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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Today: Document patterns of wealth mobility across life cycle

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

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   - Zoom-in: *sub-clusters* show heterogeneity in paths for groups starting in different sections of the distribution
3. Predict trajectories with individual circumstances
   - Determinants of paths through the distribution: prev. generation, education, etc.

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)
- We link to administrative records (Education, Civil Status, Income)
- We adjust the tax value to reflect market values (Fagereng, Holm, Torstensen, 2023, 2023)
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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 (217,383 after balancing)

Ranks and Histories

- Compute within cohort ranks as

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

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- Histories of ranks (trajectories)

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

  - Vector of rank outcomes (for balanced panel)

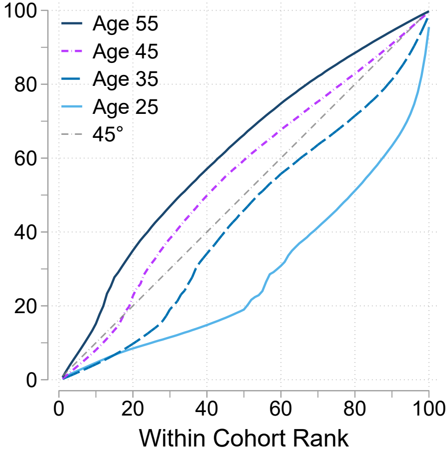
We are interested in the distribution of the vectors $\mathbf{Y}_i$

- Significant changes in wealth levels as the cohort ages

- Significant changes in wealth levels across ranks

Birth Cohort Ranks vs Population Ranks vs Wealth Levels

BC Ranks vs Pop Ranks



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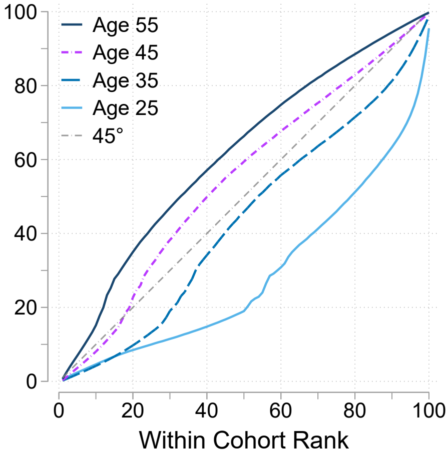
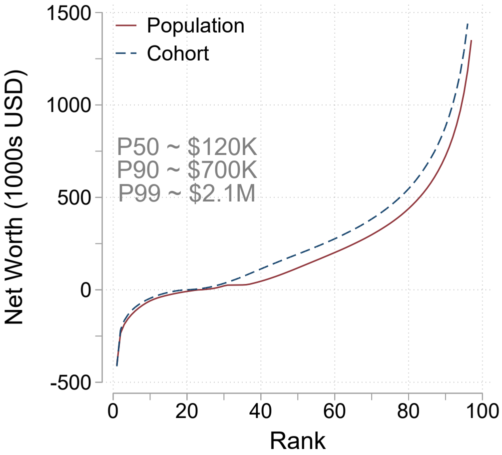


Net Worth CDF (2014)



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

Patterns of Mobility

How much does people's wealth rank $y_{i,t}$ change over time?

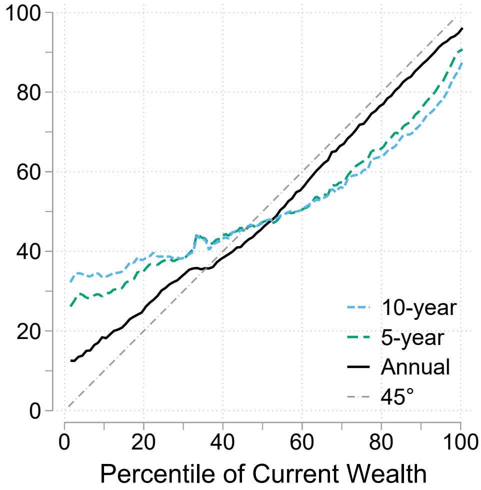
Distribution of future ranks conditional on current rank

- Conditional mean $E\left[y_{i,t+h} | y_{i,t}\right]$ (also higher order moments)
- Conditional quantiles $Q_{y_{i,t+h}|y_{i,t}}(\tau)$ for $\tau \in \{0.1, 0.25, 0.75, 0.9\}$

How Non-Linear is Wealth Mobility?

▸ Age 31 ▸ Income

Age 35 – Cond. Mean



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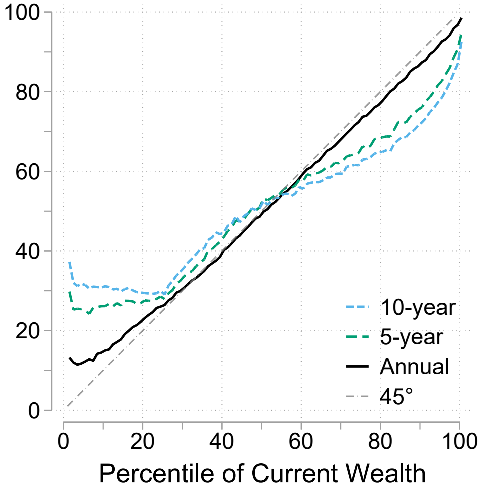
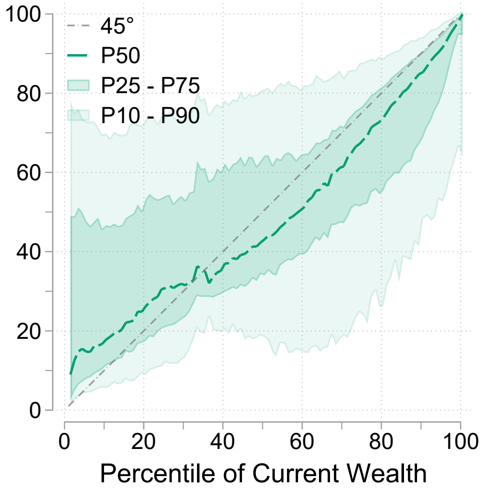


The Distribution of Rank Changes (5-year)

▸ 1y Chg ▸ 10y Chg

Age 35



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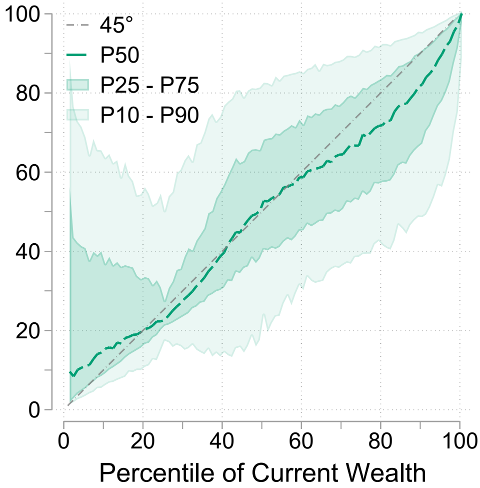

At the top few fall, but cushioned Middle class rarely climb, but some fall

Distribution of rank changes is non-linear and age-dependent!

- Mean reversion in ranks weakens at the top
- Dispersion $\downarrow$ with age (consistent w evidence on income) and initial rank
  - Median change is close to no change at all ages(!)

▸ std. dev. ▸ skew. ▸ kurt.

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  - Variability in 1y changes is misleading about long-run variability
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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

- Uncover rising, falling, and stable trajectories

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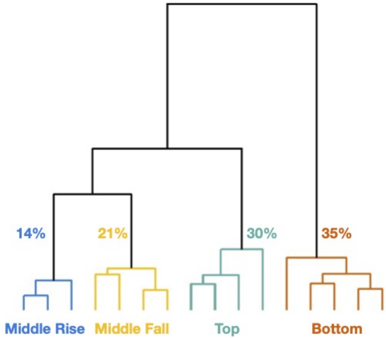
Result: Hierarchy of partitions ranging from $G = N$ to $G = 1$.

- Similar results for alternative clustering (cum. change, log-assets, "Lorenz" position)

Two Levels of Clustering

1. Focus on 4 major clusters (branches)
   - Explain majority of variation in rank histories (R^2=0.52)

Clustering Tree



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2. Zoom into each major cluster
   - Pick 3 main sub-clusters
   - Reveal heterogeneity in major trajectories
   - 12 clusters explain 20% additional variation (R^2=0.63; 16 Cl, R^2=0.66)

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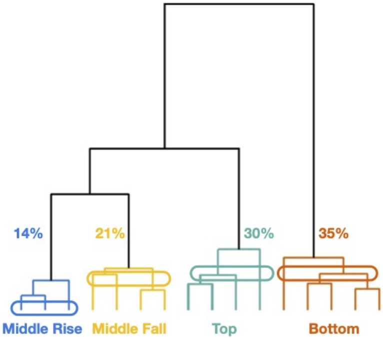
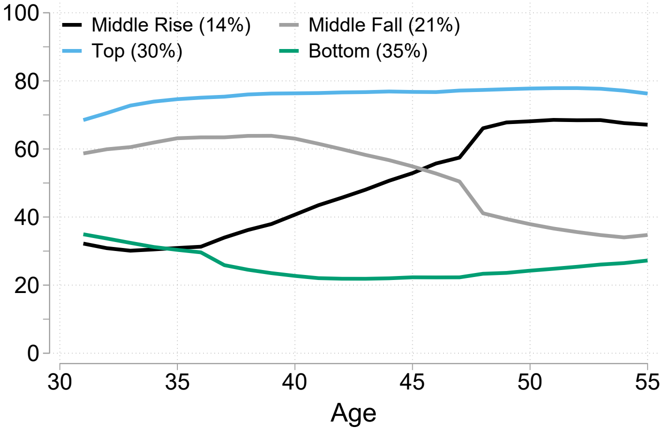


Typical Rank Histories: Segmented Mobility

Cohort Ranks

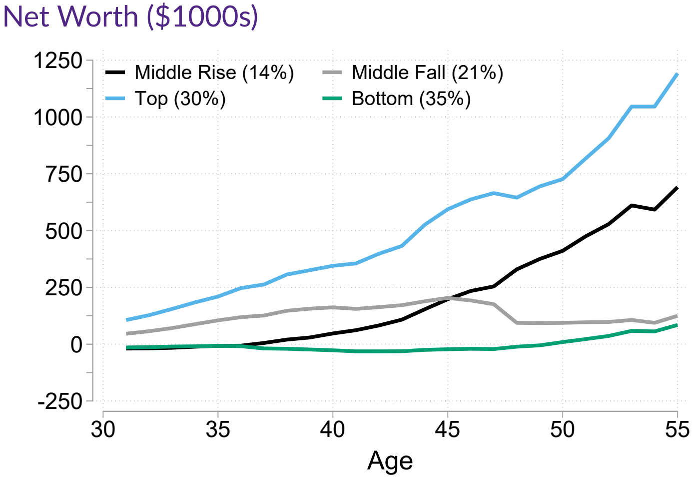


4 Main clusters show patterns of segmented mobility

- Individuals move within segments of the distribution
- The mean trajectory of a group hides rank swaps within
- Segments overlap:
  Top 40% // Bottom 40% //
  Middle 80%

Next: Levels + Heterogeneity

Wealth Histories Across Segments of the Distribution



Differences in ranks imply significant wealth differences:

- Risers: start with no wealth + grow like top group
- Fallers: ahead in 30s + low growth + great recession
- Top: Maintaining rank means rapid growth
- Bottom: Close to no wealth + growth in 50s (housing)

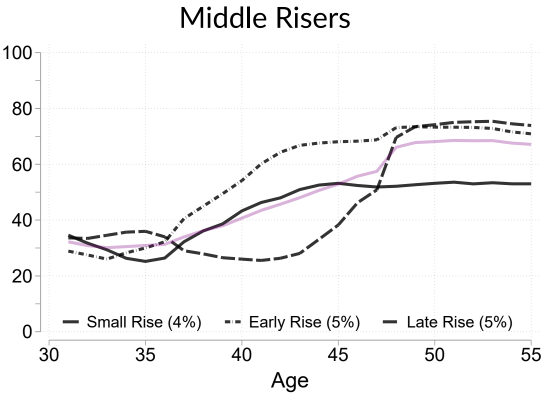
What Else Happens Along These Paths?

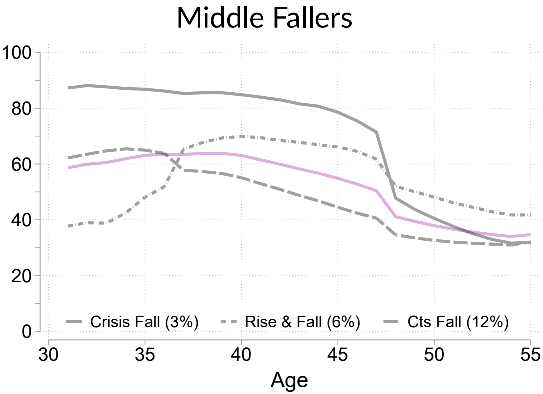
- Housing: Increasing trends except for *fallers* ▸ details
  - Fallers home-ownership: 40%$\longrightarrow$70%$\longrightarrow$65%
  - Risers home-ownership: 20%$\longrightarrow$85% (as high as top group)
- Civil Status: Similar marriage/cohabitation rates by cluster ▸ details
  - Bottom group have lowest marriage rates, top group the highest
- Portfolio Composition + Income: Soon!

Next Step: Zoom into heterogeneity within group

Heterogeneity in Trajectories: Levels vs Timing

Wealth Levels





- Risers differ mainly in timing of changes (Rise from rank 20 to 70, similar initial conditions)
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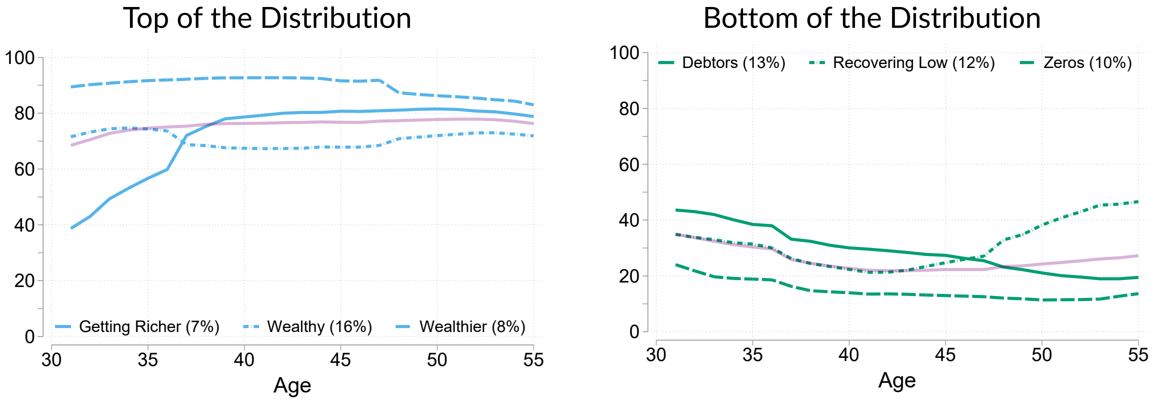

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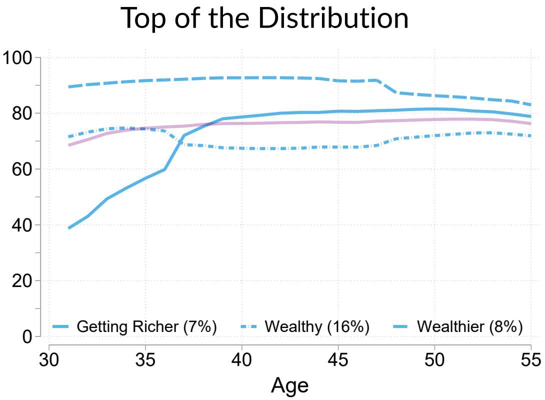

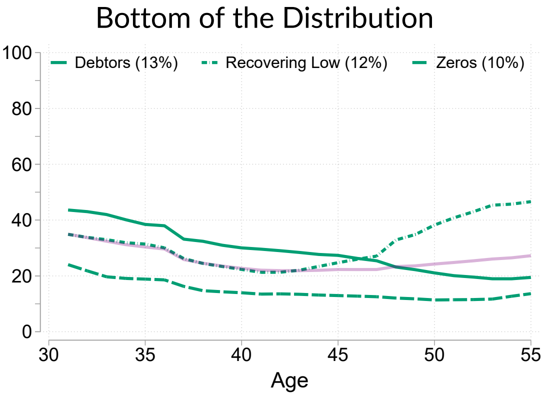

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Towards Determinants of Trajectories

Hereditary Advantage vs Human Capital

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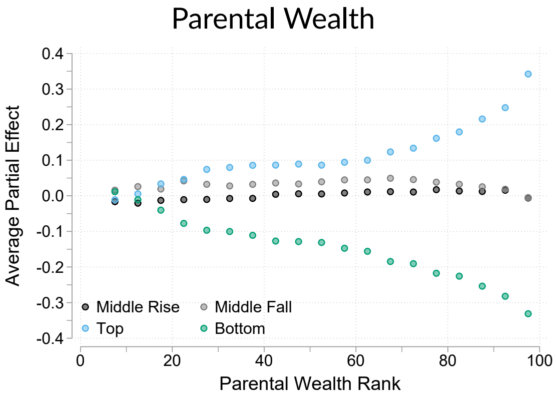
Predictors explain at most 6.4% of cross-group variation (same as rank-rank inter-gen reg) ▸ Results

The Non-Linear Effect of Parental Wealth and Education

▸ PW CIs ▸ ED CIs



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

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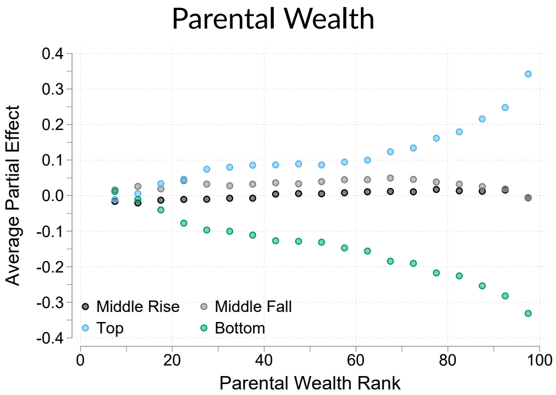
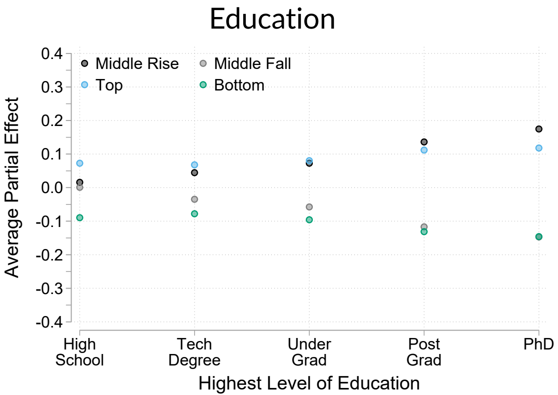
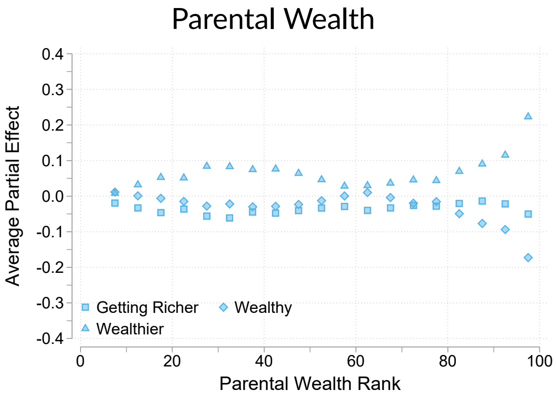


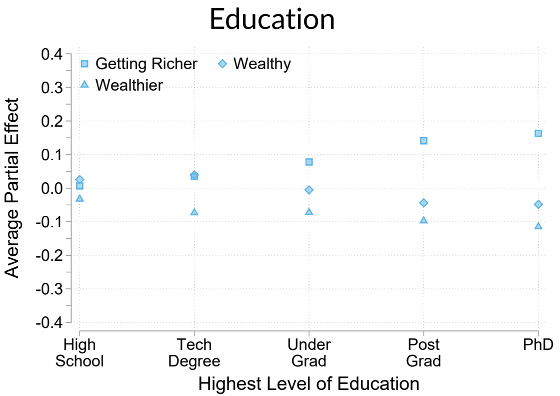


- Parental wealth's explanatory power: High for top/bottom, limited for middle groups
- Education tells risers/fallers apart: Equalizing effect but doesn't overcome initial cond.

What about heterogeneity within clusters? Top Group

▸ Other CI ▸ PW ▸ ED





- Even within the top group, movers are hard to predict with parental wealth
- Education does not matter for those born rich but helps those getting to the top

Conclusions

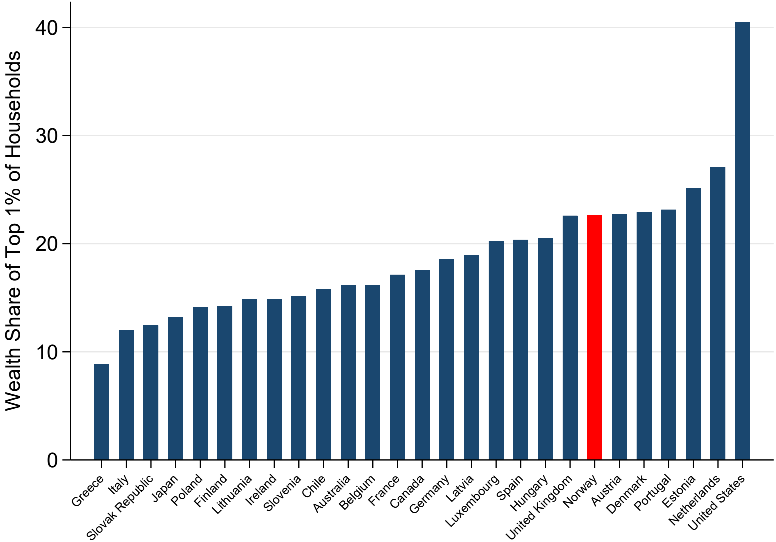
Conclusions

- 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

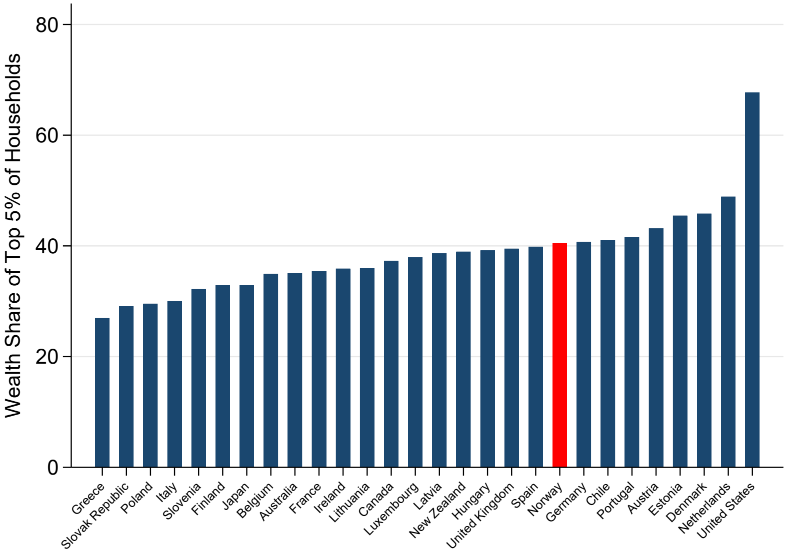
Norway in Context

Back



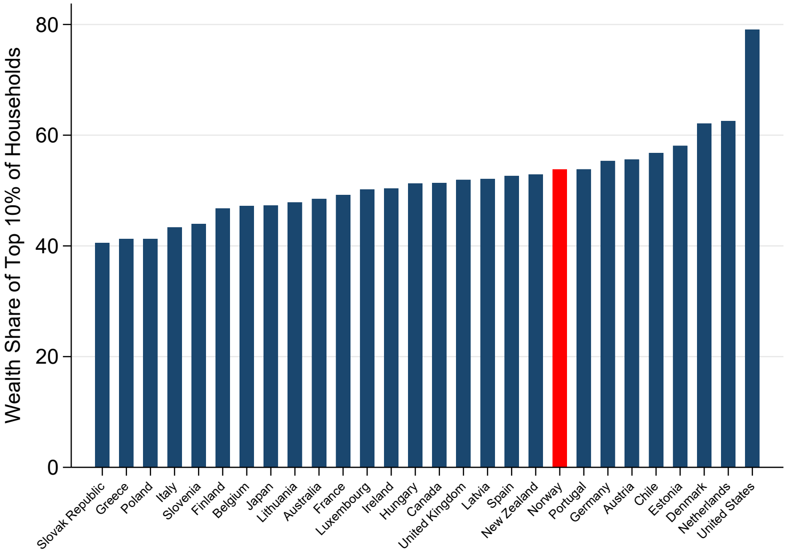
Norway in Context: Top 5% Share

Back



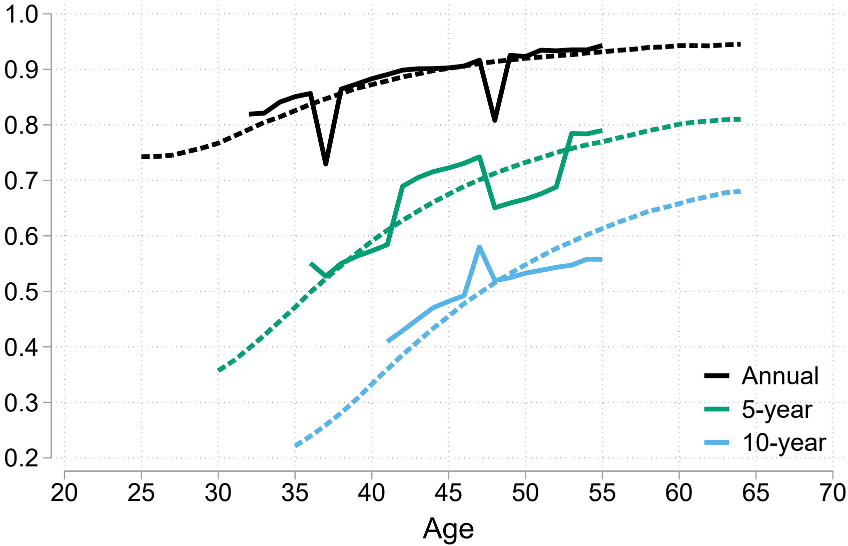
Norway in Context: Top 10% Share

Back



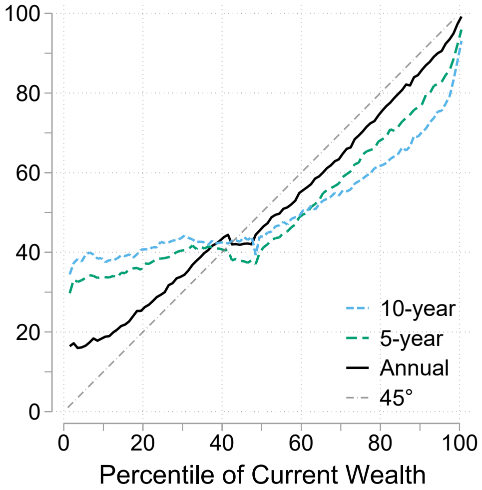
Persistence in Wealth Rank: Within Cohort

All Cohorts vs 1960-1964 Birth Cohort

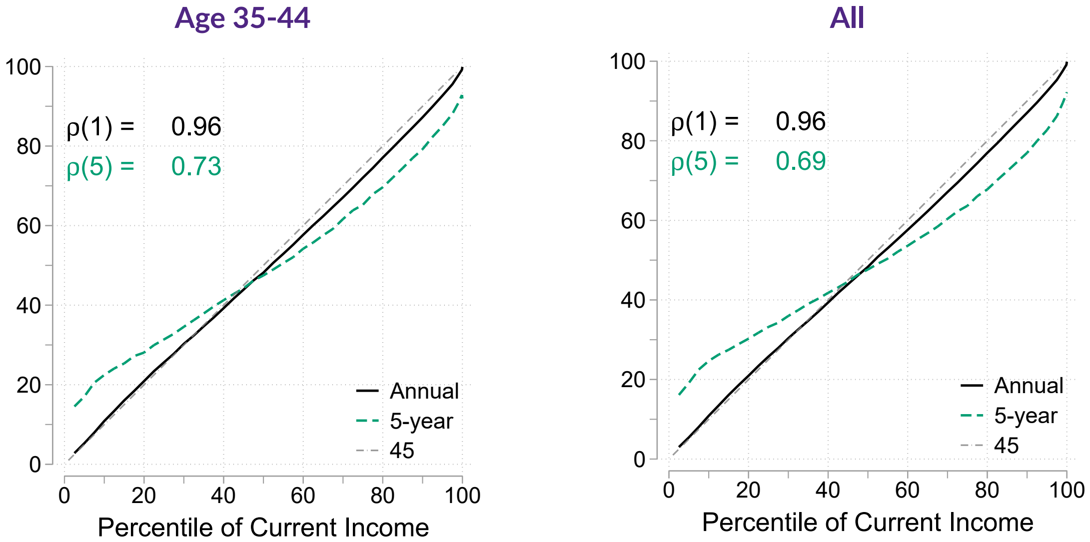


How Non-Linear is Wealth Mobility? back

Age 31

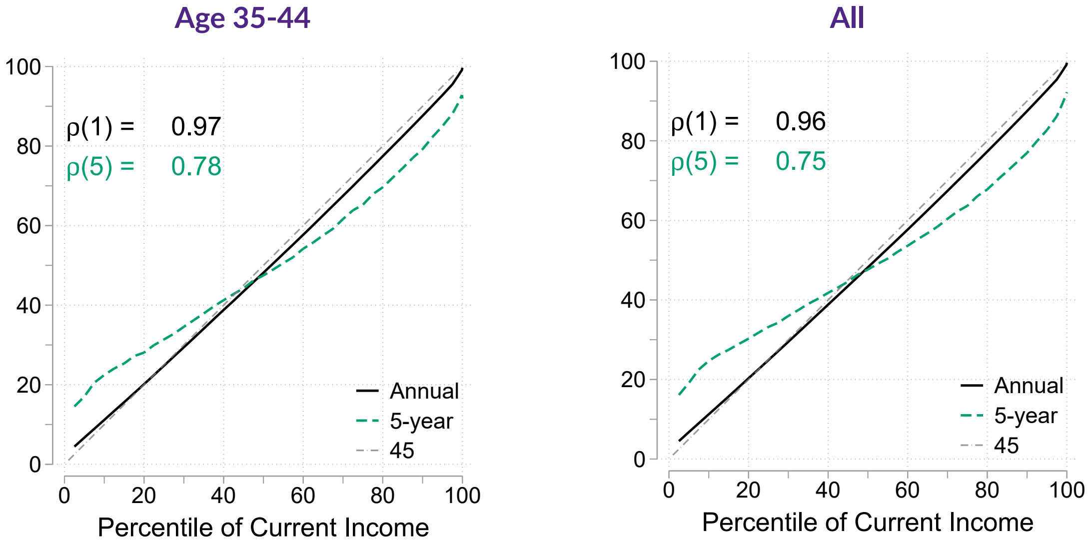


How Non-Linear is Income Mobility in Norway? ◂ back ▸ USA



Source: GRID database for 2005

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



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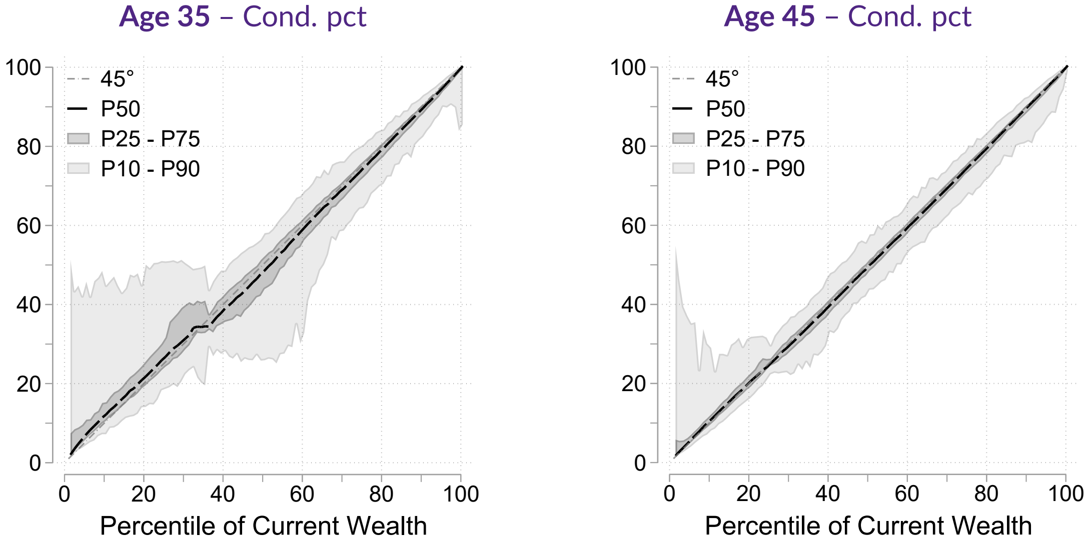
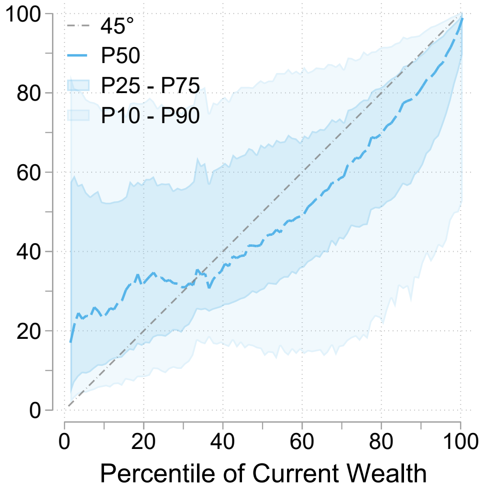
The Distribution of Rank Changes (1-year) ◂ back ▸ 10y Chg

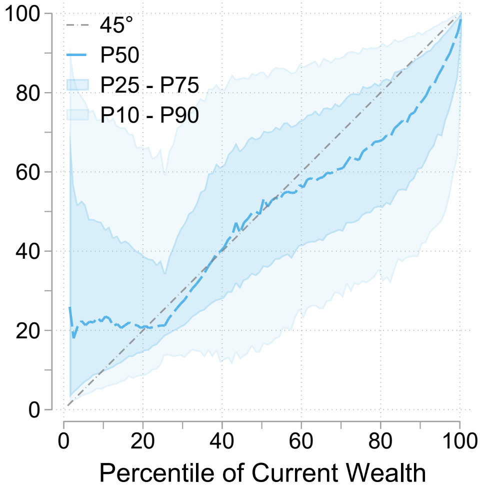


The Distribution of Rank Changes (10-year) back

Age 35

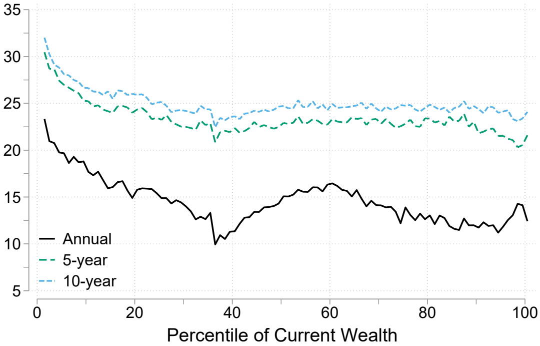


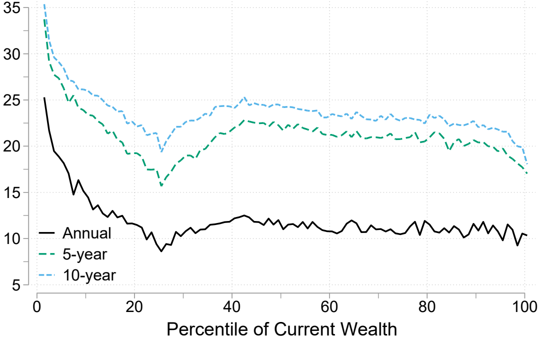
Age 45



Over longer horizons more evenly spread and dispersion growing

Rank Changes: Standard Deviation ◂ back

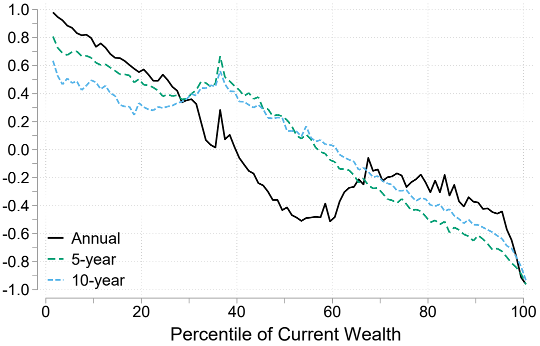


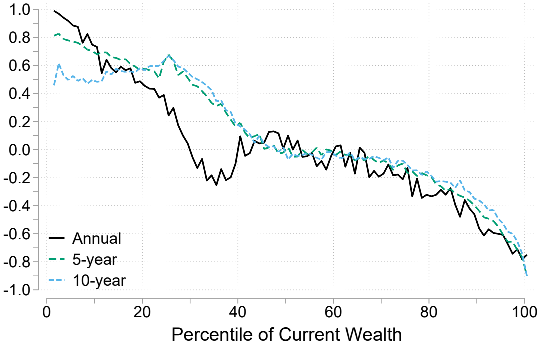


- Dispersion grows slowly with time horizon
- Dispersion level depends (asymmetrically) on rank: Lower dispersion at the top!

Rank Changes: Skewness

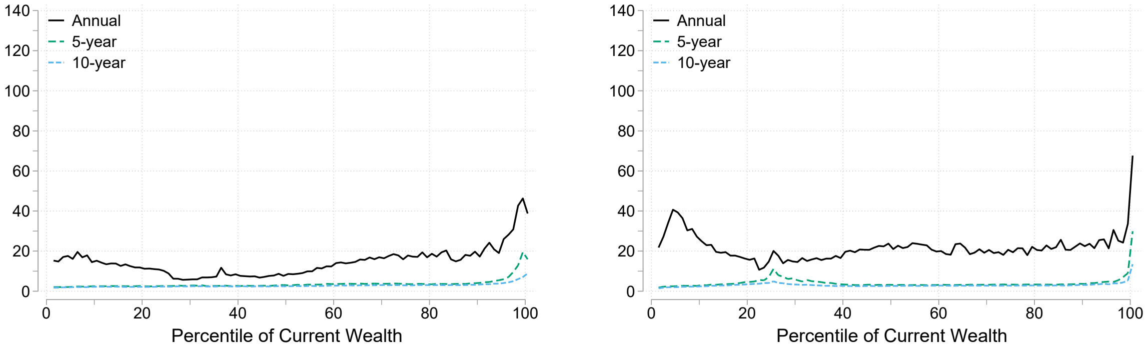
back





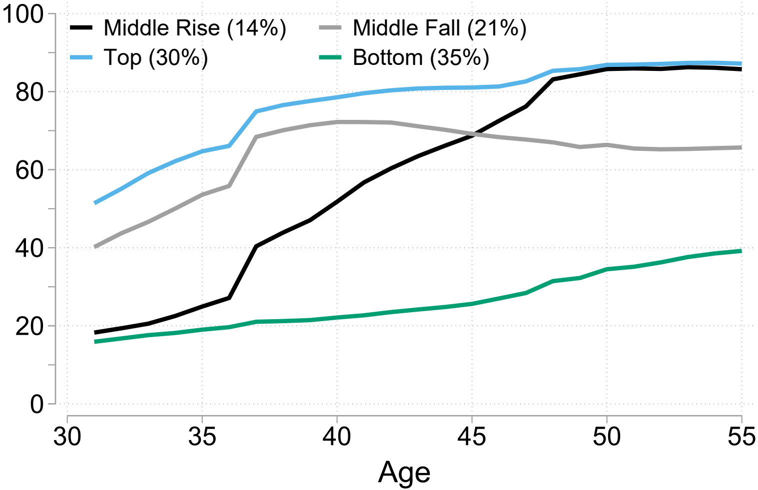
- Skewness decreases by construction
- Changes in ranks: No way to go but up/down for low/high ranks

Rank Changes: Kurtosis back



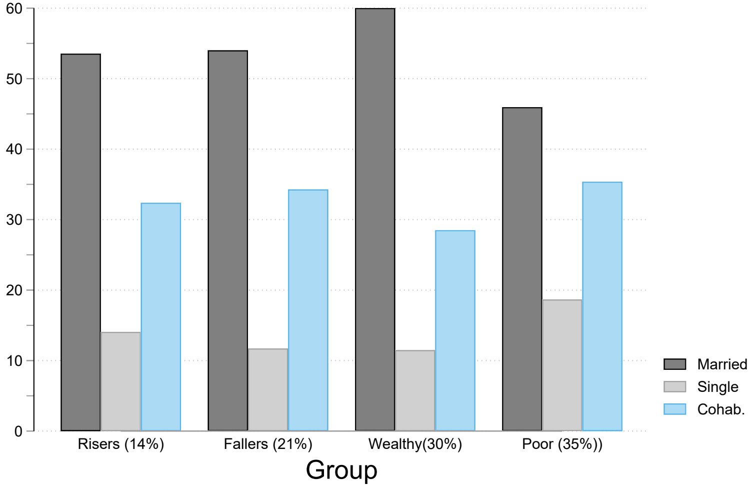
- Distribution of rank changes is *leptokurtic*
- Most individuals experience small changes with some individuals having large changes
- Holds across ranks but is particularly so at short horizon (1y) and upper tail

Home-ownership Rates by Cluster ◂ Back



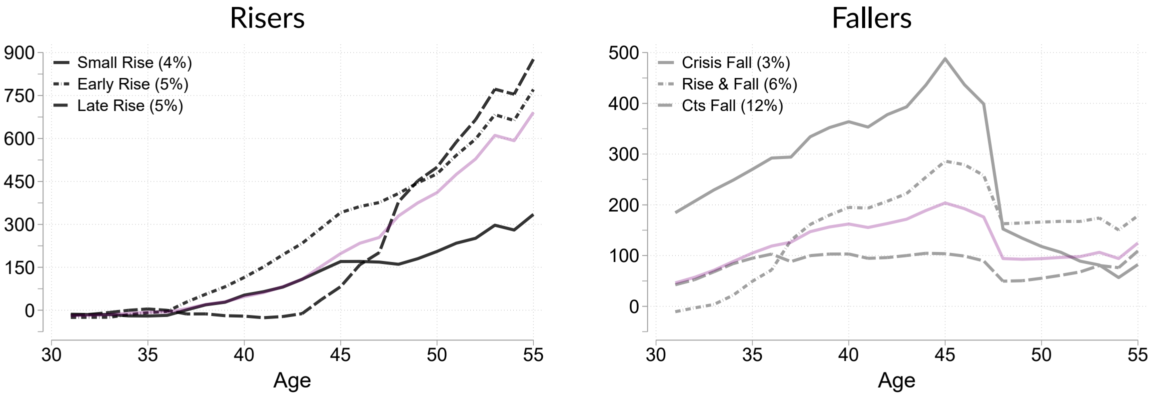
Civil Status at Age 55 by Cluster

Back



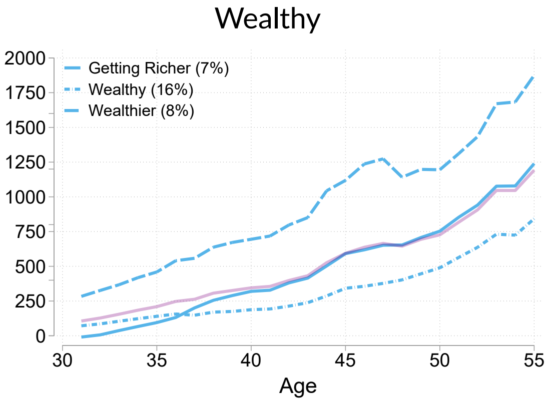
Sub-Clusters - Wealth Level

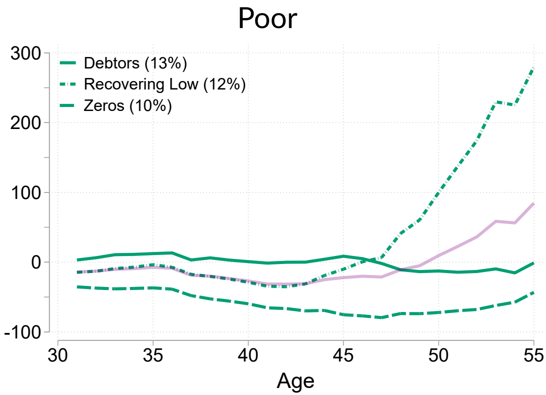
back



Sub-Clusters - Wealth Level

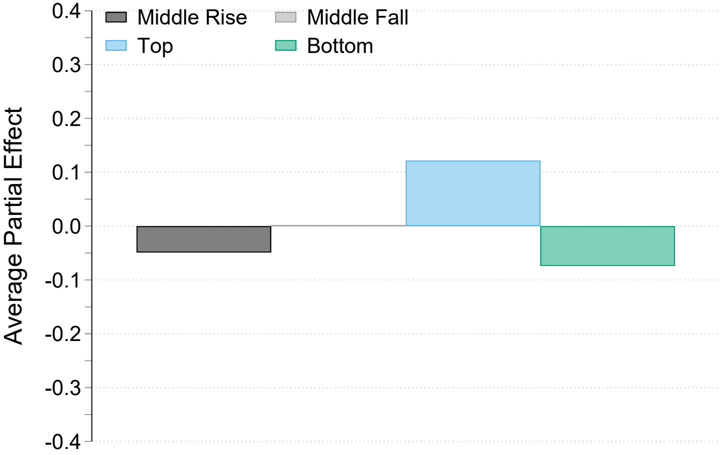
back





Sex Average Partial Effect

back

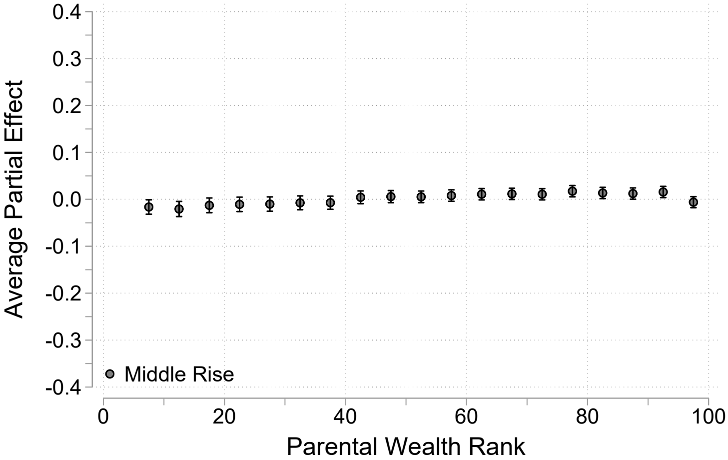


Where Is The Land of Opportunity? Norway

back

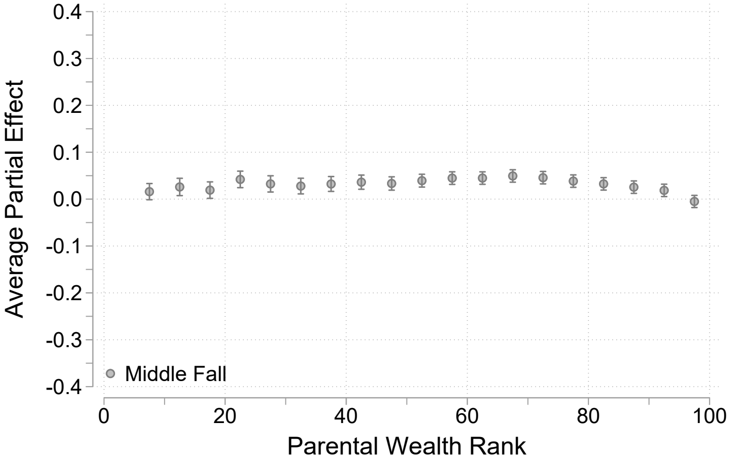
The Non-Linear Effect of Parental Wealth: CI

◂ back



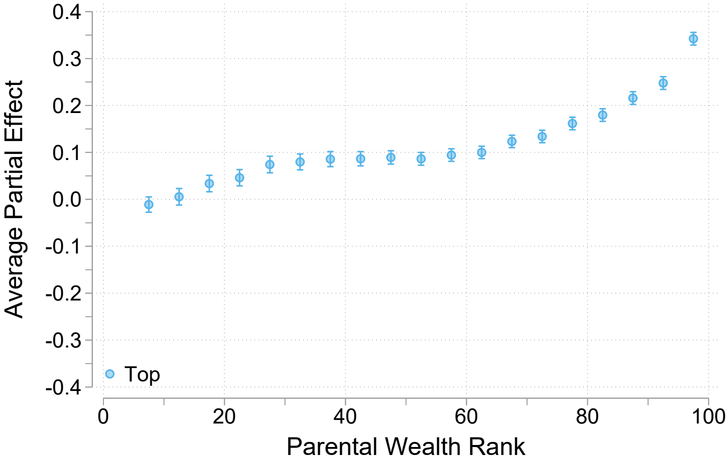
The Non-Linear Effect of Parental Wealth: CI

back



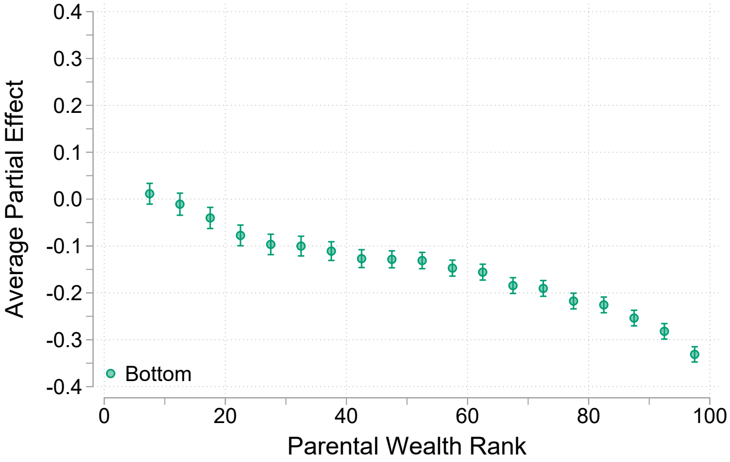
The Non-Linear Effect of Parental Wealth: CI

back



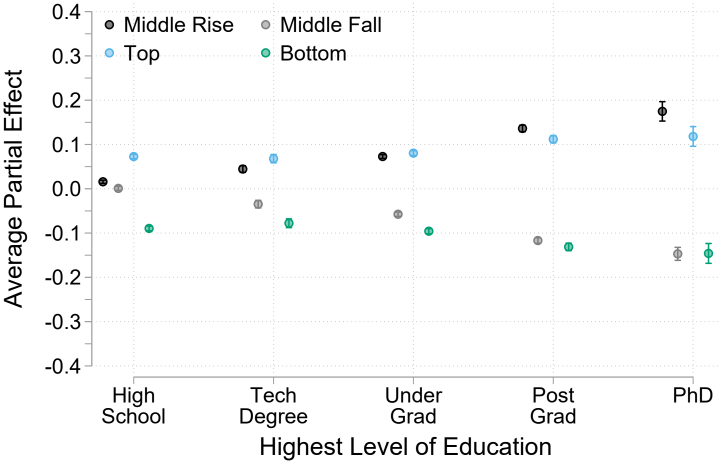
The Non-Linear Effect of Parental Wealth: CI

◂ back



Learn & Rise?: CI

back



How Important Are Ex-Ante Explanations? ◂ back

Share of Cross-Group Variation Explained by Variable

Group	Full Model	Partial Contribution			
		Parent	Sex	Education	Birth Place
1	2.12	0.15	0.55	1.35	0.06
2	1.23	0.17	0.02	0.65	0.4
3	9.15	4.89	1.61	2.54	0.12
4	7.70	4.37	0.92	2.33	0.08
All	6.44	3.34	0.95	1.99	0.15

How Important Are Ex-Ante Explanations? back

Share of Individuals Correctly Classified

Group	Full Model	Total Contribution*	Partial Contribution			
			Parent	Sex	Birth Place	Education
1	14.33	1.99	0.13	0.46	0.08	1.32
2	21.16	1.29	0.17	0.02	0.37	0.74
3	30.46	4.99	2.59	1.02	0.10	1.28
4	34.05	3.65	2.11	0.34	0.02	1.18
All	27.44	3.28	1.52	0.49	0.13	1.14

*Contribution relative to random classification using population shares.

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

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

How Important Are Ex-Ante Explanations? ◂ Back

Total Contribution*	Partial Contribution			
	Parent	Sex	Education	Birth Place
Share of Distance Variation Explained by Variable (pp)				
6.44	2.32	3.38	0.65	0.08

*Contribution relative to random classification using population shares.

▸ Breakdown D ▸ Breakdown C

How Important Are Ex-Ante Explanations? Back

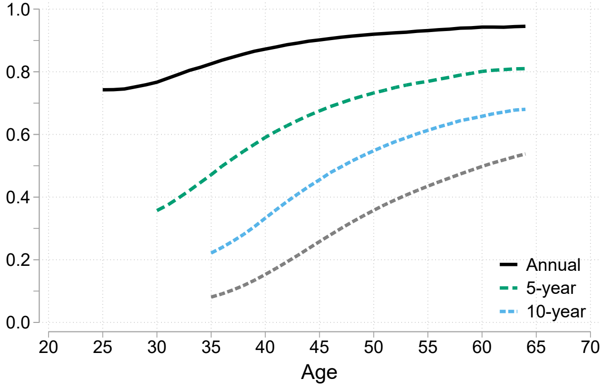
Total Contribution*	Partial Contribution			
	Parent	Sex	Education	Birth Place
Share of Distance Variation Explained by Variable (pp)				
6.44	3.34	0.95	1.99	0.158
Share of Individuals Correctly Classified (pp)				
3.28	1.52	0.49	0.13	1.14

* Contribution relative to random classification using population shares.
Share of individuals correctly classified by random classification 17.63% vs 21.02% with full model.

Breakdown D Breakdown C

Persistence in Wealth Rank: Higher at long-run ◂ back

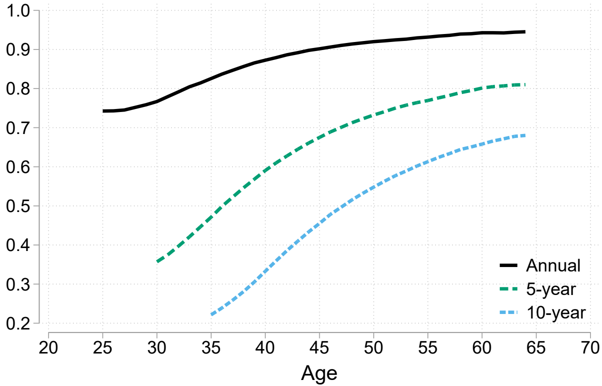
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



- **10y Iteration bias:** Dramatic bias! Actual $\rho(10)$ is 50-250% implied persistence

Persistence in Wealth Rank: Higher at long-run ▸ 1960bc ▸ 10yr ◂ Back

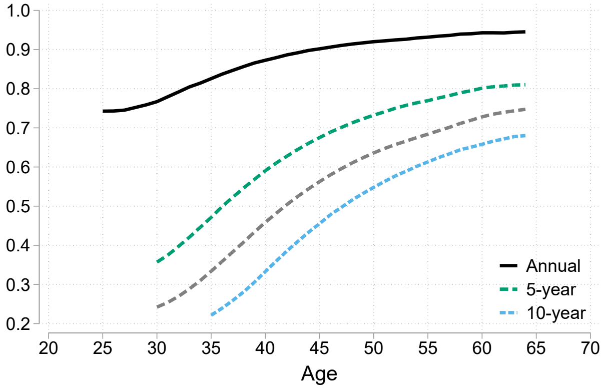
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



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

Persistence in Wealth Rank: Higher at long-run ▸ 1960bc ▸ 10yr ◂ Back

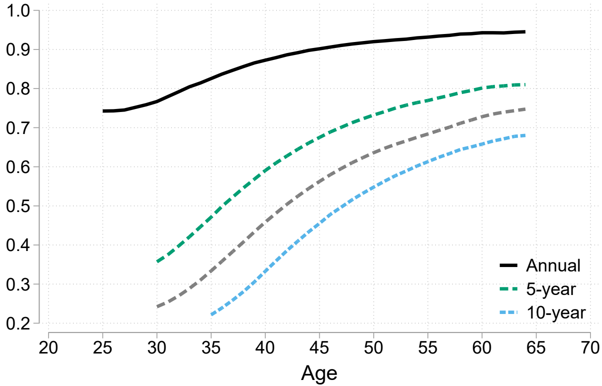
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



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

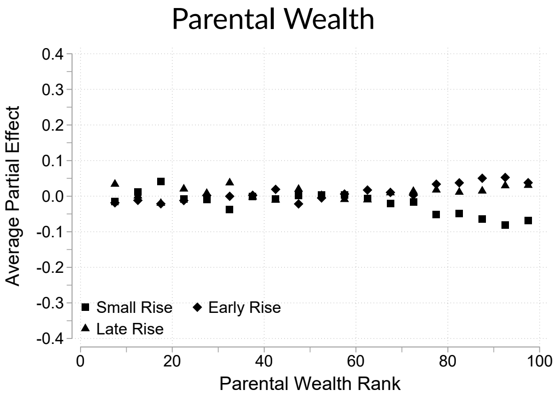
Persistence in Wealth Rank: Higher at long-run ▸ 1960bc ▸ 10yr ◂ Back

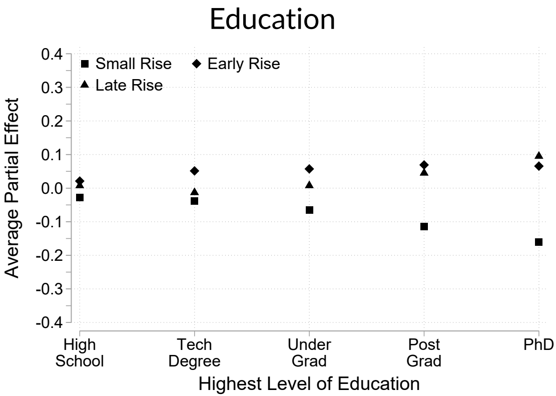
$$y_{i,t} = \alpha_t(h) + \boldsymbol{\rho_t(h)} y_{i,t-h} + u_{i,t}, \qquad \text{for } h \in \{1, 5, 10\}$$



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

What about heterogeneity within clusters? Middle Risers ◂ Back

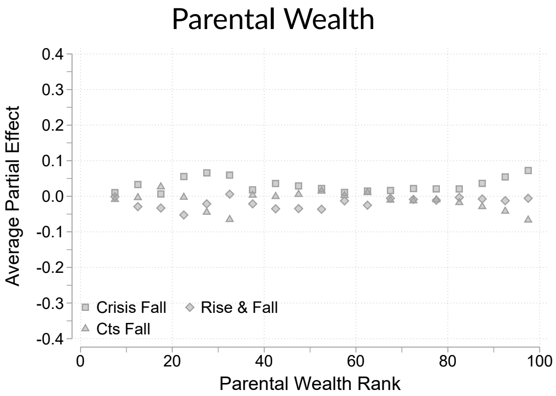


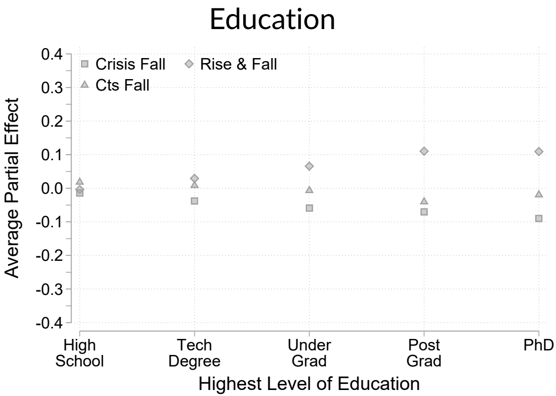


- Within Risers, movers not predicted by parental wealth
- Education predicts timing

What about heterogeneity within clusters? Middle Fallers

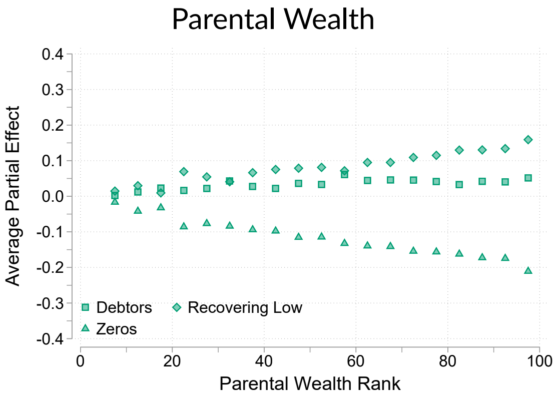
Back

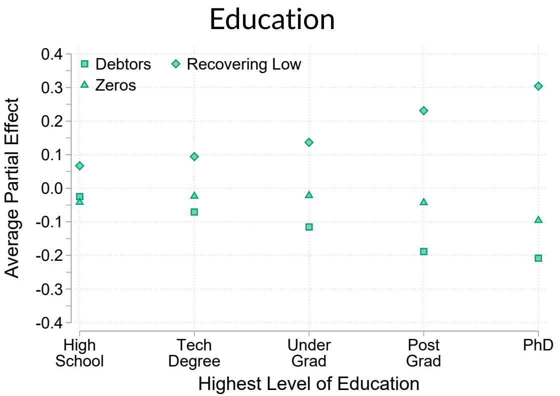




- Similar to Risers, little role for parental wealth
- But Education predicts dynamics

What about heterogeneity within clusters? Bottom Group Back

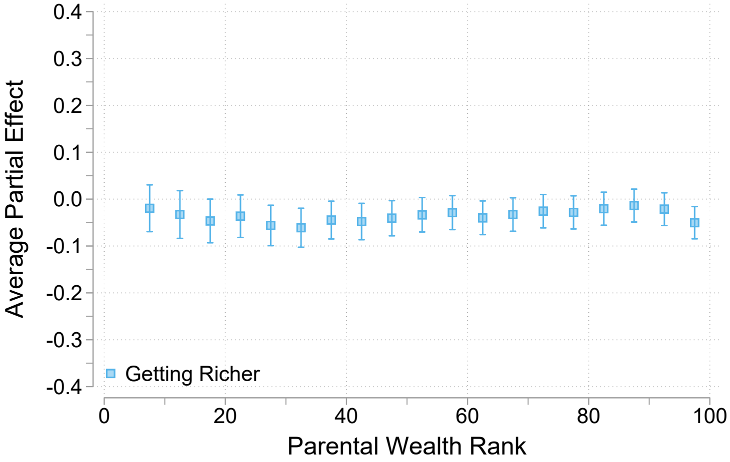




- Among poor, parental wealth does not predict movements
- Education predicts recovery

The Non-Linear Effect of Parental Wealth for Wealthy: CI

back



The Non-Linear Effect of Parental Wealth for Wealthy: CI

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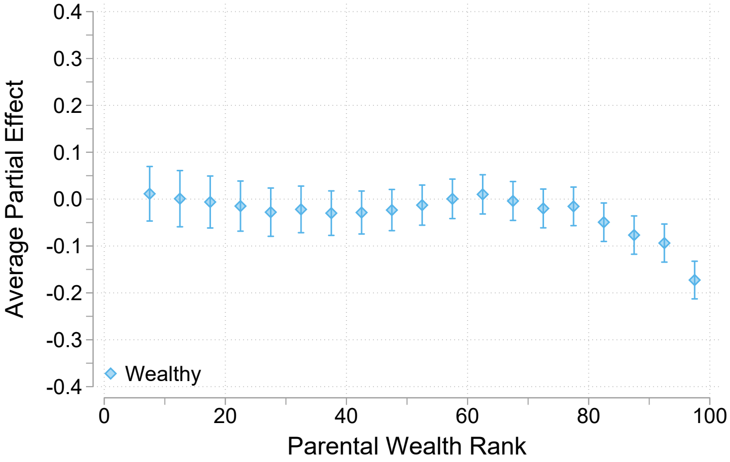

The Non-Linear Effect of Parental Wealth for Wealthy: CI

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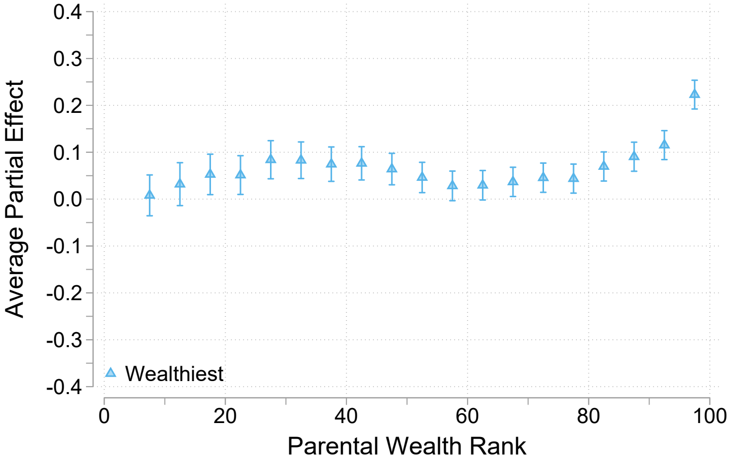

Learn & Rise for Wealthy: CI

back