The Life-Cycle Dynamics of Wealth Mobility*

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Abstract

We use 25 years of tax records for the Norwegian population to study the mobility of wealth over people's lifetimes. We find considerable wealth mobility over the life cycle—exceeding income mobility. To understand the underlying mobility patterns, we group individuals with similar wealth histories using agglomerative hierarchical clustering, a tool from statistical learning. The mobility patterns we elicit provide evidence of *segmented mobility*. Over 60 percent of the population remains at the top or bottom of the wealth distribution throughout their lives. Mobility is driven by the remaining 40 percent, who move only within the middle of the distribution, reflecting *glass ceilings* preventing most people from rising to the top or from the bottom of the distribution. We show parental wealth is the key predictor of who is persistently rich or poor, while human capital is the main predictor of those who rise and fall through the middle of the distribution. Highly-educated individuals drive upwards mobility by converting high labor incomes into property wealth early in life and financial assets afterwards. Downward mobility is primarily driven by declining or stalling business wealth.

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1. Introduction

Do rich and poor people remain this way throughout their lives? Is it typical for people to experience reversals of fortune moving up or down the wealth distribution? If so, how large are the reversals, and when do they happen? These movements across the wealth distribution reflect the outcomes of critical events and choices in people's lives, including their human capital accumulation, earnings, and business activities. Wealth mobility thus speaks to the opportunities that people face.[1] However, despite growing evidence on the dynamics of wealth concentration for the wealthiest,[2] we know little about the life-cycle dynamics of wealth mobility for the population as a whole and the different income and savings patterns that generate this mobility.

Our main contribution lies in documenting wealth mobility over the life cycle. We conduct a comprehensive study of the complete distribution of lifetime individual wealth trajectories, which we construct using a quarter century of administrative data from the Norwegian tax registry (1993–2017). Across a variety of measures of relative and absolute mobility, we find *increasing wealth mobility* over the life cycle, so that an individual's initial wealth matters less as they age. Moreover, wealth mobility is higher than income mobility despite wealth being a stock. For instance, only one-quarter of individuals are in the same quintile of the wealth distribution after 25 years, whereas almost half of individuals stay in the same income quintile. However, standard mobility measures do not, by themselves, tell us much about the underlying life-cycle patterns that drive mobility. Who is actually moving? And how?

To answer these questions, we elicit typical wealth trajectories from the distribution

[1]Low wealth mobility can be a symptom of limited equality of opportunity and can exacerbate the effects of high inequality. In the context of income inequality, Alan Krueger, then Chairman of the Council of Economic Advisors under President Obama, remarked that "*if we had a high degree of income mobility we would be less concerned about the degree of inequality in any given year*" (Krueger 2012, pg. 3).

[2]See Gomez (2023) for evidence from the *Forbes* 400 list and Hubmer, Halvorsen, Salgado, and Ozkan (2024) for evidence on the top 0.1 percent of Norwegian wealth holders. Quantitative analysis of the origins of the wealthiest individuals dates back at least to Wedgwood (1929).

of 25-year wealth histories using *agglomerative hierarchical clustering*, a tool from statistical learning that groups individuals based on their entire realized trajectories. This provides a new characterization of the data in terms of *mobility groups*. By doing so, we are the first to flexibly and non-parametrically characterize wealth mobility over the life cycle. Our methodology quantifies mobility beyond transitions between any two periods or any specific sections of the distribution, while still providing a tight and economically meaningful characterization of the data. We focus on the largest four groups, whose typical wealth trajectories explain over 50 percent of the variation in population wealth histories. But we also study wealth accumulation within each group, as the hierarchical nature of our clustering implies that any increase in the number of groups sub-divides the four mobility groups we focus on.

The mobility patterns we uncover show that wealth mobility is not broad-based and is not driven by movements spanning the whole distribution, but is instead *segmented*. The life cycle dynamics of wealth mobility are well captured by a combination of two largely immobile groups (60 percent of the population) that stay relatively rich and poor, and two groups that undergo large transitions that are nevertheless contained within the middle of the wealth distribution.[3] The two groups driving increasing mobility along the life cycle experience a reversal of fortunes as they age; one climbs through the middle of the distribution as the other slides. We interpret these patterns as evidence of segmented wealth mobility: *mobility takes place only for some groups of individuals and within a section of the distribution*.

Segmented mobility also provides new evidence of *glass ceilings* and *floors*: limited opportunity to rise to the top, or from the bottom, of the wealth distribution. This has important implications for a large portion of the population, as we document that more than 40 percent of individuals are not only wealthless, but stay that way throughout

[3] Differences in wealth rank trajectories correspond to meaningful differences in levels. For instance, the wealth gap at age 55 between the two groups in the middle of the distribution is 600,000 US dollars.

their lives. Thus, much of the population remains stuck at the lowest rungs of the wealth ladder, while those at the top do not fall.

Inferring these typical wealth trajectories provides insight into how individuals move: who arrives where and how long they stay in one place. Although the grouping into stable groups—of high- and low-ranked individuals—and moving groups—of climbers and sliders—seems natural, it is a nontrivial feature of choices and events shaping wealth accumulation. In fact, we show that a set of candidate wealth accumulation processes generate mobility groups different from those we document, ranging from groups with almost no mobility (each staying in a segment of the wealth distribution) to almost identical groups (who move across the entire distribution). Therefore, the pattern of segmented mobility in our data, while intuitively appealing, is not a necessary feature of wealth dynamics in general, nor of our clustering approach.

Further, we establish how different economic factors—such as portfolio composition, sources of income, family structure, and inheritances—relate to the large gaps in wealth accumulation between groups. We find that, while property is the primary asset for all groups, there are important differences in business assets and private equity, which are concentrated in the top and sliding groups. In fact, sliders have similar, but ultimately less successful, entrepreneurial activities than those at the top. Notably, climbers engage in less business activity and instead rely on employment income as they move up the distribution. Their labor income is higher than that of the sliders, and their household incomes match those of the top group (who nevertheless have a larger share of capital income). The 40 percent of individuals at the bottom of the distribution are different: their incomes are persistently low, they remain renters, and rarely own businesses.

We also analyze the role of ex-ante circumstances, including parental wealth and education, in predicting wealth mobility groups. We find an important and nonlinear role for family background. Individuals born to poor parents are more likely to be poor throughout their lives. In comparison, those born to the wealthiest parents are almost 30 percentage points more likely to be persistently at or near the top of their own generation's distribution. But, for individuals who move through the distribution, education is the main predictor of their evolution. Highly educated individuals are more likely to climb as they age. Those without post-secondary education are 5 to 10 percentage points more likely to slide than those with at least undergraduate degrees.[4]

Together, differences in human capital early in life and subsequent portfolio choices account for the reversal of fortunes of climbers and sliders. The initial wealth gap between these groups disappears when we calculate *human wealth*: the discounted value of future realized labor income fully offsets their lower initial net worth. Climbers' wealth converges with sliders' as they first accumulate housing out of income, matching the initially higher rates of homeownership of sliders (see also Kuhn, Schularick, and Steins 2020). The reversal begins after age 45, when climbers accumulate non-property assets and the business wealth of sliders declines.

Our main methodological contribution is to propose a data-driven approach to summarizing heterogeneous mobility in large-scale datasets. In our application we study the distribution of 25-dimensional wealth histories. The agglomerative hierarchical clustering algorithm we employ works by recursively grouping individuals with similar realized histories.[5] This delivers a global hierarchy of clusters that minimizes the distance between the paths taken by individuals in each group. Crucially, our methodology allows us to characterize mobility patterns without resorting to a single summary statistic; it also does not require us to specify which elements of the history determine the groups (such as initial or final conditions) or to rely on a specific parametric model for the evolution of wealth. To the best of our knowledge, this approach has not been applied to the study of mobility prior to this paper.

[4]Our results also complement those in Huggett, Ventura, and Yaron (2011), who study lifetime inequality using a model-driven approach. Although we focus on mobility, we both find important roles for human capital and initial conditions, including the initial wealth level of individuals.

[5]See Hastie, Tibshirani, and Friedman (2009, ch. 14) for an introduction to clustering; Borysov, Hannig, and Marron (2014), and Egashira, Yata, and Aoshima (2024) derive asymptotics for hierarchical clustering.

Related literature. We provide new evidence on wealth mobility over the life cycle, documenting the ways in which individuals move as they age by characterizing their typical trajectories. In this way we contribute to the literature on mobility that has focused on intergenerational links in wealth (see, for instance, Charles and Hurst 2003; Boserup, Kopczuk, and Kreiner 2017; Adermon, Lindahl, and Waldenström 2018; Fagereng, Mogstad, and Rønning 2021; and Sabelhaus 2024) and income (see, for instance, Solon 1992; Chetty, Grusky, Hell, Hendren, Manduca, and Narang 2017; and Halvorsen, Ozkan, and Salgado 2022).

In related work for Norway, Hubmer, Halvorsen, Salgado, and Ozkan (2024) focus on the origins of wealth for the wealthiest 0.1 percent at age 50, an economically relevant subpopulation in the context of high wealth inequality. They find a crucial role for high saving rates and returns in explaining mobility towards the very top of the wealth distribution. We see our results as complementary, extending analyses beyond the dynamics of wealth accumulation of the wealthiest individuals and towards mobility in the whole population, revealing broader groups with economically significant differences in wealth patterns across the distribution.

For the United States, studies have focused on how wealth mobility and accumulation differ across socio-economic groups using the Panel Study of Income Dynamics. Hurst, Luoh, Stafford, and Gale (1998) study how saving differs over a decade by race, education, household demographics, and initial wealth. Shiro, Pulliam, Sabelhaus, and Smith (2022) consider individuals' "prime wealth accumulation years," and document limited wealth mobility for Black and low-educated Americans. Relative to these studies, we recover heterogeneity in wealth trajectories without conditioning on ex-ante characteristics. Our results point to these latent differences also being relevant for mobility, as observable characteristics predict little of the variation in mobility in our context.

Our methodology does not require to choose a single statistic or to restrict attention to changes between two given points in time (see, for instance, Chetty, Hendren, Kline, Saez, and Turner 2014; Fields and Ok 1996, 1999; and Ray and Genicot 2023) or to specify a parametric model of wealth dynamics. We provide a novel and non-parametric approach to obtain a data-driven low-dimensional representation of the distribution of wealth histories without needing to specify partitions in advance (as in Shorrocks 1978; and Bartholomew 1973). See Deutscher and Mazumder (2023) for a recent survey of methodologies to measure mobility between two points in time.

More generally, the clustering method we employ constitutes a feasible way to study trajectories of longitudinal outcomes, such as mobility, in high-dimensional datasets. Similar approaches have been used in sociology to summarize mobility between discrete states (Dijkstra and Taris 1995; McVicar and Anyadike-Danes 2002; Dlouhy and Biemann 2015). In economics, clustering has been used to analyze sorting and transitions in the labor market (see, among others, Bonhomme, Lamadon, and Manresa 2019; Gregory, Menzio, and Wiczer 2025; Humphries 2022; and Ahn, Hobijn, and Şahin 2023) and to identify latent heterogeneity, as in Lewis, Melcangi, and Pilossoph (2021).

Many of these applications use variants of K-means clustering, whose asymptotic properties are derived in Bonhomme and Manresa (2015) and Bonhomme, Lamadon, and Manresa (2022). In our 25-dimensional problem, numerical issues prevent us from implementing K-means. These issues come from the intractable geometry of hyper-spheres in high-dimensional spaces. Nevertheless, we show in Section 7 that K-means does not deviate from our partition when initialized from it. Relative to these methods, our approach provides a global hierarchy of partitions that facilitates studying within cluster heterogeneity and is feasible in the context of large, high-dimensional, datasets.

2. Data: A panel of wealth histories for the Norwegian population

Our analysis is made possible by longitudinal data on the distribution of wealth histories compiled by Statistics Norway. Prior studies have used this data to investigate factors driving wealth accumulation, such as the role of return heterogeneity (Fagereng, Guiso, Malacrino, and Pistaferri 2020), differences in saving behaviors (Fagereng, Holm, Moll, and Natvik 2019), the importance of gifts and inheritances for lifetime resources (Black, Devereux, Landaud, and Salvanes 2025), and the relationship between wealth and lifetime income (Black, Devereux, Landaud, and Salvanes 2023).

We use data from the Norwegian tax registry between 1993 and 2017 and its associated population characteristics files. We are able to link these various datasets at the individual and household levels using unique (anonymized) identifiers. The resulting data contains information on wealth (net worth), assets, debt, income, and a variety of individual characteristics. We provide a detailed description of the data in Appendix A. We report monetary values in 2019 US dollars.

The coverage and properties of the Norwegian administrative data sets it apart from survey and administrative data available in other countries. We start by highlighting why it is uniquely suited to the study of wealth mobility over the life cycle.[6]

First, Norway records wealth in its tax returns since 1993, providing us with twenty-five years of observations. This long panel allows us to track individuals through important phases of their lives. Tracking individuals is crucial to understand mobility over long horizons and to differentiate the life-cycle trajectories experienced by individuals, which we do using the clustering procedure described in Section 4.

Second, the Norwegian income and wealth tax records cover the entire population. We therefore construct accurate measures of an individual's rank in the wealth distribution, within cohorts and the population at large. Furthermore, the data covers individuals at the very bottom and top of the distribution, who are typically difficult to

[6]The quality and detail of this data have proven useful in a variety of studies. More information on the Norwegian administrative wealth data can be found in Fagereng, Guiso, Malacrino, and Pistaferri (2020), Fagereng, Mogstad, and Rønning (2021), and Fagereng, Holm, and Natvik (2021). Additionally, Blundell, Graber, and Mogstad (2015) provides a detailed discussion of income tax records.

capture in survey data.[7] Moreover, most of the components of income and wealth are third-party reported and are not top- or bottom-coded, eliminating concerns about measurement error from self-reporting and censoring that are common in survey data.

Third, we are able to link individuals within households and across generations, as well as to their demographic and educational information. This wealth of information lets us link the trajectories of wealth mobility to the individual circumstances that help determine them, such as parental background and educational attainment.

2.1. Wealth and asset data

We observe each individual's assets, debt, and net worth, as reported in their wealth tax return from which we are able to construct the market value of wealth as described in Appendix A. These are individual returns, where the value of assets jointly owned by a couple is split equally between each partner. We focus on wealth at the individual level, but also report robustness results for wealth at the household level. We observe the value of various asset classes included in the tax returns, but not transactions within classes which prevents us from computing asset returns at the individual level.

The single largest asset for most individuals is housing. We adjust housing values using the adjustments reported in Fagereng, Holm, and Torstensen (2020) for owner-occupied housing, secondary housing, and cabins (holiday homes), treating condominiums separately from other properties.[8] Other asset classes included in the tax returns are vehicles, public and private equity, and safe assets. These asset classes correspond to those studied in Fagereng et al. (2020) who provide average returns by

[7]This problem has led to methods that oversample the tails of the distribution. These methods are ill-suited to the focus of our study. For example, the U.S. Panel Study of Income Dynamics oversamples lower income households (the Survey of Economic Opportunity households), while the Survey of Consumer Finances oversamples wealthier households. Researchers often resort to ad hoc methods to build more accurate measures of the upper tail of the wealth distribution, for example, by augmenting the Survey of Consumer Finances with the Forbes 400 list of the 400 richest Americans or estate tax data (see, for example, Vermeulen 2016). Davies and Shorrocks (2000) provide an extensive review of these methods.

[8]We thank Fagereng, Holm, and Torstensen for providing updated adjustments for our sample.

asset class. Vehicles includes cars and boats. Public equity is defined as directly owned stocks that are traded on the Norwegian Stock Exchange. Private equity includes the value of business assets and unlisted stocks. Our measure of safe assets includes government bonds, checking accounts, and shares in money market and mutual funds.[9] An individual's wealth tax return also lists foreign non-property assets and a residual class that includes hard-to-value assets—such as jewellery and paintings. We include these in wealth, but do not report results for them in the paper.

Two types of assets are missing from our data. First, assets individuals obscure from the tax authority. Although third-party reporting should minimize opportunities for tax evasion, these assets are not observed in tax data by definition.[10] Second, we lack information on pensions, including employer-provided pension plans. Private pensions represent less than 20 percent of all pensions in Norway, with pay-as-you-go public pension entitlements making up the remaining (Hubmer et al. 2024).[11]

2.2. Additional data: income and demographics

We also use high-quality information from individual income tax records, analogous to the wealth tax records described above. These records allow us to study gross and net income. Furthermore, we observe several components of income, including wage earnings, self-employment earnings, capital income, and transfers from social assistance programs. We relate income and wealth profiles in our analysis.

We also have access to detailed information on individual education levels and fields of study, according to the Norwegian Standard Classification of Education (NUS2000).

[9] We view the last of these items as less safe than government bonds and deposits; however, data restrictions prevent us from considering an alternative definition where we pool this with public equity.

[10] We conjecture that tax evasion does not pose a large measurement issue for wealth ranks because most evasion is likely to be monotonic in post-evasion wealth rank.

[11] Pay-as-you-go pensions are annuities, and do not constitute wealth that can be accessed or pledged as collateral by working-age households. Hence, they are not included in wealth tax records, and we do not include them in our baseline measure of wealth. See Fagereng, Holm, Moll, and Natvik (2019, Appendix C.6) for details on the Norwegian Public Pension system and the imputation of Public Pension wealth.

This classification provides nine levels of education, ranging from no education to post-graduate PhD level, as well as 350 fields of study.

In addition, we merge several key demographic variables. These include individual attributes such as date, place, and sex at birth, as well as parents' identifiers, date of death, and immigration status. Finally, we observe the individuals' civil status, as well as their cohabitation status for each tax year as recorded by Statistics Norway (SSB).

2.3. Sample selection

We begin with the universe of Norwegian tax residents between 1993 and 2017. We then create a broad cross-cohort sample with individuals born after 1905 (Norwegian independence) and before 1990. We also exclude individuals who ever emigrated from Norway and those who either immigrated after the age of 25 or who arrived after 2011.

Our main sample is the 1960–64 birth cohort. We use this sample to calculate the within-cohort wealth ranks that we use throughout.[12] This birth cohort is observed for a significant fraction of their work lives, starting in their early thirties. In addition, this cohort is not affected by the 1959 changes in the compulsory school age which were not implemented uniformly across place and time; see Black, Devereux, and Salvanes (2005) and Bhuller, Mogstad, and Salvanes (2017). When balanced over our 25-year panel, our sample has a total of 279,002 individuals.

2.4. Wealth ranks and the Norwegian distribution of wealth

For our cohort of interest, born 1960–64, we construct yearly individual ranks of wealth (net worth) using the unbalanced sample from 1993 to 2017. Formally, given individual

[12]To illustrate the value of our data, our full sample includes 292,222 individuals in the 1960–64 birth cohort. By contrast, there are only 1,463 households in the Panel Study of Income Dynamics (PSID) in that cohort, and their wealth is only observed consistently since 1999, implying an average of just six consecutive observations (ten years) per household. Hurst, Luoh, Stafford, and Gale (1998) study mobility using three observations from the PSID between 1984 and 1994, pooling all cohorts together to increase the sample size. They thereby combine effects of the age-profile and mobility among peers.

i's wealth in year t, $w_{i,t}$, we compute ranks within the cohort for each year as

$$r_{i,t} = 100 \times F_w \left(w_{i,t} \mid t, i \in \text{Birth Cohort: 1960–64} \right), \tag{1}$$

where F_w denotes the empirical cumulative distribution of wealth. Crucially, all comparisons use other individuals in the same cohort as the reference group. As a result, our rank measure is not affected by cross-cohort or cross-age comparisons.[13] Moreover, differences in ranks reflect significant differences in wealth levels because wealth in Norway is very unequally distributed, even at young ages.[14] For instance, moving from percentile 50 to 60 means going from 190,000 to 250,000 US dollars of net worth. See Appendix A for more on the Norwegian wealth distribution.

We focus on percentile ranks in most of our study of mobility. Ranks have several attractive properties over other transformations of wealth. They are well defined for individuals with negative or zero net worth and easily interpretable in terms of *relative mobility*. In addition, they capture diminishing marginal gains from wealth because they compress the right tail of the distribution, although not as much as the logarithm transformation (which we also consider). We also study Lorenz ranks, that emphasize differences between those at the top of the wealth distribution by taking into account the degree of wealth concentration. We view ranks as a conservative choice between these two extremes when studying wealth mobility throughout the whole distribution.

[13] Importantly, doing this also purges ranks from time effects varying by age. We consider cross-cohort differences in life cycle wealth accumulation by analyzing the mobility patterns of the 1965–69 birth cohort in Section 7. See, for example, Gale, Gelfond, Fichtner, and Harris (2021); and Paz Pardo (2024), for cross-cohort changes in wealth accumulation in the US.

[14] For reference, the 90$^{\text{th}}$ percentile of wealth in Norway is close to 860,000 US dollars, higher than in the US where it is 620,000 dollars (Smith, Zidar, and Zwick 2023).

3. Measuring wealth mobility over the life cycle

To what extent do individuals transition across the wealth distribution over their lives? We show that *wealth mobility rises steadily over peoples' lives*, so that initial wealth matters less with age, while *intergenerational mobility decreases*, reflecting that individuals' position in the wealth distribution becomes closer to that of their parents' over time. Moreover, we show that *income mobility is markedly more limited than wealth mobility* within, and across, generations. These patterns are present across several standard measures of mobility that we compute in our data and that use both wealth ranks and levels, capturing relative and absolute mobility:[15]

(a) ***Rank persistence.*** The persistence of wealth ranks over time captures mobility in the relative position of individuals in the wealth distribution. We compute it as the auto-correlation of ranks, $r_{i,t}$ defined in (1). Formally, we estimate $r_{i,t} = \alpha_t + \rho_t r_{i,1993} + u_{i,t}$.[16] The mobility measure corresponds to $M_t^R \equiv 1 - \rho_t$.

(b) ***Shorrocks (1978) trace mobility.*** A measure of relative mobility across sections of the wealth distribution. In particular, let $Q_{i,t}$ be individual i's wealth quintile at age t. The mobility measure is $M_t^S \equiv 1 - \sum_i \mathbb{1}\left\{Q_{it} = Q_{i,1993}\right\}$.

(c) ***Fields and Ok (1999) mobility.*** A measure of the average absolute log-change in wealth over time,[17] defined as $M_t^{F\&O} \equiv \frac{\left|\log w_{i,t} - \log w_{i,1993}\right|}{N}$.

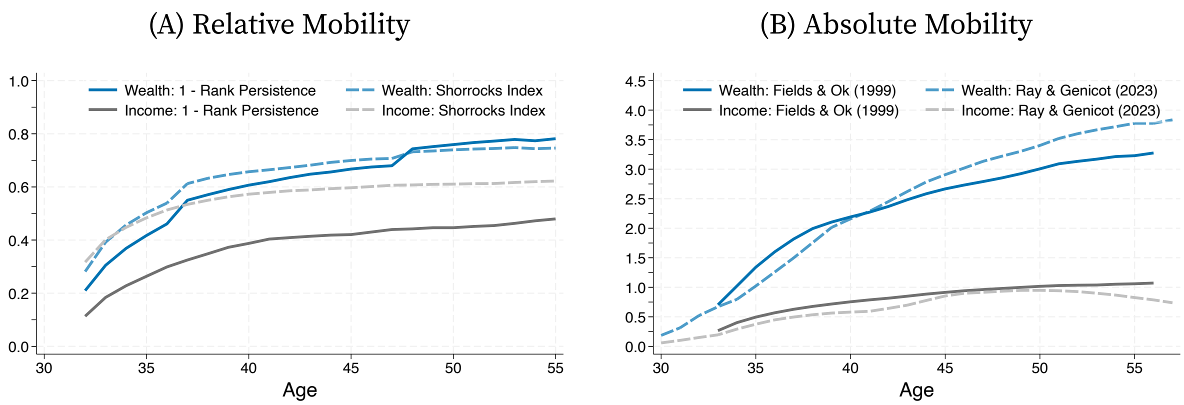
(d) ***Ray and Genicot (2023) mobility.*** A measure of absolute mobility penalizing increased inequality. Specifically, it measures aggregate changes in instantaneous upward mobility, reflected in the growth of the Atkinson-equivalent wealth over time: $M_t^{R\&G} \equiv \log\left(\frac{1}{N_t}\sum_i w_{i,t}^{-\alpha}\right)^{\frac{-1}{\alpha}} - \log\left(\frac{1}{N_{1993}}\sum_j w_{j,1993}^{-\alpha}\right)^{\frac{-1}{\alpha}}$. We use their baseline curvature ($\alpha = 0.5$).

[15] The similarities between mobility measures has been long noted in the literature, see, for example, Deutscher and Mazumder (2023). McGee (2025) shows that this behavior is expected as all measures reflect the underlying concordance between the wealth or income distributions being compared.

[16] Chetverikov and Wilhelm (2023) derive the asymptotic distribution of ρ_t which is non-standard.

[17] We bottom code wealth at 1,000 Norwegian Kroners to deal with negative values. We find the same results for the absolute change in wealth or income levels (Fields and Ok 1996).

FIGURE 1. Wealth and income mobility over the life cycle



Notes: The figures present different measures of intragenerational wealth and income mobility over age. Panel A plots two measures of relative mobility, 1 minus the auto-correlation of ranks and 1 minus the Shorrocks (1978) index. Panel B plots two measures of absolute mobility, the Fields and Ok (1999) mobility measures and the Ray and Genicot (2023) mobility measure.

Mobility over the life cycle. Figure 1 shows that *wealth mobility increases as individuals grow older*, that is, individuals' wealth accumulation over their life cycle results in persistent changes in their position in the wealth distribution. These patterns are reflected in both relative (panel A) and absolute mobility measures (panel B). Most changes take place before age 40, a period of rapid mobility increases. Relative mobility stabilizes and the growth in absolute mobility declines afterwards.[18]

By contrast, despite wealth being a stock, *income mobility is markedly more limited than wealth mobility*. For instance, the rank-persistence of income stabilizes around 0.55 by age 40, and, on average, income less than triples over the life cycle. By contrast, the persistence of wealth ranks stabilizes at 0.2 with wealth growing by a factor of over 30. In sum, individuals' position in the income distribution tends to be mostly stable throughout their working life even as their wealth position changes.

[18] Our results are consistent with Boserup, Kopczuk, and Kreiner (2018) who find a rank-correlation between age 18 wealth and age 45 wealth of 0.22 in Danish administrative tax records. Using broadly similar definitions, Shiro, Pulliam, Sabelhaus, and Smith (2022) estimate greater persistence in wealth ranks (0.59) for the US over the same prime wealth accumulation years we study.

Intergenerational mobility along the life cycle. A trend of *declining intergenerational mobility* along the life cycle mirrors the increasing trend of *intragenerational* mobility. Specifically, intergenerational rank persistence increases from 0.10 to 0.25, showing lower mobility with respect to parental wealth ranks as individuals get older, while income mobility remains the same as the cohort grows older, with a rank persistence around 0.20, consistent with the lower intragenerational mobility of income relative to wealth described above.[19] We provide a detailed account of these trends in Appendix B.

Taking stock: What we learn from mobility measures. These results establish that wealth mobility increases over the life cycle, but they remain silent over how broad-based mobility is. All the mobility measures in Figure 1 collapse the myriad of wealth trajectories experienced by individuals into a single aggregate time series. Some of these trajectories correspond to individuals with relatively stable ranks (and low mobility), and some to individuals who undergo large changes, rising or falling through the wealth distribution. Put another way, Figure 1 tells us that there are meaningful movements in wealth levels and ranks, but does not tell us the shapes of individuals' typical wealth histories, or what the usual timing and magnitude of their wealth changes are. We next introduce an alternative approach to summarizing the joint distribution of life-cycle wealth trajectories that allows us to answer these questions and link them to other characteristics of individuals that shape how they accumulate wealth over their lives.

[19]The magnitude and downward mobility trend, captured by an increasing parent-child correlation in wealth ranks, are similar to those reported by Boserup, Kopczuk, and Kreiner (2017) for Denmark, and slightly lower than the magnitudes reported by Adermon, Lindahl, and Waldenström (2018) and Black, Devereux, Lundborg, and Majlesi (2019) for Sweden. Charles and Hurst (2003) report a correlation of 0.37 for log-wealth between generations in the US.

4. Methodology: Grouping life-cycle trajectories of mobility

To understand the life-cycle patterns behind increasing mobility—who is moving? how much? and when?—as well as the economic mechanisms that shape them, we move to analyzing the 25-dimensional copula that describes the distribution of wealth trajectories. We do this by clustering individuals into groups with *typical life-cycle trajectories* that capture the variation in wealth histories, as we explain next. These typical trajectories capture persistent differences in life experiences, describing a pattern of segmented wealth mobility. In a second step, we study the characteristics of each group and relate them to their wealth trajectories.

The life-cycle trajectory of an individual through the wealth distribution is described by the vector of within-cohort wealth ranks (defined in equation 1):

$$\mathbf{R}_i = (r_{i,1993}, r_{i,1994}, \ldots, r_{i,2016}, r_{i,2017}) \in [0, 100]^{25} \ . \tag{2}$$

The distribution of $\mathbf{R}_i$ across the population is a high-dimensional object and therefore we proceed by reducing it to a small number of groups. We recover a set of $G > 1$ disjoint groups of individuals, so that each individual i is assigned to one of these groups, $g_i \in \{1, \ldots, G\}$. This induces a partition $\mathcal{G}_G = \{g_i\}_{i=1}^N$ over the set of individuals.

Specifically, we define groups of individuals with similar life cycles of wealth mobility using an *agglomerative hierarchical clustering* algorithm. Hierarchical clustering works recursively, starting from the lowest level of hierarchy, where $G = N$ and each observation is assigned to its own group, and sequentially combining (or agglomerating) one pair of groups in each iteration. This process results in a global hierarchy of partitions ranging from $G = N$ to $G = 1$. At each level of hierarchy $G > 1$, the algorithm creates the partition at the next level $\mathcal{G}_{G-1}$ by combining the two groups with the lowest dissimilarity. We use Ward's method to agglomerate clusters and adopt the total within-cluster variance as the dissimilarity metric:[20]

$$\underset{g,g' \in G,\, g \neq g'}{\operatorname{argmin}} \quad d\left(g, g'\right) = \sqrt{\frac{2N_g N_{g'}}{N_g + N_{g'}}} \times \left\| \bar{\mathbf{R}}^{g} - \bar{\mathbf{R}}^{g'} \right\|_2 , \tag{3}$$

where g and g' are disjoint groups, N_g denotes the number of observations in group g, and $\bar{\mathbf{R}}^g$ is the centroid (average) of the observations in group g.[21]

Crucially, we use the complete vector of ranks $\mathbf{R}_i$ when grouping the life-cycle trajectories of mobility. This has the key advantage that we do not need to pre-specify which subset of the elements of $\mathbf{R}_i$ are informative, as is the case when focusing on transitions over fixed horizons or between sections of the distribution. Neither do we need to reduce the dimensionality of the object of interest to a single summary statistic, such as those in Figure 1.

Selecting the number of groups. A key feature of this approach, which distinguishes it from other commonly used algorithms like K-means, is that we do not need to pre-specify the number of groups to study. Instead, implementing the algorithm recovers a complete hierarchy of nested groups. This makes it straightforward to study typical trajectories for any number of groups and to decompose the heterogeneity within each group by exploiting the nested structure, as we discuss in Appendix F. Therefore, we

[20] It is possible to include other outcomes or covariates that differ across groups, such as their income or portfolio composition. However, in practice, doing this introduces more noise than additional information; accordingly, we focus on wealth ranks in our main analysis. Alternative specifications of the dissimilarity metric, including maximum or median distance, are also possible. See Humphries (2022) for another application of Ward's method in the context of Sequence Analysis, where it is used to cluster panel data with discrete states. We produce our Agglomerative Hierarchical Cluster Tree using Matlab, see https://www.mathworks.com/help/stats/linkage.html.

[21] Given a set of underlying groups $G^{\star}$, a classifier is asymptotically consistent if, as the length T of observed trajectories increases, the classifier does not produce mixtures over these groups until it is asked to provide a partition into $G < G^{\star}$ groups. Borysov, Hannig, and Marron (2014) show this is the case for Ward's method as either $T/N \to \infty$, with T growing faster than N, or only $T \to \infty$, when the true group specific densities are jointly normal. For fixed population size N, Egashira, Yata, and Aoshima (2024) strengthen these results for arbitrary densities. Simulations confirm these results: 2-period panels produce crossing by construction as some individuals move up the distribution, necessarily pushing others down in rank even for i.i.d. outcomes. These results highlight the importance of long panels such as ours that provide sufficiently long enough trajectories to distinguish among groups.

select the number of groups for our main analysis after we obtain the full hierarchy.

To select the number of groups we trade off two objectives: (*i*) having enough groups to represent the distribution of wealth rank histories, and (*ii*) having a parsimonious description of trajectories. We find that the typical trajectories of the four largest groups ($G = 4$) capture just over 50 percent of the variation in wealth ranks trajectories of the 279,002 in our sample (see Appendix C) and use this as our baseline. Importantly, any increase in the number of groups necessarily comes as a sub-division of our main groups. We describe the largest three sub-groups of each main group in Appendix F.

5. Segmented wealth mobility

The typical life-cycle trajectories of individuals through the wealth distribution reveal a pattern of *segmented wealth mobility*: only some groups of individuals drive the increase in mobility over the life cycle (Figure 1). Moreover, they only move within the middle segment of the distribution. This is new evidence of *glass-ceilings* and *floors* in wealth mobility: limited opportunity to rise to the top, and from the bottom, of the wealth distribution, coupled with high persistence in the positions of those at the top.

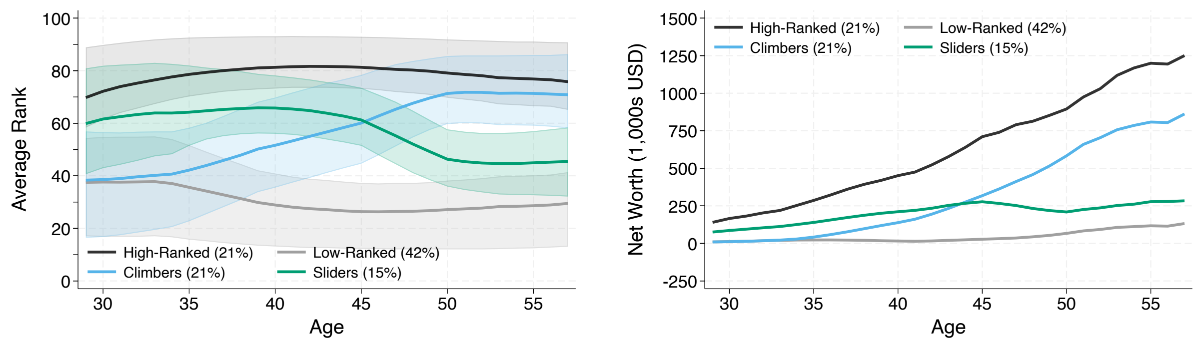
5.1. Typical wealth trajectories over the life cycle

We begin by reporting the typical wealth trajectories (in ranks and levels) of individuals in each of our four main clusters, or groups, in Figure 2. The typical trajectories have groups remaining at the bottom, in the middle, and at the top of the distribution throughout their lives, with the two groups in the middle exhibiting rising and falling trajectories, respectively (Panel A). Moreover, despite within-group heterogeneity, the interquartile range of the rank distribution for each group reveals that individuals' movements lie within segments of the wealth distribution. We interpret these patterns

FIGURE 2. Life-cycle dynamics of wealth mobility

(A) Average wealth rank by group

(B) Average wealth level by group



Notes: The figures plot the average wealth trajectories in each clustered group against individuals' age. Panel A reports within-cohort wealth ranks. The shaded areas correspond to the interquartile range of the rank distribution of each group. Panel B reports he average wealth level in thousands of 2019 US dollars. All individuals belong to the 1960–64 birth cohort. The clusters are constructed using hierarchical agglomerative clustering and Ward's method with a dissimilarity measure (3).

as evidence of *segmented wealth mobility*.[22]

Two groups of individuals, which we label "high-ranked" and "low-ranked," start their lives at the top or bottom of the wealth distribution and tend to stay there. They make up 21 and 42 percent of the cohort, respectively. This does not imply that their wealth rank is fully stable (as we show in Appendix F) but that it tends to stay within the upper or lower segments of the wealth distribution, as made clear by the small changes in the interquartile range of the distribution of ranks of these groups.

The other two groups, which we label "climbers" and "sliders", correspond to the remaining 21 and 15 percent of the cohort, respectively. They stay in the middle part of the distribution, but have, respectively, increasing and decreasing rank trajectories. These trajectories lead them to overlap with the high-ranked and low-ranked groups by age 55, but not to overtake them, evidencing *glass ceilings* for the mobility of those in the middle and bottom of the distribution, and a *glass floor* for those at the top.

[22]The same patterns arise for alternative outcomes, such as clustering on wealth levels and outcomes that weight more differences among the poor or the wealthy. We discuss these alternatives in Section 7.

The large reversals in fortune experienced by climbers and sliders reflect meaningfully different trajectories of wealth accumulation and not spurious mobility generated by a compressed wealth distribution, as we show in Figure 2B. We capture these differences in the wealth trajectories of individuals because our long panel allows us to identify slow-moving patterns typical of wealth accumulation and because rank-differences in Norway reflect economically significant differences in wealth.

Figure 2B also gives several insights into the wealth mobility patterns of each group. Climbers have zero net worth, on average, at age 30, but their rank improves by accumulating wealth at a similar pace to the high-ranked group (who remain wealthier throughout). By contrast, sliders have larger net worth than risers at age 30, but accumulate wealth slowly, leading them to fall down the distribution even as they become wealthier. The effects of the Great Recession are visible for this group, with a drop in their net worth around ages 45–50, when the recession hits the 1960–64 birth cohort.[23] Finally, the individuals in the low-ranked group have close to zero net worth, on average, for most of their work life and a very gradual increase starting at age 45.

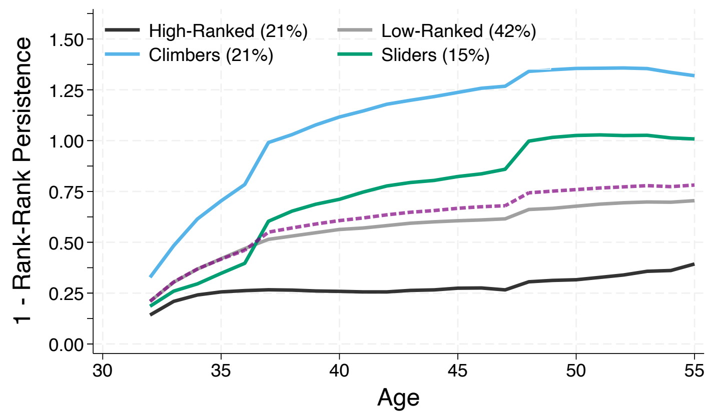
5.2. Decomposing aggregate mobility patterns

Segmented wealth mobility in Figure 2 captures permanent differences in mobility between groups that explain what (and who) is driving the increase in intragenerational mobility in Figure 1. The reversal of fortune experienced by the climbing and sliding groups is the key driver of intragenerational mobility. In particular, the trajectory of the climbers evidences the highest mobility over the life cycle, contrasting with the lower mobility of the high- and low-ranked groups. In this way, mobility is not universal; rather, it is limited to segments of the population in the middle of the distribution.[24]

[23]In Section 7.3 we show that the mobility trends we document are also present in other cohorts which were affected by the Great Recession and other macroeconomic events at different ages.

[24]There are also other mobility patterns that are specific to smaller groups of the population. For instance, Hubmer, Halvorsen, Salgado, and Ozkan (2024) show that one-fourth of the wealthiest 0.1 percent at age 50 come from the bottom half of the distribution.

FIGURE 3. Intragenerational wealth mobility across groups



Notes: The figure presents intragenerational wealth mobility for our four main groups. The pooled cohort-level persistence measure is shown in dashed lines. The plot reports 1 minus the persistence measures of wealth and income against age, corresponding to the auto-correlation of wealth and income ranks, respectively, $r_{i,t}$, with their value in 1993, $r_{i,1993}$. To compute the rank-rank persistence for each group, we compute the auto-correlation from deviations from the cohort-wide average rank.

To see this, we decompose the persistence of wealth ranks in Figure 3 by computing the rank-rank persistence measure separately for each of our main four groups.[25] The high-ranked group is particularly immobile; it exhibits a high and stable persistence of individual wealth ranks with only a minor increase in mobility after age 45. Mobility is relatively higher in the low-ranked group as they experience more frequent movements within their segment of the distribution, in part reflecting the larger size of this group. Mobility is highest for climbers, for whom reversals of fortune happen within the first 15 years of our panel and whose rank persistence measure eventually becomes negative. Sliders' mobility increases as persistence falls to zero: their rank at older ages becomes untethered from their early prosperity.

Overall, we find the trend of increasing intragenerational mobility is not driven by broad-based mobility across the population or by large reshuffling across the distribution. Instead, the trend comes from a combination of stable groups at the top

[25]Formally, we compute the auto-correlation for each group g, ρ_t^g, estimating $r_{i,t} = \alpha_t + \rho_t^{g(i)} r_{i,1993} + u_{i,t}$. We discuss other mobility measures including intergenerational mobility in Appendix B.

and bottom of the distribution and two groups undergoing transitions that are nevertheless contained to the middle of the wealth distribution. In essence, *mobility is segmented: it takes place for only some individuals and within a section of the distribution.*

5.3. Interpreting mobility groups

A key advantage of our clusters is that they do not impose a specific representation for the process describing wealth accumulation; instead, estimation non-parametrically characterizes mobility groups. Hence, they are robust to misspecification of the wealth accumulation process and capture rich dynamics present in the data.

However, to interpret our results it is useful to contextualize them in a model of wealth dynamics. To this end, we propose a statistical process for wealth in the spirit of Benhabib and Bisin (2018) and Gomez (2023). We simulate it under different assumptions and apply our clustering to study under which conditions it can or cannot replicate the patterns we observe in our data. This simple illustration allows us to show that the mobility patterns described by our four main clusters are non-trivial, but can nevertheless be replicated with a transparent covariance structure between initial conditions in the presence of heterogeneity in the speed of wealth accumulation.

Specifically, let the wealth for individual i at age t, $w_{i,t}$, evolve according to

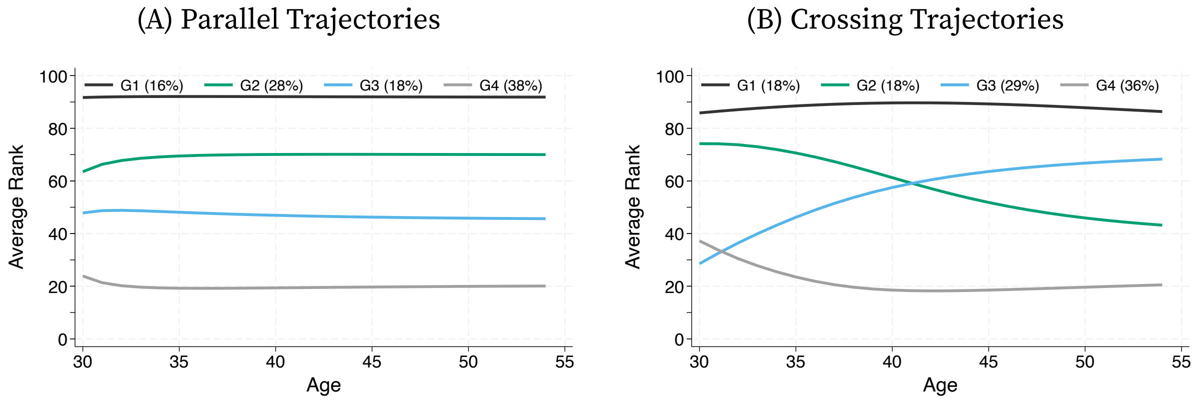
$$w_{i,t+1} = \left(1 + r_i\right) w_{i,t} + s\, y_{i,t}, \tag{4}$$

where s is the savings rate out of non-capital income, $y_{i,t}$, and $r_i \sim N\left(\bar{r}, SD\left(r\right)\right)$ is the rate of return.[26] Income evolves according to

$$\log y_{i,t+1} = \rho \log y_{i,t} + \epsilon^y_{i,t}; \quad \epsilon^y_{i,t} \sim N\left(0, SD\left(\epsilon^y\right)\right) . \tag{5}$$

[26] Note that the notation differs from Section 3, in which r_i represented wealth ranks.

FIGURE 4. Typical Rank Trajectories Across Exercises



Notes: Panel A displays the baseline simulation. Baseline parameterization has an rate of return $\bar{r} = 3.5\%$, savings rate $s = 0.25$, income persistence $\rho = 0.937$, income standard deviation $SD(\epsilon^y) = 0.024$, and no dispersion in returns. Panel B assumes a negative correlation between initial wealth and initial income, $\rho = -0.98$, and $SD(r) = 0.055$. Legend titles show group sizes.

We assume that initial income and wealth are log-normally distributed with their empirical means and variances for our cohort of interest.

We focus on two exercises that differ in the correlation between initial conditions and sources of heterogeneity. In the baseline we assume initial wealth and income are independent, and no heterogeneity in returns, $SD(r) = 0$, so that differences in wealth trajectories depend only on initial conditions and realized income over time. We set other parameters to values obtained from previous literature on Norway: $\bar{r} = 0.035$ (return to net worth in Fagereng et al. 2020), $s = 0.25$ (gross savings rate in Fagereng et al. 2019), $\rho = 0.937$ and $SD(\epsilon^y) = 0.024$ (Fagereng, Holm, and Natvik 2021). In our second exercise initial conditions are negatively correlated and $SD(r) = 0.055$, in line with the dispersion of returns in Norway (Fagereng et al. 2020).[27] We include heterogeneity in savings rates as well as different parameter values in Appendix D.

These exercises deliver two key insights. First, Figure 4A shows that the segmented mobility patterns in our data are not necessarily implied by any process of wealth

[27]To capture the behavior of returns in our exercise we set $\bar{r}$ to the average between the mean (0.0379) and median (0.0321) return in the data, and $SD(r)$ to be consistent with the p90-p10 gap of returns of 0.1477.

accumulation, nor by our clustering algorithm. Instead, the baseline exercise, in which mobility is driven only by differences in income, results in parallel wealth ranks.[28] That is, groups stay in the same segments of the wealth distribution as they age, implying *limited wealth mobility*. In other words, the Norwegian data displays significant *excess* wealth mobility, over and above the prediction from this parsimonious specification.[29]

Second, Figure 4B shows that a crossing pattern, qualitatively similar to our data, arises when initial income and wealth are negatively correlated and individuals differ in their returns to wealth. Namely, the observed pattern can be generated with sufficient differences in the speed of wealth accumulation across individuals, and with some people whose initial wealth is relatively low compared to their growth potential, and vice-versa.[30] Return heterogeneity alone is not always enough to match the dynamics of wealth mobility, as it delivers similar crossing patterns in only 40% of our simulations. Instead, when combined with a negative correlation in initial conditions we obtain climbers and sliders over 70% of the time.

We see these exercises as illustrative of the role of different dimensions of ex-ante and ex-post heterogeneity in generating wealth mobility. The patterns we observe are consistent with a reasonable representation of wealth dynamics, while rejecting a wide range of alternative representations. In the next section we turn to observable dimensions of heterogeneity and relate them to wealth mobility patterns. In Appendix D we move beyond the parsimonious model of wealth accumulation in (4) and prove that, for a broad class of life cycle models with endogenous savings decisions, there exists a tight link between primitives and wealth mobility. In this way, typical wealth trajectories can inform statistical and structural models of wealth accumulation.

[28] Figure D.1 in Appendix D shows that this feature is robust to changing the interest rate, savings rate, and the persistence of income. It is also implied by homothetic buffer-stock models with homogeneous returns, as we show in Proposition A1.

[29] Figure E.3 in Appendix E shows that income groups exhibit parallel rank trajectories, consistent with lower income mobility relative to wealth, as documented in Figure 1.

[30] These forces, and differences in savings rates, are also emphasized in Guvenen et al. (2023), Hubmer et al. (2024), and Guvenen, Ocampo, and Ozkan (2025) when accounting for self-made billionaires.

6. Heterogeneity across groups

We now turn to exploring ex-post and ex-ante sources of life cycle differences for the four main wealth mobility groups and show how they account for mobility.

6.1. Ex-post heterogeneity: Portfolios, Incomes and Demographics

We leverage the information available in the Norwegian Registry data to consider the main drivers of wealth accumulation over an individual's work life. Specifically, we look at portfolio composition, inheritances, sources of income, entrepreneurship, and marriage and divorce. These factors have been shown to be key determinants of wealth accumulation and wealth inequality (De Nardi and Fella 2017; Kuhn, Schularick, and Steins 2020; Hubmer, Krusell, and Smith 2021).

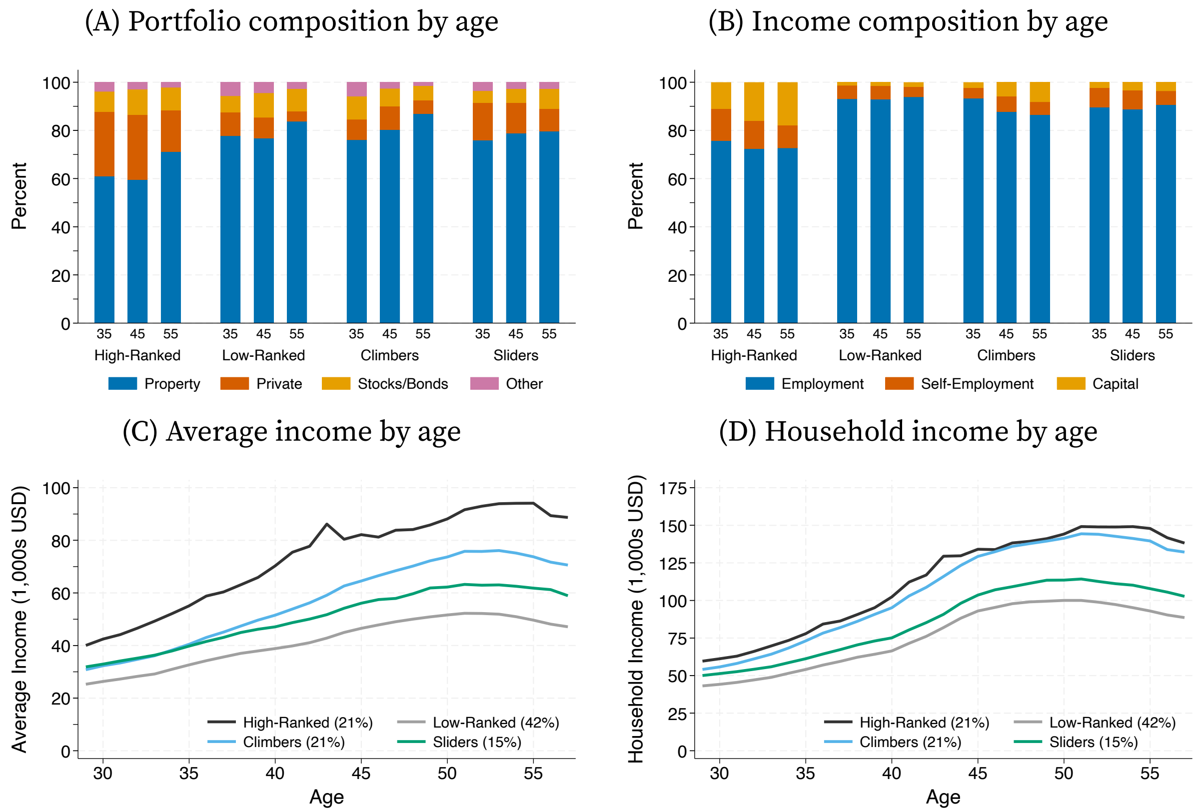
We quantify important differences between the four main wealth mobility groups that help explain their divergent wealth accumulation and mobility patterns. However, the typical trajectories we recover encapsulate a wide variety of heterogeneous life-cycle events and choices. Consequently, we find no single factor that, in isolation, can account for these differences. Figure 5 summarizes key differences across groups.

Portfolios and Incomes. Panel A describes the portfolio composition of each group, displaying the share of assets accounted for by property, private business assets, financial assets (stocks, bonds, and bank accounts), and a residual category including vehicles and foreign assets. Residential property represents the majority of portfolios in all groups. Likewise, panel B shows that the vast majority of income comes from wages and salaries in all groups.[31]

High-ranked individuals have a higher share of private business wealth, around 25

[31]We focus on sources of earned income, excluding public benefit programs whose receipt is concentrated in that low-earning, low-wealth individuals.

FIGURE 5. Portfolios and income across groups



Notes: Panel A reports the share of assets accounted for by property, privately held assets, financial assets, and other assets, defined as the total value of each asset class divided by the total assets within a group. Panel B plots the share of each group's income accounted for by employee, self-employment, and capital income. Panel C plots the average income in 2019 US dollars for each group. Panel D plots average household income trajectories in 2019 US dollars.

percent, while it is around 15 percent for sliders and less than 10 percent for climbers.[32] Although they have a lower housing portfolio share, they are more likely to be homeowners at younger ages. High-ranked individuals also have the highest individual and household incomes across all groups (Panels C and D, respectively). Conversely, the individuals who remain at the bottom of the distribution have the lowest income.

[32]Differences in the extensive margin of business operation, as well as the high-ranked group's higher shares of capital income and self-employment income (Panel B) explain differences in privately held assets. Notably, the business ownership rate of the high-ranked group is close to 10 percentage points higher than that of the sliders (who also have a larger share of privately held assets at younger ages) and much higher than that of the climbers; the climbers' rate is never above 15 percent, although it increases as they age. We report home and business ownership rates in Figure E.1.

Sliders have higher property shares than the high-ranked individuals and also have more wealth in privately held assets than other groups. Relative to climbers, they are significantly more likely to be homeowners up to age 45, when their homeownership rates converge, and more likely to have business income. Nevertheless, they have low individual and household income (Panels C and D).

Despite smaller differences in income than in wealth, it is clear that the trajectory of income plays a relevant role in wealth mobility.[33] Sliders begin with more wealth than climbers and a similar level of income; yet, their incomes diverge after age 40. This widening income gap is coupled with a rapid increase in wealth for the climbers and a reversal of their relative position with respect to the sliders. We show in Section 6.2 that these life-cycle differences in income are partly explained by higher educational attainment of climbers, pointing to an important role for human capital accumulation in explaining wealth mobility.

Taken together, these patterns suggest that the ownership and operation of profitable business assets are crucial characteristics for many individuals who start and remain near the top of the wealth distribution; however, they do not play an equally important role for climbers in the middle of the wealth distribution. Accumulation of property is the main driver of their rise before age 45 (see also, Kuhn, Schularick, and Steins 2020), moving afterwards to increases in non-housing wealth.

Marriage and Assortative Mating. We also track the civil status and cohabitation of individuals in each group. We find limited differences between groups. By age 45, over 80 percent of individuals in all groups are married or cohabiting, although individuals in the low-ranked group are slightly more likely to be single (Figure E.4). The high rates of marriage and cohabitation make the trajectories of household income that we report

[33] In fact, the different groups are remarkably similar in terms of their average rank in the income distribution, with average differences of not more than 20 percentage points between the low- and high-ranked groups, as we show in Figure E.2 in Appendix E.

in Figure 5D relevant for the accumulation of wealth. In fact, the life-cycle profiles of household income reinforce, rather than reduce, the differences in labor income across groups (Figure 5C), so that the trajectories of household wealth ranks exhibit the same mobility patterns we document in Figure 2 (see Section 7.1).

There is a large gap in household income between the high-ranked and climbing groups on the one hand and the low-ranked and sliding groups on the other. The patterns we find are consistent with higher-earning individuals marrying or cohabiting with higher-earning spouses, a pattern that is strengthened by households also sorting on the basis of their initial wealth and returns as documented by Fagereng, Guiso, and Pistaferri (2022). This assortative matching mechanism is particularly relevant for the individuals in the rising group, for whom household income is almost as high as that of the households of the high-ranked individuals.

Other Mechanisms. In Appendix E, we provide additional results on portfolio composition and incomes. We compute portfolio-implied returns and show that differences between groups are at most 2.5 percentage points and disappear by age 45, except for the low-ranked group (Figure E.1). This small gap in portfolio-implied returns is consistent with Fagereng et al. (2020), who report most of the differences in returns in Norway take place within instead of between asset classes.[34]

Wealth accumulation is also partially affected by intergenerational transfers, such as inheritances. For instance, the share of individuals that received an inheritance by age 55 ranges from 7 percent in the low-ranked group to 17 percent in the high-ranked group. In the same context, Black, Devereux, Landaud, and Salvanes (2025) find gifts and inheritances are a small fraction of an individual's net wealth at any point in time.[35]

[34]In the United States, Athreya, Gordon, Jones, and Neelakantan (2025) find rate of return differences between White and Black households can overcome higher initial wealth among Black individuals.

[35]In contrast, Adermon, Lindahl, and Waldenström (2018) emphasize the importance of intergenerational transfers in the form of bequests and gifts in Swedish data. Consistent with the results we document below, they also find an important role for human capital.

Within group heterogeneity. Finally, we exploit the hierarchical nature of our clustering algorithm to study the subgroups that make up each of the four major groups. This is a direct approach to study within group heterogeneity which further illustrates the value of our method in uncovering typical trajectories from rich panel data. We provide a detailed discussion of the subgroups in Appendix F, and focus here on the main lessons drawn from this exercise. We find further evidence of segmented wealth mobility within groups by examining the typical trajectories of subgroups. Overall, mobility within each main group remains contained within segments of the wealth distribution (as in Figure 2A). Instead, the main differences across subgroups come in the timing of changes in rank and wealth levels for the groups of climbers and sliders. This highlights distinct subgroups including individuals with higher levels of education who rise later in life and a group of sliders characterized by higher-than-average rates of business ownership relative to the population at large. Declines in their business wealth lead them to experience the largest fall in wealth ranks.

6.2. Ex-Ante heterogeneity: Parental background, education, and mobility

Having identified distinct life-cycle trajectories of wealth mobility, we now consider the role of individuals' *ex-ante characteristics*. We focus on characteristics emphasized in the broader intergenerational mobility literature, such as parental wealth, education, and birthplace (e.g., Chetty et al. 2014; Boserup, Kopczuk, and Kreiner 2017).

We quantify the predictive power of parental wealth, education, sex, and place of birth for group-assignment using a multinomial logit specification

$$\Pr\left(g_i = j\right) = F\left(\alpha_0^j + \beta_{q(i)}^j + \gamma_{\text{educ}(i)}^j + \delta_{\text{subj}(i)}^j + \lambda_{\text{pareduc}(i)}^j + \mu_{\text{male}(i)}^j + \nu_{\text{bplace}(i)}^j\right), \quad (6)$$

where $F(\cdot)$ denotes the logit transformation. Specifically, we include ventiles of parental wealth fixed effects, $\beta^j_{q(i)}$.[36] We also include education fixed effects (post-compulsory high school, technical college, undergraduate, post-graduate, and doctoral degree), $\gamma^j_{\text{educ}(i)}$, and subject-specific fixed effects, $\delta^j_{\text{subj}(i)}$, for individuals with undergraduate or graduate degrees.[37] Finally, we include a fixed effect for the highest level of parental education, $\lambda^j_{\text{pareduc}(i)}$, a sex fixed effect, $\mu^j_{\text{male}(i)}$, and birthplace fixed effects, $\nu^j_{\text{bplace}(i)}$, which allow for place-based differences among the Oslo metropolitan area, other major cities, and rural regions.[38]

We find parental wealth and the individuals' own education play a significant role in influencing group membership, accounting for over 80 percent of the fit of the model in classifying individuals, and relegate discussion of other factors to Appendix G.[39]

Parental wealth. Figure 6A reports the average partial effects of parental wealth rank on predicted group assignment and their 95 percent confidence intervals. Individuals with wealthier parents are progressively more likely to belong to the high-ranked group and less likely to belong to the low-ranked group: those with parents in the top wealth ventile are 25 percentage points more likely to belong to the high-ranked group than those with parents in the bottom ventile. By contrast, parental background has limited ability to differentiate those who are ultimately climbers and sliders.

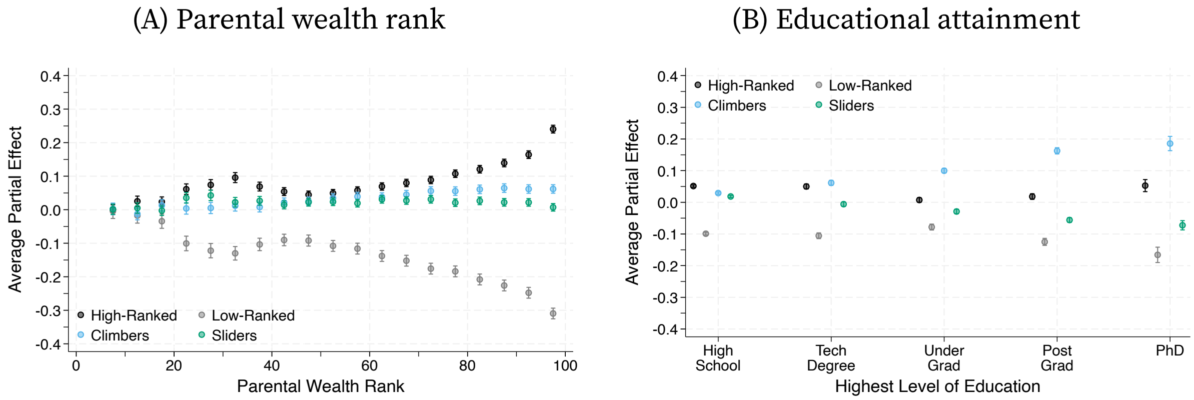
[36] Formally, $q(i)$ is the ventile of the richest parent of individual i in the parent's own cohort wealth distribution in 1993 at the start of our sample.

[37] In practice, we aggregate the 350 degree-specific codes into six categories: arts and humanities; business, economics, and agricultural management; computer science and engineering; natural sciences; health; and education specialists.

[38] Appendix G shows alternative specifications including parental education and business ownership, and individuals' initial conditions.

[39] We also find that most of the uncertainty over group membership is not explained by these factors. This is to be expected as the value of our clustering approach, which exploits the entire life-cycle history of individuals, lies in revealing a low-dimensional representation that is not easily summarized by observable variables. We calculate the share of variation in group membership explained by (6) and decompose the partial contribution of parental wealth, education, and initial characteristics using the Shapley-Owen decomposition (Shorrocks 2013) in Appendix G. This additive decomposition provides a single value per covariate category that is permutation invariant (Audoly et al. 2025).

FIGURE 6. Parental wealth, education and the probability of group assignment



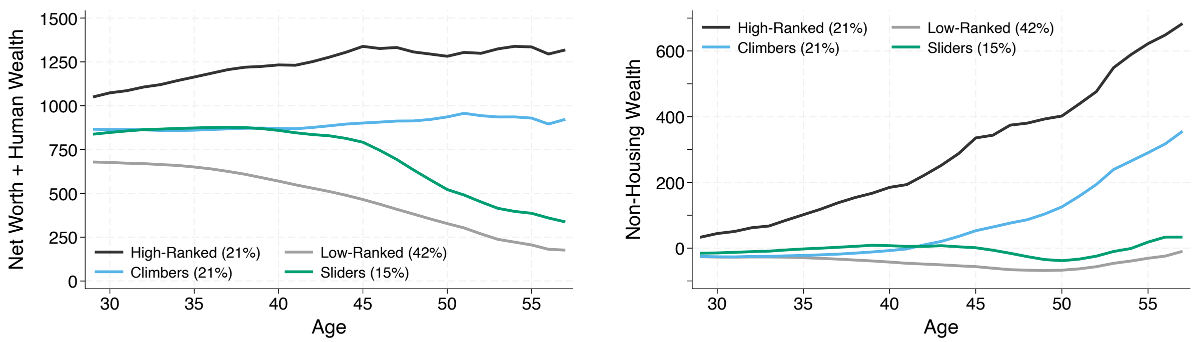
Notes: Panel A plots the average partial effect of Parental Wealth (measured in 1993) relative to being born to parents in the bottom ventile of the distribution. Panel B plots the average partial effect of educational attainment relative to compulsory schooling age. We construct the average partial effect by integrating over the empirical joint distribution of other covariates. We report the probability of being assigned to each of our four groups, along with their 95 percent confidence intervals.

Education. Figure 6B reports the estimated average partial effects of educational attainment and their 95 percent confidence intervals. Higher educational attainment is associated with a higher probability of being a climber. Specifically, a university graduate is 10 percentage points more likely to belong to the climbers' group than an individual with only compulsory schooling. This difference increases to up to 20 percentage points for PhDs, providing evidence that climbers are characterized by higher human capital, consistent with the earnings profiles we report in Figure 5. More generally, more educated individuals are less likely to be low-ranked or sliders.

Even though there is a limited effect of education on belonging to the high-ranked group, these individuals are more likely to have a business or STEM degree, and those of the low-ranked group are less likely. Interestingly, the field of study is not relevant for distinguishing climbers and sliders. Similarly, there is no significant role for parental education after taking into account the direct role of parental wealth and the individuals' own education as we show in Figure G.1 of Appendix G.

FIGURE 7. Beyond total wealth: Human and non-housing wealth

(A) Wealth plus human wealth (B) Non-housing wealth



Notes: Panel A presents the value of wealth plus human wealth, defined as the discounted value of future labor income calculated from the realized income trajectories of individuals obtained from the tax registry. We discount future income using the average return on net worth for Norway, 3.21 percent, reported in (Fagereng et al. 2020, Table 3). Panel B reports the average levels of non-housing wealth, defined as total wealth minus the value of primary residences.

6.3. How ex-ante and ex-post heterogeneity determine mobility

We now show how the differences in human capital early in life, and the accumulation of different types of assets through people's work lives, account for the life cycle dynamics of mobility for climbers and sliders.

Taking into account *human wealth*—the discounted value of future realized labor income—closes the initial wealth gap between climbers and sliders. That is, the climbers' higher earnings potential fully offsets for their lower initial wealth, as we show in Panel A of Figure 7. The sum of net worth and human wealth remains relatively constant for the two groups until age 45 when their trajectories diverge, coinciding with the crossing pattern in wealth in Figure 2.

Climbers with high-earnings potential first convert their higher incomes into wealth by accumulating property, highlighting the crucial role of housing in wealth accumulation. Strikingly, there is no gap in non-housing wealth—wealth excluding the value of primary residences—between the climbers and sliders before age 40, as shown in Panel B of Figure 7, and the gap closes as climbers become homeowners. At older ages, the wealth accumulation patterns of the two groups diverge. Climbers accumulate non-housing–in addition to housing–wealth while sliders' non-housing wealth stalls and even decreases, driven by declining values of their business assets (see Figure 5). Absent this divergence in wealth accumulation after age 40, mobility would be driven by a *convergence* of fortunes, rather than a reversal.

7. Robustness and method discussion

In this final section, we discuss the sensitivity of our results to a number of alternative methodological choices. Reassuringly, our results do not substantively depend on either the transformation of wealth we use, including measures of *absolute* mobility based on trajectories of (log) wealth levels, or the clustering algorithm we choose to implement. We also repeat our analysis for the 1965–69 cohort to compare our findings and discuss the role of time effects and cross-cohort differences.

7.1. Robustness to alternative clustering variables

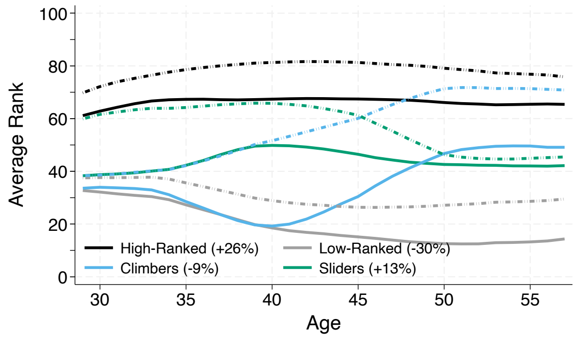
As we show in Figure 8, the qualitative mobility patterns we document are a robust feature of the data. They emerge when using transformations of wealth histories that emphasize differences in wealth levels, top wealth holders, or when using household wealth ranks (accounting for marriage and cohabitation). Similarly, our results are preserved when using the K-means algorithm to cluster individuals.

We begin by performing two robustness exercises in which we group individuals based on their log-wealth histories and the trajectories of their "Lorenz" ordinates using agglomerative hierarchical clustering.[40] Log-wealth is a concave transformation of wealth levels providing a measures of *absolute* wealth mobility that magnifies differences

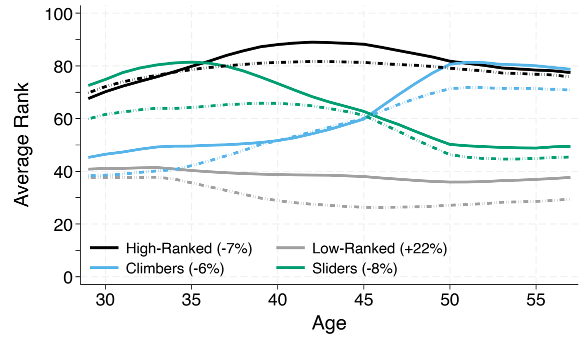
[40] In both cases we bottom code wealth at 1,000 Norwegian Kroners to deal with negative values.

FIGURE 8. Robustness of wealth rank clusters with $G = 4$

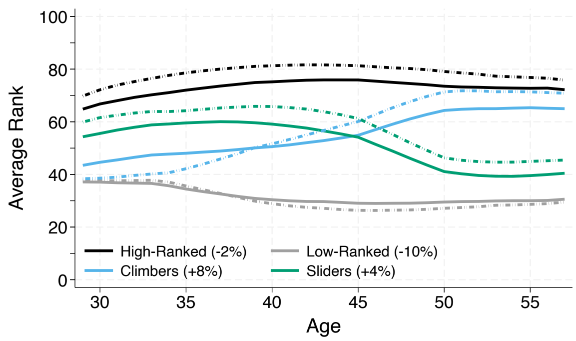
(A) Log net worth



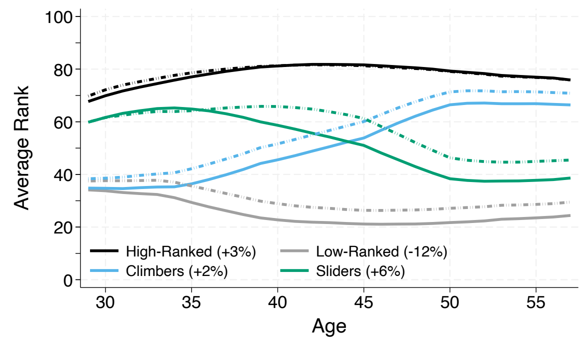
(B) "Lorenz" ordinates



(C) Household cohort ranks



(D) K-means on ind. cohort ranks



Notes: Average wealth rank by group against age for alternative clustering exercises. The clusters are constructed using hierarchical agglomerative clustering and Ward's method with a dissimilarity measure (3). Panel D constructs clusters using the K-means algorithm. The dashed lines show the average wealth rank of the baseline clustering done with respect to individual cohort ranks, presented in Figure 2A.

among low-wealth individuals, relative to top wealth holders. Lorenz ordinates, given by individuals' positions in the cohort's Lorenz curve, measure the distance between individuals by the share of total wealth that lies between them.[41] Formally,

$$r_{i,t}^{Lorenz} = \frac{\sum_{\{j:w_{j,t} \leq w_{i,t}\}} w_{j,t}}{\sum_j w_{j,t}}. \tag{7}$$

This is a convex transformation of wealth ranks, magnifying differences at the top of the distribution, making inequality more salient than either wealth ranks or log-wealth.

[41]The Lorenz curve maps each individual to the share of wealth held by those poorer than they are.

As Panels A and B show, these alternative clustering exercises do not change the mobility patterns described in Figure 2 (reproduced in dashed lines).[42] Nevertheless, the groups' composition and size do change as a result of the characteristics highlighted by these exercises. Using a concave transformation of wealth, like the logarithm, makes the high-ranked group larger and the low-ranked group smaller, emphasizing differences in the bottom of the wealth distribution. By contrast, the Lorenz curve transformation makes the low-ranked group much larger as high wealth inequality makes the Lorenz curve flat at the bottom. Nevertheless, the typical trajectories of each group are similar.

Finally, in Panel C, we group individuals based on their household's wealth rank. This turns out to imply little changes for the resulting main groups with only a slight compression in the gaps between groups. The changes are ultimately small in part because the majority of the sample are married or cohabiting and the Norwegian tax registry already equivalizes by dividing equally the value of joint assets.

7.2. Alternative clustering approaches

Several procedures have been proposed to construct latent groups from a sequence of realized outcomes. We briefly contrast our approach to two alternatives with applications to economic data.

First, agglomerative hierarchical clustering is closely related to applications of *Sequence Analysis* tools that summarize histories of categorical outcomes. These tools originate in quantitative sociology (Dijkstra and Taris 1995; McVicar and Anyadike-Danes 2002; Dlouhy and Biemann 2015) and have been applied in economics (see, for example, Humphries 2022). Our approach is better suited to the continuous variation in wealth because *(i)* it avoids categorizing wealth ranks or levels into arbitrary discrete groups and *(ii)* it exploits the cardinality of wealth movements.

[42] All the panels of Figure 8 report the typical individual wealth rank trajectories implied by the respective clustering exercise, regardless of the outcome variable used in the construction of the groups.

Another procedure to retrieve latent groups is *K-means clustering*. Bonhomme and Manresa (2015) and Bonhomme, Lamadon, and Manresa (2022) discuss this approach and derive its asymptotic distribution. Conceptually, K-means uses a different distance metric to the one in equation (3), resulting in potentially distinct groups.

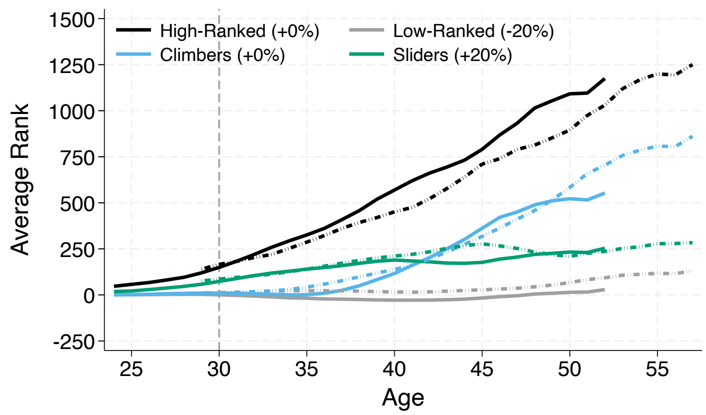
For large administrative datasets, such as the one we analyze in this paper, hierarchical clustering offers three important advantages over K-means. First, K-means clustering is a partitioning algorithm implemented through local optimization techniques that require many multi-start evaluations for a given number of groups G. Second, in high dimensions, K-means struggles to converge due to the geometry of hyper-spheres that makes it difficult to search for partitions as opposed to agglomerating similar observations, although the solution is typically fast in low-dimensional spaces given an initial guess of the partition. Third, the procedure must be repeated whenever the number of target groups G changes. By contrast, hierarchical clustering recovers all optimal groups for $G \in \{1, \ldots, N\}$ as an outcome of a global search for the sequential agglomeration of clusters.

Nevertheless, in Figure 8D we group individual wealth rank trajectories with the K-means clustering algorithm, using $G = 4$ groups for comparison with our main exercise. To implement this, we initialize the algorithm using our clusters as a seed. Reassuringly, we find the results only differ due to minor recomposition across groups—suggesting our partition is a local optimum for the alternative K-means objective function. For example, the low-ranked group is smaller and, as a result, poorer on average, while some of its members are reclassified as sliders, lowering that group's wealth rank profile.

7.3. Time and age effects

Our results use one birth cohort (1960–64) and describe life-cycle patterns including age and calendar-time effects. However, patterns of segmented mobility are not exclusive to

FIGURE 9. Life-cycle dynamics of wealth mobility 1965 birth-cohort



Notes: Average wealth level by group against age for individuals in the 1965–69 birth cohort. The clusters are constructed using hierarchical agglomerative clustering and Ward's method with a dissimilarity measure (3). We use only the latter 20 years of data corresponding to the time for which the cohort is on average 30 years or older. These years are indicated in the figure by a vertical dashed line.

this cohort, even though aggregate events affect other cohorts differently. We show this by replicating our analysis for the 1965–69 birth cohort and impose the same age-based selection rule as in our primary sample (yielding a 20 year panel).

As we show in Figure 9, there are two groups of persistently poor and rich individuals and two crossing groups in the middle in the 1965–69 cohort, maintaining the patterns of our main cohort. Remarkably, the wealth levels for each group at each age are very similar to those of the 1960-64 cohort, although the wealth of the fallers stagnates earlier, which could be explained by the fact that this cohort experienced the Great Recession at a younger age. Data availability does not allow us to repeat the main exercise for very distinct cohorts and, thus, completely separate age and time effects.

8. Conclusion and directions for future research

We use 25 years of administrative records to study the life-cycle dynamics of wealth mobility in Norway. Wealth mobility is markedly higher than income mobility and increases throughout the life cycle. However, mobility is *segmented*. It is driven by two groups of individuals that switch position in the middle of the wealth distribution as they age, and is limited for the majority of individuals who remain either near the top or bottom the distribution. The segmentation of mobility evidences *glass ceilings* limiting the rise of individuals in the middle and bottom of the distribution.

Our approach clusters individuals with similar wealth trajectories. Importantly, a snapshot of the wealth distribution or aggregate mobility measures would not contain enough information to recognize the differential paths of those climbing and sliding through the middle of the distribution. In this sense, our results complement recent work on the dynamics of wealth for the wealthiest (Gomez 2023; Hubmer et al. 2024) and adds to the use of clustering methods in economics.

Finally, the dynamics of wealth mobility that we document inform us about drivers of wealth accumulation for individuals across the entire distribution. Capturing these dynamics is key to understanding savings motives and, hence, to study a wide array of economic problems, from the pass-through of monetary policy (for example, Kaplan, Moll, and Violante 2018; Auclert 2019), to the crowding-out effects of social security (for example, Samwick 2003; Scholz, Seshadri, and Khitatrakun 2006; Blau 2016), and the optimal taxation of capital (Guvenen et al. 2023).

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Appendix A. Detailed description of the measurement of wealth

TABLE A.1. Data Sources and Variables

Source	Variable	Metadata
Befolkningsstatistikk		
Fixed variables	Individual annonimized ID	https://www.ssb.no/a/metadata/codelist/datadok/1668202/no
	Mother's, Father's, Spouse's, Cohabitant's, & Family ID	
	Sex	https://www.ssb.no/a/metadata/codelist/datadok/1385084/no
	Birth city	https://www.ssb.no/a/metadata/codelist/datadok/637597/no
	Immigration category	https://www.ssb.no/a/metadata/solr.cgi?q=invkat
	Birth date	
	Immigration: First year of record	
	Emmigration date	
Family and cohabitation	Civil status	https://www.ssb.no/en/klass/klassifikasjoner/19
Utdanningsstatistikk		
	Highest level of education	https://www.ssb.no/en/klass/klassifikasjoner/36
	Field of study	https://www.ssb.no/en/klass/klassifikasjoner/36
Inntekts og formuesstatistikk		
Selvangivelsesregisteret	Taxable net worth	https://www.ssb.no/a/metadata/conceptvariable/vardok/18/nb
(Section 4 –Formue– of the tax	Taxable assets	https://www.ssb.no/a/metadata/conceptvariable/vardok/662/nb
declaration form)	Debt	https://www.ssb.no/a/metadata/conceptvariable/vardok/17/nb
	Inheritance/Gifts	https://www.ssb.no/a/metadata/conceptvariable/vardok/3494/nb
	Bank deposits	https://www.ssb.no/a/metadata/conceptvariable/vardok/591/nb
	Bonds (VPS-registered)	https://www.ssb.no/a/metadata/conceptvariable/vardok/1210/nb
	Shares (VPS-registered)	https://www.ssb.no/a/metadata/conceptvariable/vardok/3109/nb
	Mutual funds	https://www.ssb.no/a/metadata/conceptvariable/vardok/679/nb
	Foreign deposits	https://www.ssb.no/a/metadata/conceptvariable/vardok/3239/nb
Housing wealth database	Value of housing (including cabins and secondary homes)	
	(Adjusted using \citealt{fagereng2020housing})	
Inntektsstatistikk	Employment income (incl. par. & sickness ben.)	https://www.ssb.no/a/metadata/conceptvariable/vardok/15/en
	Self-emp. income (incl. sickness ben.)	https://www.ssb.no/a/metadata/conceptvariable/vardok/13/en
	Capital income	https://www.ssb.no/a/metadata/conceptvariable/vardok/10/en
	Interest income	https://www.ssb.no/a/metadata/conceptvariable/vardok/560/nb
	Dividends	https://www.ssb.no/a/metadata/conceptvariable/vardok/561/en
	Realized capital gains	https://www.ssb.no/a/metadata/conceptvariable/vardok/562/en
	Realized capital losses	https://www.ssb.no/a/metadata/conceptvariable/vardok/563/en
	Social security benefits	https://www.ssb.no/a/metadata/conceptvariable/vardok/615/en
	Retirement pension	https://www.ssb.no/a/metadata/conceptvariable/vardok/25/nb
	Disability pension	https://www.ssb.no/a/metadata/conceptvariable/vardok/33/nb
	Unemployment benefits	https://www.ssb.no/a/metadata/conceptvariable/vardok/666/en
	Sickness benefits	https://www.ssb.no/a/metadata/conceptvariable/vardok/3366/en
	Parental benefits	https://www.ssb.no/a/metadata/conceptvariable/vardok/3367/en
	Child allowance	https://www.ssb.no/a/metadata/conceptvariable/vardok/567/en
	Dwelling support	https://www.ssb.no/a/metadata/conceptvariable/vardok/667/en
	Student grant	https://www.ssb.no/a/metadata/conceptvariable/vardok/576/en
	Child care benefits	https://www.ssb.no/a/metadata/conceptvariable/vardok/568/en

Notes: The table reports selected variables used in the analysis along with their source and corresponding metadata. Not all variables are included for space. Variable definitions come from https://www.ssb.no/a/metadata/definisjoner/variabler/main.html.

Tax Returns. We construct our main variable of interest, a measure of an individual's wealth, using data from tax returns. We use tax returns for all individuals who are tax resident in Norway between 1993 and 2017. Norwegians who live abroad are not tax resident in Norway and do not have to file a tax return in that year. All values are measured on December 31st of each year. Thus, we observe an annual snapshot of an individual's balance sheet.

We observe both income tax records and wealth tax records. All income is taxed at the individual level. In contrast, wealth is jointly taxed for married couples. Cohabitant couples (with or without children) are taxed separately even though they may own assets jointly. For jointly owned assets, the division of assets follows formal ownership share in the case of housing, but couples can elect to assign mortgages to individual tax records in a different proportion. The majority of individuals assets on the tax records are divided equally because only a small minority of individuals actually pay wealth taxes. This is because the wealth tax is levied on the value of 'taxable wealth' which differs from market wealth because the tax code includes discounts on a number of assets (Thoresen et al. 2022). We use the discounted values that appear on individuals' tax records to reverse engineer the tax assessed market value of their wealth.

Similarly, for income tax records we observe taxable incomes, taxes paid, and benefits received at the individual level. We observe both total values and disaggregated values in broad categories. For instance, this allows us to observe employee income separately from self-employed income, interest income, or dividend income. We construct indicators for receiving a type of income or benefit by assigning the value of 1 to all individuals reporting a positive flow in that year and a value of 0 otherwise.

The majority of the information in these tax records is third-party reported. For example, employers report employee income directly to the tax authority and, similarly, financial institutions (banks, brokers, the Norwegian Central Securities Depository–VPS, etc.) report the value of assets held in their accounts. This greatly reduces concerns of measurement error (e.g., recall bias) or misreporting. However, some components of the tax return are not reported by third parties. These include foreign income or dividends not registered in the VPS and the values of some other assets—including foreign assets and valuables including art, paintings, and jewelry.[43] Individuals are responsible for disclosing the values of these incomes and assets. They are required to substantiate reported valuations (or deductions) which are checked by the tax authority (see Hebous et al. 2023 for a discussion of the Norwegian Tax Authority auditing process). In addition, the tax authority has automated control routines that flag tax returns with extreme movements in either income or wealth (which may indicate large evasion), and the tax authority checks these returns in more detail. This eliminates measurement error from self-reporting and censoring that is common in household surveys.[44]

Housing wealth database. The Norwegian tax authority directly estimates the market value of housing using a procedure that updates original transaction prices for houses

[43] We include these last two wealth components when constructing the market value of wealth. However, when we disaggregated wealth and discuss portfolio components we do not report results for these categories. This is for two reasons. First, they are only important for a small share of individuals and, second, because are self reported and hard to value we view them as less reliable when disaggregated. As we discuss in the main text, the nature of our rank measure minimizes the impact of these concerns.

[44] Measurement error from censoring and misreporting has a limited effect on mean estimates, but represents an important challenge for the study of dynamics of individual observations, typically attenuating persistence measures. In the income dynamics literature this has lead to the popularity of errors in variables estimators.

that are not transacted. As Fagereng, Holm, and Torstensen (2020) discuss, this can lead to systematic measurement error in the valuation of housing wealth. We use an updated version of the correction series reported in Fagereng, Holm, and Torstensen (2020) for the period 1993 to 2017 provided by the authors to adjust the value of housing.[45] The imputation procedure applies a different correction to owner-occupied housing, secondary housing, and cabins (holiday homes). Finally, we allocate the fraction of the house owned by an individual to their wealth. We aggregate primary and secondary residences with leisure properties, and foreign residences into a property-asset class. We define home ownership excluding secondary and foreign properties.

Inheritance tax records. Information about inheritances and inter-vivos gifts as derived from Inheritance tax records 1995-2013. The inheritance tax in Norway was abolished in 2014. The tax registry reports gifts and inheritances above 10,000 NOK between 1993 and 1996 and above 100,000 NOK after 1996. Absent the tax relevance of this information the values are not subject to verification and the number of individuals reporting gifts or inheritances is severely reduced after 2014.

Central population register and Norwegian educational database. This is an annual national register available since 1964. It contains anonymized identification numbers, residence, marital status, highest completed education, and field of study. We link individuals to spouses, children to parents, and calculate educational attainment. We use this register in our sample selection to construct an individual's migration history.

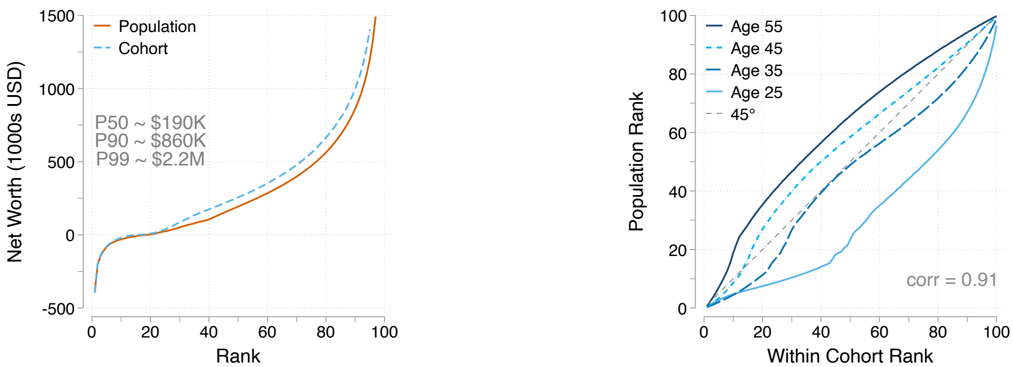
We have detailed information on individual education levels and fields of study, according to the Norwegian Standard Classification of Education (NUS2000).[46] This classification provides nine levels of education, ranging from no education to post-graduate PhD level, as well as 350 fields of study. The 9 levels of education corresponding to the NUS 1 digit categories are: No education or preschool education; Primary education; Lower secondary education; Upper secondary basic education; Upper education final year education; Post-secondary but non-tertiary education; Undergraduate degree; Graduate degree up to PhD(c); Post-graduate level (PhD). We aggregate the fields of study at the NUS 3 digit level into six groups: Humanities; Economics, Business, Law and Management; Computer Science and Engineering; Natural Sciences; Medicine and Health Care; and Teaching. To construct our education levels We pool all post-graduate degrees that do not result in the award of a doctorate and, additionally, pool all education levels less than high school. Finally, we use the group "technical degree" for those additional levels of education that do not result in an undergraduate degree, but require additional study beyond high school.

[45] Fagereng, Holm, and Torstensen (2020) use an ensemble machine learning method on housing transaction data to produce their correction series. They show that this has considerable in- and out-of-sample performance improvements over comparable hedonic price regression based imputations.

[46] See https://www.ssb.no/en/klass/klassifikasjoner/36.

FIGURE A.1. Norwegian wealth distribution

(A) 2014 Distribution (B) Population vs within-cohort ranks



Notes: Panel A shows the inverse CDF of the 2014 wealth distribution for the entire population (solid-orange line) and the 1960–64 birth cohort (dashed-blue line) who are ages 50–54. Panel B shows average wealth rank in the Norwegian population of individuals in the 1960–64 birth cohort at different ages.

Household income and equivalization. To build household income, we construct households based on marriage and cohabitation using the complete population files; we assign to each individual in the 1960–64 birth cohort their household's income; and we equivalize using Organization for Economic Co-operation and Development's (OECD) equivalence scale based on the number of adults and children in the household. We also compute household wealth ranks, reported in Appendix E, and show that our main results are robust to using household wealth instead of individual wealth in Section 7.

A.1. Cohort wealth ranks vs population wealth ranks

Figure A.1A reports wealth by rank. Changes in ranks are associated with significant changes in wealth levels. For instance, moving from percentile 50 to 60 means going from 190,000 to 250,000 US dollars of net worth. The only part of the distribution in which rank changes do not translate into substantial movements in net worth is the narrow window around zero wealth (15^{th}–20^{th} percentile). Moreover, changes in rank reflect meaningful differences in wealth even at younger ages, as we show next.

The dispersion of wealth within our cohort of interest increases as the cohort ages. This means that the correspondence between wealth ranks and wealth levels changes over time. Figure A.1B visualizes this by plotting the correspondence between within-cohort ranks and population ranks at different ages. The correspondence between population wealth ranks and wealth levels is shown in Figure A.1A.

As expected, the distribution of wealth of the 1960–64 birth cohort is to the left of the population distribution for young ages and it moves to the right as the cohort ages. Nevertheless, it is clear that changes in within-cohort wealth ranks always correspond to meaningful changes in wealth levels, more so for later periods.

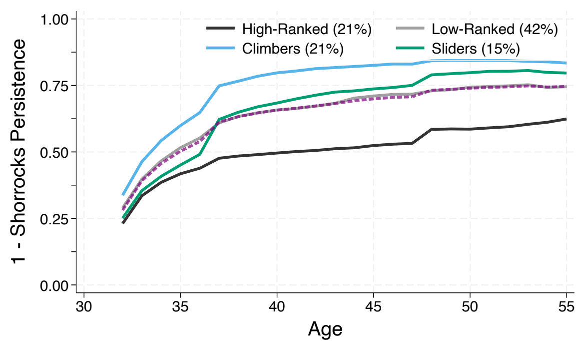
Appendix B. Additional results on wealth ranks and mobility

B.1. Decomposing alternative measures of wealth mobility

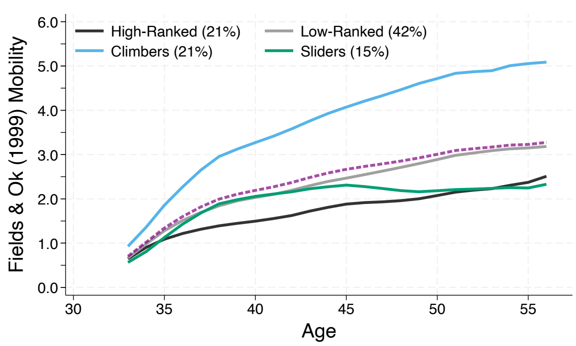
Figure B.1 replicates the exercise of Figure 3 for rank persistence for the Shorrocks (1978), Fields and Ok (1999), and Ray and Genicot (2023) mobility measures. The intragenerational mobility trends of all the groups follow the same qualitative pattern as in Figure 3. Climbers drive the increase in intra-generational wealth mobility, with other groups showing lower increases. For instance, in the case of Shorrocks (1978) measure, the high-ranked are almost twice as likely to remain in the same quintile they were in at age 30 by age 55 than other groups.

FIGURE B.1. Intragenerational wealth mobility across groups

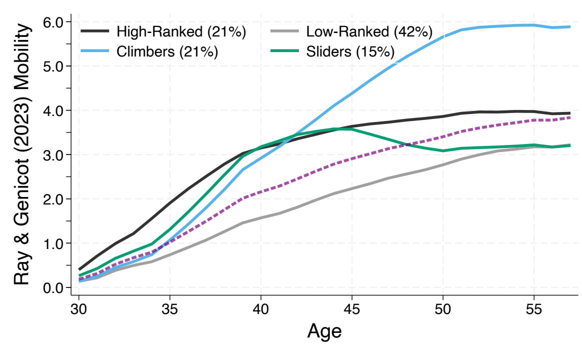
(A) Shorrocks (1978) mobility



(B) Fields & Ok (1999) mobility



(C) Ray & Genicot (2023) mobility

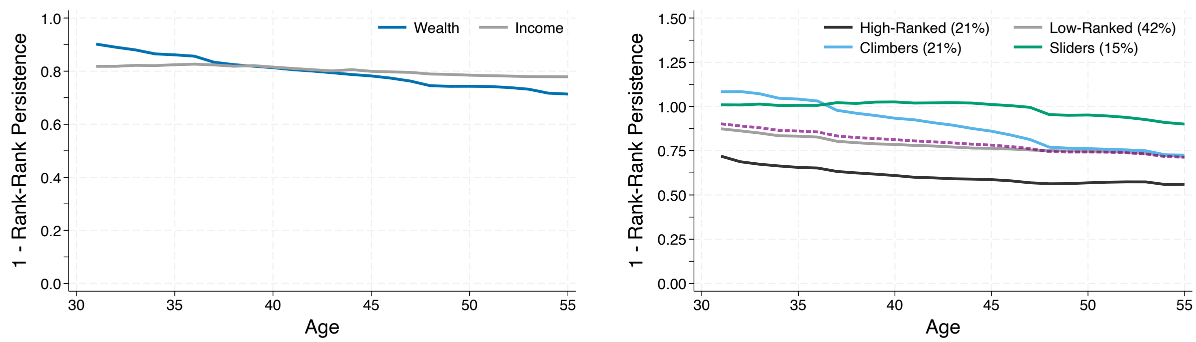


Notes: The figures present different measures of intragenerational wealth mobility for our four main groups. The pooled cohort-level persistence measure is shown in dashed lines. Panel A plots the Shorrocks (1978) index. Panel B plots the Fields and Ok (1999) mobility measures that corresponds to the per capita aggregate change in log-wealth or incomes. Panel C plots the Ray and Genicot (2023) mobility measure that corresponds to the growth in the Atkinson level of wealth or income.

FIGURE B.2. Intergenerational Rank Mobility

(A) 1960–1964 birth cohort

(B) Four main groups



Notes: Panel A shows the intergenerational rank-rank persistence coefficient in wealth and income for the whole cohort. Panel B plots the intergenerational rank-rank wealth coefficient for the four main groups with the pooled cohort-level persistence measure shown with a dashed line.

B.2. Relationship to intergenerational mobility

We document a trend of *declining intergenerational mobility* over the life cycle, which mirrors the increasing trend of intragenerational mobility in Section 3. We measure intergenerational mobility as the correlation between individuals' wealth rank at each age and their parents' rank in 1993, when they were 55 years old on average. Panel A of Figure B.2 shows the estimates for the entire cohort. For comparison, we also report similar estimates for the intergenerational mobility of income ranks.

Intergenerational wealth mobility decreases with age, with intergenerational rank persistence increasing from 0.10 to 0.25, while income mobility remains the same as the cohort grows older, at around 0.20.

Panel B of Figure B.2 shows that, despite significant level differences, the trend of declining intergenerational wealth mobility is common to all the main mobility groups. The high-ranked are the least mobile group (the correlation with their parents' ranks increases from 0.30 to 0.45). At the other end, the sliders exhibit a much lower correlation with their parents' wealth rank throughout their lifetime (ranging from 0.00 to 0.10). Notably, the climbers exhibit increasingly more intergenerational wealth persistence as they age (correlation going up to 0.25 starting from -0.10), which suggests it is more accurate to measure wealth ranks at the end of individuals' careers since some of the correlation with their parents' wealth materializes at that stage. Overall, these results are consistent with the role of parental wealth for individuals' intragenerational wealth mobility documented in Figure 6A.[47]

[47] Interestingly, although the increase in intergenerational wealth persistence is largest for the group rising through the wealth distribution, parental wealth is not a first-order determinant for this group once we control for education. This suggests that, for them, the role of parental wealth is mediated by investments in human capital.

Appendix C. Additional results on clustering

R^2 measures for partitions. We operationalize our choice of the number of groups, G, using the R^2 measure, the share of the variation in trajectories explained by the cluster average (or typical) trajectory. For a partition $\mathcal{G}_G = \{g_i\}_{i=1}^N$, this measure is

$$R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t} - \bar{r}_t^{g(i)}\right)^2}{\sum_{i,t}\left(r_{i,t} - \bar{r}\right)^2}, \tag{C.1}$$

where $r_{i,t}$ is the rank of individual i at time t, $\bar{r}_t^{g(i)}$ is the average rank for the individual i's group, and $\bar{y}$ is the average rank of individuals in the (balanced) sample.

Figure C.1A presents the R^2 for the partitions produced by our hierarchical clustering algorithm for $G = 1, \ldots, 40$. With $G = 4$, we capture 50 percent of the variation in rank trajectories, while keeping the exercise parsimonious. Going up to $G = 14$ groups (the thinnest level of granularity shown in Figure C.1B) only increases the R^2 to 65 percent.

Sub-groups. The nested nature of our clustering algorithm allows us to transparently illustrate how our choice of $G = 4$ groups affects our findings. The hierarchy of groups is summarized by the dendrogram in Figure C.1B. Each of the small branches at the bottom represents smaller groups obtained at the step $G = 14$. The tree shows how they are recursively agglomerated by the procedure into a single cluster ($G = 1$). We highlight in different colors the four baseline groups that we select. We can then directly assess how sensitive these groups are to alternative values of G. For instance, $G = 5$ splits group 4 in two, while $G = 3$ would merge groups 1 and 2. It is therefore straightforward to see which groups are closest through the lens of the procedure. We study the wealth trajectories of the main subgroups of our baseline groups in Appendix F.

Between and within R^2. The R^2 defined in (C.1) is a function of the variation between groups, captured by the *between* R^2, and within groups, captured by the *within* R^2.

$$R^2_{between} = 1 - \frac{\sum_i(\tilde{r}_i - \bar{\tilde{r}}^{g(i)})^2}{\sum_i(\tilde{r}_i - \bar{\tilde{r}}_i)^2} \qquad \text{between } R^2 \tag{C.2}$$

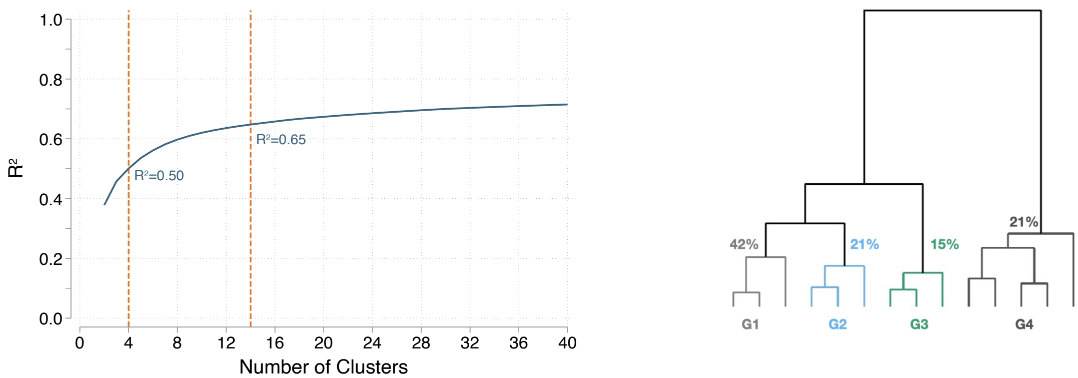
$$R^2_{within} = 1 - \frac{\sum_i\sum_t((r_{i,t} - \tilde{r}_i) - (\bar{r}_t^{g(i)} - \bar{\tilde{r}}^{g(i)}))^2}{\sum_i\sum_t((r_{i,t} - \tilde{r}_i) - (\bar{r} - \bar{\tilde{r}}_i))^2} \qquad \text{within } R^2 \tag{C.3}$$

The between R^2 captures how dissimilar the typical trajectories are across groups, an indicator of whether the groups are meaningfully different. It measures the share of the cross-sectional variation in ranks (having averaged over the longitudinal dimension of the panel) explained by the clusters' typical trajectories. For this define $\tilde{r}_i = \sum_t r_{i,t}/T$ as the within person average rank, $\bar{\tilde{r}}_i$ its average across individuals, and $\bar{\tilde{r}}_i^{g(i)}$ its average

FIGURE C.1. Choice of number of groups

(A) Share of total variation explained

(B) Dendrogram



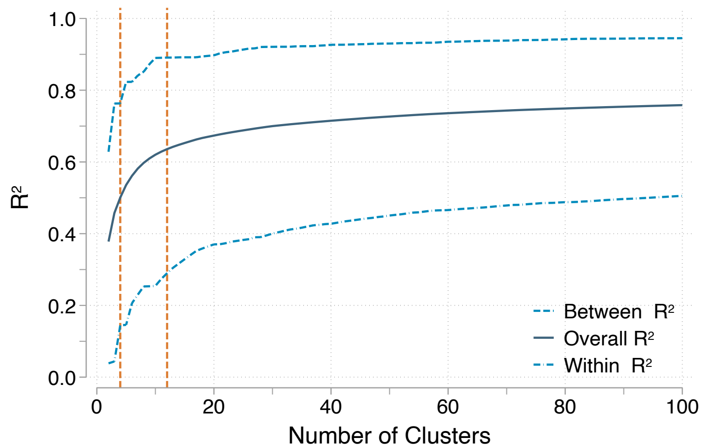
Notes: Panel A shows the share of the variation explained as the number of cluster increases. Panel B presents the dendrogram of the hierarchical agglomerative clustering procedure as executed on the balanced sample for the 1960–64 birth cohort. The dendrogram shows the tree of clusters up to a hierarchy of $G = 14$ groups. The tree shows how groups are merged as the clustering procedure recursively reduces the number of groups.

for cluster $g(i)$. The between R^2 for $G = 4$ groups is close to 80 percent.

The within R^2 measures within-group heterogeneity. It gives the share of the variation in ranks along the longitudinal dimension of the panel explained by the clusters' typical trajectories. For this define the deviation of an individual's rank in time t relative to the own average rank as $r_{i,t} - \tilde{r}_i$ and contrast it with the population wide average deviation in ranks $\bar{r} - \bar{\bar{r}}_i$. This gives the total *within* variation. The cluster's deviation, $\bar{r}_t^{g(i)} - \bar{\bar{r}}^{g(i)}$, where $\bar{r}_t^{g(i)}$ is the cross-sectional average of ranks for cluster $g(i)$ in time t and $\bar{\bar{r}}^{g(i)}$ is its average over time, measures the explained within variation produced by the clusters' typical trajectories. The within R^2 for $G = 4$ groups is close to 15 percent, but it more than doubles for $G = 14$ groups.

Figure C.2 presents the three R^2 measures for the largest 100 clusters. With 100 clusters it is possible (but not optimal) to group individuals based on their initial (or final) wealth rank and trace their trajectories. Most of the increase in explanatory power takes place with the first 20 clusters. As expected, the vast amount of variation in the data is hard to capture, reflected by the lower value of the within R^2, even when clusters increase. In contrast to this, the between R^2 reaches 0.8 with 4 clusters and close to 0.9 with 14, showing that the wealth trajectories of our main groups are significantly different and capture most of the overall variation in wealth mobility.

FIGURE C.2. R^2 Measures, up to 100 clusters



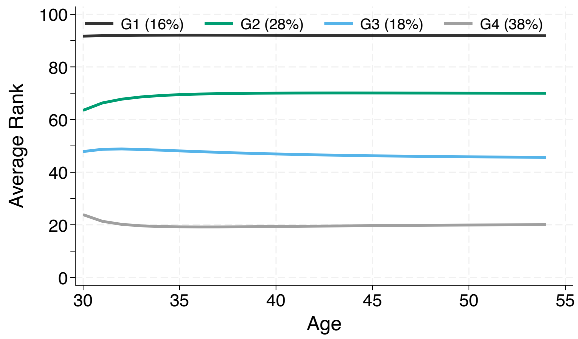
Notes: The figure plots R^2 measures of partitions induced by agglomerative hierarchical clustering algorithm for $G = 1, \ldots, 100$ groups. The overall R^2, defined in equation (C.1), and also presented in Figure C.1A. The between R^2, defined in equation (C.2), captures the share of variation across clusters. The within R^2, defined in equation (C.3), captures the average share of variation within each clusters.

Appendix D. Interpreting mobility groups: Additional results

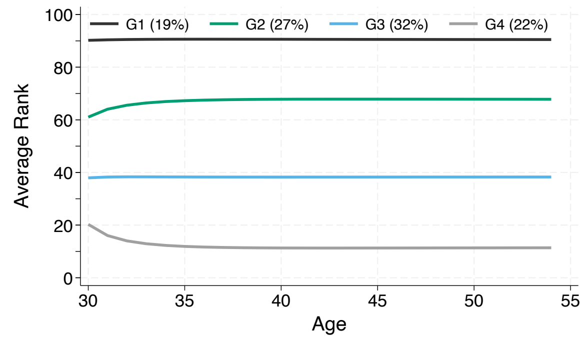
Figures D.1 and D.2 report additional exercises simulating the wealth accumulation model in (4) under different configurations of parameters. Exercises in Figure D.1 have homogeneous returns and saving rates. Exercises in Figure D.2 have both return and saving rate heterogeneity. In Panel A we consider return heterogeneity with no correlation between initial conditions (or between returns and initial conditions). The figure presents a crossing pattern that aligns with that in our data, but additional simulations show that this is not a robust feature of the model with no correlation in initial conditions. The remaining panels of Figure D.2 add heterogeneity in saving rates.

Figure D.1. Typical Rank Trajectories Across Simulations: Additional Results I

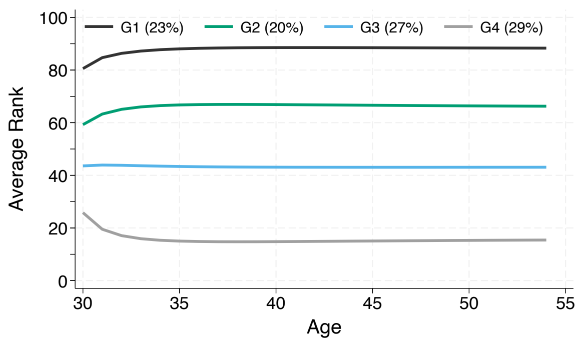
(A) Baseline Parameterization



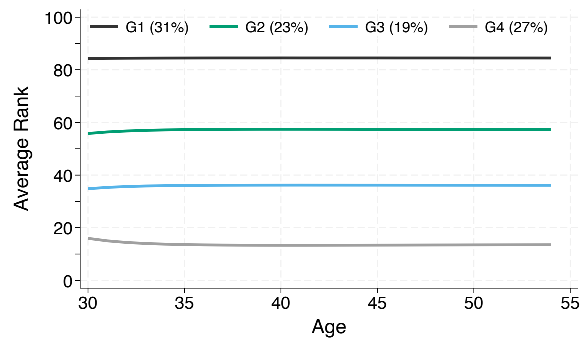
(B) Higher Returns: $\bar{r} = 0.05$



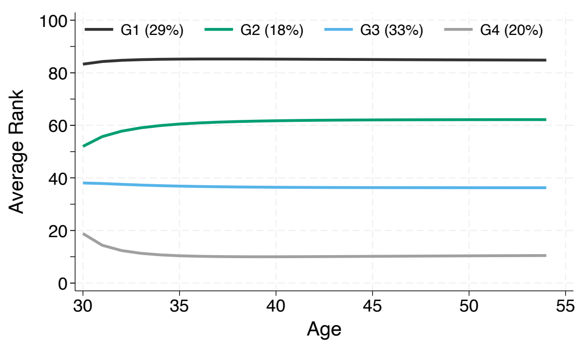
(C) Higher Savings Rate: $\bar{s} = 0.50$



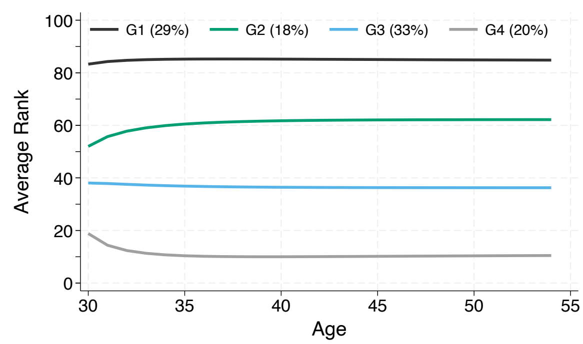
(D) Lower Savings Rate: $\bar{s} = 0.07$



(E) Lower Income Persistence: $\rho = 0.70\%$



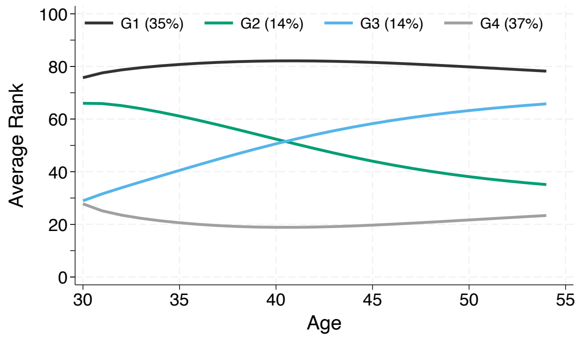
(F) Higher Income Persistence: $\rho = 0.99\%$



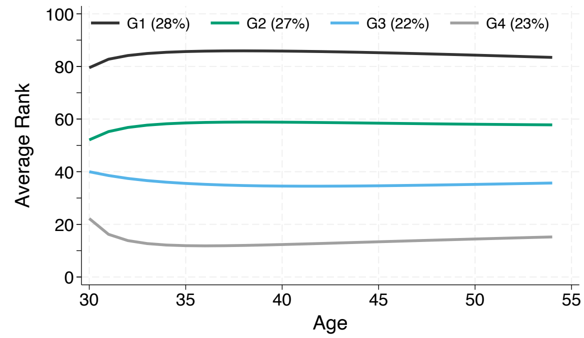
Notes: Clustering under different simulations with single deviations from the baseline parameterization defined in the figure titles. Baseline parameterization has an rate of return $\bar{r} = 0.035$, savings rate $s = 0.25$, income persistence $\rho = 0.937$, income standard deviation $SD(\epsilon_{it}^{y}) = 0.024$, and no dispersion in returns or saving rates.

FIGURE D.2. Typical Rank Trajectories Across Simulations: Additional Results II

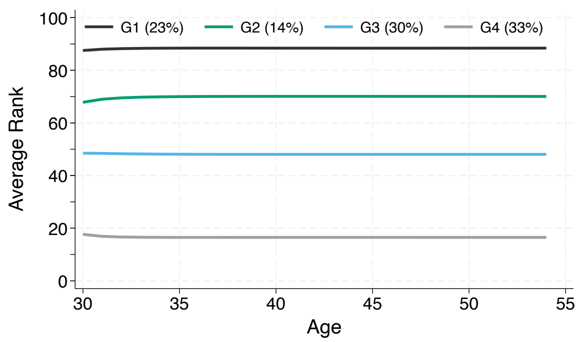
(A) Return Heterogeneity and $corr(w_{i,0}, s_i) = corr(w_{i,0}, r_i) = 0$



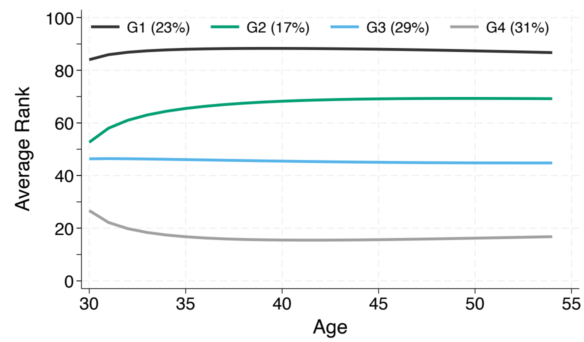
(B) Savings and Return Heterogeneity with $corr(s_i, r_i) > 0$, $corr(w_{i,0}, s_i) = corr(w_{i,0}, r_i) = 0$



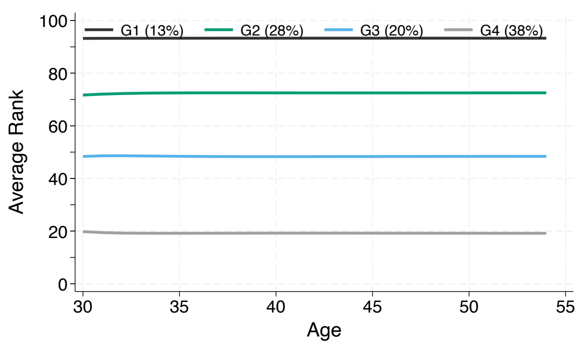
(C) Savings and Return Heterogeneity and $corr(s_i, r_i), corr(w_{i,0}, s_i), corr(w_{i,0}, r_i) > 0$



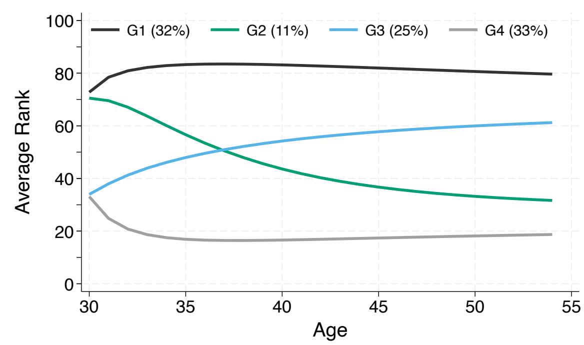
(D) Savings and Return Heterogeneity and $corr(s_i, r_i), corr(y_{i,0}, w_{i,0}) > 0$



(E) Heterogeneity with $corr(y_{i,0}, w_{i,0}) < 0$ and $corr(w_{i,0}, s_i), corr(w_{i,0}, r_i) > 0$



(F) Heterogeneity with $corr(y_{i,0}, w_{i,0}) < 0$ and $corr(w_{i,0}, s_i), corr(w_{i,0}, r_i) = 0$ and $corr(s_i, r_i) > 0$



Notes: Clustering under different simulations with single deviations from the baseline parameterization defined in the figure titles. Baseline parameterization has an rate of return $\bar{r} = 0.035\%$, savings rate $\bar{s} = 0.25$, income persistence $\rho = 0.937$, income standard deviation $SD(\epsilon^y_{it}) = 0.024$, and no dispersion in returns or saving rates. Exercises with return heterogeneity have $SD(r) = 0.055$ and exercises with saving rate heterogeneity have $SD(s) = 0.20$.

D.1. Buffer-Stock models of wealth accumulation

We consider a common class of life-cycle buffer-stock savings models under homotheticity. These models are a useful benchmark as they are extensively used in applications studying joint income, consumption and saving dynamics (e.g., Zeldes 1989, Deaton 1991, Carroll 1992, and the large literature that followed them). They also imply a tight and testable link between income and wealth mobility that elucidates the role of heterogeneity in saving rates and returns. Precautionary savings are not enough to generate the mobility patterns we observe in the data.

In this class of models, finitely-lived agents choose how much to consume and save each period, earn a constant (and homogeneous) return on savings, r, and receive exogenous labor income that depends on a permanent component I (e.g., skill heterogeneity) and idiosyncratic shocks z. We assume that income is log-separable in its permanent and transitory components, so that total income is $I \cdot y_t(z)$, where $\ln y_t(z) = \alpha_t + \beta_t \ln z$, captures how efficiency units of labor reflect the value of z at age t, and the coefficients capture age-dependent non-linearity. . This assumption agrees with a wide range of approaches to modeling permanent income heterogeneity separating permanent traits (like education) from the dynamics of income (see, among others, Storesletten, Telmer, and Yaron 2004; Low and Pistaferri 2015; Guvenen, Karahan, Ozkan, and Song 2021). We consider differences in returns later on.

This setup implies that income profiles are, by construction, ordered by permanent income (skill). Thus, there is no mobility in income between groups, as the relative positions of individuals reflect differences in their permanent income components. This is consistent with our data, see Figure E.3.

Under homotheticity in preferences, the properties of income are inherited by wealth and consumption, in a way that hierarchical clustering can recover. So, in the absence of other sources of heterogeneity, we should recover a pattern of no wealth mobility, with wealth groups corresponding to income groups. This is clearly not the case in our data,[48] as is clear when comparing wealth mobility groups in Figure 2A and income groups in Figure E.3—rejecting the simple buffer-stock model.

We make the argument precise in the following proposition. The proof relies on Straub (2019), who proves that both policy functions and distributions over state variables are homothetic and extends this to a setting with endogenous factor prices and the receipt of bequests in an overlapping generations economy.

PROPOSITION A1 (**Income and wealth trajectories in the buffer-stock model**). *Suppose agents with permanent income component, I, choose policy functions $c_t(a, I, z)$ and $a_{t+1}(a, I, z)$ to maximize utility from consumption, $u(\cdot)$, and bequests, $\upsilon(\cdot)$, in the following program*

$$\max_{\{c_t, a_{t+1}\}} \mathbb{E}_0 \left[\sum_{t=0}^{T} \beta^t S_t \left(u(c_t) + \frac{S_{t+1}}{S_t} \upsilon(a_{t+1}) \right) \right] \tag{D.1}$$
$$\text{s.t.} \quad c_t + a_{t+1} = (1+r)\, a_t + I\, y_t(z_t)\,; \quad a_{t+1} \geq 0; \quad a_0 = 0;$$

[48] Further, the fact that risers and fallers have the same level of total (financial plus human) wealth until age 45 poses an additional challenge for explanations based solely on non-homotheticity in preferences.

where z is the agent's idiosyncratic income shock that follows a Markov chain, $z_t \in \mathcal{Z}$, with age-dependent transition probabilities $\Pi_{zz'}(t)$ from state z to state z', and S_t is the probability of survival until age t. If $u(\cdot)$ and $\upsilon(\cdot)$ are homothetic with the same constant elasticity, then policy functions are also homothetic, so that

$$c_t\,(a, I, z) = I \times c_t\left(\frac{a}{I}, 1, z\right) \quad \textit{and} \quad a_{t+1}\,(a, I, z) = I \times a_{t+1}\left(\frac{a}{I}, 1, z\right) \quad \forall a \textit{ and } \forall z \in \mathcal{Z}. \tag{D.2}$$

Therefore, wealth and consumption profiles are ordered in logs and ranks by permanent income.

Remarks. *(i) We allow for arbitrary concavity in the consumption function and do not require linearity of household decisions. (ii) This result extends to richer frameworks as long as cross-group differences are meaningful, in the sense that differences in average outcomes between groups are larger than the variance of outcomes within groups.*[49] *(iii) If the model were the data generating process, hierarchical agglomerative clustering is an asymptotically consistent classifier partitioning by permanent skill differences, $I = 1, \ldots G$, when clustering on wealth, income, or consumption (in ranks or logs), see Egashira, Yata, and Aoshima (2024).*

Proof. The model we present satisfies Assumptions (1)-(3) in Straub (2019). With these, Lemma 1 in Straub gives the fact that log-wealth age profiles are parallel and shifted by permanent income I.[50] Formally, Lemma 1 in Straub directly implies $F(a \,|\, t, I) = F(a \times \frac{I'}{I} \,|\, t, I')$, where $F(a \,|\, t, I)$ denotes the distribution of wealth (a) at age t for permanent income group I. We can further normalize $I = 1$ because the age-income profile can always be shifted by a constant, and therefore $F(a \,|\, t, 1) = F(a \times I \,|\, t, I)$.

Average wealth in permanent income group I is then

$$E[a \,|\, t, I] \; = \int_0^{\bar{a}(t,I)} a\; f(a \,|\, t, I) da \; = \int_0^{\bar{a}(t,I)/I} [\tilde{a} \times I]\; [f(\tilde{a} \times I \,|\, t, I) \times I] d\tilde{a} \; = I \times E[a \,|\, t, 1], \tag{D.3}$$

where the second line uses the change of variable $a = \tilde{a} \times I$ and the third line uses $f(a \,|\, t, 1) = f(a \times I \,|\, t, I)I$. The notation $\bar{a}(t, I)$ denotes the upper bound of the wealth distribution for age t and permanent income group I.

Let $p_I(t) = \lim_{a \downarrow 0} F(a|t, I)$ denote the mass point associated with the binding borrowing constraint. It follows that this mass point is the same size for all permanent income groups, $p_I(t) = p_{I'}(t) = p(t)$, so that the borrowing constraint binds for the same fraction of individuals in each permanent income group.

Then, for all $t > 0$ and $a > 0$,

$$F(a \,|\, t, 1, a > 0) = \frac{F(a \,|\, t, 1)}{1 - p(t)} = \frac{F(a \frac{I'}{1} \,|\, t, I')}{1 - p(t)} \longrightarrow H(\ln a \,|\, t, 1) = H(\ln a + \ln I' \,|\, t, I'), \tag{D.4}$$

[49] For example, when classifying on income with group-specific income risk, it must be that this risk is smaller than average differences in permanent income. See Meghir and Pistaferri (2011) for examples of this case, and Gourinchas and Parker (2002) and Meghir and Pistaferri (2004), who find that variability in residualized income is smaller than Mincer differences by education.

[50] Like Straub, we require an additional uniqueness assumption ruling out degenerate income risk.

where $H(\cdot)$ denotes the distribution of log wealth and h its corresponding density.

Average log-wealth in permanent income group I can then be written

$$E[\ln a \,|\, t, I] = \int \ln a \; h(\ln a|t, I) \; d\ln a \;=\; \int \ln a' \; h(\ln a' + \ln I|t, I) \; d\ln a' \;+\; \ln I$$
$$= E[\ln a'|t, 1] \;+\; \ln I, \tag{D.5}$$

where the third equality uses the change of variable $\ln a = \ln a' + \ln I$ and the final step uses the equality in D.4. Then, for any two values of skill heterogeneity, and any t,

$$E[\ln a \,|\, t, I] - E[\ln a \,|\, t, I'] = \ln I - \ln I', \tag{D.6}$$

implying parallel wealth profiles. The same steps apply for consumption. □

COROLLARY A1 (**Ordered expected ranks**). *The income and wealth ranks of each permanent income group are also ordered, that is,*

$$E_t[rank_{i,t} \,|\, I^{'}] < E_t[rank_{i,t} \,|\, I] \; \forall t, I^{'} < I, \tag{D.7}$$

where $rank_{i,t}$ corresponds to the income or wealth rank of individual i at age t.

PROOF. Without loss of generality, we set $I^{'} = 1$. We show here that the inequality above holds for wealth ranks. The result for income ranks is immediate because income is homogeneous of degree 1 in I and, thus, so is the *distribution* of income.

Let $Q_t(a) = F^{-1}(a|t)$ denote the population quantile function, so that $\text{rank}_{i,t} = Q_t(a_i)$. This is a monotonic function in a for all values of t. There is no conditioning on permanent income group. Additionally, Let X and Y be random variables that correspond to the wealth of individuals in permanent income groups $I^{'}$ and I, respectively. It is from the ordering of these distributions that we derive the order for the expected rank across groups. The distribution function of X is $F_X(a) = F(a|t, I^{'})$ and the distribution of Y is $F_Y(a) = F(a|t, I) = F(a|t, 1)$. It follows from Lemma 1 in Straub (2019) (scaling of distributions) and from the fact that $I > 1$ that

$$F_X\,(a) \;=\; F_Y\left(\frac{a}{I}\right) \;\longrightarrow\; F_X(a) \;<\; F_Y(a) \;\forall a, \tag{D.8}$$

therefore X (with higher permanent income) dominates Y in the usual stochastic order.

Expected group ranks then satisfy

$$E_t[rank_{i,t} \,|\, I^{'}] \;=\; E_t[Q_t(X)] \;<\; E_t[Q_t(Y)] \;=\; E_t[rank_{i,t} \,|\, I], \tag{D.9}$$

where we use the fact that X and Y have the distributions defined above. This inequality follows immediately from stochastic dominance and Q being an increasing function. □

D.2. Portfolio choice models and return heterogeneity

We now highlight the role of persistent differences in returns in driving wealth accumulation and mobility patterns. We show, in a standard life cycle problem with portfolio choice and endogenous saving, that high-return individuals who start from relatively low wealth can overtake low-return individuals who start life wealthier. Individuals have access to two assets, a risk-free bond, b, that pays gross returns R_f, and a risky asset, x, with stochastic returns, R. Crucially, individuals differ (permanently) in income, that follows a deterministic path and depends on a permanent factor I_Y, $Y_t(I_Y)$, and in the distribution of returns they face determined by a factor I_R,

$$R = I_R \times r \quad \text{and} \quad R_f = I_R \times r_f \,, \tag{D.10}$$

with r_f fixed and r an iid random variable. The permanent component of returns affects risky and risk-free returns alike, in line with the findings of Fagereng et al. (2020) who report persistent and meaningful differences even among the returns to risk-free assets, such as bank deposits.

Individuals choose consumption and portfolio allocations to maximize

$$\begin{aligned} &\max_{\{c_t, b_{t+1}, x_{t+1}\}} \mathbb{E}_0 \left[\sum_{t=0}^{T} \beta^t u(c_t) + \upsilon(a_{T+1}) \right] \\ &\text{s.t.} \quad c_t + b_{t+1} + x_{t+1} = a_t + Y_t \,; \quad a_{t+1} = R_f b_{t+1} + R_{t+1} x_{t+1} \,; \end{aligned} \tag{D.11}$$

where we abstract from mortality risk for the sake of tractability and assume, as in Appendix D.1, that $u(\cdot)$ and $\upsilon(\cdot)$ are homothetic with the same constant elasticity $\gamma \geq 1$; $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ and $\upsilon(a) = \Upsilon \frac{a^{1-\gamma}}{1-\gamma}$. We show the growth rate of total (financial plus human) wealth, $W_t \equiv R_t a_t + Y_t + H_t$, is independent of income and increasing in returns, where (future) human wealth is

$$H_t = \sum_{h=1}^{T-t} \frac{Y_{t+h}}{R_f^h} = \frac{1}{R_f} \left(Y_{t+1} + H_{t+1} \right) \,, \tag{D.12}$$

PROPOSITION A2. *The growth rate of total (financial plus human) wealth, W_t, depends on permanent attributes I_Y and I_R only through their effects on returns. Moreover, the expected growth rate of total wealth is increasing in the permanent component of returns at all ages,*

$$\frac{\partial \log E\left[\frac{W_{t+1}}{W_t}\right]}{\partial \ln I_R} \geq 0 \,, \tag{D.13}$$

if the bequest-motive parameter satisfies

$$\Upsilon \leq \left(1 - \left(\beta E_{R'}\left[\left(R_f + \rho^\star\left(R' - R_f\right)\right)^{1-\gamma}\right]\right)^{\frac{1}{\gamma}}\right)^{-\gamma}, \tag{D.14}$$

where $\rho^\star = \text{argmax}\, E_{R'}\left[\frac{\left(R_f+\rho^\star\left(R'-R_f\right)\right)^{1-\gamma}}{1-\gamma}\right]$, *so that the savings rate out of* W_T *satisfies*

$$s_T \leq \left(\beta E_{R'}\left[\left(R_f + \rho^\star\left(R' - R_f\right)\right)^{1-\gamma}\right]\right)^{\frac{1}{\gamma}} \leq 1\,. \tag{D.15}$$

COROLLARY A2. *When initial wealth is homogenous within permanent income groups ($a_{0,i}(I_{Y,i}) = \bar{a}_0(I_Y)$), differences in permanent income (I_Y) induce permanent differences in the consumption and total wealth profile. As in Proposition A1, permanent income does not produce differences in consumption or wealth growth rates.*

Restricting the bequest motive ensures that the effect of an increase in returns on consumption (and savings) is strongest at younger ages. An increase in permanent returns increases average returns at all ages (recall that the intertemporal elasticity of substitution $1/\gamma < 1$), and its effect is strongest at younger ages (unless the bequest motive is too strong). This ensures that wealth grows faster when returns are higher.

PROOF. We first establish the recursive solution of the problem (D.11). The steps are standard from finite-horizon dynamic programming and we omit them for space.

The solution to the life cycle problem in (D.11) consists of saving a fraction $s_t(R)$ of total wealth, $c_t\,(a, R) = (1 - s_t\,(R))\,W$, and investing a fraction of savings $\rho_t(R)$ into risky assets, such that $x_t(a, R) = \rho_t(R)s_t(R)W$, where

$$\rho_t(R) = \rho^\star = \underset{\{\rho\}}{\text{argmax}}\; \mathbb{E}_{R'}\left[\frac{\left(R_f + \rho\left(R' - R_f\right)\right)^{1-\gamma}}{1-\gamma}\right]. \tag{D.16}$$

Moreover, saving rates are independent of the realization returns and satisfy the following recursive condition

$$(1 - s_t)^{-1} = 1 + \left(\beta\,(1-\gamma)\,\mathbb{E}_{R'}\left[\frac{\left(R_f + \rho^\star\left(R' - R_f\right)\right)^{1-\gamma}}{1-\gamma}\right]\right)^{\frac{1}{\gamma}}(1 - s_{t+1})^{-1}\,. \tag{D.17}$$

Now, we show that expected growth rate of (total) wealth is increasing in (the permanent component of) returns.

$$\frac{\partial \log E\left[\frac{W_{t+1}}{W_t}\right]}{\partial \log I_R} = \frac{\partial \log E\left[\left(R_f + \rho^\star\left(R - R_f\right)\right)\right]}{\partial \log I_R} + \frac{\partial \log s_t}{\partial \log I_R} = 1 + \frac{\partial \log s_t}{\partial \log I_R} \geq 0; . \tag{D.18}$$

We can use the recursive formula in (D.17) to obtain

$$\frac{\partial \log s_t}{\partial \log I_R} = \frac{1}{\gamma}\frac{\partial \log (1-\gamma)\,\Gamma^\star}{\partial \log I_R} - \frac{\partial \log (1-s_{t+1})}{\partial \log I_R} + \frac{\partial \log (1-s_t)}{\partial \log I_R}; \tag{D.19}$$

where

$$(1-\gamma)\,\Gamma^\star \equiv \mathbb{E}_{R'}\left[\left(R_f + \rho^\star\left(R' - R_f\right)\right)^{1-\gamma}\right]. \tag{D.20}$$

From (D.20) we know that $\frac{\partial \log(1-\gamma)\Gamma^\star}{\partial \log I_R} = 1-\gamma$. So, the condition we want reduces to

$$\frac{\partial \log E\left[\frac{W_{t+1}}{W_t}\right]}{\partial \log I_R} = \frac{1}{\gamma} - \frac{\partial \log (1-s_{t+1})}{\partial \log I_R} + \frac{\partial \log (1-s_t)}{\partial \log I_R}; . \tag{D.21}$$

A sufficient condition for this to hold is that the increase in the propensity to consume out of W is stronger for younger ages (lower t)

$$0 \leq \frac{\partial \log (1-s_{t+1})}{\partial \log I_R} \leq \frac{\partial \log (1-s_t)}{\partial \log I_R}. \tag{D.22}$$

Once again, from (D.17) get

$$\frac{\partial \log (1-s_t)}{\partial \log I_R} = s_t\left(\left(1-\frac{1}{\gamma}\right) + \frac{\partial \log (1 - s_{t+1})}{\partial \log I_R}\right). \tag{D.23}$$

In the terminal age T this elasticity is

$$\frac{\partial \log (1-s_T)}{\partial \log I_R} = s_T\left(1-\frac{1}{\gamma}\right) \geq 0 \tag{D.24}$$

Replacing on (D.22),

$$(1-s_{t+1})^{-1}\left(\beta\,(1-\gamma)\,\Gamma^\star\right)^{\frac{1}{\gamma}}\left(1-\frac{1}{\gamma}\right) > \frac{\partial \log (1-s_{t+1})}{\partial \log I_R}. \tag{D.25}$$

We verify (D.25) by induction. First for a given age t under the induction hypothesis that the condition holds in the future, then verifying it directly in the terminal age T.

For a given age t we have from (D.25)

$$\left(1 + \left(\beta\left(1-\gamma\right)\Gamma^{\star}\right)^{\frac{1}{\gamma}}\left(1-s_{t+2}\right)^{-1}\right)\left(\beta\left(1-\gamma\right)\Gamma^{\star}\right)^{\frac{1}{\gamma}}\left(1-\frac{1}{\gamma}\right) > s_{t+1}\left(\left(1-\frac{1}{\gamma}\right)+\frac{\partial\log\left(1-s_{t+2}\right)}{\partial\log I_R}\right) \tag{D.26}$$

we can express this in terms of $t+2$ variables only by using (D.25) to replace for s_{t+1},

$$\left(1 + \left(1-s_{t+2}\right)^{-1}\left(\beta\left(1-\gamma\right)\Gamma^{\star}\right)^{\frac{1}{\gamma}}\right)^2 > \left(1-s_{t+2}\right)^{-1} + \left(1-s_{t+2}\right)^{-1}\frac{\frac{\partial\log(1-s_{t+2})}{\partial\log I_R}}{1-\frac{1}{\gamma}} \tag{D.27}$$

This expression is useful because we take as given (by induction) that

$$\left(1-s_{t+2}\right)^{-1}\left(\beta\left(1-\gamma\right)\Gamma^{\star}\right)^{\frac{1}{\gamma}}\left(1-\frac{1}{\gamma}\right) > \frac{\partial\log\left(1-s_{t+2}\right)}{\partial\log I_R} \tag{D.28}$$

and so it is sufficient to prove that

$$1 + \left(1-s_{t+2}\right)^{-1}\left(\beta\left(1-\gamma\right)\Gamma^{\star}\right)^{\frac{1}{\gamma}} > \left(1-s_{t+2}\right)^{-1} . \tag{D.29}$$

Conveniently, this condition is satisfied if and only if it is satisfied in the future, that is, if it also holds for $t+3$ and so on (this is immediate after some manipulation and using D.17 to replace s_{t+2} in terms of s_{t+3}). And so, to verify (D.25) in period t we only need to verify (D.29) in T. This holds if and only if

$$\left(\beta\left(1-\gamma\right)\Gamma^{\star}\right)^{\frac{1}{\gamma}} > s_T \tag{D.30}$$

This condition gives the upper bound on Υ in (D.14). Finally, we verify (D.25) for $t = T$,

$$\left(1-s_T\right)^{-1}\left(\beta\left(1-\gamma\right)\Gamma^{\star}\right)^{\frac{1}{\gamma}}\left(1-\frac{1}{\gamma}\right) > \frac{\partial\log\left(1-s_T\right)}{\partial\log I_R} \tag{D.31}$$

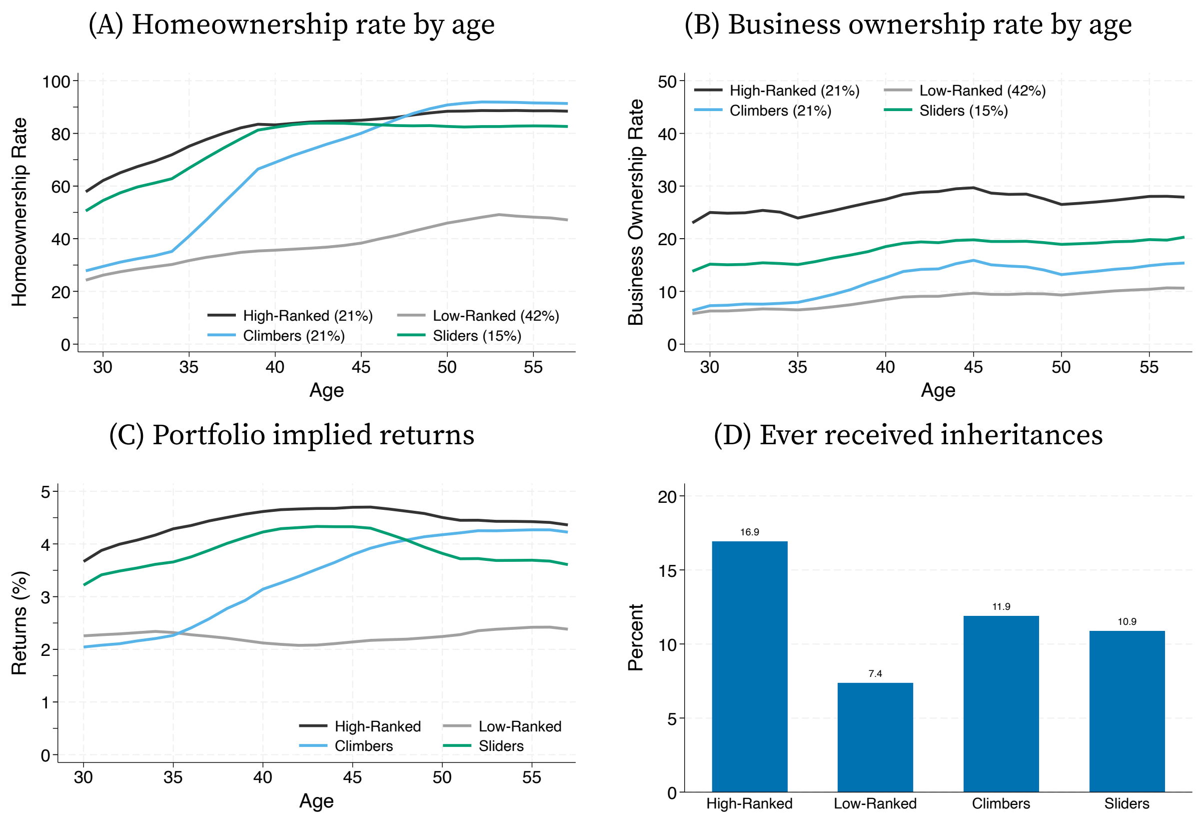
Standard manipulation delivers $\left(1-s_T\right)^{-1}\left(\beta\left(1-\gamma\right)\Gamma^{\star}\right)^{\frac{1}{\gamma}} > s_T$, which is more stringent than (D.30) and so it is verified immediately.

□

Appendix E. Additional Results on Typical Trajectories

The characteristics of the four main wealth clusters can be summarized as follows. The high-ranked individuals are homeowners early on and more likely to have business income. They also have the largest income levels across all groups. Conversely, the individuals who remain at the bottom of the wealth distribution have the lowest labor income and are less likely to own a home. Individuals sliding through the wealth

FIGURE E.1. Portfolio statistics by group



Notes: The figures present characteristics of the four main groups presented in Figure 2A. Given individual returns we compute within-group averages at each age. Panels A and B plot, respectively, the share of individuals who are homeowners and who own business assets. Panel A presents average returns implied by the portfolio shares of each individual and the average return on each asset category reported in (Fagereng et al. 2020, Table 3). Panel D reports the share of individuals in each group that have received inheritances by the age of 55.

distribution are more likely to have business income and to be homeowners at age 30, but they have low household income. Finally, individuals climbing through the wealth distribution have higher labor income relative to the sliders (particularly so at the household level) and become homeowners in their 30s and 40s. We find a role for ex post differences in rate or return motivated by the trajectories of sliders and the the limited differences in returns implied by portfolio differences across groups.

E.1. Portfolio composition

Property represents the majority of household portfolios across all groups; its share increases slightly as homeownership rates increase. The increase in homeownership across groups differ in its timing (Figure E.1A). The sliders are more likely to be homeowners than climbers up to age 45, when their homeownership rates converge.

As for the low-ranked, their homeownership rate starts at a similar level as the climbers, 25 percent, but it ultimately stalls at 50 percent—well below other groups that have rates over 80 percent by age 55.

The portfolio composition of the high-ranked group stands out because of the lower share of property assets in their portfolio and correspondingly higher share of private business wealth, relative to the other groups. This pattern is driven by differences in the extensive margin of business operation (Figure E.1B), as well as the group's higher shares of capital income and self-employment income, which we discuss below. Notably, the business ownership rate of the high-ranked group is close to 10 percentage points higher than that of the sliders and much higher than that of the climbers; the climbers' rate is never above 15 percent, although it increases as they age.

We leverage the variation in portfolio choices across individuals to compute portfolio-implied returns and report averages by group in Figure E.1C. We assign to each asset class its average return as reported in Fagereng et al. (2020, Table 3) and compute yearly portfolio-weighted returns for each individual of our sample. We observe assets separately from outstanding debt and, thus, account for leveraged returns. A striking fact is that for much of their life-cycle they imply that climbers earn lower returns than sliders. However, differences in portfolio allocations generate small variation implied returns relative to the dispersion in returns observed in the data (Fagereng et al. 2020).

E.2. Income trajectories

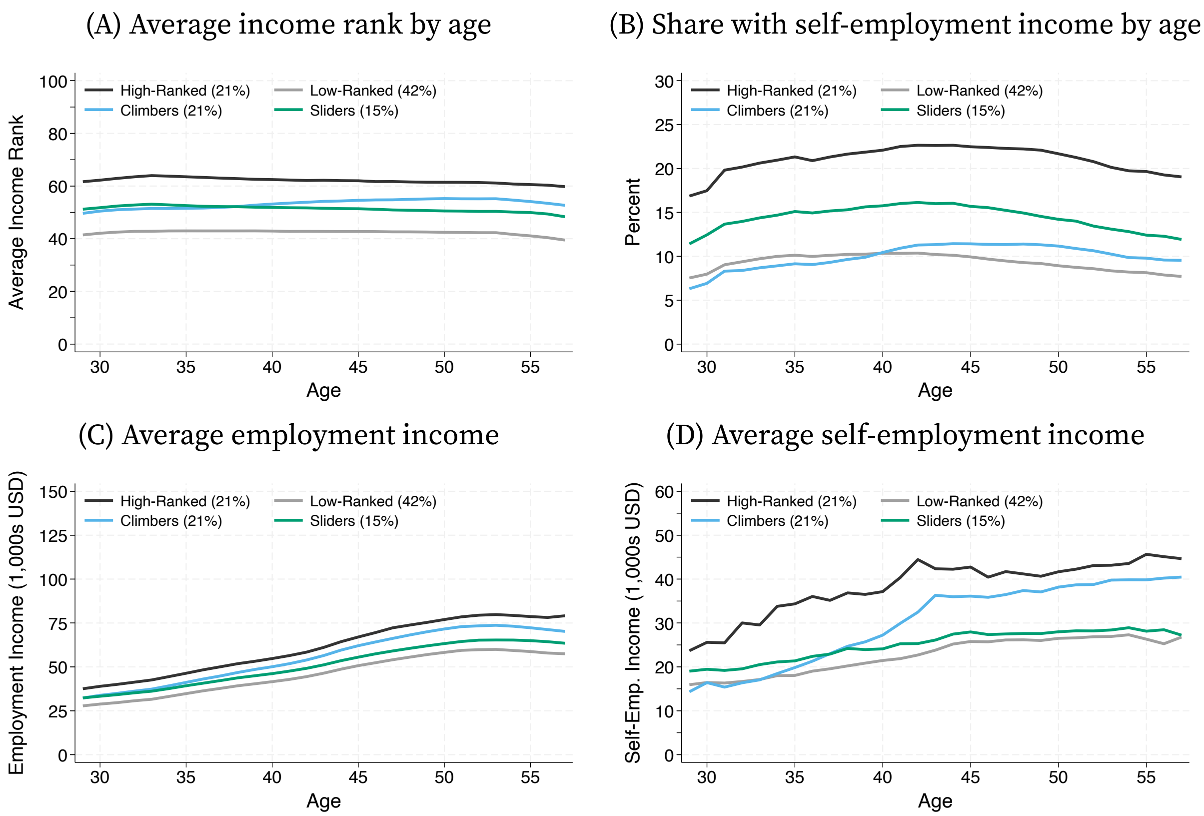
The income profiles of our main four groups are broadly consistent with the patterns of wealth mobility described previously, Figure E.2. Nevertheless, the differences in income are smaller than the differences in wealth. There is a 20-rank gap between the high- and low-ranked groups — a difference of 60-90 percent in income levels. This gap is significant, but smaller than the 30- to 55-rank gap between the groups' wealth rank profiles — a difference of at least 10 times in wealth levels.

Turning to sources of income, the high-ranked are the only ones for who capital and self-employment represent a sizable source of income (up to 30 percent on average). Over 20 percent of the individuals in the high-ranked group have self-employment income at age 45 (Panel B), more than double that of the low-ranked group. Sliders are more likely to be self-employed than climbers—16 percent compared to 11 percent.

Panel C shows that the differences in employment income among groups follow the same trends as the differences in overall income shown in Figure 5C but are not as large. The remaining income differences between groups come from the life-cycle profile of capital income. Capital income is low for all groups except for the high-ranked group. The high-ranked group has, on average, 10,000 to 15,000 US dollars of capital income, while all other groups have at most 5,000 dollars. Climbers receive a larger share of capital income at older ages (Figure 5B).

Importantly, the differences in income are very persistent, as discussed in Section 3. We verify this by clustering individuals based on income trajectories: we obtain four lines in income ranks with no mobility between groups, pointing to the importance of permanent skill heterogeneity for income dynamics, see Figure E.3.

FIGURE E.2. Income by group



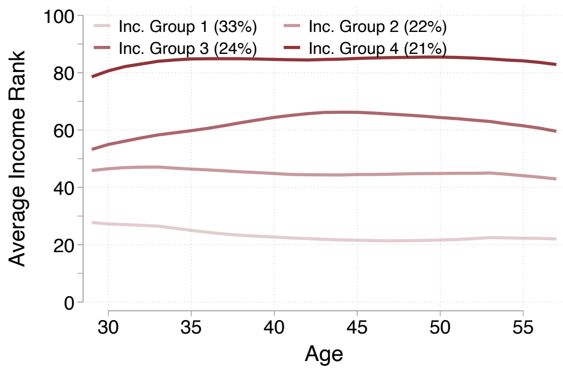
Notes: Panel A plots the average income rank trajectories for the individuals in each of the four main groups presented in Figure 2A. Panel B plots the share of individuals in each group with self-employment income. Panels C and D plot, respectively, the average employment and self-employment income trajectories in 2019 US dollars for the individuals in each of the four main groups presented in Figure 2A. The average is taken over all the individuals in the group and therefore is a result of the intensive and extensive margin of employment and self-employment.

E.3. Household characteristics

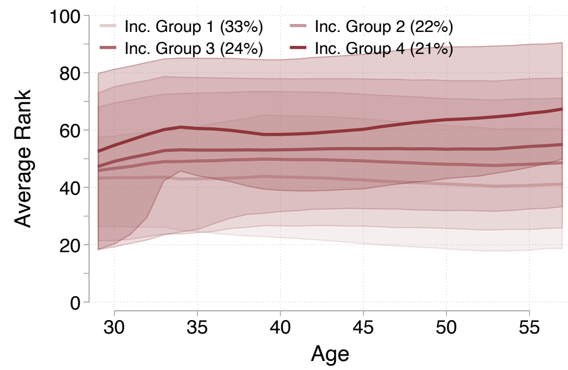
Figure E.4A reports the share of individuals who are married, cohabiting, and single at several points during the panel. We find limited differences between groups. Figure E.4B presents the life cycle profile of household wealth ranks, which have the same qualitative (and even quantitative) behavior as individual wealth ranks. To construct households, we match individuals in the 1960–64 birth cohort with their spouses or partners if married or cohabitating. The matching uses the complete population file. Individuals are then assigned their households' wealth before computing within-cohort household wealth ranks.

FIGURE E.3. Grouping on income trajectories

(A) Life-cycle dynamics of income mobility



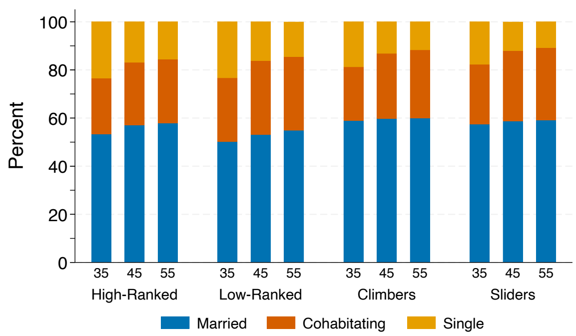
(B) Wealth mobility by income group



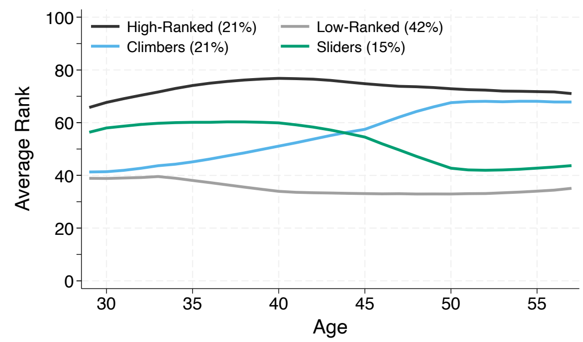
Notes: The figures present characteristics of four main groups recovered by clustering on income (analogously to results in Figure 2A). All individuals belong to the 1960–64 birth cohort. The clusters are constructed using hierarchical agglomerative clustering and Ward's method with a dissimilarity measure (3). Panel A plots the average income rank in each clustered group against individuals' age. Panel B plots the average wealth rank in each clustered group against individuals' age. The shaded areas in Panel B correspond to the interquartile range of the rank distribution of each group for each age.

FIGURE E.4. Household characteristics by group

(A) Civil status by age and cluster



(B) Household wealth ranks by group

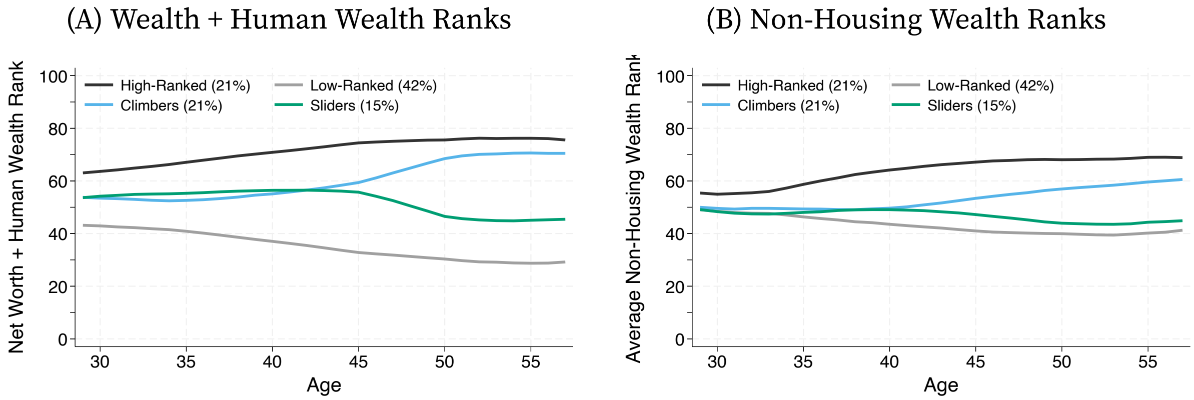


Notes: Panel A reports the share of married, cohabitating, and single individuals at ages 35, 45, and 55. To construct households, we match individuals in the 1960–64 birth cohort with their spouses or partners, corresponding to their civil status of married or cohabitating. The matching uses the complete population file. Individuals are then assigned their households' wealth before we compute within-cohort household wealth ranks. Panel B plots the rank of household wealth for the individuals in each of the four main groups presented in Figure 2A.

E.4. The role of human wealth and housing for mobility

We show in Figure E.5A how taking into account the value of human wealth translates into different mobility patterns, showing divergence in total human and non-human

FIGURE E.5. Mobility in Human and Non-Housing Wealth



Notes: Panel A presents the ranks of the sum of human wealth and the market value of wealth. Human wealth is defined as the discounted value of future labor income calculated from the realized income trajectories of individuals obtained from the tax registry. We discount future income using the average return on net worth for Norway, 3.21 percent, reported in (Fagereng et al. 2020, Table 3). Panel B reports the ranks of non-housing wealth, defined as total wealth minus the value of primary residences.

wealth rather than crossing, as discussed in Figure 7. Human wealth plays a lesser role for the mobility of high- and low-ranked groups because of their respective high- and low-income trajectories. Nevertheless, the distance between groups narrows when taking into account human wealth, reflecting differences in income trajectories not accounted for by differences in financial wealth.

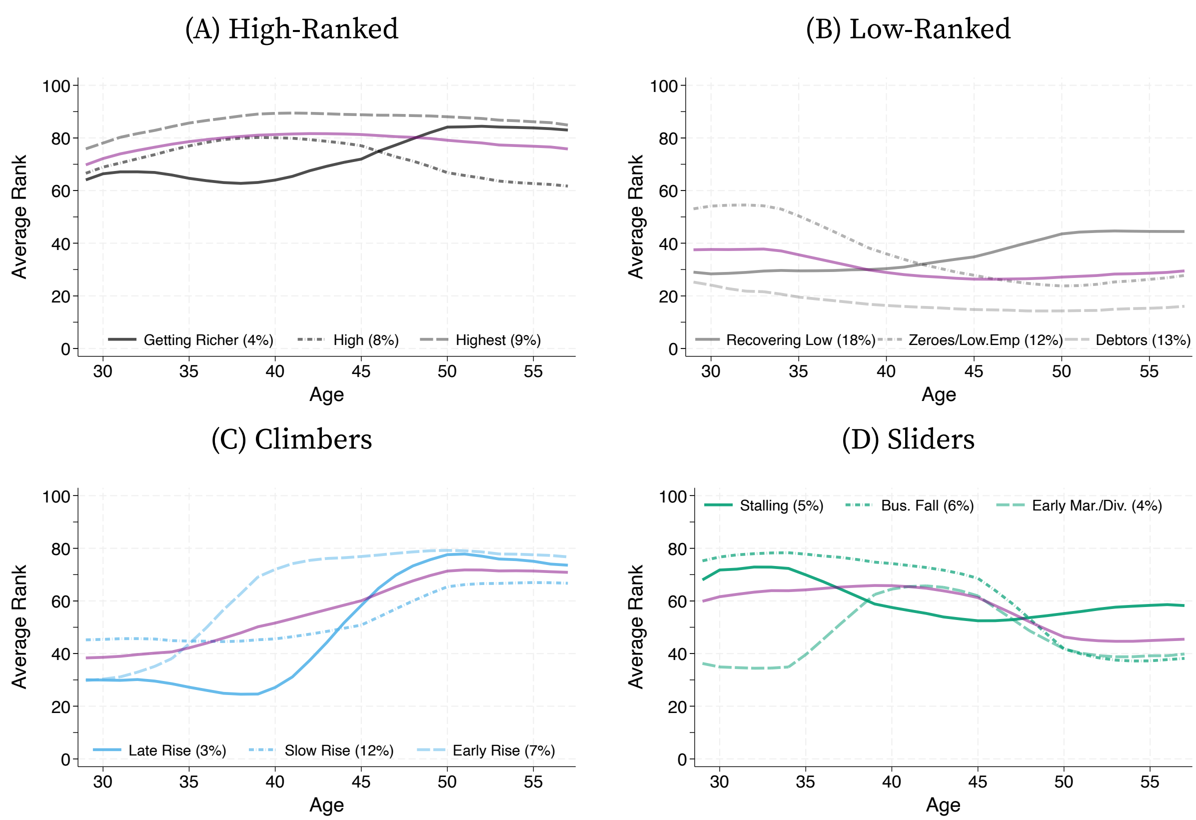
We separately analyze the accumulation of non-housing wealth, that is, wealth excluding the value of primary residences, as in Figure 7B. Figure B depicts the evolution of non-housing wealth in the four main groups both in ranks. Differences in non-housing wealth are subdued relative to those in total wealth. This is in part because, as shown in Figure B, non-housing wealth is mostly accumulated by the high-ranked and climbers groups. The other groups barely accumulate any non-housing wealth over their lifetime.

Appendix F. Heterogeneity within groups

We now turn to examining the heterogeneity within each of the main four groups. We do so by exploiting the hierarchical nature of the clustering, that allows us to directly study the subgroups that make up each of the four major groups. Specifically, we look at the three main subgroups of each baseline group (see Figure C.1B).

We report each subgroup's wealth rank trajectory in Figure F.1, along with their respective baseline group in pink. Overall, mobility within each main group remains contained within segments of the wealth distribution, although there is overlap between groups, as shown by the interquartile range in Figure 2A. We now turn to describing the wealth mobility patterns that emerge for each subgroup.

FIGURE F.1. Rank paths by subgroups



Notes: The figure plots the average wealth rank age profiles in the three main sub-clusters of each of the baseline clustered groups. Each panel corresponds to one of the four baseline groups reported in Figure 2A. The light pink solid lines correspond to the average wealth rank in the corresponding main group. All individuals belong to the 1960–64 birth cohort. The clusters are constructed from the balanced sample using hierarchical agglomerative clustering and Ward's method with a dissimilarity measure (3). The groups and subgroups are identified out of the dendrogram reported in Figure C.1B.

High-ranked subgroups. Within the high-ranked, we find a group of individuals who are consistently at the top of the wealth distribution and two other groups that swap relative positions over the life cycle.[51] As with the baseline groups, we also find the subgroups differ in more than their wealth levels. Individuals in the group at the top have a consistently higher share of their wealth concentrated in privately held assets (such as businesses) and earn a larger fraction of their income from capital (including dividends), relative to individuals in the other two subgroups. By contrast, individuals in the rising subgroup, labeled as "getting richer" in Figure F.1A, have a larger fraction of their wealth in property (although homeownership rates are similar between subgroups) and labor income makes up for the majority of their income. These characteristics make this group more similar to climbers than to the rest of the high-ranked group.

Low-ranked subgroups. The three subgroups at the bottom move similarly to those at the top. There is a subgroup of individuals that stay at the bottom of the wealth distribution throughout their lives and two groups that swap relative positions. We find that, throughout their lives, those lower in the distribution are net debtors; those falling always hold zero wealth, which makes them relatively poorer as the cohort ages; those recovering in ranks accumulate wealth after age 45, mostly in the form of property.

Climbers' subgroups. These subgroups reveal differences in the timing of movements, with early and late risers that nevertheless begin and end the sample in similar positions relative to each other (Figure F.1C). Not surprisingly, late risers are more likely to earn graduate degrees and also take longer to acquire property, particularly relative to the "slow rise" subgroup.

Sliders' subgroups. Finally, the three subgroups within this group capture individuals who fall continuously through the distribution, who could not sustain their rise, and who stalled, remaining around the median of the wealth distribution as they grew older. The largest subgroup is characterized by a larger share of business owners, whose businesses produce a declining share of their income as they age, leading us to label this group "business fall".[52] The smaller subgroup has individuals who rise early but then fall after age 45. These individuals marry younger, on average, and have higher divorce rates relative to other groups; most of the increase in their wealth in their late 30s is tied to a rise in their homeownership rate.

[51] The groups and subgroups produced by our empirical strategy are designed to capture typical mobility patterns. The resulting typical trajectories turn out to capture the behavior of relatively large groups of individuals. For instance, the wealthiest group makes up 9 percent of our sample. See Hubmer et al. (2024) for a detailed discussion of individuals in the top 0.1 percent of the Norwegian wealth distribution.

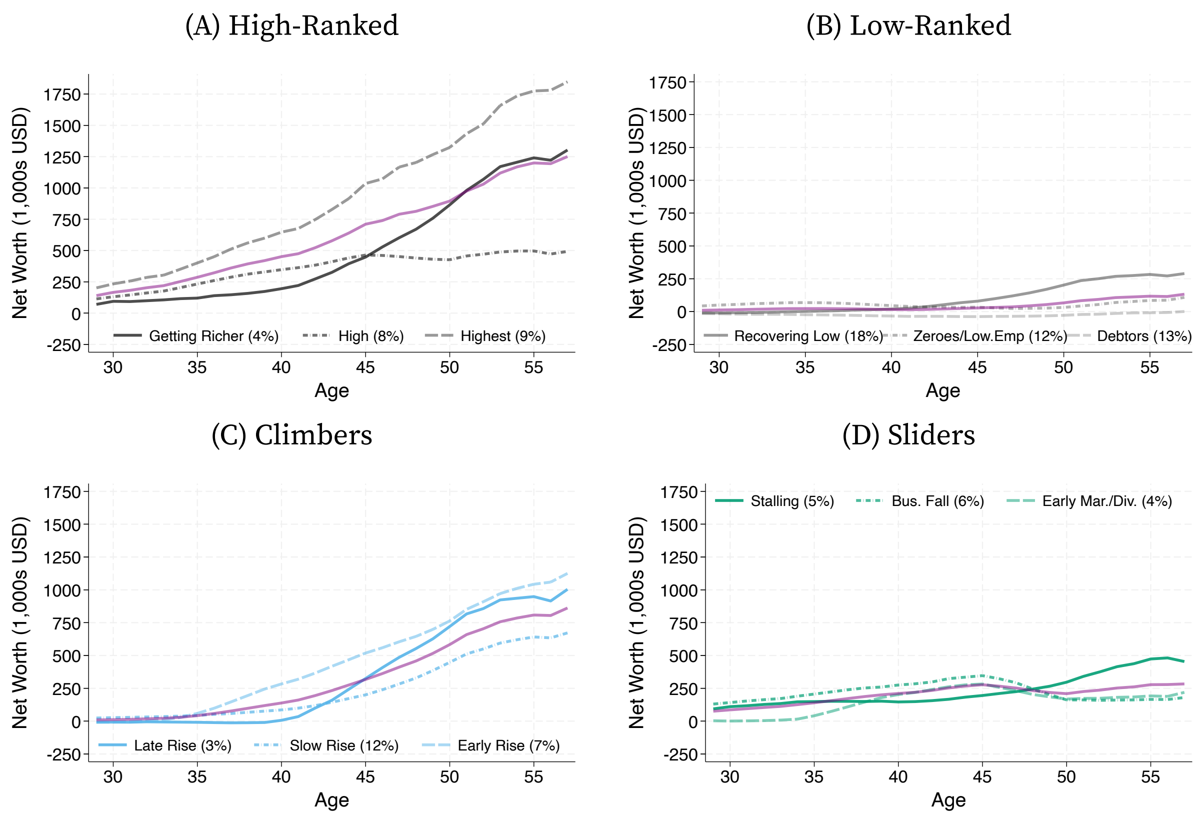
[52] The continuous decline of this group is accentuated by a substantial drop between ages 45 and 50. This drop coincides with the timing of the 2008 global financial crisis, hinting at a potential larger exposure of their businesses to foreign financial conditions. We turn to the role of time effects next.

F.1. Group characteristics for subgroups

The typical wealth trajectories are in Figure F.2. The common scale in the figure highlights the vast differences in net-worth across subgroups. These are much larger than the differences across groups because of the "highest" group among the high-ranked. Among the climbers there is convergence between the late and early risers despite starting to accumulate wealth at different ages. For the low-ranked, the lowest subgroup is the only one that has consistently negative net-worth, hence the moniker of "debtors". The "recovering" subgroup differs from the others in its accumulation of property. The differences among the fallers are less pronounced. The early marriage/divorce group stands out because of the accumulation of property. This group's moniker follows from its household formation and dissolution dynamics.

Figures F.3 present the composition of portfolio and income. Once again the largest differences are in the high-ranked group. The "highest" subgroup has a larger share of private assets and stocks than any other group. Correspondingly, it also has the highest share of capital and self-employment income. Interestingly, the "getting richer" subgroup is closer to climbers in terms of its portfolio and income composition, even though it have larger shares of private assets and stocks and the income share of capital and self-employment income increases faster for this group than for climbers. Most other groups have high shares of property assets and labor income throughout.

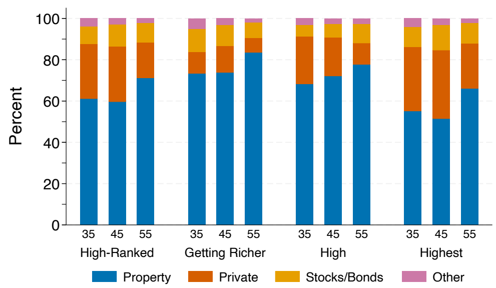
FIGURE F.2. Wealth levels by subgroup



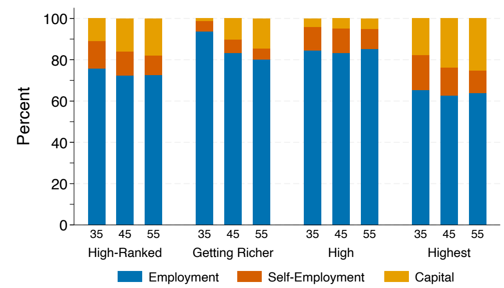
Notes: Average wealth levels by subgroup. For each subgroup, we also report the major group's values.

FIGURE F.3. Portfolio and income composition by subgroup

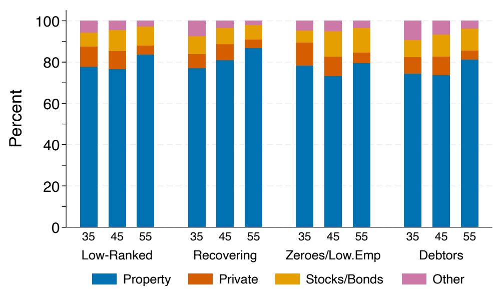
(A) Portfolio – High-Ranked



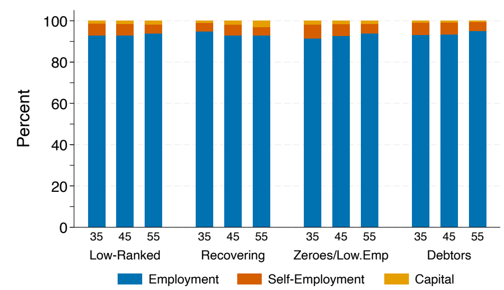
(B) Income – High-Ranked



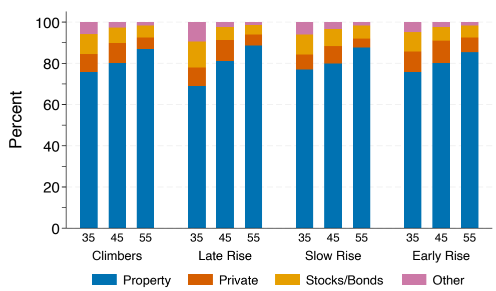
(C) Portfolio – Low-Ranked



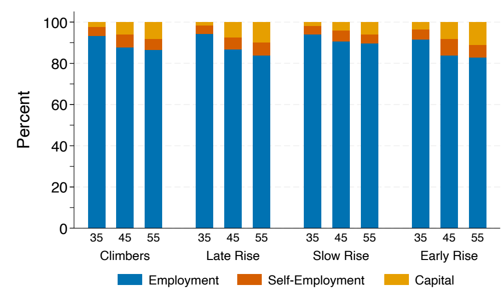
(D) Income – Low-Ranked



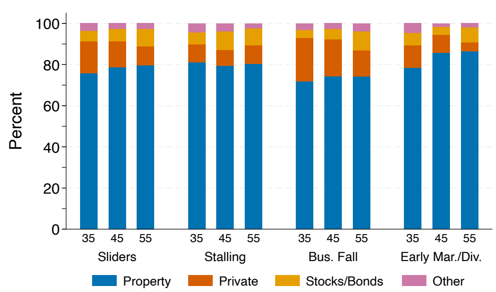
(E) Portfolio – Climbers



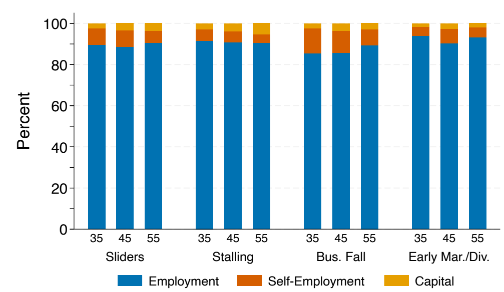
(F) Income – Climbers



(G) Portfolio – Sliders



(H) Income – Sliders



Notes: Left panels: Share of assets accounted for by property, privately held assets, financial assets, and other assets, defined as the total value of each asset class divided by the total assets within a subgroup. Right panels: share of each group's income accounted for by employee, self-employment, and capital income. For each subgroup. For each subgroup, we also report the major group's values.

Appendix G. Additional results on ex ante analysis

G.1. The role of parental education, sex, and birthplace

Field of study. Panel A of figure G.1 shows the average partial effects associated with the field of education for individuals with at least an undergraduate degree.

Parental education. Panel B of figure G.1 shows the average partial effects associated with the highest level of parental educational attainment. We find that the effects are muted throughout, with climbers being the only group with a differential educational attainment among parents. The parents of climbers are more highly educated and thus climbers are more likely to have parents with postgraduate or PhD degrees.

Sex. Panel C of figure G.1 shows the average partial effects associated with sex at birth. Men are more likely to be in the high-ranked group and less likely to be climbers by approximately 10 percentage points. They are also slightly more likely to be sliders and less likely to be in the low-ranked group by approximately 5 percentage points.

Birthplace. Panel D of Figure G.1 reports the average partial effect estimates for the place of birth indicators. We find a positive effect of being born in Oslo or another larger Norwegian city on the probability of being in the high-ranked and middle-rise wealth mobility groups. Although significant, these effects are smaller in magnitude (about 5 percentage points) than those we find for parental wealth and education.

G.2. Additional covariates: Own and parental background

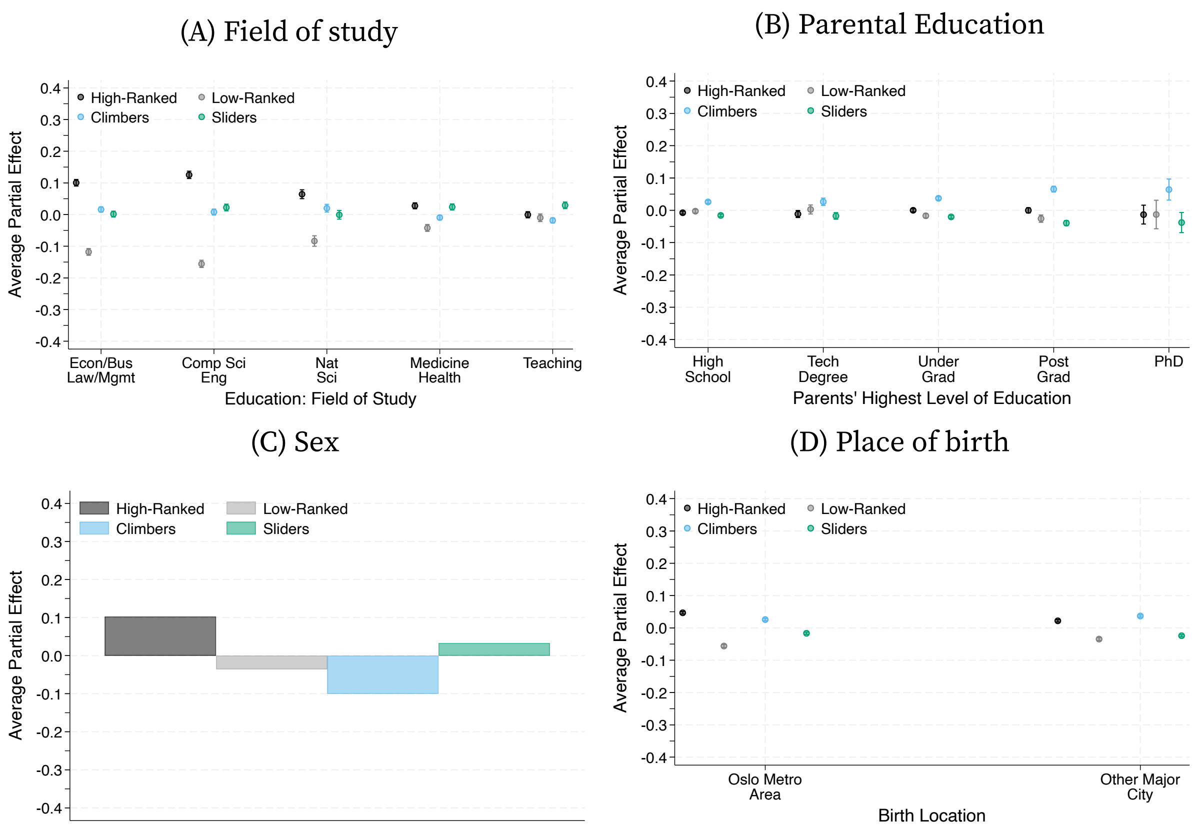
We investigate the robustness of ex ante determinants in three alternative specifications. First, we include whether parents owned a business as an additional proxy for parental wealth. Second, we include *own wealth* ventile fixed effects and binary indicators for whether an individual was a homeowner or owned a business in 1993. Finally, we include both groups of variables in a third specification and report the average partial effects for this specification in Figure G.2.

We find little predictive power for parental businesses or whether an individual owned a home or business in 1993, conditional on the values of parental wealth, education, sex, and birthplace. Instead, we find a large role for own wealth in 1993, consistent with the patterns of segmented mobility in Section 5.

With these additional controls, the explanatory power of our classifier increases almost four-fold, driven almost entirely by initial wealth (see Table G.2). We are able to accurately categorize individuals because segmented mobility implies that initial wealth is an accurate discriminator of outcomes over the life cycle—especially at extremes.

Once we include this additional information on an individual's initial wealth, the role of parental wealth and education declines. In general, the point estimates for the average partial effects decline by 25–40 percent, Panel E and F of Figure G.2, but

FIGURE G.1. Demographics and the probability of group assignment



Notes: Panel A plots the average partial effect (APE) of field of study (for those with technical degree or above) relative to a humanities degree. Panel B plots the APE of parental educational attainment relative to compulsory schooling age. Panel C plots the APE of men relative to women. Panel D plots the APE of urban areas relative to rural areas. We construct the average partial effect by integrating over the empirical joint distribution of other covariates. We report point estimates, the probability of being assigned to each of our four groups, along with their 95 percent confidence intervals.

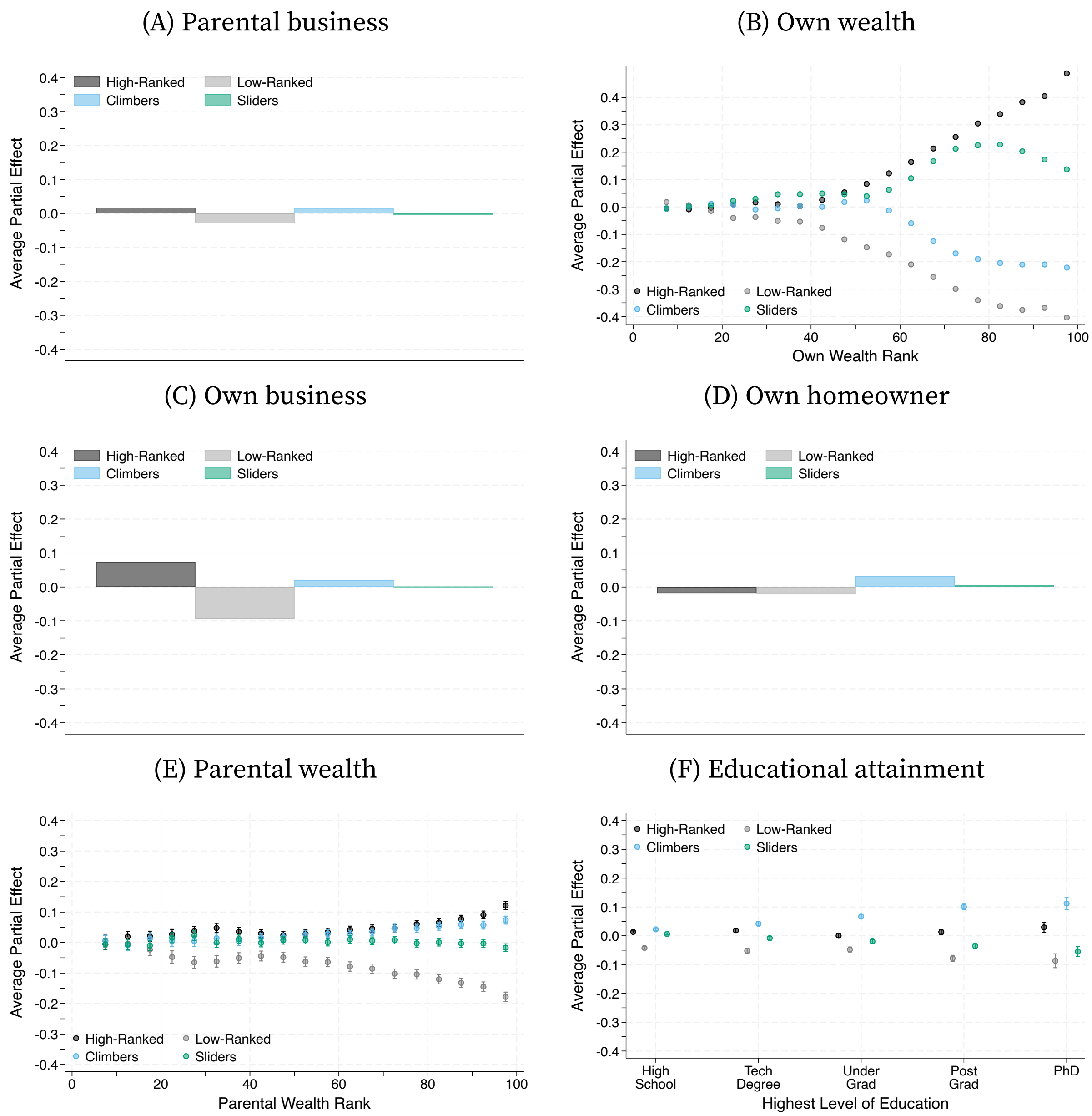
remain significant and display the same qualitative patterns—confirming the relative importance of education and parental wealth among climbers and the high-ranked.

G.3. Relative predictive power of ex ante characteristics

We now explore how each set of ex ante covariates in Equation (6) helps to explain the variation across groups. We use two measures to gauge the predictive power of the ex-ante characteristics of individuals. First, we measure the share of variation explained using the Distance-Weighted Classification Rate

$$1 - \frac{\sum_{i=1}^{N}\sum_{k=1}^{G}\widehat{\Pr}(g=k|X_i)d(g(i),k)}{\sum_{i=1}^{N}\sum_{k=1}^{G}\widehat{\Pr}(g=k)d(g(i),k)}, \tag{G.1}$$

FIGURE G.2. Parental portfolio, own wealth and the probability of group assignment



Notes: Average partial effect (APE) of whether parents have a business in 1993 (panel A), the individual's own wealth ventile in 1993 (panel B), whether the individual own a business in 1993 (panel C), and whether the individual owns a house in 1993 (panel D). The effects of own wealth ventiles are reported relative to being in the bottom ventile of the distribution in 1993. Panel E presents the APE of parental wealth ventiles in 1993, relative to being born to parents in the bottom ventile of the distribution. Panel F presents the APE of educational attainment, relative to compulsory schooling age. We construct the APE by integrating over the empirical joint distribution of all other covariates. We report point estimates, the probability of being assigned to each of our four groups, along with their 95 percent confidence intervals.

where $d(g, g')$ corresponds to Ward's distance metric in equation (3). This measure corresponds to the average implied distance between an individual's true group and their predicted group $\widehat{\Pr}(g = k|X_i)$ weighted against a naive predictor $\widehat{\Pr}(g = k)$ that uses proportional random assignment. As the distances between disjoint groups are positive, the numerator of the fraction in equation (G.1) can be interpreted similarly to the residual sum of squares in the coefficient of determination, while the denominator can be interpreted as the total sum of squares. A value of one implies perfect classification, while a value of zero implies that the covariates contain no information. Because this measure considers the distance across groups, it penalizes more strongly classifying a low-ranked as a high-ranked rather than as a slider.

The second measure we use is the Unweighted Classification Rate

$$\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{G} \widehat{Pr} \left(g = k \,|\, X_i \right) \mathbb{1}[g(i) = k]. \tag{G.2}$$

This measure only cares about the rate of correctly classified individuals relative to proportional random assignment, $\widehat{\Pr}(g = k)$, regardless of the type of misclassification, and its units are interpretable as the (extra) share of correctly classified individuals.

Table G.1 reports the total contribution from our four groups of ex-ante regressors to the distance-weighted and unweighted classification rates. We also report in each table a decomposition of the partial contribution of each regressor using a Shapley-Owen decomposition (Shorrocks 2013), described in Audoly et al. (2025). This decomposition allows us to calculate a single value per covariate category that is permutation-invariant and additively-decomposable despite the nonlinearity of the classification rates.

Parental background and education account for the majority of the model's explanatory power. Parental wealth accounts for over 40 percent of the fit of the model in classifying individuals across groups (Table G.1). This takes into account how parental wealth varies jointly with other individual characteristics. It is 45 and 46 percent for the high- and low-ranked groups, respectively, while it is only 20 percent for climbers and 4.3 percent for sliders. Education accounts for another 40 percent of the fit. Education variables are most relevant for classifying climbers, where it accounts for almost 55 percent of correct classification rate. By contrast, sex and birthplace explain less than 20 percent of the fit of the model in classifying individuals, mostly coming from sex differences in the groups' composition.

Although, on average, the discriminating power of education is lower than that of the parental background, its ability to classify individuals is much more consistently spread across groups. By contrast, parental background is most effective at correctly classifying those at the extremes of the distribution (the high- and low-ranked); it only has limited informational content for predicting those who will rise or fall through the churn in the middle of the distribution. We view this as highlighting an important notion of equality of opportunity: extreme comparisons point to *inequality* of opportunity, but there is more *equality* of opportunity in the middle of the distribution.

We find that, on average, these covariates explain around 6 percent of our distance

TABLE G.1. Predictive power of ex ante characteristics

(a) Share of distance variation explained by variable (pp)

Group	All	Partial Contribution			
	Effects	Parent	Education	Sex & Birthplace	Par. Edu.
All	5.91	41.28	39.11	13.47	6.14
High-Ranked	7.91	44.99	29.33	20.51	5.16
Low-Ranked	7.00	46.01	41.57	4.85	7.57
Climber	4.63	20.08	54.94	20.82	4.16
Slider	0.28	4.30	15.50	82.18	-1.98

(b) Share of individuals correctly classified (pp)

Group	Random	All	Partial Contribution			
		Effects	Parent	Education	Sex & Birthplace	Par. Edu.
All	29.33	3.15	34.31	40.41	19.23	6.04
High-Ranked	21.03	4.40	41.08	23.57	30.52	4.83
Low-Ranked	42.51	3.34	45.28	44.33	3.24	7.15
climbere	20.91	3.52	12.58	50.14	33.59	3.70
Slider	15.55	0.73	11.88	47.63	25.83	14.67

Notes: Distance-weighted and unweighted probability of belonging to an individual's true group, across the cohort in row "All" and conditional on groups in the remaining rows. The distance corresponds to the measure in equation G.1. Column "All" reports the combined explanatory power of all covariates. The remaining columns report the partial contribution of each variable category (in percentage points) to the combined explanatory power in column "All." The classification model corresponds to that in equation (6). Explanatory power is computed relative to random classification. The partial contribution of each variable category is obtained through the Shapley-Owen decomposition.

measure. The share of variation explained by the variables in (6) is similar in magnitude to the R^2 values reported in intergenerational estimates of the rank correlation in wealth—specifically to those for Norway, reported in Fagereng, Guiso, Malacrino, and Pistaferri (2020); and for Denmark, reported in Boserup, Kopczuk, and Kreiner (2018). Here, however we explain 25-year long wealth histories. Thus, we view this comparable magnitude as evidence for the success of our procedure. Moreover, we take the explanatory power of ex ante variables as showing that there is substantial variation in outcomes later in life not captured by initial characteristics. It is common to find relatively low explanatory power of observables in applications recovering latent groups (e.g., Ahn, Hobijn, and Şahin 2023; or Lewis, Melcangi, and Pilossoph 2021).

G.4. Explanatory power of additional covariates

We also compute distance-weighted and unweighted classification rates of the estimated multinomial logit model (equation 6) with the additional covariates described in Appendix G.2. Results are in Table G.2. The distanced-weighted classification rate increases up to 20 percent, with the introduction of the individuals' initial wealth ventile accounting for 15 percentage points. A similar increase takes place for the unweighted classification rate that increases to 10.6 percent (over the random classification rate of 29.3 percent). The individuals' initial wealth ventile accounts for 7.9 percentage points of the total classification rate. As we discussed in Appendix G.2, we see the large role of initial wealth as being consistent with the patterns of segmented wealth mobility we document.

TABLE G.2. Predictive power of ex ante characteristics with additional covariates

Total	Partial Contribution					
Contribution	Par. Wealth	Edu.	Sex & Birthplace	Par. Edu.	Par. Bus.	Own State
Share of Distance Variation Explained by Variable (pp)						
20.0	8.1	9.9	2.8	1.5	3.0	74.6
Share of Individuals Correctly Classified (pp)						
10.6	7.2	10.7	4.0	1.7	2.5	73.9

Notes: DDistance-weighted and unweighted probability of belonging to an individual's true group relative to random classification with an unweighted classification rate of 29.3 percent. The distance corresponds to the measure in equation G.1. Column "Total Contribution" reports the combined explanatory power of all covariates. The remaining columns report the partial contribution of each variable category (in percentage points) to the total combined explanatory power. The classification model corresponds to that in equation (6) with the additional covariates introduced in Appendix G.2. Explanatory power is computed relative to random classification. The partial contribution of each variable category is obtained through the Shapley-Owen decomposition.