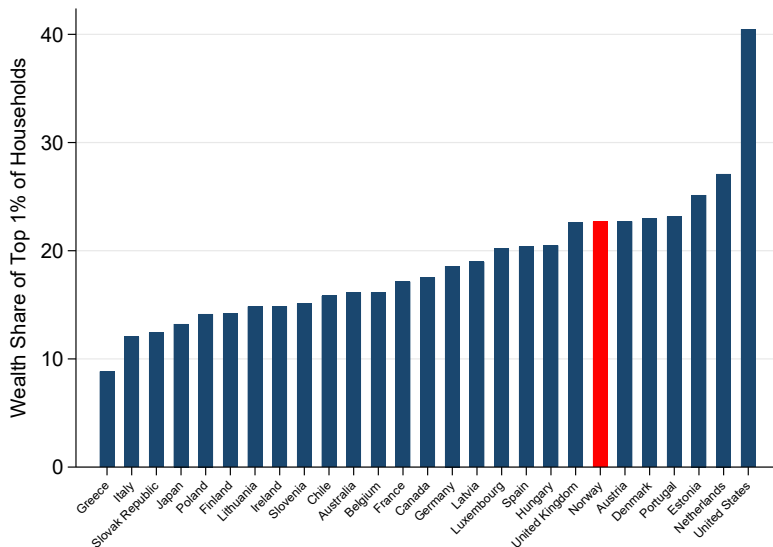
Conclusions

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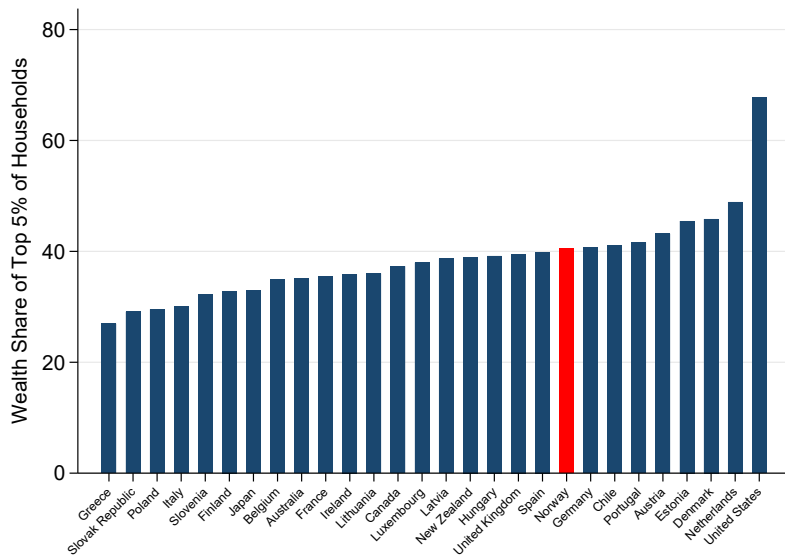
- Document intra- and inter-generational wealth mobility over the life cycle
- Uncover typical trajectories of individuals through the wealth distribution
 - Find important evidence of reversals in fortune over a quarter century
- Mobility driven my reversal of fortune for selected groups in the middle of the distribution
- Intergenerational background an important predictor of whole history
- Education is key for movements through the wealth distribution

Extra

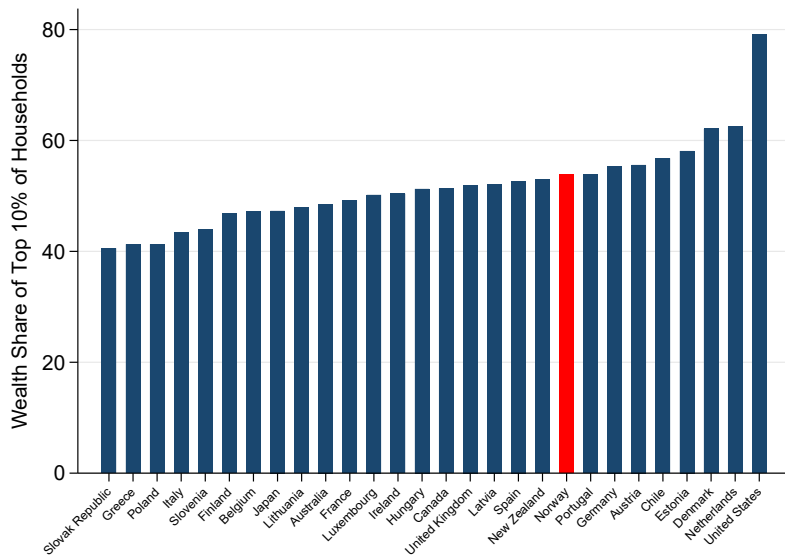
Norway in Context

[◀ Back](#)

Norway in Context: Top 5% Share [◀ Back](#)



Norway in Context: Top 10% Share [◀ Back](#)



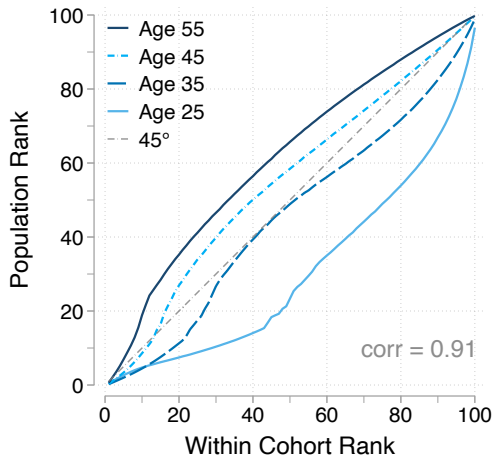
Key Variables

[< back](#)

- **Wealth:** Net worth = assets-debt → **Primary Variable**
- **Assets & Debt:** Total assets and debt, and major asset categories
 - Domestic, foreign, property, vehicles, “safe,” publicly and privately traded
 - Leverage, some assets are net positions
- **Income:** Including gifts/bequests, transfers, asset income, & earnings
- **Demographics:** Age, sex, education, civil status, place-of-birth
- **Lineage:** Match individuals to their parents and siblings

Birth Cohort Ranks vs Population Ranks [◀ back](#)

BC Ranks vs Pop Ranks

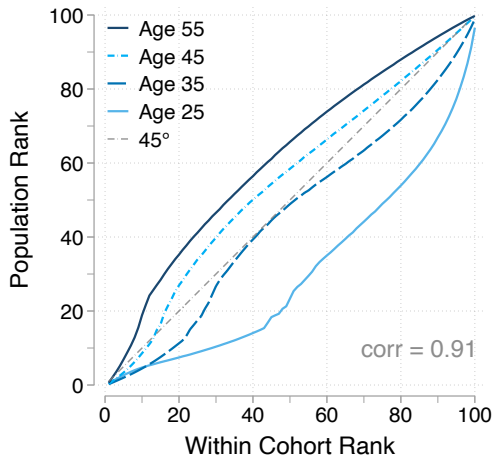


- Changes in wealth levels at each rank as the cohort ages
- 75 percent of age 25 individuals are below the median
- 35 percent of age 55 individuals are below the median

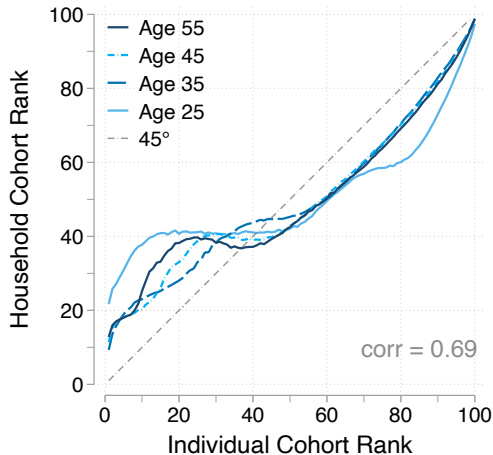
[▶ Household Ranks](#)

Birth Cohort Individual Ranks vs Household Ranks [◀ back](#)

BC Ranks vs Pop Ranks

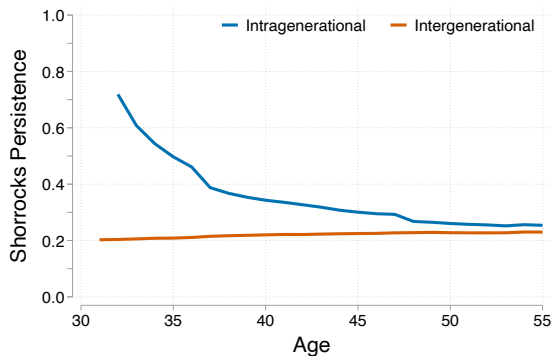


BC Individual Ranks vs Household Ranks



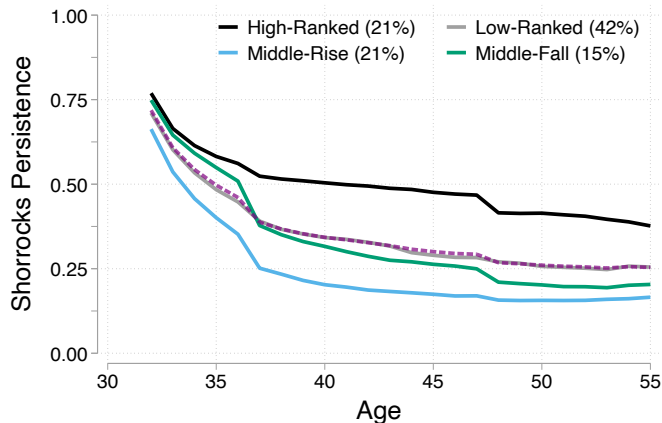
Shorrocks Mobility Index [◀ back](#)

Trace of transition matrix: Divide individuals by quintiles.



- Declining intra-generational persistence
→ Increased mobility
- Increasing inter-generational persistence
→ Decreased mobility

Intra-Generational Shorrocks Mobility Index [◀ back](#)

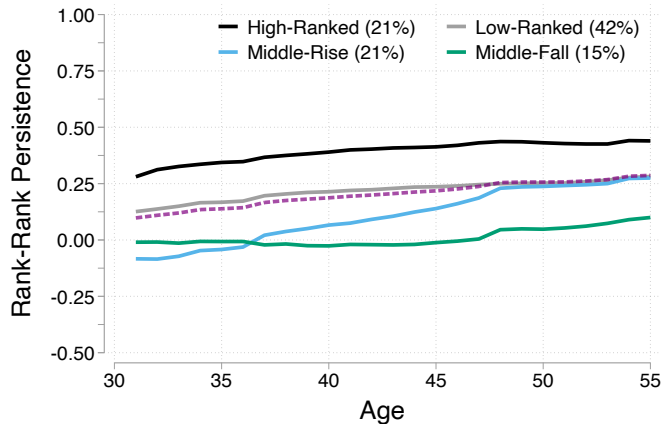


- **Top:** Higher persistence than population
- **Fallers:** Lower persistence than population

Decreasing Inter-Generational Mobility

[< back](#)

$$y_{i,t}^k = \alpha_t + \rho_t^{g(i)} y_{i,0}^p + u_{i,t}$$

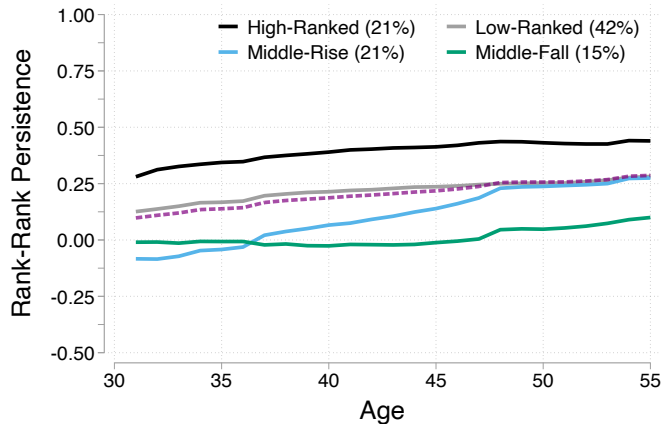


- Persistence rises for all groups
- Level differences are parallel

Decreasing Inter-Generational Mobility

◀ back

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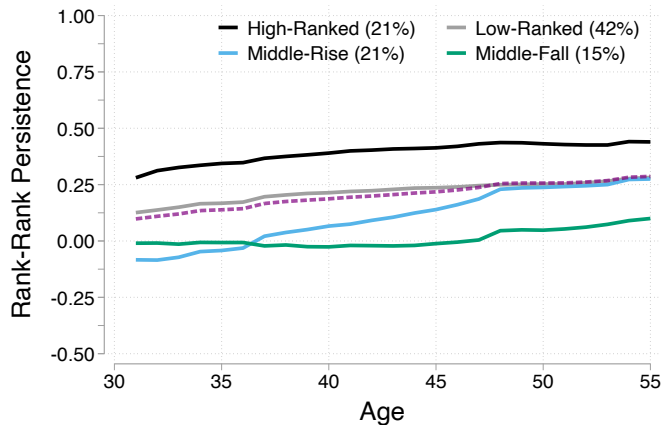
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- Risers' mobility trends from get-go
 - Reversal of fortune increases inter-generational persistence

▶ Shorrocks

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◀ back

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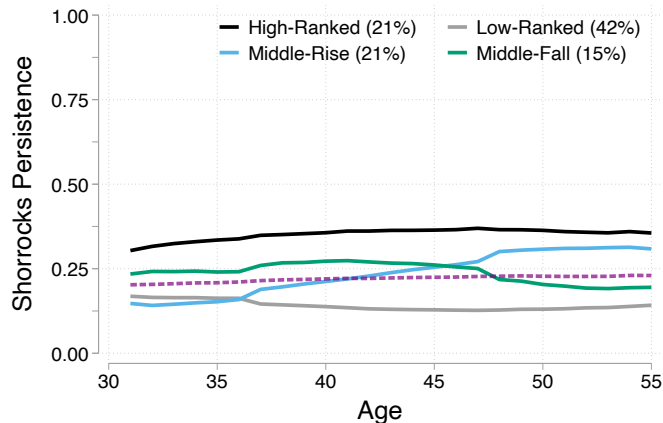


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► Shorrocks

- Clustering of trajectories captures persistent differences in mobility

Inter-Generational Shorrocks Mobility Index [◀ back](#)



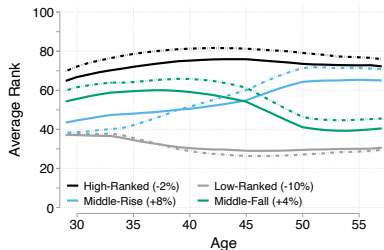
- Risers have clear upwards persistence trend
- Flat patterns for other groups

Characteristics of Main Clusters

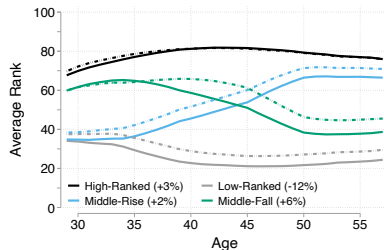
Alternative Clustering

[◀ Back](#)

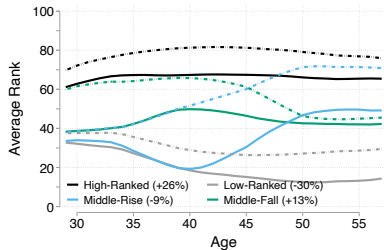
Household Cohort Ranks



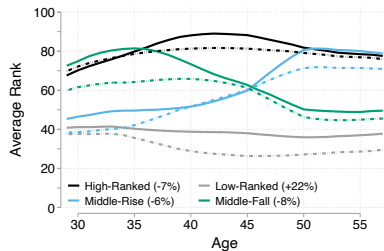
K Means on Ind. Cohort Ranks



Log Net Worth



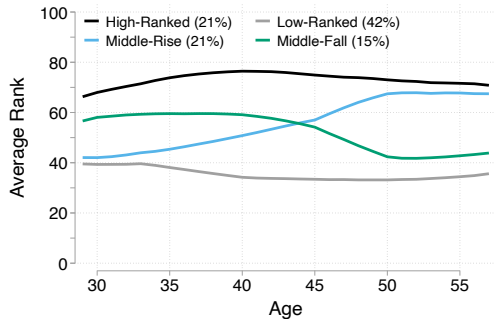
“Lorenz” Ordinates



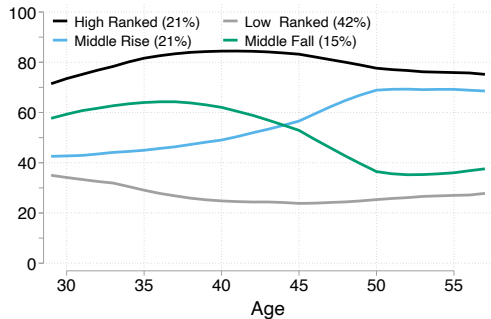
Household Wealth Ranks

[◀ Back](#)

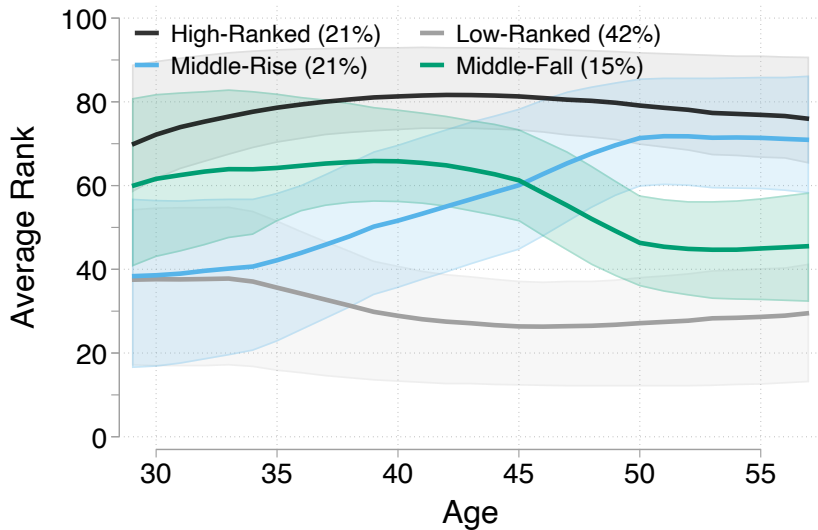
Household Cohort Ranks (Ind. CI)



Household Cohort Ranks (HH. CI)



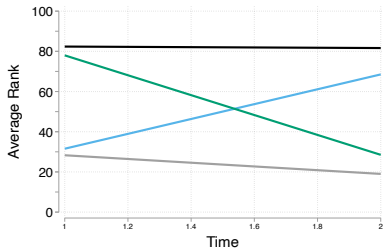
Distribution of Trajectories by Cluster

[◀ Back](#)

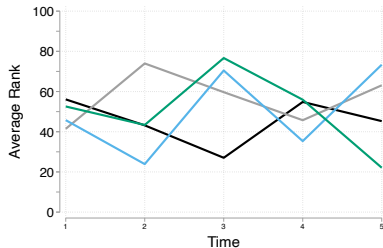
Clustering Random Ranks

[◀ Back](#)

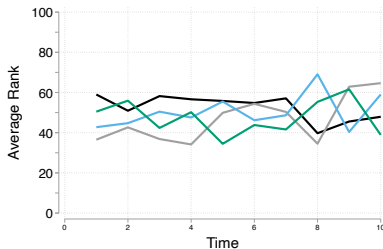
2 Periods



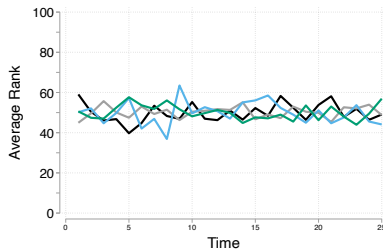
5 Periods



10 Periods



25 Periods

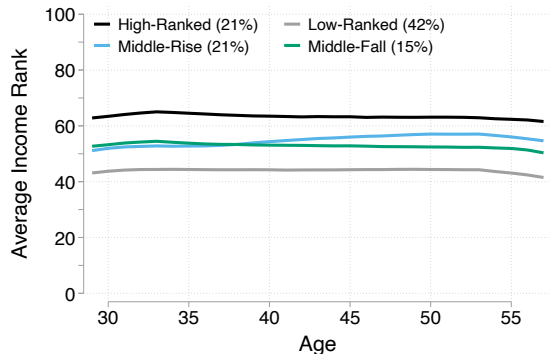


Heterogeneity Across and Within Groups

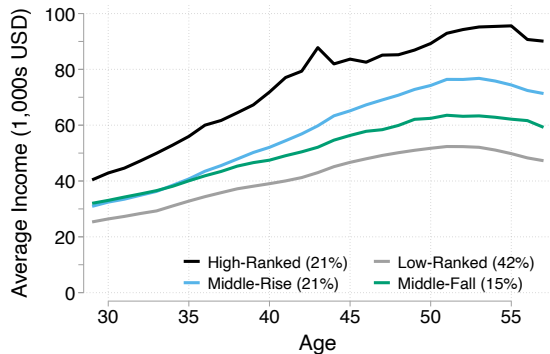
Income Histories Across Segments of the Distribution

[◀ back](#)

Income Cohort Ranks



Income (\$1000s)



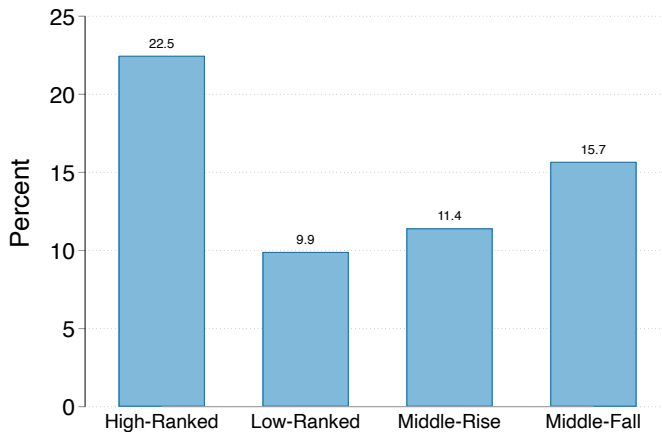
- Distribution of income across clusters compressed relative to wealth

[▶ Median Income](#)

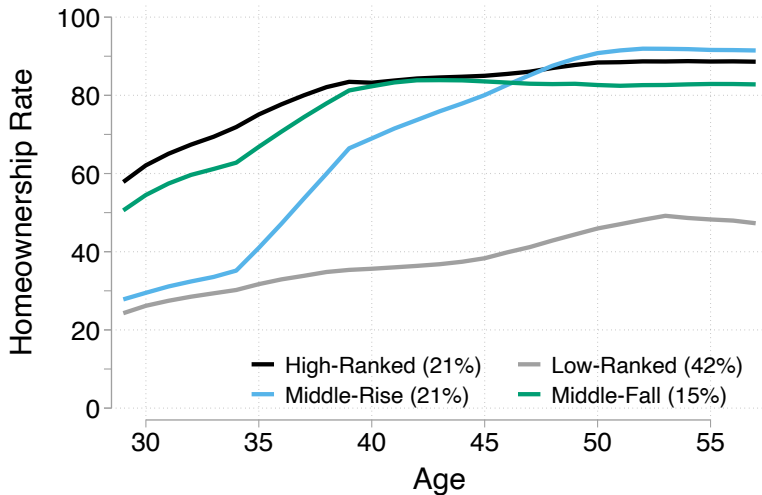
- Similar patterns for HH income; Risers same inc. as high ranked on average

[▶ HH Inc.](#)[CS](#)

Share with Self-Employment Income (%)



Homeownership Rates by Cluster

[◀ back](#)

Taking stock: four largest clusters

[< back](#)

- High-Ranked

- Stable at the top
- Accumulate wealth fast
- Homeowners, likely to own businesses
- Largest labour market income

- Middle-Risers

- Start out low
- Accumulate wealth fast
- Income similar to Wealthy
- Become homeowners along the way

- Middle-Fallers

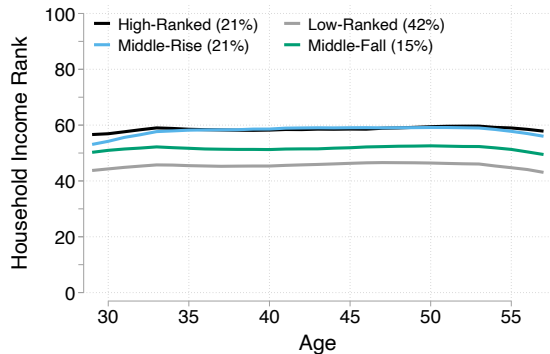
- Start out relatively well off
- Relatively lower labour market income
- Likely to be self-employed
- Usually own assets

- Low-Ranked

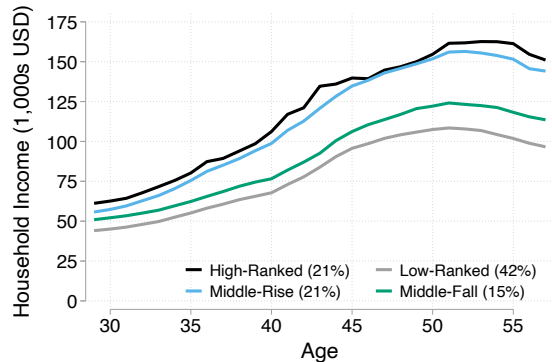
- Stuck at the bottom
- Little rise at the end
- Lowest incomes
- Non-homeowners

Household Income [◀ Back](#)

Household Income Cohort Ranks



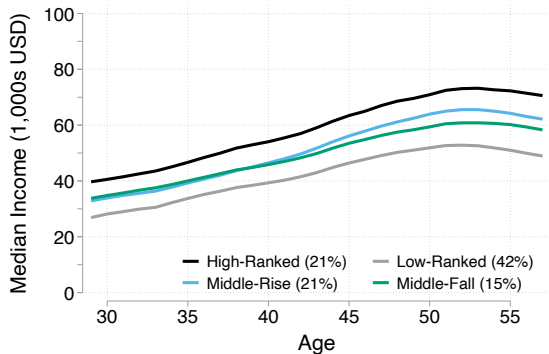
Household Income (\$1000s)



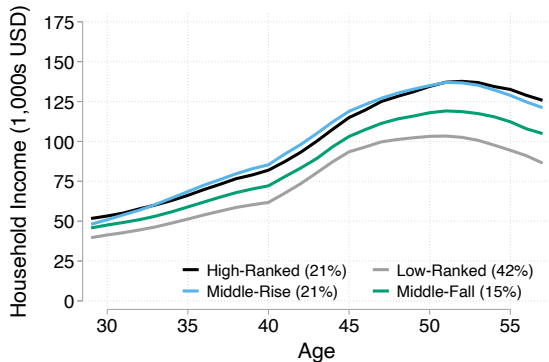
Median Income Histories

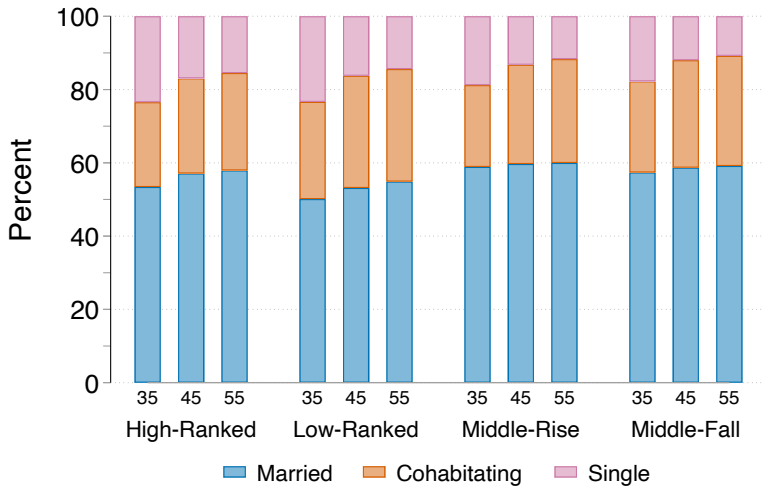
[◀ Back](#)

Median Income

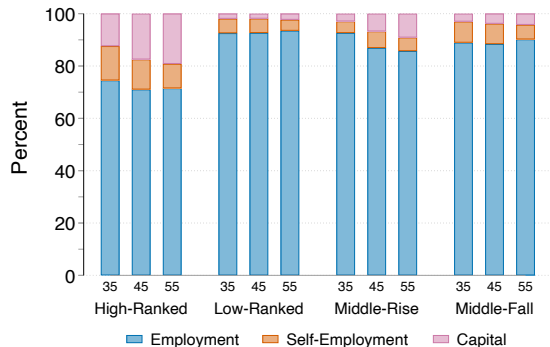


Household Median Income (\$1000s)





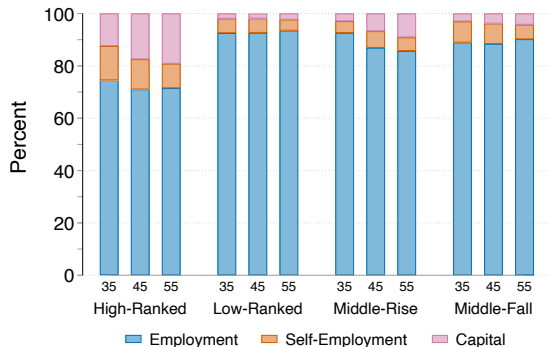
Income Sources



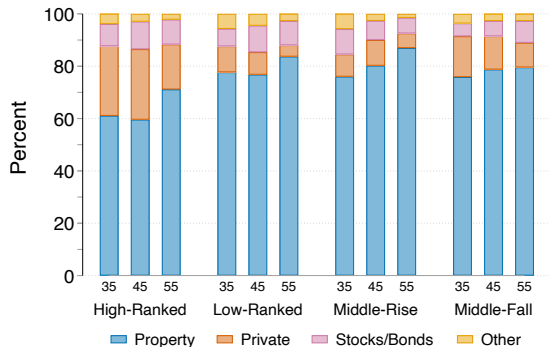
- Income differences in Self-Employment and Capital

Portfolio and Income Composition [◀ Back](#)

Income Sources



Asset Portfolio



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

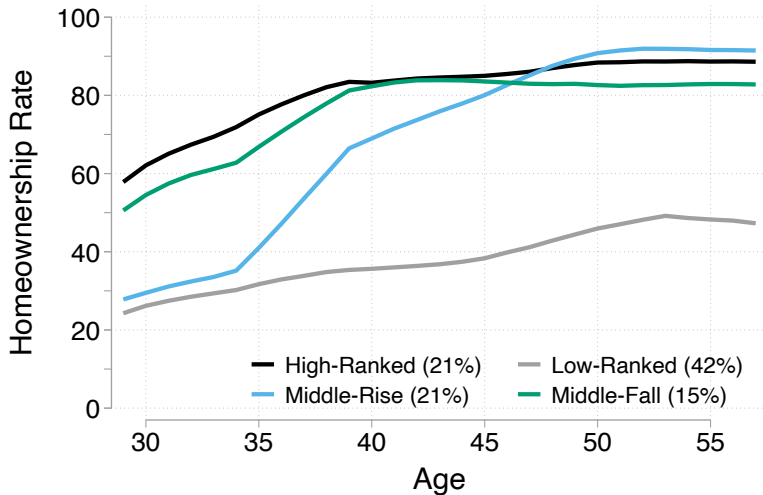
▶ SE

▶ Transfers

▶ Gifts

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

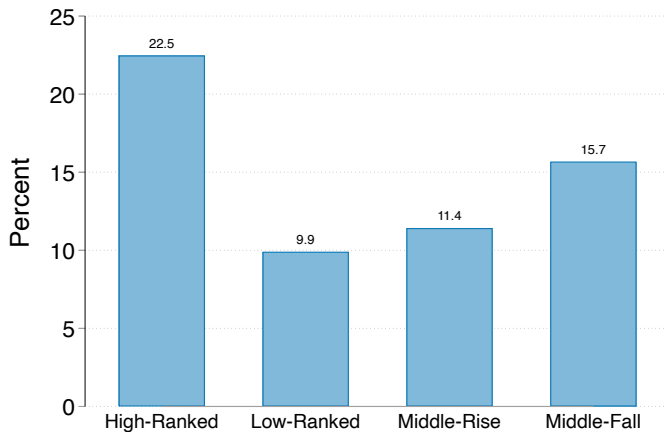
Home-ownership Rates by Cluster

[◀ Back](#)

Self-Employment Rates, Age 45

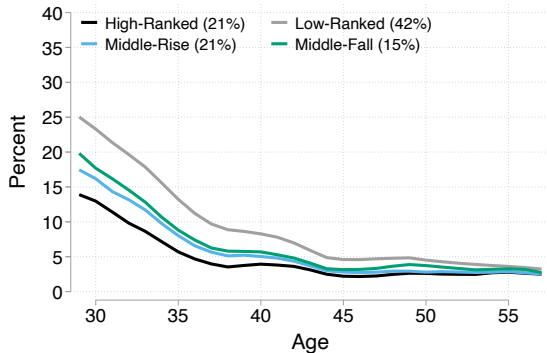
[◀ Back](#)

Share with Self-Employment Income (%)

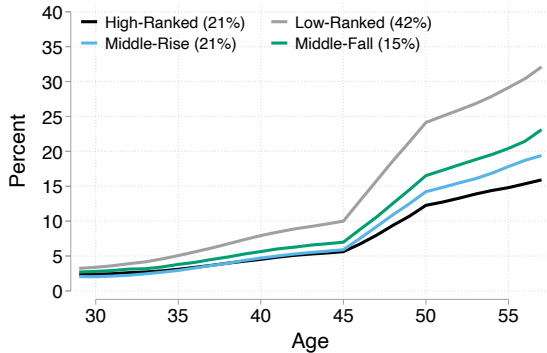


Transfers: Unemployment, Disability, Sick Leave, Nursing [◀ Back](#)

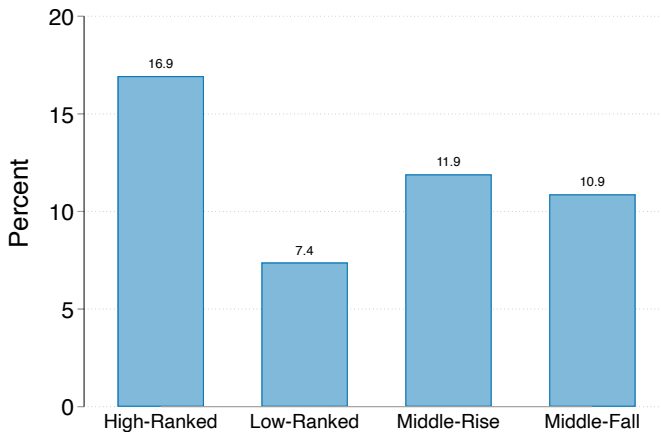
Share with Unemployment Benefits (%)



Share with Health-Related Transfers (%)



Share Received Gifts by 2014 (%)



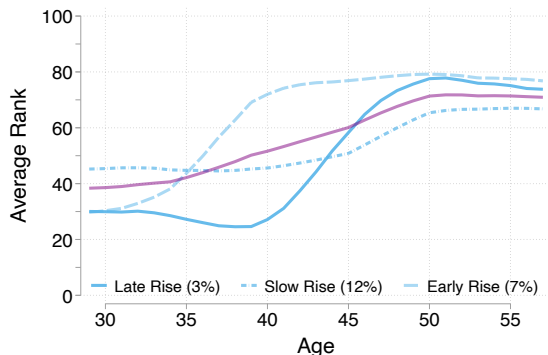
Notes: Total received > NOK 470K (\approx \$47K) before 2014

Characteristics of Sub-Clusters

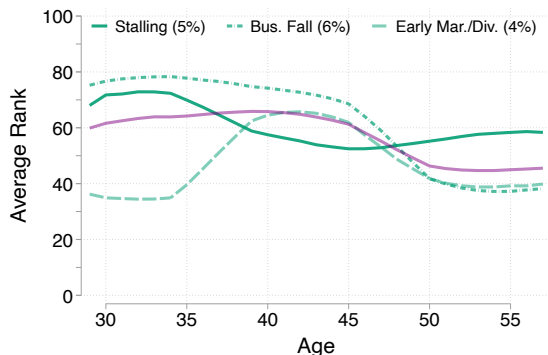
Heterogeneity in Trajectories

[▶ Wealth](#)[▶ Portfolio](#)[▶ Homeownership](#)[▶ Inc.](#)[▶ SE](#)[▶ Edu.](#)

Middle-Risers



Middle Fallers



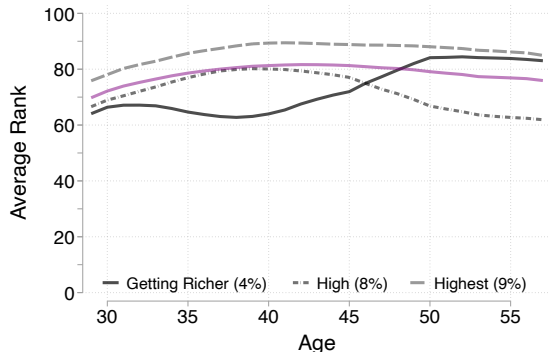
- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)

[◀ back](#)

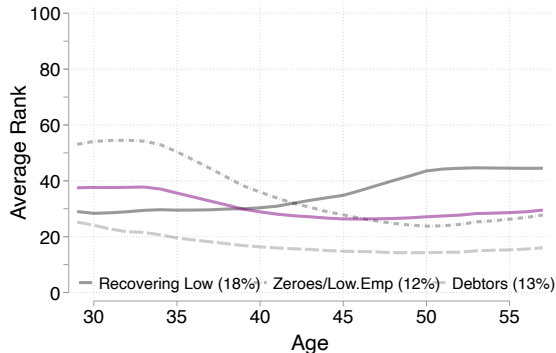
Heterogeneity in Trajectories

[▶ Wealth](#)[▶ Portfolio](#)[▶ Homeownership](#)[▶ Inc.](#)[▶ SE](#)[▶ Edu.](#)

High-Ranked



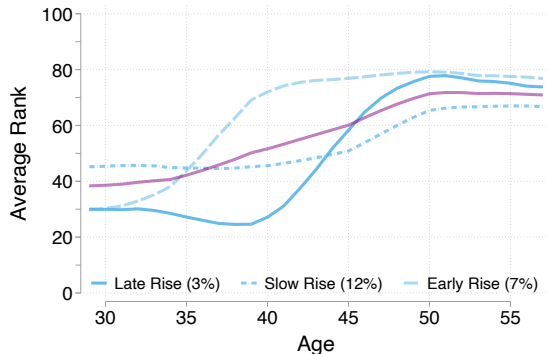
Low-Ranked



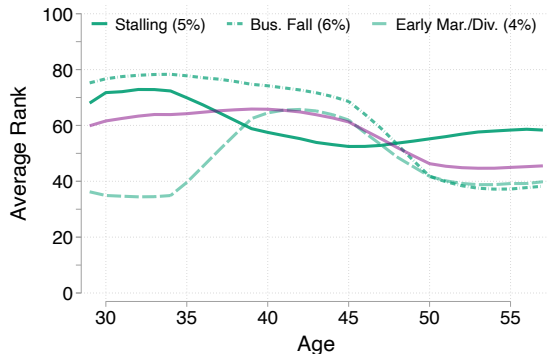
- Top and bottom groups differ mainly in avg. levels
- Zeros are quite different from debtors

Heterogeneity in Trajectories: Levels vs Timing [◀ Back](#)

Middle-Risers



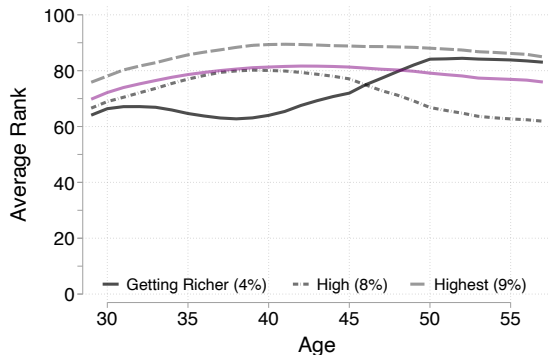
Middle-Fallers



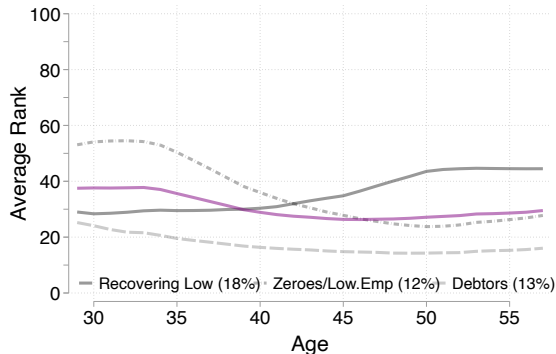
- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)

Heterogeneity in Trajectories: Levels vs Timing [◀ Back](#)

High-Ranked



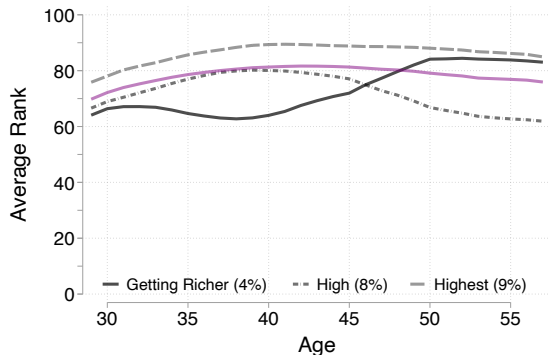
Low-Ranked



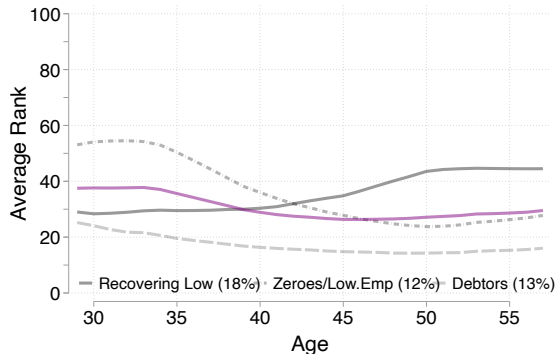
- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)
- Top and bottom groups differ mainly in avg. levels (with a rising sub-group in each)

Heterogeneity in Trajectories: Levels vs Timing [◀ Back](#)

High-Ranked



Low-Ranked

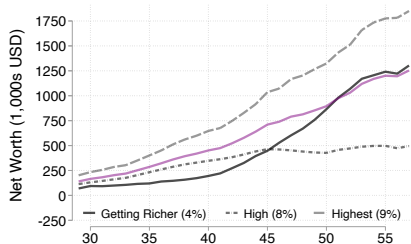


- Risers differ mainly in timing of changes (similar initial conditions)
- Fallers differ in initial conditions and timing of changes (similar final conditions)
- Top and bottom groups differ mainly in avg. levels (with a rising sub-group in each)

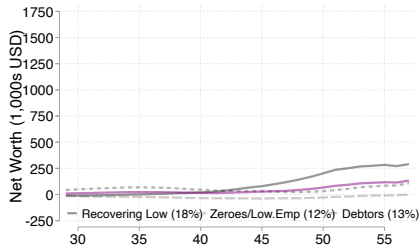
Sub-Clusters: Wealth Levels

[◀ Back](#)

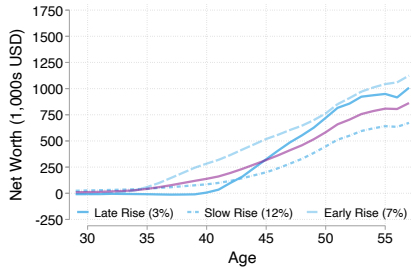
High Ranked



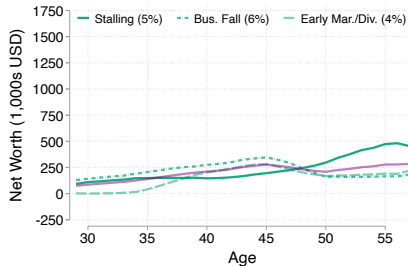
Low Ranked



Middle Risers



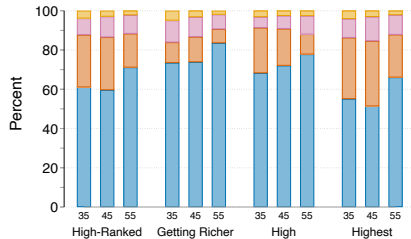
Middle Fallers



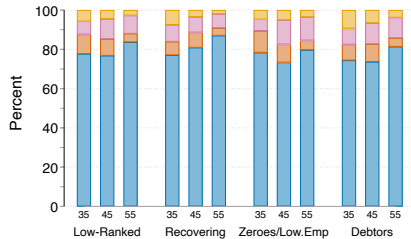
Sub-Clusters: Portfolio

[◀ Back](#)

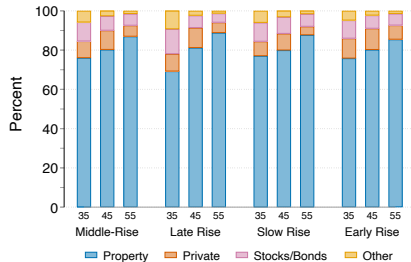
High Ranked



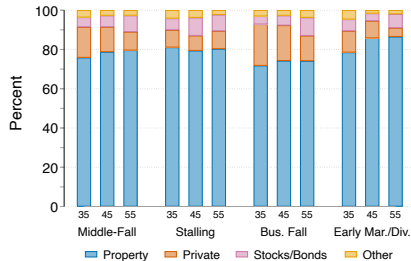
Low Ranked



Middle Risers



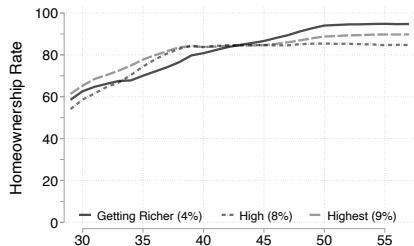
Middle Fallers



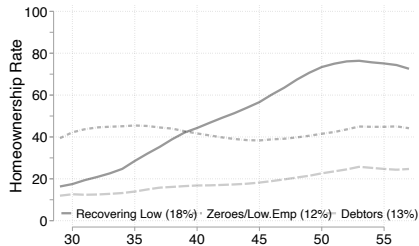
Sub-Clusters: Homeownership

[◀ Back](#)

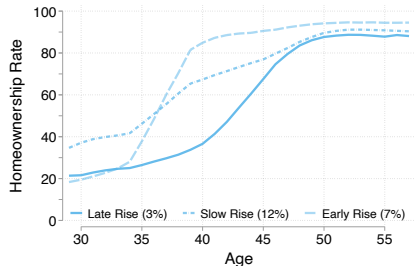
High Ranked



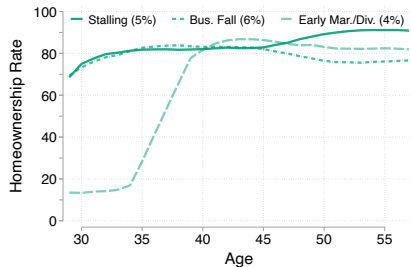
Low Ranked



Middle Risers



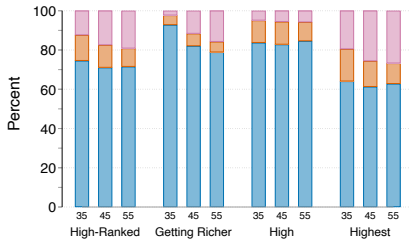
Middle Fallers



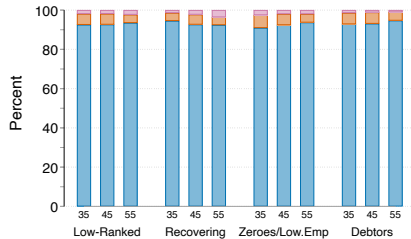
Sub-Clusters: Income Composition

[◀ Back](#)

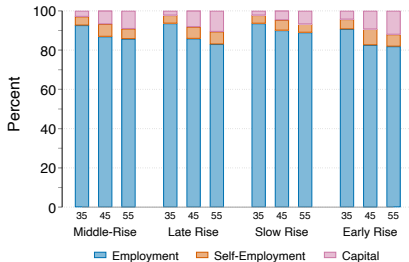
High Ranked



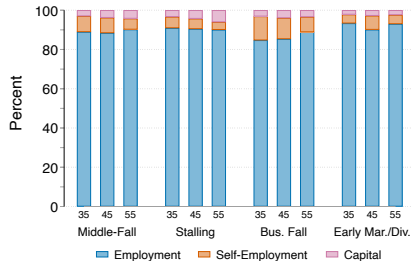
Low Ranked



Middle Risers

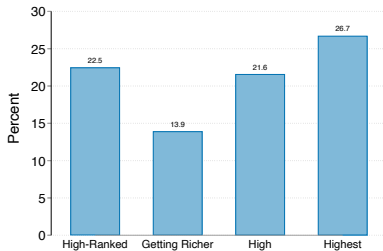


Middle Fallers

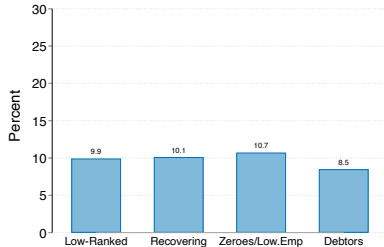


Sub-Clusters: Self-Employment [◀ Back](#)

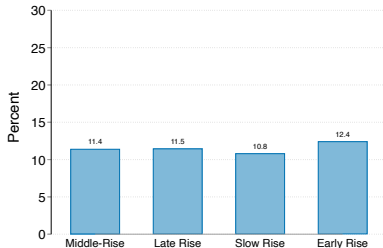
High Ranked



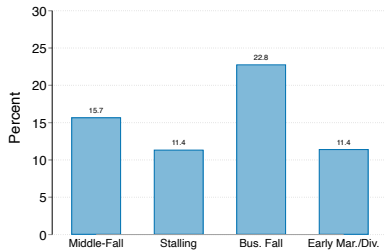
Low Ranked



Middle Risers

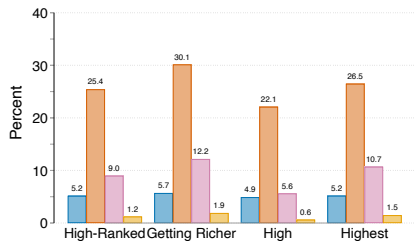


Middle Fallers

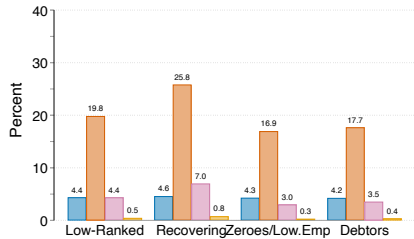


Sub-Clusters: Education [◀ Back](#)

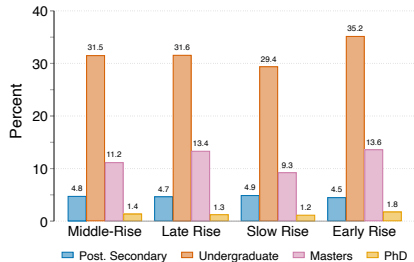
High Ranked



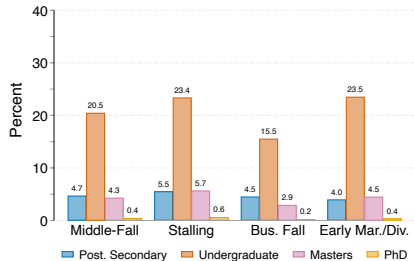
Low Ranked



Middle Risers



Middle Fallers



Shapley-Owen Decomposition

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

Two measures:

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

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

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

- 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.

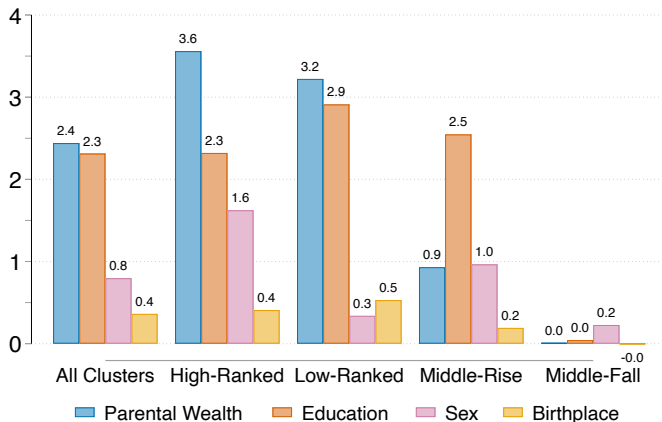
Share of individuals correctly classified by random classification 29.3% vs 32.5% with full model.

[▶ D by Cluster](#)

[▶ C by Cluster](#)

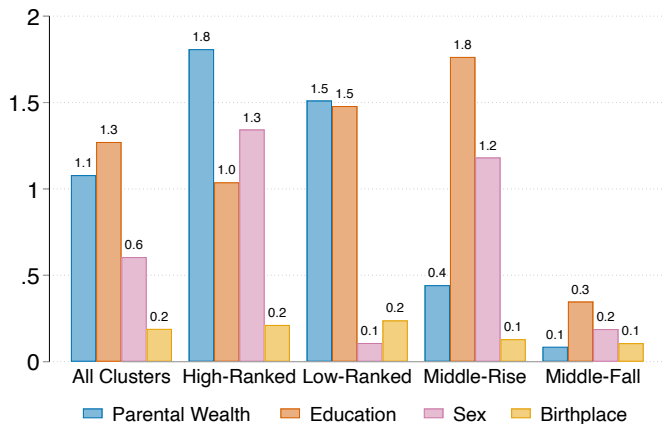
How Important Are Ex-Ante Explanations? [◀ back](#)

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.

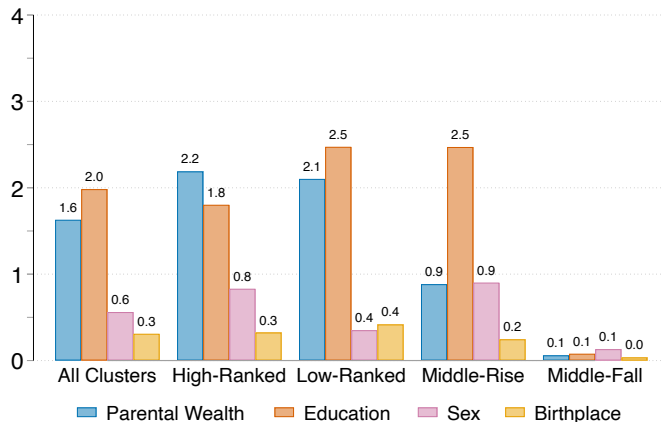
Share of individuals correctly classified by random classification 29.3% vs 40.0% with full model.

[▶ D by Cluster](#)

[▶ C by Cluster](#)

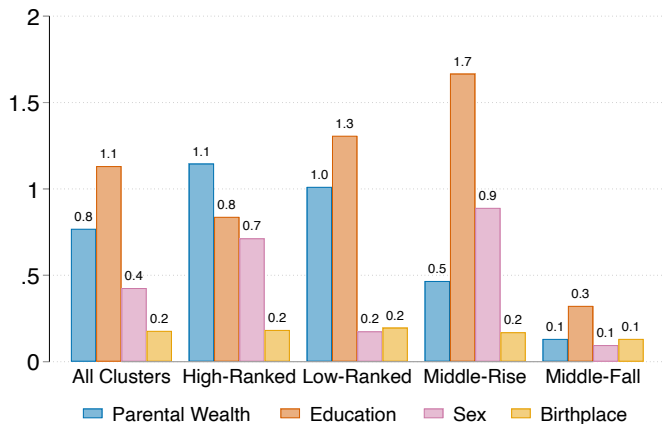
How Important Are Ex-Ante Explanations? [◀ back](#)

Share of Cross-Group Variation Explained by Variable



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

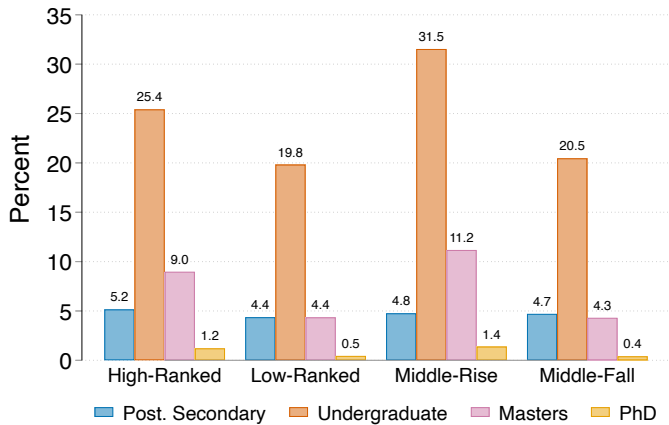
Share of Individuals Correctly Classified



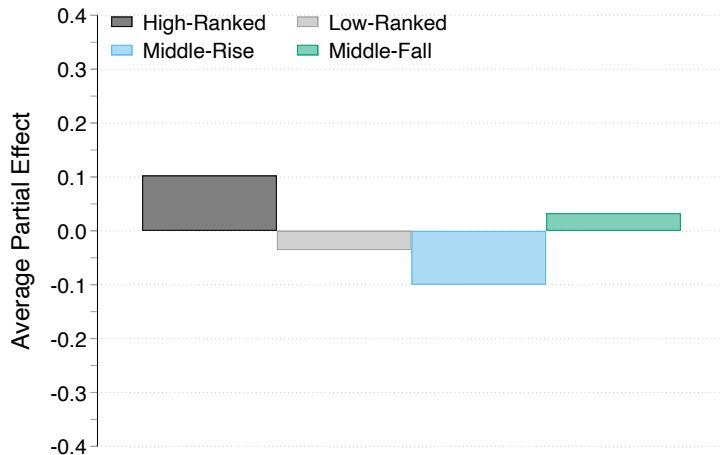
* Contribution relative to random classification using population shares.

Classification Results for Main Clusters

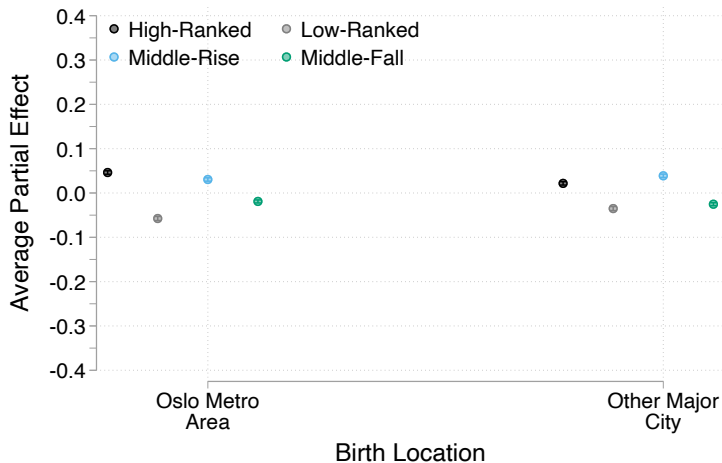
Highest Education Level Shares (%)



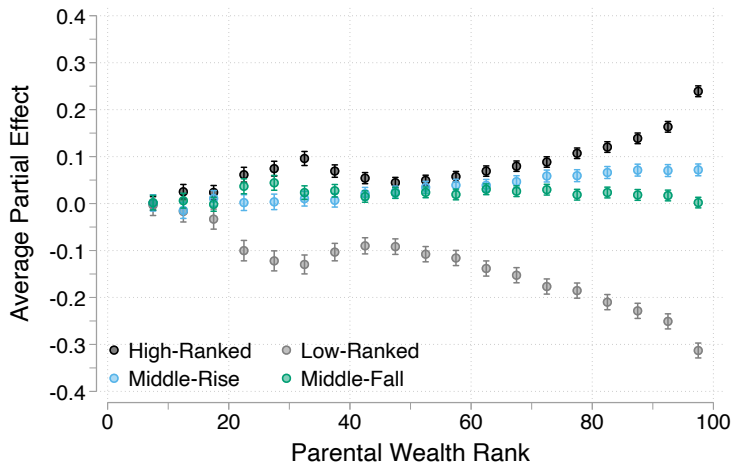
Sex Average Partial Effect

[◀ back](#)

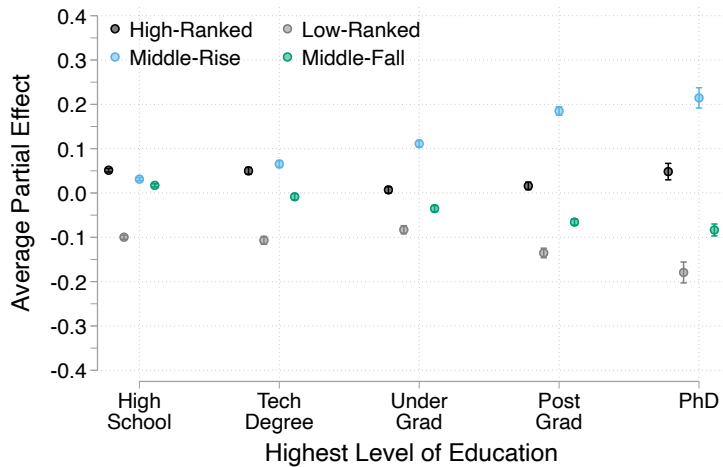
Where Is The Land of Opportunity? Norway

[◀ back](#)

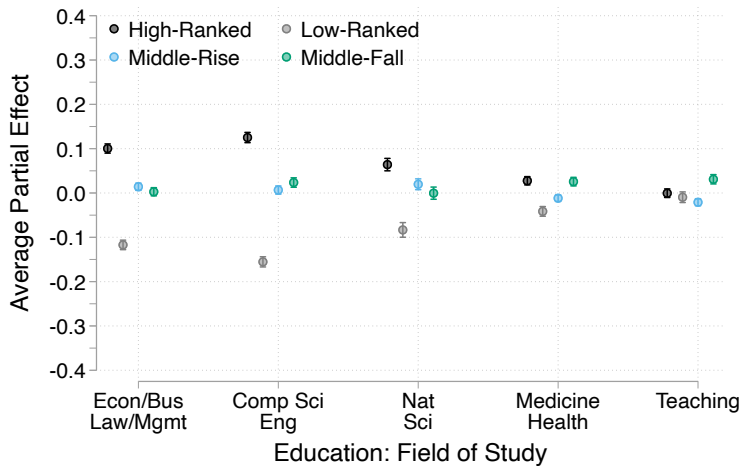
The Non-Linear Effect of Parental Wealth: CI

[◀ back](#)

Learn & Rise?: CI

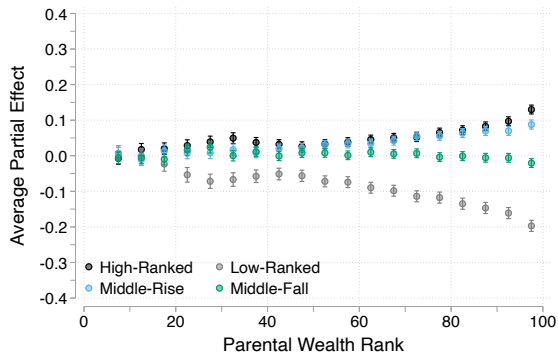
[◀ back](#)

Education: Fields

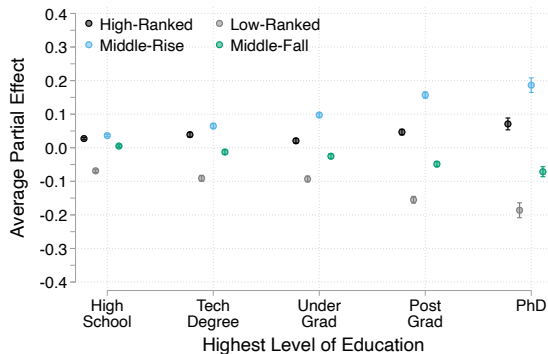
[◀ Back](#)

Patterns still present after conditioning on own initial wealth [◀ Back](#)

Parental Wealth



Education



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

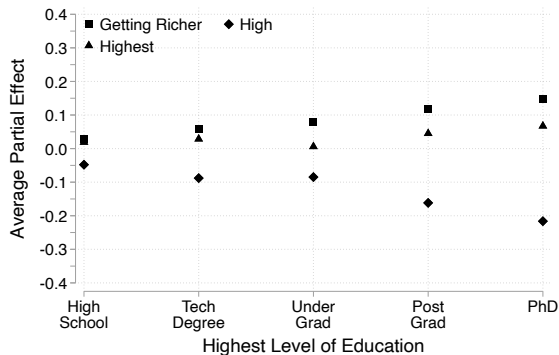
Classification Results for Sub-Clusters

What about heterogeneity within clusters? High-Ranked [◀ Back](#)

Parental Wealth



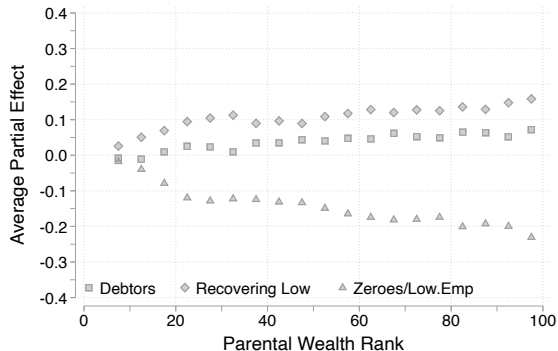
Education



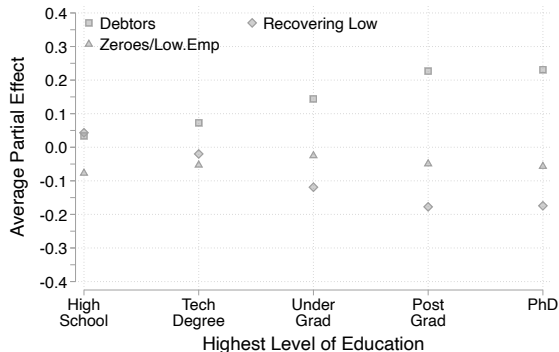
- Even within the groups, movers are hard to predict with parental wealth [▶ PW CI](#)
- Education predicts dynamics within groups (e.g., getting richer vs already wealthy) [▶ ED CI](#)

What about heterogeneity within clusters? Low-Ranked [◀ Back](#)

Parental Wealth



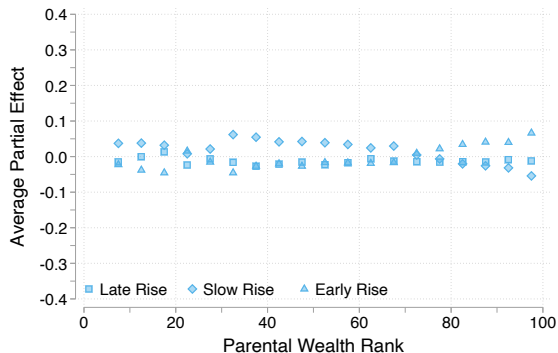
Education



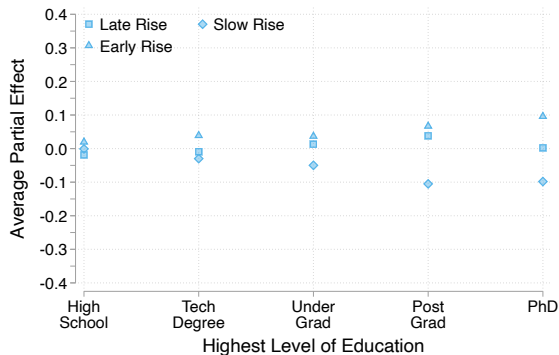
- Among poor, parental wealth does not predict movements
- Education predicts recovery

What about heterogeneity within clusters? Middle-Risers [◀ Back](#)

Parental Wealth



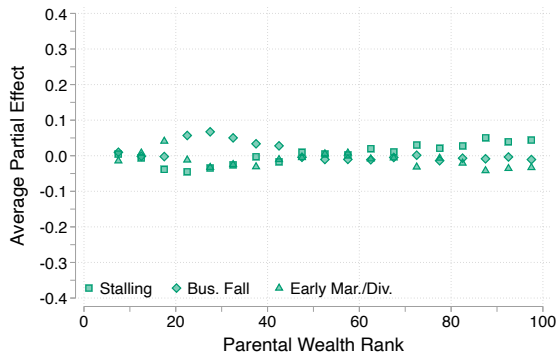
Education



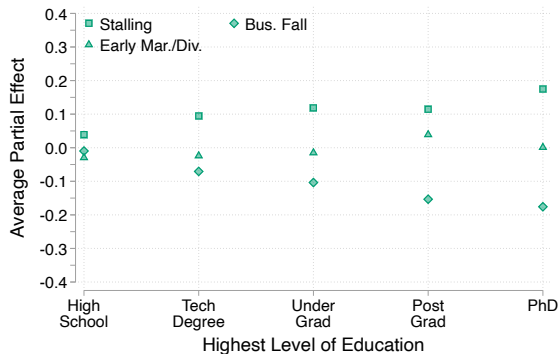
- Within Risers, movers not predicted by parental wealth
- Education predicts timing

What about heterogeneity within clusters? Middle-Fallers [◀ Back](#)

Parental Wealth

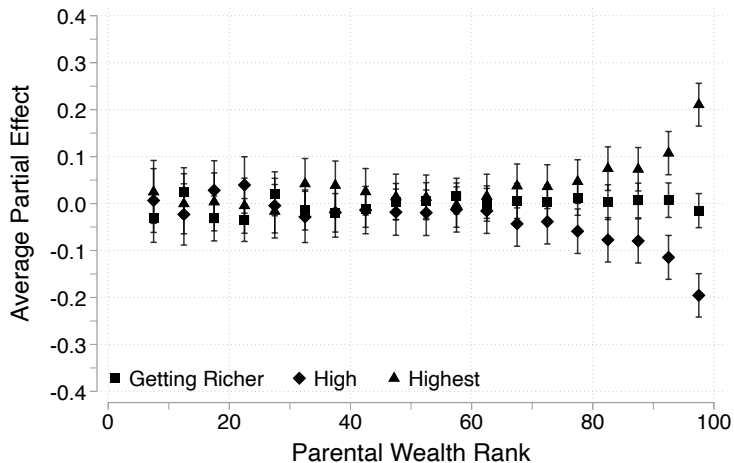


Education

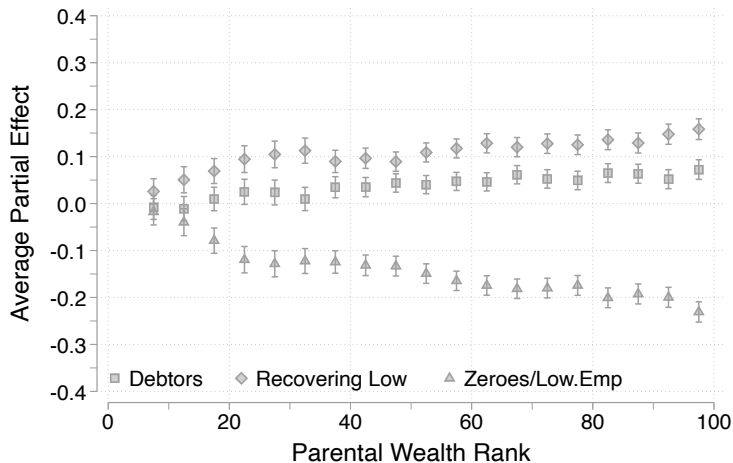


- Similar to Risers, little role for parental wealth
- But Education predicts dynamics

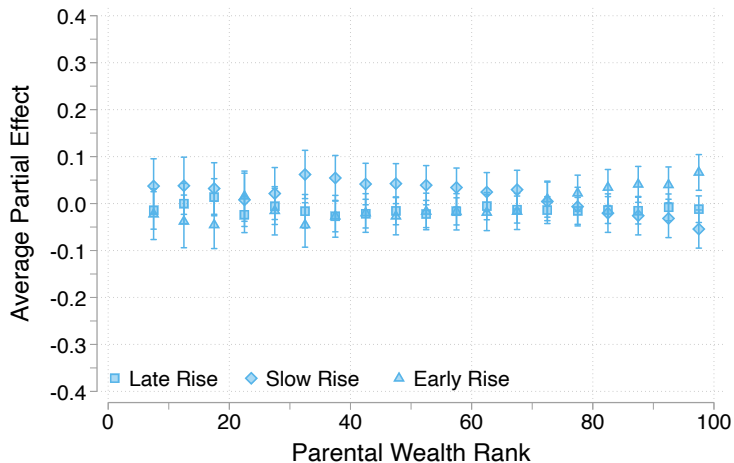
The Non-Linear Effect of Parental Wealth: CI

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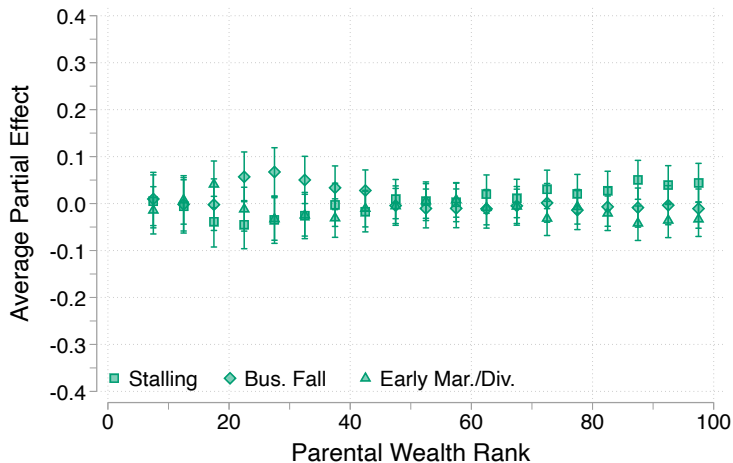
The Non-Linear Effect of Parental Wealth: CI

[◀ back](#)

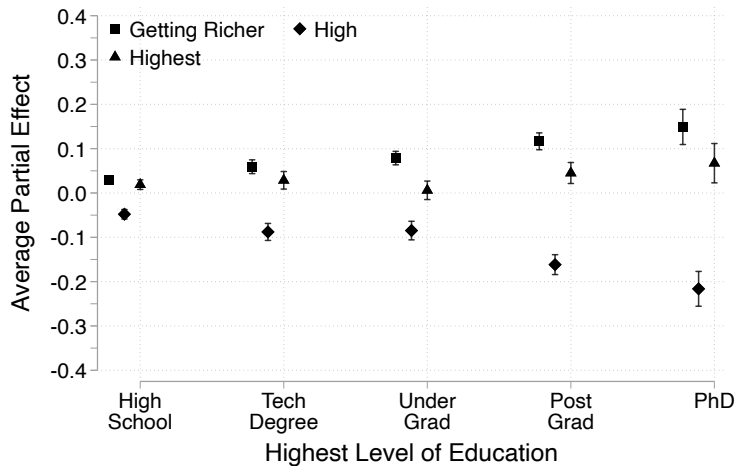
The Non-Linear Effect of Parental Wealth: CI

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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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1. New evidence on wealth mobility and wealth accumulation: Full life cycle trajectories
 - Add to results for the super wealthy (Gomez; Ozkan, Hubmer, Salgado, Halvorsen), the role of individual factors (Hugget, Ventura, Yaron; Black, Devereux, Landaud, Salvanes), and short-run mobility and race (Hurst, Luoh, Stafford, Gale).
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. Inter-generational 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