WORKING PAPER

WEALTH MOBILITY IN THE UNITED STATES: EMPIRICAL EVIDENCE FROM THE PSID

Christophe Van Langenhove

January 2025
2025/1104

GHENT UNIVERSITY

Department of Economics

Faculty of Economics and Business Administration
Campus Tweekerken, St.-Pietersplein 5, 9000 Ghent - BELGIUM

Wealth Mobility in the United States: Empirical Evidence from the PSID

Christophe Van Langenhove*

January 30, 2025

Abstract

This paper leverages data from the Panel Study of Income Dynamics (PSID) to analyze inter- and intra-generational wealth mobility in the United States. Having constructed a gradient-boosting ML-model to obtain wealth rank approximations until 1969, I provide a rich set of empirical wealth mobility moments. Several findings stand out. First, overall inter-generational wealth mobility and intra-generational wealth mobility at the top have declined over time. Second, wealth mobility in the United States is lower compared to most other countries for which wealth mobility data is available. Third, the majority of wealth mobility occurs between ages 30 and 39, and wealth rank resemblance between (grand)parents and their (grand)children increases with age. Fourth, wealth mobility at the top is significantly higher across three versus two generations, while the difference in mobility at the bottom is comparatively weaker. Fifth, there exists positive inter-dependence between individuals' wealth rank trajectories and those of their parents over the same time period. Sixth, diverging wealth mobility outcomes across families and individuals are associated with variation in inter-generational transfers, business ownership, labor income, health and non-mortgage indebtedness.

JEL classification: D14, D15, E21

*Ghent University (email: christophe.vanlangenhove@ugent.be). I acknowledge the financial support from the Research Foundation Flanders (FWO, project number: 11I5324N). I would like to thank Freddy Heylen, Dirk Van de gaer, Arthur Apostel and Marthe Mareels for their valuable comments on this working paper. The Online Supplement is accessible on my website: https://christophevanlangenhove.github.io/.

1 Introduction

Over the past decade, empirical research on wealth inequality has expanded considerably. This holds both for the United States and at an international level (e.g. Saez & Zucman, 2016; Smith et al., 2023; Zucman, 2019). In contrast, studies investigating relative inter- or intra-generational wealth mobility − changes in families' or individuals' wealth ranks across and within generations − remain hard to come by. Specifically, for the United States, research on inter-generational wealth mobility over the past decades is limited to Charles & Hurst (2003), Conley & Glauber (2008), Menchik (1979), Pfeffer & Killewald (2018) and Siminsky & Yu (2022). Among these, only Pfeffer & Killewald (2018) extend their analysis to mobility across three generations (grandparents-grandchildren). Furthermore, research on intra-generational wealth mobility in the United States is restricted to Conley & Glauber (2008) and Shiro et al. (2022)[1][2]. For the Nordic countries (Norway, Denmark and Sweden), there exist a handful of wealth mobility studies: Adermon et al. (2018), Black et al. (2020), Boserup et al. (2017) and Fagereng et al. (2021) investigate inter-generational mobility, while Audoly et al. (2024) and Hubmer et al. (2024) analyze intra-generational mobility. Finally, Gregg & Kanabar (2023) and Levell & Sturrock (2023) produce evidence on inter-generational wealth mobility for the United Kingdom, while Siminsky & Yu (2022) do so for Australia.

Our primary interest lays in welfare mobility across and within generations. In an attempt to approximate welfare, a large literature has been written on income mobility. Nonetheless, there are three main reasons to be interested in wealth mobility also. First, insights into inter- and intra-generational wealth mobility may inform academic and popular debates on estate taxation, wealth taxation and the economics of opportunity. In addition, it may serve as a key input in shaping cultural narratives on the American dream and the United States as land of opportunity. Second, a theoretical literature on heterogeneous agent macro models uses wealth inequality as key outcome variable (e.g. De Nardi & Fella, 2017; Hubmer et al., 2021; Xavier, 2021). This does not allow to take an explicit stance on the importance of type versus scale dependence: an unequal stationary wealth distribution could be generated by ex-ante heterogeneity in individuals' behavioral parameters (type dependence), or by cascading effects in response to idiosyncratic shocks when individuals' behavior relates to their wealth levels (scale dependence). Calibrating these models jointly to inequality and mobility moments could be a starting point in solving this type versus scale dependence puzzle. It would also enhance model realism and generate more comprehensive predictions and policy recommendations. While there exists some theoretical work that incorporates wealth mobility outcomes (Atkeson & Irie, 2022; Benhabib et al., 2019; Fernholz, 2016; Gomez, 2023), this literature is constrained

[1]In addition, Kuhn et al. (2020) and Kalsi & Ward (2025) conduct some limited intra-generational wealth mobility analyses using the PSID. These analyses serve as a robustness to their baseline results.

[2]There does exist a literature on inter- and intra-generational wealth mobility in the United States during the Gilded Age era (e.g. Ager et al., 2021; Dupont & Rosenbloom, 2022; Kalsi & Ward, 2025).

by the unavailability of extensive wealth mobility data for the United States. Third, an individual's wealth level reflects the complex interplay between numerous outcome variables (labor income, inter-generational transfers, health, asset returns) and behavioral decisions (saving rates, portfolio allocation, household formation). The study of wealth mobility therefore offers indirect evidence on the dynamics and importance of these different underlying variables.

To address the scarcity of wealth mobility data over recent decades, this paper leverages the Panel Study of Income Dynamics (PSID) to provide evidence on inter- and intra-generational wealth mobility outcomes in the United States. Three research questions are addressed. First, from an inter-generational (family-level) perspective, the paper investigates how the within-cohort wealth ranks of individuals compare to the within-cohort wealth ranks of their parents or grandparents at identical lifecycle stages (if available) or different lifecycle stages (otherwise). Second, from an intra-generational (individual-level) perspective, I use individuals' wealth rank trajectories to assess the degree of turnover across the wealth distribution over the lifecycle. In addition, I investigate how these trajectories relate to individuals' socio-economic characteristics and inter-generational transfer receipts. Third, bridging the inter-generational (family-level) and intra-generational (individual-level) perspectives, this paper is the first to analyze the inter-dependence between individuals' wealth rank trajectories and those of their parents over the same (historical) time period. In answering these three questions, I provide a wide range of empirical moments that are useful to the heterogeneous agent macro literature. Moreover, I look into the evolution of wealth mobility over time and compare wealth mobility outcomes in the United States to the rest of the world.

Contributions There are six contributions to this paper. First, I harmonize the data from the Panel Study of Income Dynamics (PSID). The appropriateness of this dataset for studying wealth inequality and wealth mobility is validated by contrasting aggregate wealth and wealth inequality outcomes in the PSID to the outcomes in the top-wealth-adjusted Survey of Consumer Finances (SCF). This exercise contributes to a literature spanning Cooper et al. (2019), Insolera et al. (2021) and Pfeffer et al. (2016) by validating outcomes over time rather than for a specific year. Two key findings persist. On the one hand, the PSID under-estimates most aggregate wealth components relative to the SCF, but accurately captures their time trends. On the other hand, wealth share trajectories in the PSID closely align with those from the SCF, notwithstanding an under-estimation of the top 10% wealth share by moderately over 10%-points in the PSID. Regardless of this top-wealth bias, I argue that the PSID can be effectively used to study wealth-related questions. This is particularly true for the study of wealth mobility (compared to wealth inequality) given that wealth mobility metrics employ the number of households across the wealth distribution as calculation inputs (rather than their wealth levels).

Second, questions on asset holdings and debt levels in the PSID date back only to 1984. This limits their usefulness for comparing wealth mobility across age cohorts and investigating wealth mobility across three generations. However, data on main housing values and rental payments are available as early as 1969. A common strategy is then to assume that renters have zero wealth and to naively approximate total household wealth by main housing values (e.g. Chetty et al., 2020; Pfeffer & Killewald, 2018). Instead, I contribute to the literature by developing a gradient-boosting (GB) machine learning model trained on post-1984 data. This ML-model incorporates additional socio-economic variables from the PSID as input variables, and significantly out-performs the naive proxies in predicting household wealth levels out-of-sample. Throughout the paper, it is demonstrated that such proxies provide a useful tool for extending wealth mobility analyses across generations. Nonetheless, these proxies under-estimate the actual degree of intra-generational wealth mobility during working life, as well as the actual degree of inter-generational wealth mobility (contrary to the conclusion in Pfeffer & Killewald, 2018).

Third, unlike previous wealth mobility studies − which either examine inter-generational (family-level) or intra-generational (individual-level) wealth mobility − the PSID allows for an integrated analysis of both. This has two main advantages. On the one hand, this integrated framework allows to investigate the inter-dependence between individuals' wealth rank trajectories and those of their parents over the same (historical) time period: parents of individuals experiencing upward or downward mobility within their cohort are likely to face similar wealth rank trajectories in their own cohort. At the same time, individuals that consolidate their position at the top are the most common to have wealthy parents. This paper is the first to demonstrate the existence of such wealth rank inter-dependence within families. It suggests the presence of altruism across generations and/or the exposure of parents and their children to identical sources of idiosyncratic risk. On the other hand, the integrated framework allows to comprehensively compare the wealth mobility in the United States to the wealth mobility in other countries for which wealth mobility data is available. Overall, both inter- as intra-generational wealth mobility in the United States are found to be lower than in the rest of the world.

Fourth, to investigate the evolution of wealth mobility over time, I compare wealth inequality and mobility outcomes across age cohorts in the United States. As a key finding, wealth inequality has increased, while wealth mobility has declined. From an inter-generational perspective, I find that wealth mobility across two generations (parent-child mobility) has declined between ages 35 and 44. This complements evidence on the decline in wealth mobility among the top 400 wealthiest families in the United States (Fernholz & Hagler, 2023). It also aligns with the decline in inter-generational wealth mobility established for Sweden (Adermon et al., 2018) and the United Kingdom (Gregg & Kanabar, 2023; Levell & Sturrock, 2023). From an intra-generational perspective, this paper is the first to show that there has occurred (over time) a simultaneous increase in within-cohort wealth inequality and a decline in intra-generational (individual-level) wealth mobility at the top of the wealth distribution. There additionally exists a negative correlation between inequality and overall intra-generational wealth mobility, but this finding is comparatively weaker.

Fifth, I explicitly investigate the role of lifecycle biases and timing effects in wealth mobility for the United States. Several findings persist. On the one hand, age strongly affects inter-generational (family-level) wealth mobility outcomes: wealth rank resemblance between parents and their children rises significantly with parents' and children's age (parent-child lifecycle bias). In addition, wealth rank resemblance between grandparents and their grandchildren is higher when grandchildren are older than 35 years (grandchild lifecycle bias). On the other hand, timing effects indicate that the majority of intra-generational (individual-level) wealth mobility occurs early in working life, between ages 30 and 39. Furthermore, grandparent-grandchild mobility (three generations) exceeds parent-child mobility (two generations). The effect is non-linear over the wealth distribution, however: while mobility at the top is significantly higher across three versus two generations, the difference in mobility at the bottom is comparatively weaker. Finally, wealth mobility during working life (ages 30-54) exceeds the mobility observed during older age (ages 55-74).

Sixth, this paper explores the sources of wealth mobility in the United States. I accomplish this by allocating individuals to groups and clusters with distinct wealth rank trajectories and by subsequently calculating aggregated composition metrics for each of these groups and clusters. The analysis indicates that consolidation at the top (bottom) of the wealth distribution is associated with the most substantial (an absence of) inter-vivos transfer and inheritance receipts. However, even for the wealthiest, these receipts make up only a relatively limited fraction of their lifetime resources. Furthermore, business ownership is linked with consolidation at the top and downward wealth mobility, while its association with upward wealth mobility is inconclusive. Last, consolidation at the bottom and downward mobility to the bottom are associated with low labor income, poor and deteriorating health, elevated non-mortgage indebtedness and modest asset ownership. Instead, at the top, labor income and asset ownership are high.

Roadmap Section 2 introduces a theoretical framework to understand the driving forces behind inter- and intra-generational wealth mobility. Moreover, it defines the three research questions of interest to this paper. Section 3 summarizes the data and empirical methods used, building on the detailed exposition provided in Appendices A to F. Section 4 compares the wealth rank outcomes of individuals to those of their parents at the same lifecycle stage and to those of their grandparents at different lifecycle stages. Section 5 presents the results of the intra-generational wealth mobility analyses during working life and older age. Section 6 investigates the inter-dependence between the within-cohort wealth rank trajectories of individuals and those of their parents. Section 7 reports composition statistics for groups and clusters of individuals with distinct wealth rank trajectories, shedding exploratory light on potential channels of wealth mobility. Section 8 concludes and provides directions for future work.

2 Wealth inequality & mobility: framework & channels

2.1 Framework

To define wealth mobility outcomes and their sources, let us consider the following simplified budget constraint for an individual j:

$$w_j(t+1) = \left[1 - \theta_j(t)\right] \left[w_j(t)(1 + \alpha_j^a(t) r^a(t) + \alpha_j^i(t) r_j^i(t)) + y_j(t) + m_j(t) + \mu_j(t)\right] \quad (1)$$

where w_j denotes the individual's wealth level, θ_j its consumption rate out of total resources available, α_j^a and r^a the allocation to and return on aggregate investment risk, α_j^i and r_j^i the allocation to and return on idiosyncratic investment risk, y_j labor income, m_j net receipts of inter-vivos transfers and inheritances, and μ_j a residual variable that captures household formation effects. I assume that the return on the riskless asset equals zero. In addition, I abstract from taxation for simplicity. Furthermore, an individual j is assumed to belong to a family, which consists of individuals across multiple generations. In this paper, an individual's family is equaled to its parents and grandparents (so that siblings and great-grandparents are excluded).

θ_j, α_j^a and α_j^i constitute the behavioral parameters of the individual. The level of any $z_j \in \{\theta_j, \alpha_j^a, \alpha_j^i\}$ is assumed to be determined by an interplay of type- and scale-dependence. Formally:

$$z_j(t) = \bar{z}\left[\kappa_j(t)\right] + \epsilon_j(t) \quad (2)$$

where $\bar{z}\left[\kappa_j\right]$ denotes the level of parameter z specific to wealth rank κ, and ϵ_j the individual-specific variation around $\bar{z}$. ϵ_j is defined as type dependence, whereas $\bar{z}\left[\kappa_j\right]$ represents scale dependence[3]. Specifically:

- Type dependence captures structural parameter heterogeneity across individuals, or − equivalently − ex-ante heterogeneity. For example, despite having near-identical wealth ranks, individual a may display higher saving rates or higher aggregate or idiosyncratic investment risk allocations compared to individual b. This could follow from structural heterogeneity in preferences, cultural attitudes or social norms. If long-lasting, these favorable characteristics of individual a are expected to generate higher wealth accumulation over time for individual a relative to individual b.
- Scale dependence captures the change in parameter z in response to variation in an individual's wealth rank κ_j − or ex-post heterogeneity. Suppose individuals c and d are initially identical in terms of wealth levels, labor income and type-dependent parameter

[3]There may also be a lifecycle bias underlying the parameter z_j. In this paper, I abstract from this bias for simplicity.

levels. However, individual c experiences a positive idiosyncratic shock, e.g. an increase in its labor income or the receipt of an inter-vivos transfer. As the wealth level of individual c rises, its aggregate risk allocation or saving rate may increase as a result of behavioral (non-homothetic preferences) or institutional determinants (higher expected returns thanks to superior investment fund access).

2.2 Three research questions

Using the framework from Section 2.1, the remainder of this paper uses data from the Panel Study of Income Dynamics (PSID) to investigate three research questions:

1. From an inter-generational perspective, I investigate how the within-cohort wealth ranks of individuals compare to the within-cohort wealth ranks of their parents (at identical points in their lifecycles) and grandparents (at different points in their lifecycles). Such static comparison of wealth ranks across generations is the approach commonly taken in the literature (e.g. Adermon et al., 2018; Boserup et al., 2017; Pfeffer & Killewald, 2018; Siminsky & Yu, 2022). I investigate this in Section 4 of the paper.
2. From an intra-generational perspective, the paper analyzes the within-cohort wealth rank changes of individuals over their lifecycle. For example, given one's within-cohort wealth rank at the age of 30 or 55, what is the probability of this individual moving upward or downward the wealth rank distribution as it progresses through working life or older age? And how do the observed wealth rank trajectories relate to individuals' inter-generational transfer receipts and socio-economic characteristics? I evaluate intra-generational mobility outcomes in Section 5 of the paper, and report composition statistics in Section 7.
3. Bridging the inter- and intra-generational perspectives, this paper is the first to investigate the inter-dependence between individuals' wealth rank trajectories and those of family members (i.e. within-family inter-dependence in intra-generational wealth mobility). That is, does there exist covariance between the changes in individuals' wealth ranks and those of their parents, grandparents or siblings over the same time period? If yes, this suggests the presence of altruism across generations and/or the exposure to identical sources of idiosyncratic risk across family members. I investigate this for individuals and their parents in Section 6 of the paper.

In addition, I investigate the time trend and cross-country differences in inter- and intra-generational wealth mobility. That is, has the increase (over time) in overall wealth inequality (e.g. Saez & Zucman, 2016; Smith et al., 2023; Zucman, 2019) coincided with changes in inter- or intra-generational wealth mobility? And how does wealth mobility in the United States compare to other countries for which data is available?

2.3 Wealth mobility channels

The budget constraint in Equation 1 allows to differentiate between five channels of inter-generational wealth transmission, as well as four channels of intra-generational wealth mobility. While this paper does not quantify the importance of these channels, they aid the interpretation of the reported wealth mobility outcomes later in the paper.

Inter-generational channels There are five channels of inter-generational (family-level) wealth transmission. First, an individual may receive inter-vivos transfers or inheritances from its parents or grandparents. This introduces a positive association between an individual's wealth rank posterior to the transfer receipt and the wealth ranks of the parents or grandparents prior to their transfer or death. Moreover, wealthy parents may be more likely to finance consumption expenditures of their children (inter-vivos transfers in kind). Second, there exists strong evidence that parental wealth positively affects labor market outcomes as a result of genetic, social, education and network effects (e.g. Holmberg et al., 2024; Karagiannaki, 2017; Pfeffer, 2018; Staiger, 2023). As high labor income is associated with higher wealth accumulation over the lifecycle, this creates a positive association between wealth ranks across generations. Third, investment in high-return assets (such as housing or business) may require substantial upfront expenditures, meaning that individuals might experience borrowing constraints (e.g. Lee et al., 2020). Access to parental or grandparental wealth could provide the required collateral to circumvent these constraints and allow for higher wealth accumulation over the lifecycle. Fourth, the type-dependent level of an individual's parameters may be influenced by the type-dependent levels of its parents or grandparents. For example, children could inherit saving and risk-taking behavior from their parents with a non-random probability as a result of genetic or social effects (e.g. Black et al., 2020; Fagereng et al., 2021; Lindquist et al., 2015). Fifth, wealth levels may play a critical role in social network formation. If children have access to the social networks of their parents or grandparents, individuals from high-wealth families might be more likely to create a household with individuals from similar-wealth families (e.g. Charles et al., 2013; Wagner et al., 2020; Fagereng et al., 2022).

Intra-generational channels In addition to the sources of inter-generational wealth transmission, I distinguish between four channels of intra-generational (individual-level) wealth mobility. First, diverging idiosyncratic risk realizations may generate individual-level wealth mobility over time. In the framework of Section 2.1, there exist two sources of idiosyncratic risk: labor income and investment idiosyncratic risk (which may include the business-specific risk in a non-Markovian portfolio or the idiosyncratic risk to housing). Second, individuals are type-dependent in behavioral parameters. Insofar as an individual's wealth-rank neighbors have dissimilar type-dependent levels, the individual is expected to experience downward or upward mobility over time even when facing identical aggregate and idiosyncratic risk realizations to its wealth rank neighbors. Third, an individual may experience wealth mobility as a result of inter-generational transfer receipts that diverge from those received by its wealth rank neighbors. Fourth, an individual can move up or down the wealth distribution through its own and its wealth rank neighbors' choices of relationship or marriage partners (household formation).

Two remarks are in place. First, the presence of scale dependence widens absolute differences in wealth levels over time and hence generates a more unequal stationary wealth distribution. However, it does not trigger changes in individuals' wealth ranks, and therefore does not constitute a distinct source of wealth mobility. Second, there may exist type and scale dependence in non-financial variables that affect the idiosyncratic risk realizations or behavioral parameters from Equation 1. A prime example of such non-financial variable is health (e.g. De Nardi et al., 2024; Mahler & Yum, 2024). Specifically, an individual's health may affect its labor income outcomes, as well as its saving rates or risky asset allocations. At given wealth ranks, some individuals face better health than others due to genetics or health habits over the lifecycle (a type dependence). At the same time, health may be directly linked with wealth due to the access to healthcare facilities that wealth buffers enable (a scale dependence).

3 Data & methods

3.1 Data

This paper uses data from the Panel Study of Income Dynamics (PSID), which was conducted annually between 1968 and 1997 and bi-annually from 1999 to 2021. All survey waves infer about family units' gross main housing value, gross main housing mortgage debt and rental payments. The waves in 1984, 1989, 1994 and 1999-2021 add to this questions about other assets and debts, which allows to define wealth. In the remainder of this paper, I refer to a full sample Ω (spanning years 1969 to 2021) and a reduced sample Ψ (which contains only the years where wealth-related questions were inquired). A more detailed description of the dataset is provided in Appendix A.

The harmonization and validation of PSID-data constitutes a key contribution of this paper, as does the construction of ML-proxies to approximate wealth ranks starting in 1969 (over the full sample Ω). However, to limit the technicality of the main text, I place these contributions in the Appendices. Appendix A provides a detailed description and validation of the PSID-data, while Appendix B harmonizes the wealth variables and reports variable-specific outliers. Appendix C describes the construction of the gradient boosting (GB) ML-model used to proxy wealth levels and ranks prior to 1984. It underscores the superior performance of this model compared to naive proxies (which are used in e.g. Chetty et al. (2020) and Pfeffer & Killewald (2018)) in predicting household wealth levels.

A key concern related to the PSID involves its inaccurate representation of the top wealthiest. The validation exercise in Appendix A underscores this concern: the PSID under-estimates the top 10% wealth share by slightly over 10%-points compared to the top-wealth-adjusted Survey of Consumer Finances (SCF). This relative error becomes larger the smaller the group of top wealthiest households under consideration. However, there are two reasons why the PSID can effectively be used to study wealth-related topics, and wealth mobility in particular. First, wealth mobility metrics use the number of households across the wealth distribution as calculation inputs. If one defines top wealth broadly (e.g. the top 10%), excluding a small number of high-wealth households therefore has a much more limited impact on these wealth mobility measures than for wealth inequality metrics (which instead rely on total wealth owned by households). Second, despite its under-estimation of top wealth, the PSID does accurately capture wealth inequality and accumulation trends over time (see Appendix A).

3.2 Empirical strategy

The empirical strategy can be described in three steps. A detailed explanation of these steps is provided in Appendix D. In what follows, I provide a concise summary. First, given that individuals may switch households over time, we are ultimately interested in individuals' wealth rank trajectories rather than those of households. I convert household-level to individual-level data based on the status of the household that the individual belongs to (single, relationship, marriage). Second, individuals are allocated to age cohorts (defined over ten-year intervals) and observations for all variables are summarized by taking the median per lifecycle stage (spanning ages 30-34 to ages 75+). Such summarizing over multiple years is a common approach in the mobility literature (e.g. Boserup et al., 2017; Gregg & Kanabar, 2023). It has several advantages: it smooths out remaining transitory measurement errors and survey non-response, minimizes noise from household transitions, and circumvents the non-uniform timing of PSID survey waves. Third, I define individual-level within-cohort wealth ranks (with maximum ranks normalized to 100), which constitute the principal inputs in the wealth mobility analyses in this paper. The usage of ranks (as opposed to for instance log wealth) has the advantage of dealing with zero and negative observations appropriately and being robust to data transformations (e.g. Boserup et al., 2017).

Two within-cohort wealth ranks series are defined: κ^{Ψ} is computed from actual wealth data in the reduced sample (Ψ), while $\hat{\kappa}^{\Omega}$ is based on proxied wealth data in the full sample (Ω). Mobility outcomes based on these two benchmark series are reported in the main text. As a robustness, I have additionally computed mobility outcomes using $\hat{\kappa}^{\Psi}$, which is calculated from proxied wealth in the reduced sample. Across all wealth mobility analyses in this paper, $\hat{\kappa}^{\Psi}$ yields mobility outcomes that align very closely to those based on $\hat{\kappa}^{\Omega}$. Consequently, differences in outcomes between κ^{Ψ} and $\hat{\kappa}^{\Omega}$ are due to the usage of a different measure (κ versus $\hat{\kappa}$) rather than differences in underlying samples (Ψ versus Ω). Throughout this paper, I will demonstrate that the proxy wealth series $\hat{\kappa}$ under-estimate the actual degree of inter- and intra-generational wealth mobility (based on κ).

3.3 Outcome metrics

The inter- and intra-generational analyses rely on a comprehensive set of inequality and mobility metrics, defined in detail in Appendix E. These measures allow to study overall inter- and intra-generational wealth inequality and mobility, as well as mobility at the bottom and top of the wealth distribution. In what follows, I provide an overview of the mobility and inequality metrics.

To study overall wealth mobility (across the entire wealth distribution), I compute rank-rank coefficients β. These regress within-cohort wealth ranks at some final lifecycle stage on within-cohort wealth ranks at some initial lifecycle stage using Ordinary Least Squares (OLS). This is a common approach in the mobility literature (e.g. Deutscher & Mazumder, 2021; Mogstad & Torsvik, 2023). As a robustness, I have also computed overall mobility outcomes based on a squared mobility metric that attaches greater weight to large wealth rank changes (see Appendix E). It produces the same conclusions as the rank-rank coefficients, so that I do not report this squared mobility metric in the main text.

To investigate mobility at the bottom and top, I primarily rely on transition probabilities, which compute the ex-ante (ex-post) probability of a family or individual moving towards (originating from) a specific wealth bin given their starting position in some initial (final) wealth bin. In addition, I categorize families or individuals into discretionary groups and hierarchical clusters. More precisely:

- Discretionary groups: families or individuals with distinct wealth rank combinations or trajectories are allocated to a discretionary group. At the bottom, (i) the steady poor include the families or individuals that start and end in the bottom 20%, (ii) the past poor those that display upward wealth mobility to the top 50% originating from the bottom 20%, and (iii) the new poor start off in the top 50% but experience downward mobility to the bottom 20%. At the top, (iv) the steady wealthy start and end in the top 10%, (v) the past wealthy begin in the top 10% but display downward mobility to the bottom 70%, and (vi) the new wealthy experience upward mobility to the top 10% after starting off in the bottom 70%.
- Hierarchical clusters[4]: individuals are grouped into clusters based on their wealth rank trajectories over the lifecycle, in line with Audoly et al. (2024). These provide complementary evidence to the discretionary groups: while the discretionary groups capture only the subset of individuals with the most extreme wealth rank trajectories, the clusters group every single individual in the sample into a distinct cluster. The clusters therefore provide insight into how broad-based the overall wealth mobility is. A mathematical derivation of the clustering algorithm is provided in the Online Supplement.

[4]This hierarchical clustering procedure is applied only in the intra-generational analysis as it requires wealth rank trajectories (rather than combinations) as input.

In addition, for the intra-generational analysis, I define variables that capture within-cohort wealth inequality and accumulation. These encompass within-cohort wealth shares, wealth to average labor income ratios, and the proportion of low- and high wealth individuals across the lifecycle. The latter are defined as individuals with wealth levels below annual average labor income (low wealth) and in excess of twenty times annual average labor income (high wealth).

4 Inter-generational family-level mobility

This section investigates wealth mobility within families from a static perspective. Wealth rank outcomes of individuals are compared to those of their parents at identical lifecycle stages and to those of their grandparents at different lifecycle stages (due to unavailable data at the same lifecycle stages). Section 4.1 provides the outcomes across two generations (parent-child), while Section 4.2 produces the results across three generations (grandparent-grandchild).

I restrict the sample to (grand)children's age cohorts that have at the minimum 750 observations in at least one (grand)parent-(grand)child lifecycle stage combination[5]. The analyses below report rank-rank coefficients, as well as transition probabilities across two and three generations. Crucially, the rank-rank regressions do not include age controls. Instead, they are computed across different (grand)parent-(grand)child lifecycle combinations to more distinctly quantify the impact of (grand)parent and (grand)child age on rank-rank coefficient estimates.

Previewing the results, parent-children wealth rank resemblance is found to increase with parent-child age (parent-child lifecycle bias), while wealth rank resemblance between grandparents and their grandchildren is higher when grandchildren are older than 35 years (grandchild lifecycle bias). In addition to these timing effects, two-generational wealth mobility has declined over time (specifically between ages 35-44), and three-generational wealth mobility exceeds two-generational wealth mobility. The latter effect is non-linear, however: mobility at the top is significantly higher across three versus two generations, while the difference in mobility at the bottom is comparatively weaker.

4.1 Inter-generational mobility across two generations

Section 4.1 evaluates inter-generational parent-child mobility (across two generations). Using rank-rank coefficient estimates β (Figure 1), I quantify the degree of mobility across the entire

[5] Letting PC and GC denote parent-child and grandparental-grandchild linkages, the (grand)children's age cohorts that fulfill the minimum observation criterion include:

$$Y^{PC} = \{P^{PC}, 1936\text{–}45, 1946\text{–}55,\ 1956\text{–}65,\ 1966\text{–}75,\ 1976\text{–}85\}$$
$$Y^{GC} = \{P^{GC}, 1956\text{–}65,\ 1966\text{–}75,\ 1976\text{–}85\}$$

Here, P^{PC} and P^{GC} denote the pooled dataset in the two- and three-generational samples. These contain the observations across all other selected age cohorts.

wealth distribution (overall mobility) as well as the impact of the parent-child lifecycle bias on the estimations. I subsequently investigate the mobility at the bottom and top of the wealth distribution using ex-ante and ex-post transition matrices $T_{\mathrm{EA}}(a)$ and $T_{\mathrm{EP}}(a)$ (Figures 2 and 3).

Overall mobility The analysis of overall mobility across two generations generates three key findings (Figure 1). First, the estimated parent-child rank-rank coefficients β range from 0.34 to 0.38 (based on actual wealth) and from 0.36 to 0.51 (based on proxy wealth). Second, the resemblance between parents and their children in terms of within-cohort wealth ranks is significantly higher at ages 35-39 compared to ages 30-34. At later ages, the two-generational resemblance increases further, peaking between ages 60 and 64 (with no data available for later stages). This follows from the upward-sloping profile of the β-values, and indicates the presence of a parent-child lifecycle bias in two-generational wealth mobility outcomes. Third, although they accurately capture age dynamics, the proxy wealth ranks under-estimate the degree of two-generational wealth mobility, contrary to the claim in Pfeffer & Killewald (2018).

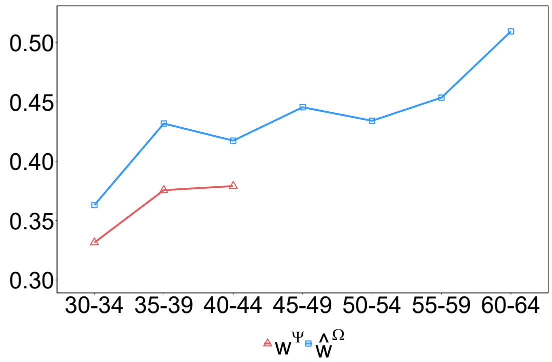
The increased parent-child resemblance with age (parent-child lifecycle bias) may be attributed to two mechanisms. First, the fraction of individuals that receives an inter-vivos transfer or inheritance increases strongly during working life, from around 10% at ages 30-34 to close to 40% by ages 50-54 (Appendix G). This is likely to generate greater alignment between parent and child within-cohort wealth ranks as children's working life progresses (channel 1 in Section 2.3). Second, individuals may have inherited labor market outcomes or type-dependent parameter levels from their parents, or could have married household partners with similar parental wealth. These channels (channels 2-5 in Section 2.3) increasingly affect individuals' wealth levels as their lifecycle progresses and are therefore expected to generate greater parent-child wealth rank resemblance after some time.

Literature comparison How do the β-estimates in Figure 1 compare to those reported in the literature? In what follows, I compare the findings to existing estimates for the United States, the Nordic countries, Australia and the United Kingdom.

For the United States, my estimated values for actual wealth (0.34 to 0.38) are slightly below those of Pfeffer & Killewald (2018): these authors find a two-generational rank-rank coefficient of 0.39 using PSID-data until 2015. Moreover, based on a PSID-sample until 2017, Siminsky & Yu (2022) produce a β-estimate of 0.34, which is similar to the estimates produced in this paper. Both Pfeffer & Killewald (2018) and Siminsky & Yu (2022) use actual wealth series in a regression where parents' and children's ages are included as control variables. Finally, using log-log regressions, Charles & Hurst (2003) and Conley & Glauber (2008) find wealth rank coefficient estimates of 0.37 and 0.28 respectively based on two-generational PSID-samples that include relatively young children.

Two-generational wealth mobility in the United States is lower than in Norway, Denmark and Australia, but similar to the United Kingdom and Sweden. Specifically, Boserup et al. (2017)

Figure 1: Two-generational rank-rank coefficients β for parents and children at identical lifecycle stages for the pooled dataset.



Note: this figure reports rank-rank coefficients β computed from parents' and children's within-cohort wealth ranks. These are compared at identical lifecycle stages (shown on the x-axis). Coefficients are reported based on actual wealth if available (from w^{Ψ}) and proxy wealth (from $\hat{w}^{\Psi}$). In the rank-rank regressions, children's wealth ranks are the dependent variable. The usage of the pooled dataset indicates that individuals across all selected age cohorts are included in the sample.

report a wealth rank coefficient of 0.27 (at age 45) for Denmark, while Fagereng et al. (2021) and Audoly et al. (2024) respectively find a rank-rank coefficient of 0.17 (regression with age controls) and a rank-rank coefficient of 0.25 (at parent-child age 55) for Norway. Moreover, Siminsky & Yu (2022) produce a β-estimate of 0.25 (regression with age controls) for Australia. These estimates lay significantly below my estimates for the United States (0.34 to 0.38). By contrast, for the United Kingdom, Gregg & Kanabar (2023) and Levell & Sturrock (2023) produce rank-rank coefficients of 0.30 and 0.36 respectively (regressions with age controls). In addition, for Sweden, Adermon et al. (2018) observe β-estimates between 0.30 and 0.39 (regression with age controls), while Black et al. (2020) produce a coefficient of 0.35 (regression with age controls). All these studies rely on actual wealth data as opposed to naive or machine learning wealth proxies.

The parent-child lifecycle bias in two-generational mobility is well established in the literature. For the United States, Pfeffer & Killewald (2018) find that two-generational wealth rank resemblance increases with parent-child age: their estimated two-generational rank-rank coefficient rises from 0.33 at ages 25-34 to 0.44 at ages 55-64. Moreover, regressing child wealth ranks between ages 20 and 45 on parent wealth ranks at age 45 for Denmark, Boserup et al. (2017) find a U-shaped pattern that bottoms at children's mid-twenties. Likewise, Audoly et al. (2024) regress child wealth ranks from ages 30 to 55 on parent wealth ranks at age 55 (on average) and report a positive linear relationship between child age and their β-estimates for Norway. Finally, Adermon et al. (2018) and Siminsky & Yu (2022) find evidence on two-generational age effects for Sweden and Australia respectively.

Cross-cohort differences Next to cross-country heterogeneity, we are interested in the evolution

Table 1: Two-generational rank-rank coefficients β across children's age cohorts $\in \Upsilon^{\mathbf{PC}}$ for parents and children at identical lifecycle stages.

Variable	Stage	1946–55	1956–65	1966–75	1976–85	1986–95	Pooled
	30–34	-	-	-	0.35	-	0.33
κ^{Ψ}	35–39	-	-	0.34	0.40	-	0.38
	40–44	-	-	0.35	0.46	-	0.38
	30–34	-	-	0.36	0.36	0.38	0.36
	35–39	-	0.38	0.44	0.45	-	0.43
	40–44	-	0.36	0.42	0.49	-	0.42
$\hat{\kappa}^{\Omega}$	45–49	0.47	0.42	0.46	-	-	0.45
	50–54	0.44	0.40	-	-	-	0.43
	55–59	0.47	0.45	-	-	-	0.45
	60–64	0.50	-	-	-	-	0.51

Note: this table reports rank-rank coefficients for parents' and children's within-cohort wealth ranks across all children's age cohorts. These are compared at identical lifecycle stages (ranging from 30-34 to 60-64) based on actual wealth ranks κ^{Ψ} and proxy wealth ranks $\hat{\kappa}^{\Omega}$. In the rank-rank regression, children's wealth ranks are the dependent variable. The rank-rank coefficients are calculated only when an age cohort has at the minimum 750 observations for the respective variable (as specified in the introduction to Section 4).

of two-generational wealth mobility over time. To this end, I compare rank-rank coefficient estimates across age cohorts (Table 1).

Inter-generational wealth mobility across two generations in the United States is found to have declined over time. The declining mobility can be established only between ages 35 and 44, however. Specifically, for the 35-39 and 40-44 lifecycle stages, two-generational β-estimates are significantly higher the more recent the child cohort. For the other lifecycle stages, no definite conclusions can be drawn[6]. The increase in β is particularly strong for the 40-44 stage, with β rising from 0.36 (1956-65 cohort) to 0.49 (1976-85 cohort) based on proxy wealth. The decline in wealth mobility across two generations is both due to stronger persistence at the bottom and at the top, as shown in the Online Supplement.

How does this relate to existing literature? This paper is the first to investigate the time trend in overall two-generational wealth mobility. As a result, it is also the first to demonstrate the decline in overall two-generational wealth mobility for the United States. However, complementary evidence is provided by Fernholz & Hagler (2023), who report a decline in inter-generational wealth mobility for the top 400 wealthiest American families since 1985 (using Forbes 400 data). Furthermore, the decline in overall inter-generational wealth mobility aligns

[6]For the 30-34 stage, the β-estimates for the 1966-75 and 1976-85 cohorts are roughly identical, and only moderately higher for the 1986-1995 cohort. No data is available for earlier cohorts. For the 45-49, 50-54 and 55-59 stages, differences between the estimates for the 1946-55 and 1956-65 or 1966-75 cohorts are very limited. These stages do not have sufficient data available for the 1976-85 cohort to generate a β-estimate.

with evidence from Blanden et al. (2023) and Gregg & Kanabar (2023) for the United Kingdom, as well as with findings from Adermon et al. (2018) for Sweden.

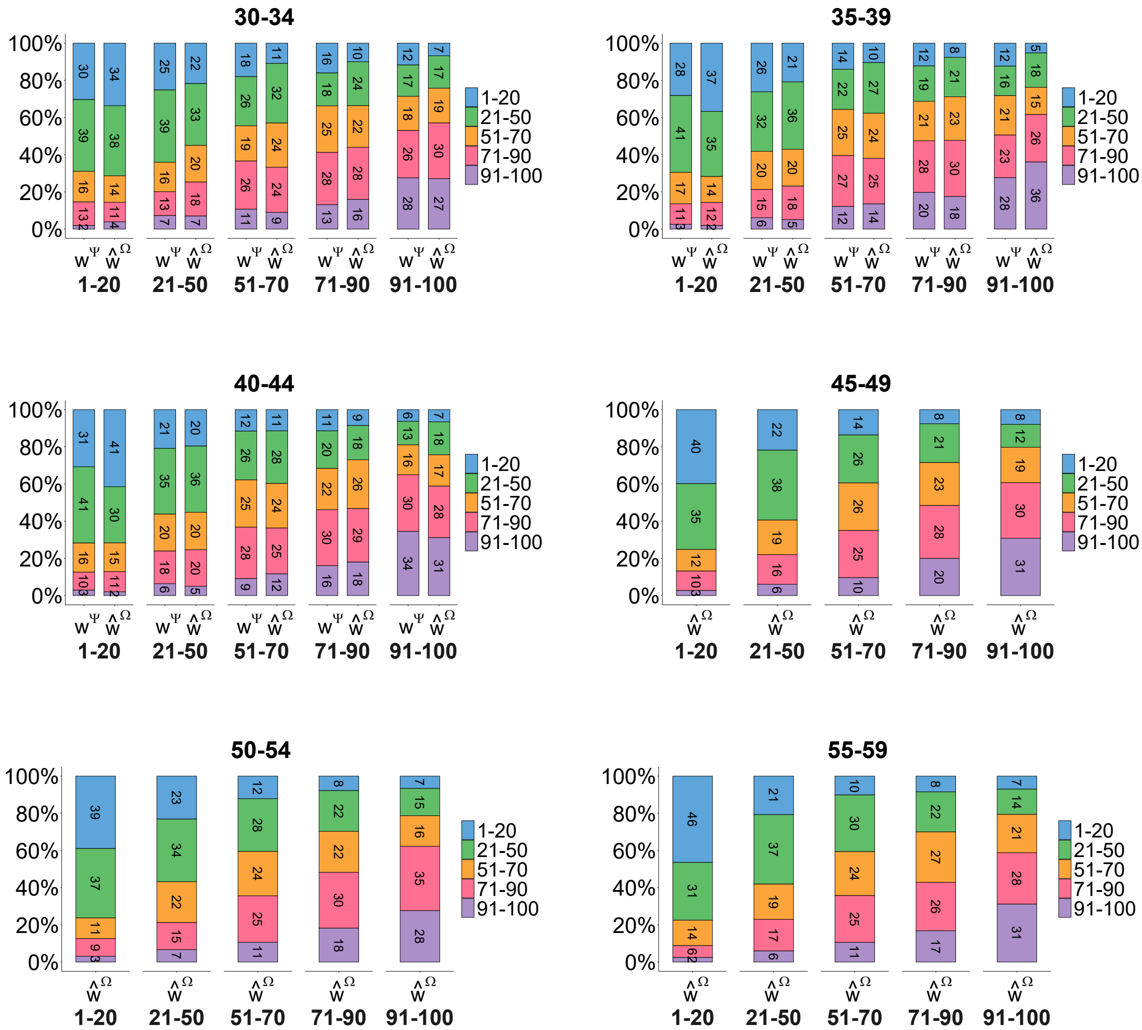
Mobility at the bottom & top The rank-rank coefficients provide insight into wealth mobility outcomes across the entire wealth distribution. Instead, the ex-ante and ex-post transition matrices ($T_{\mathrm{EA}}(a)$ and $T_{\mathrm{EP}}(a)$, Figures 2 and 3) and discretionary groups (Appendix H) provide more detail on mobility at the bottom and top of the wealth distribution. Together, the discretionary groups contain approximately 25% of parent-child pairs. In what follows, I report the baseline transition probabilities derived from κ^{Ψ} as a benchmark, and provide the results based on ML-proxy $\hat{\kappa}^{\Omega}$ in parentheses.

The pooled T_{EA} and T_{EP} show that:

- At the bottom: of parents in the bottom 20% at some lifecycle stage, 28%-31% (34%-46%) of their children end up in the bottom 20% at the same stage (Figure 2). These steady poor families constitute around 6% (7%-8%) of the sample. Moreover, 29%-31% (22%-29%) of children from parents in the bottom 20% at some stage ascend to the top 50% at the same lifecycle stage (Figure 2), representing 6% (5%) of the sample (past poor family pairs). Finally, of children in the bottom 20% at a given lifecycle stage, 28%-35% (23%-27%) originate from parents in the top 50% at that stage (Figure 3). These new poor family pairs constitute around 6%-7% (5%) of the sample.
- At the top: 28%-34% (27%-36%) of the children from parents in the top 10% at some stage end up in the top 10% at the same stage (Figure 2). These steady wealthy families constitute around 3% (3%-4%) of the sample. Furthermore, 35%-49% (38%-43%) of the children from parents in the top 10% at some stage drop to bottom 70% at the same stage (Figure 2), making up about 4%-5% (3%-4%) of the sample (past wealthy families). Last, 43%–47% (39%–43%) of children who end up in the top 10% at some stage originate from parents in the bottom 70% (Figure 3). These new wealthy make up approximately 4%-5% (4%) of the sample.

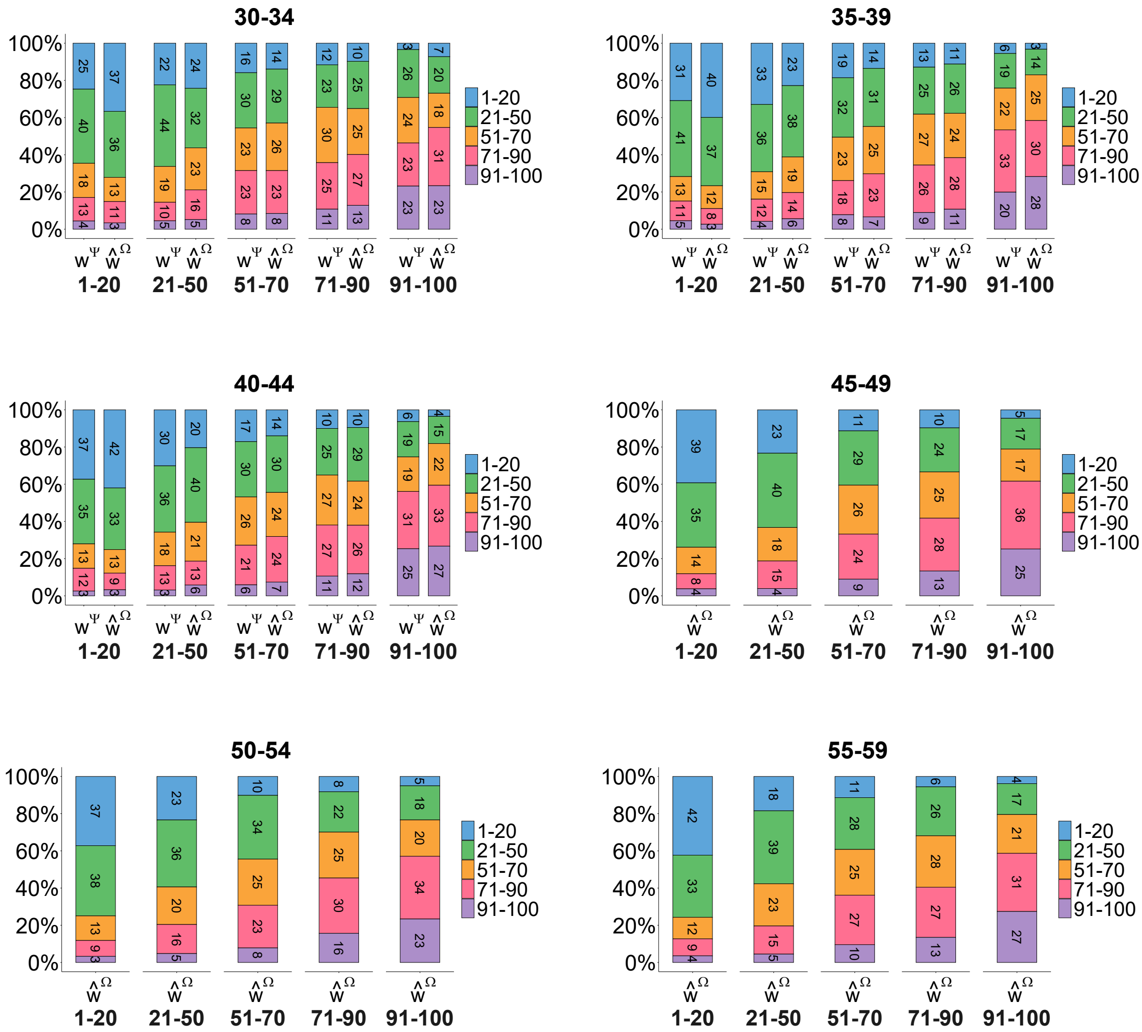
These results have three key implications. First, overall mobility across two generations (over the entire wealth distribution) is driven by both mobility at the bottom and mobility at the top. Second, the parent-child lifecycle bias in two-generational samples is stronger at the bottom than at the top. Specifically, the probability of families consolidating in the bottom 20% rises strongly with (parent-child) age considered, following the age pattern for overall mobility reported in Figure 1. By contrast, the link between parent-child age and persistence at the top is comparatively weaker. Third, in line with the overall mobility analysis, the proxy wealth ranks under-estimate the actual degree of inter-generational wealth mobility.

Figure 2: Ex-ante transition matrices $T_{\text{EA}}(a)$ between parental and children wealth ranks at identical lifecycle stages for the pooled dataset.



Note: these transition matrices compare parents' and children's within-cohort wealth ranks at identical lifecycle stages (ranging from stages 30-34 to 60-64). The transition probabilities are reported both for actual wealth w^{Ψ} (if available) and proxy wealth $\hat{w}^{\Omega}$. Given that the matrices are computed ex-ante, the x-axis represents parental wealth ranks. The y-axis displays children's wealth ranks given the wealth ranks of their parents at the same lifecycle stage.

Figure 3: Ex-post transition matrices $T_{\mathrm{EP}}(a)$ between parental and children wealth ranks at identical lifecycle stages for the pooled dataset.



Note: these transition matrices compare parents' and children's within-cohort wealth ranks at identical lifecycle stages (ranging from stage 30-34 to 60-64). The transition probabilities are reported both for actual wealth w^{Ψ} (if available) and proxy wealth $\hat{w}^{\Omega}$. Given that the matrices are computed ex-post, the x-axis represents children's wealth ranks. The y-axis displays parental wealth rank outcomes given their children's wealth ranks at the same lifecycle stage.

4.2 Inter-generational mobility across three generations

Having discussed inter-generational wealth mobility across two generations, I now discuss wealth mobility for grandparent-grandchild combinations (across three generations) for the pooled dataset. I report overall wealth mobility and age effects based on rank-rank coefficients (Figure 4), and provide more detail through the transition probabilities (Figure 5). A cross-cohort comparison is not feasible as the majority of grandchildren is concentrated in the same age cohort (1976-85).

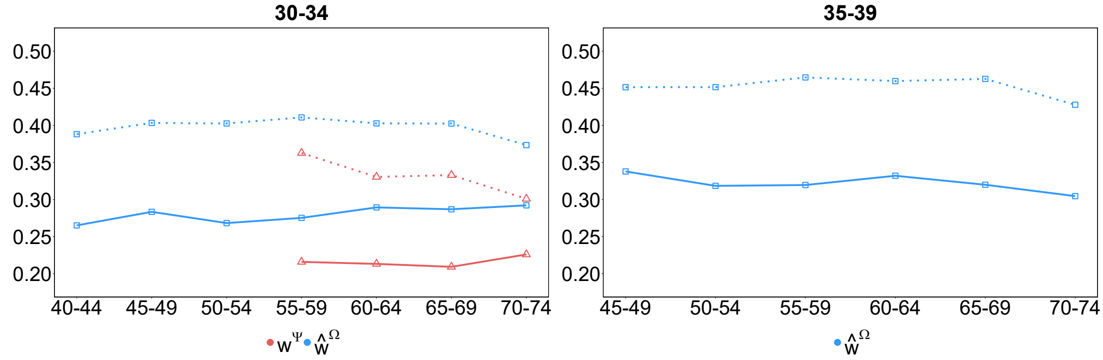
Grandparental wealth ranks are observed from age 40 or 45 onwards, while grandchild wealth ranks are recorded only between ages 30 and 39. As a result, contrary to the two-generational mobility analysis, a comparison of the within-cohort wealth ranks of grandparents and grandchildren at identical lifecycle stages is not feasible. This mismatch is a common issue in the literature on inter-generational wealth mobility across three generations (Boserup et al., 2014; Pfeffer & Killewald, 2018). To allow for a direct comparison with the degree of three-generational wealth mobility, I consistently report the two-generational outcomes over the considered stage combinations also (as dotted lines).

Overall mobility Grandparent-grandchild inter-generational wealth mobility is higher than parent-child mobility. This is evidenced by the lower three-generational rank-rank coefficient estimates (solid lines) compared to the two-generational estimates (dotted lines) in Figure 4. The three-generational rank-rank coefficient β-estimates vary in function of the grandparent-grandchild stage combination considered. For grandchildren aged between 30 and 34, rank-rank coefficients range between $0.21-0.23$ based on actual wealth and between $0.27-0.29$ based on proxy wealth. For grandchildren aged between 35 and 39, the β-range based on proxy wealth increases to $0.30-0.34$ (with no estimate available for actual wealth).

Wealth rank resemblance between grandparents and grandchildren is stronger for grandchildren aged 35-39 compared to ages 30-34: the rank-rank coefficient estimates based on the proxy wealth ranks are approximately 4 to 6 points higher for grandchildren in stage 35-39 relative to grandchildren in stage 30-34 (regardless of grandparents' ages). This follows from the higher β-levels observed on the right-hand compared to the left-hand side plot in Figure 4, and indicates the presence of a grandchild lifecycle bias. Although unsurprising in light of the parent-child lifecycle bias (see Section 4.1.1), this grandchild lifecycle bias in β-estimates constitutes a novel result in the three-generational wealth mobility literature.

The grandchild lifecycle bias has two key implications. First, the three-generational β-ranges for stage 30-34 ($0.21-0.23$ for actual wealth) likely over-estimate the degree of grandparent-grandchild inter-generational wealth mobility during midlife in the United States: rank-rank coefficients when grandchildren reach midlife are likely to be significantly higher. Given that Pfeffer & Killewald (2018) use a PSID-sample with young grandchildren, their rank-rank coefficient estimates likely suffer from the same downward bias (see below). Second, the grandchild

Figure 4: Rank-rank coefficients β for grandparents and grandchildren (solid lines) and parents and children (dotted lines) when (grand)children are aged 30-34 and 35-39.



Note: this figure produces rank-rank coefficients β computed from the within-cohort wealth ranks of grandparents-grandchildren (solid lines) and parents-children (dotted lines). These are calculated at different lifecycle stage combinations. Specifically, I compare (grand)child wealth ranks at ages 30-34 (left-hand side) and ages 35-39 (right-hand side) to (grand)parental wealth ranks across the lifecycle stages reported on the x-axis. The coefficients are computed based on actual wealth if available (from w^{Ψ}) and proxy wealth (from $\hat{w}^{\Psi}$). In the rank-rank regression, (grand)child wealth ranks are the dependent variable. The pooled dataset is used.

age effect appears to be unique to the United States: Boserup et al. (2014) do not find a link between their benchmark rank-rank coefficients and average grandchild age in their Danish sample. However, more research on international three-generational wealth mobility would be needed to validate this conclusion.

Literature comparison How do these findings compare to existing literature? For the United States, Pfeffer & Killewald (2018) report three-generational rank-rank coefficient estimates of 0.23 (using actual wealth) and 0.21 (using proxy wealth). They obtain their rank-rank coefficients through a regression that includes grandparental and grandchild age controls. Moreover, their proxy wealth series naively uses main housing values and rental payments and display inferior performance compared to the ML-proxy used in this paper (see Appendix C). While my actual wealth rank regressions ($0.21-0.23$ at grandchild ages 30-34) yield similar rank-rank coefficients to theirs (0.23), the proxy wealth rank-rank coefficients reported in this paper (0.27 to 0.29 at grandchild ages 30-34) are substantially higher than the one in Pfeffer & Killewald (2018) (0.21).

What explains this large discrepancy in proxy wealth rank β-estimates? The three-generational samples in Pfeffer & Killewald (2018) rely on grandchild observations for 2013 and 2015. As these observations follow closely after the 2008-2009 real estate bust, a naive proxy using solely main housing values may not accurately approximate individual wealth. This is shown in Appendix C: the measurement error of the naive proxy used by Pfeffer & Killewald (2018) is particularly higher during the post-crisis years. Instead, the extended sample (until 2021) and superior ML-proxy used in this paper are likely to have generated a more accurate rank-rank estimate. In line with the two-generational analysis (see Section 4.1.1), these results also imply that − contrary to the claim in Pfeffer & Killewald (2018) − rank-rank coefficients based on proxy wealth under-estimate actual three-generational wealth mobility.

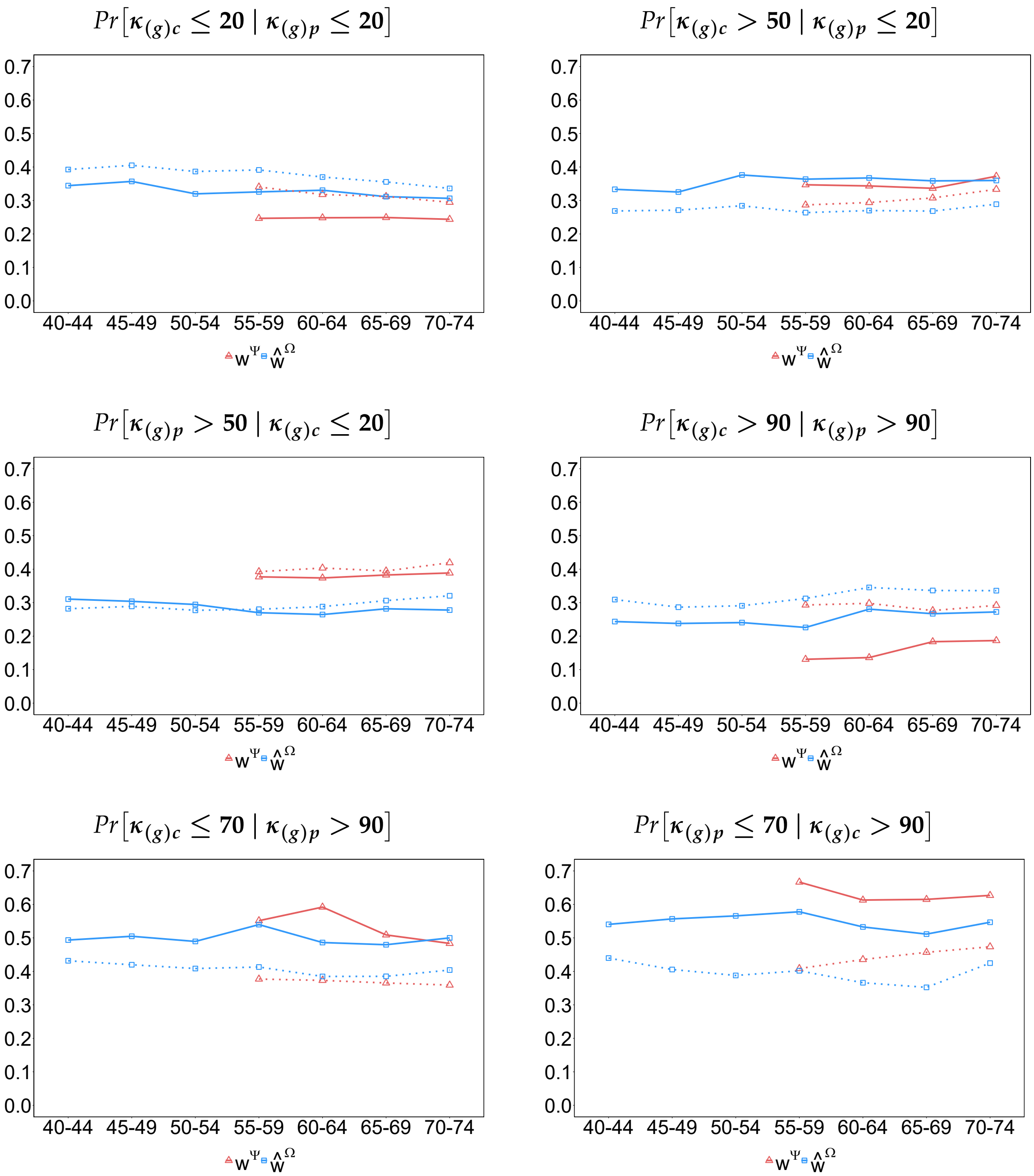
Three-generational wealth mobility in the United States is lower compared to Denmark (in line with the two-generational analysis) and lower than in Sweden (contrary to the two-generational analysis): using actual wealth, Boserup et al. (2014) report a three-generational benchmark β-estimate of 0.16 for Denmark, while Adermon et al. (2018) produce rank-rank coefficients of 0.14 to 0.17 for Sweden. The estimates in both papers are robust to the grandchild lifecycle bias. They are lower than the $0.21-0.23$ values (actual wealth, grandchild ages 30-34) established for the United States in this paper. If sufficient actual wealth data were available for later grandchild stages in the PSID, the grandchild lifecycle bias implies that the gap in three-generational mobility between the United States and Nordic countries would likely be even more pronounced.

Mobility at the bottom & top The transition probabilities affirm the conclusion of higher wealth mobility over three generations (grandparent-grandchild) compared to two generations (parent-child). This finding holds both at the top and bottom of the wealth distribution. There exists a non-linearity, however: while mobility at the top is significantly higher over three compared to two generations, the divergence in wealth mobility at the bottom is more limited.

In what follows, I quantify this non-linearity based on Figure 5. It compares the transition probabilities across three generations (solid lines) versus two generations (dotted lines) when grandchildren are aged between 30-34. Data for this grandchild stage is available for both actual wealth (reported as benchmark) and proxy wealth (reported in parentheses):

- At the bottom: 22%-23% (31%-34%) of grandchildren with grandparents in the bottom 20% during their lifecycle end up in the bottom 20% during stage 30-34, compared to 31%-33% (37%-41%) of children from bottom 20% parents (steady poor). Moreover, 31%-37% (33%-37%) of grandchildren with grandparents in the bottom 20% during their lifecycle end up in the top 50% at ages 30-34, while this number equals 29%-32% (27%-29%) for children from bottom 20% parents (past poor). Conversely, 39%-40% (29%-32%) of grandchildren belonging to the bottom 20% at ages 30-34 originate from grandparents belonging to the top 50% over their lifecycle, compared to 40%-43% (29%-31%) of children from top 50% parents (new poor).
- At the top: 12%-20% (23%-27%) of grandchildren with grandparents in the top 10% during their lifecycle end up in the top 10% during stage 30-34, compared to 28%-30% (30%-33%) of children from top 10% parents (steady wealthy). Moreover, 52%-58% (49%-52%) of grandchildren with grandparents in the top 10% during their lifecycle end up in the bottom 70% at ages 30-34, while this number equals 38%-39% (40%-42%) for children of

Figure 5: Transition probabilities for grandparents and grandchildren (solid lines) and parents and children (dotted lines) when (grand)children are aged 30-34.



Note: these plots produce transition probabilities over specific wealth bin combinations. These are defined in line with the discretionary groups (see Section 3.3 and Appendix E). In the notation above, $\kappa_{(g)p}$ denotes the within-cohort wealth ranks of (grand)parents and $\kappa_{(g)c}$ the within-cohort wealth ranks of (grand)children. The transition probabilities are computed at different lifecycle stage combinations: child wealth ranks at ages 30-34 are compared to (grand)parental wealth ranks at the stages between ages 40-44 and 70-74 (plotted on the x-axis). As an example, the values produced for the right-hand plot on the top row indicate the probability of (grand)children belonging to the top 50% at stage 30-34 given that their (grand)parents belonged to the bottom 20% at any of the x-axis stages. I report the outcomes for child lifecycle stage 35-39 in Appendix H.

top 10% parents (past wealthy). Finally, 61%-68% (53%-58%) of grandchildren belonging to the top 10% at ages 30-34 originate from grandparents belonging to the bottom 70% over their lifecycle, compared to 41%-48% (37%-44%) of children from bottom 70% parents (new wealthy).

These results show that the relative differences between grandparent-grandchild and parent-child transition probabilities are significantly higher for wealthy discretionary families (steady wealthy, past wealthy and new wealthy) compared to the poor discretionary families (steady poor, past poor and new poor). The same conclusion persists when considering grandchild lifecycle stage 35-39 (Figure 21, Appendix H). As a result, mobility at the top is significantly higher over three compared to two generations, while the difference in mobility at the bottom is comparatively more limited.

What are tentative theoretical mechanisms behind this non-linearity? I focus on channels that explain the relatively low persistence at the top, versus those that center on the relatively strong persistence at the bottom. At the top, families pass along significant wealth across generations through inter-vivos transfers and inheritances. In theory, this should generate strong persistence at the top. However, even for steady wealthy parent-child pairs, the inter-generational transfers make up only 4% of their lifetime resources on average during working life[7]. This suggests that their impact on inter-generational wealth transmission may be limited. In addition, business ownership is passed along wealthier families (either through type or scale dependence), as evidenced by high business ownership rates among steady and past wealthy families at the start of the children's working life (see Online Supplement). Given the high idiosyncratic risk involved in business ownership, this is expected to lead to downward mobility for a significant fraction of wealthy families over longer time-frames[8]. At the bottom, a non-negligible number of families are stuck in multi-generational spirals of low labor income and asset ownership, little or no saving, poor health and − as a result of their low wealth levels − minimal inter-generational transfer receipts (see Online Supplement).

5 Intra-generational wealth inequality & individual-level wealth mobility

In this section, I investigate intra-generational (individual-level) within-cohort wealth accumulation, inequality and mobility over the lifecycle. The lifecycle is split up into working life (ages 30-54) and older age (ages 55-74). Section 5.1 produces within-cohort wealth shares and wealth-to-income ratios. Section 5.2 elaborates on the determinants of the within-cohort

[7]Towards the end of working life, this fraction is higher for the most wealthy individuals (around 11%-16%). Nonetheless, in line with evidence from Black et al. (2022) for Norway, inter-vivos transfers and inheritances still make up a relatively limited fraction of lifetime resources even for individuals from wealthy families.

[8]This coincides with the argument made in Kalsi & Ward (2025), who find that persistence among the elite wealthiest during the Gilded Age period in the United States was relatively low.

wealth distribution at the start of the lifecycle. Given their initial wealth ranks at ages 30-34, individuals' wealth rank trajectories during working life and older age are investigated in Section 5.3 and 5.4 respectively. Section 5.5 compares wealth mobility outcomes across age cohorts, while Section 5.6 explores the timing of intra-generational wealth mobility.

Two sample restrictions are applied. First, I limit the working life and older age samples to individuals with wealth rank observations in both the initial (30-34 or 55-59) and final stage (50-54 or 70-74) of the respective lifecycle phase. To ensure a balanced panel, I recalculate the within-cohort wealth ranks for these restricted samples. Second, the sample is further limited to individuals in age cohorts with at least 250 observations for either κ_j^{Ψ} or $\hat{\kappa}_j^{\Omega}$ after the first restriction is applied[9]. The Ψ- and Ω-samples for the pooled data respectively contain 1957 and 3641 observations for working life, and 1327 and 2019 observations for the older age phase. Note that the samples of individuals used for working life and older age are distinct, with no overlap between the individuals of the two samples. Outcomes across the two lifecycle phases are therefore only indirectly comparable.

Previewing the results, within-cohort wealth inequality is found to be stable over the lifecycle. Wealth-to-income ratios rise around fivefold over working life, while wealth decumulation during older age occurs only after age 65. The initial wealth distribution at ages 30-34 overlaps significantly with the distribution of family wealth and distribution of cumulative inter-vivos transfers and inheritances received at that point. Next, I report rank-rank coefficients and transition probabilities. Intra-generational wealth mobility during older age is significantly lower than during working life, and most intra-generational wealth mobility is found to occur between ages 30 and 39. Finally, the data shows a negative correlation between within-cohort wealth inequality (which has increased over time) and wealth mobility at the top 10% (which has significantly declined over time).

5.1 Wealth inequality & accumulation

Within-cohort wealth inequality remains roughly stable throughout the lifecycle, as shown by the relatively flat profile of the pooled wealth shares in Figure 6. During working life, the top 10% wealth share fluctuates between 55% and 60%, while the bottom 50% own 0% to 5% of total wealth. The top 10% wealth shares track closely the SCF-estimates of Bauluz & Meyer (2024), although I do not find higher wealth inequality during the early stages of the working lifecycle (ages 30-34), except for the 1966-75 cohort. During older age, pooled top 10% wealth

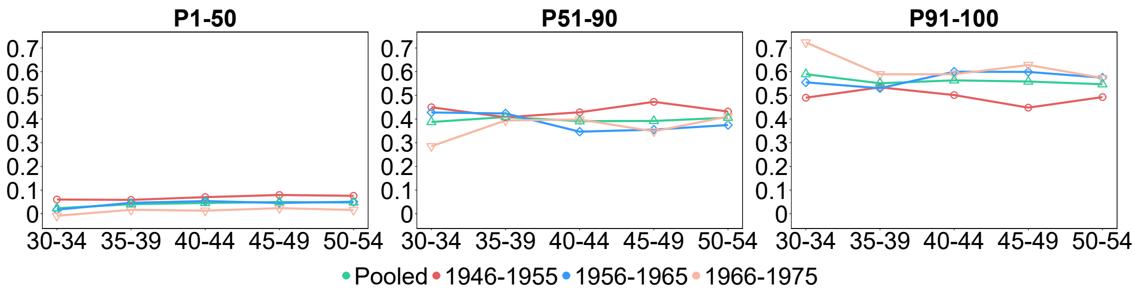
[9] The cohorts that fulfill the minimum observation criterion include:

$$\Upsilon^{\mathrm{WL}} = \{P^{\mathrm{WL}},\ 1936\text{–}45,\ 1946\text{–}55,\ 1956\text{–}65,\ 1966\text{–}75\}$$
$$\Upsilon^{\mathrm{OA}} = \{P^{\mathrm{OA}},\ 1916\text{–}25,\ 1926\text{–}35,\ 1936\text{–}45,\ 1946\text{–}55\}$$

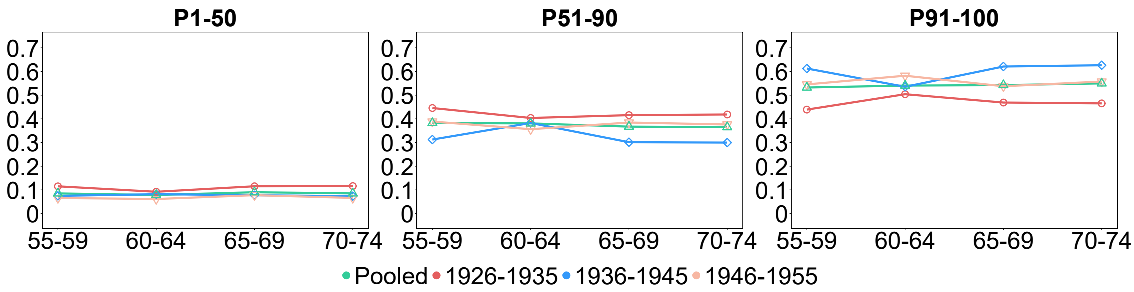
Here, P^{WL} and P^{OA} denote the pooled datasets for working life and older age respectively. These pooled datasets contain all observations from the other cohorts.

Figure 6: Wealth shares λ_b across lifecycle stages for age cohorts $\in \Upsilon^{WL}$ and $\in \Upsilon^{OA}$ based on actual wealth levels w^{Ψ}.

Working life: ages 30-54



Older age: ages 55-74



Note: these plots show the within-cohort wealth shares for the bottom 50%, middle 50%-90% and top 10% wealthiest at each lifecycle stage per age cohort. The shares are calculated using working life and older age samples for actual wealth levels w^{Ψ}. Given that the working life and older age samples contain different individuals, the wealth shares are not directly comparable across the upper and lower panel. The pooled wealth share is computed as the average of the wealth shares across the age cohorts per lifecycle stage.

shares equal approximately 53% between ages 55 and 74, while the bottom 50% owns around 8% of total within-cohort wealth (Figure 6). This leaves an approximate wealth share for the middle 50%-90% of 39%. The observed stability in within-cohort wealth inequality during older age is also consistent with the results of Bauluz & Meyer (2024).

The stability of within-cohort wealth inequality implies that wealth growth rates are similar across the wealth distribution. During working life, wealth-to-income ratios increase around fivefold for the bottom 50%, middle 50-90% and top 10% brackets (Figure 7). This substantial accumulation of wealth over the working lifecycle leads to an increase in the fraction of high wealth individuals from around 1% to 7%, and a decline in the proportion of low-wealth individuals from approximately 58% to 33% (Figure 22, Appendix H). During older age, all wealth brackets exhibit additional wealth accumulation between ages 55 and 64, followed by wealth decumulation between ages 65-74 (Figure 7). The 1946-55 cohort stands out to the others by notably higher wealth to income ratios, and a higher fraction of high-wealth individuals (Figure 22 in Appendix H). This is likely related to the extreme asset price trajectories (Dotcom bubble and Great Financial Crisis) experienced by this cohort at the end of its working life and beginning of its older age.

Within-cohort wealth inequality has increased over time, in line with the SCF-estimates from Bauluz & Meyer (2024). This follows from a cross-cohort comparison of wealth inequality outcomes (Figures 6). For working life, two findings stand out. First, the 1966-75 cohort displayed significantly higher wealth inequality at the start of the working lifecycle compared to the two earlier cohorts (1946-55 and 1956-65), with wealth shares above 70%. In addition, the 1966-75 and 1956-65 cohorts experienced higher wealth inequality from ages 40 to 54 compared to the 1946-55 cohort. Second, for the two most recent cohorts (1956-65 and 1966-75), wealth shares for the bottom 50% were significantly closer to zero compared to the 1946-55 cohort. This likely follows from increased non-mortgage indebtedness in recent decades (e.g. Bartscher et al., 2024). For older age, the two most recent cohorts (1936-45 and 1946-55) experienced higher within-cohort wealth inequality than the 1926-35 cohort: the top 10% wealth share in the most recent cohorts was at least 10%-points higher (at 63% and 56% for the 1936-45 and 1946-55 cohorts compared to 46% for the 1926-35 one). Accordingly, bottom 50% wealth shares in the most recent cohorts lay substantially below those of the 1926-35 one (around 7% versus 11%).

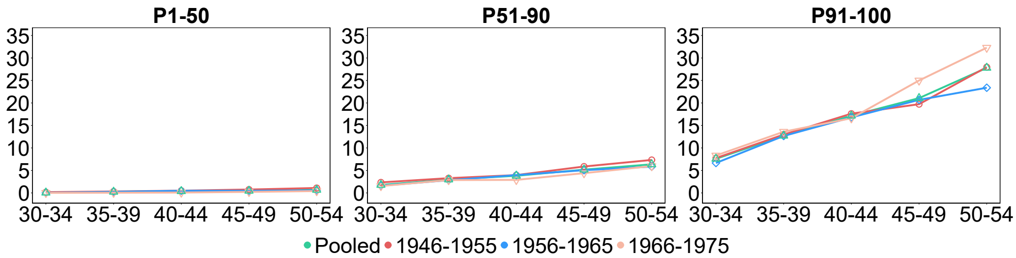
5.2 Wealth distribution: ages 30-34

Around 60% of individuals at ages 30-34 have wealth levels lower than the annual average labor income (Figure 22, Appendix H). Only around 1% of individuals display wealth levels in excess of twenty times labor income. This implies that approximately 39% of individuals start off working life with wealth levels between one and twenty times average labor income. This begs the question: where does this wealth come from?

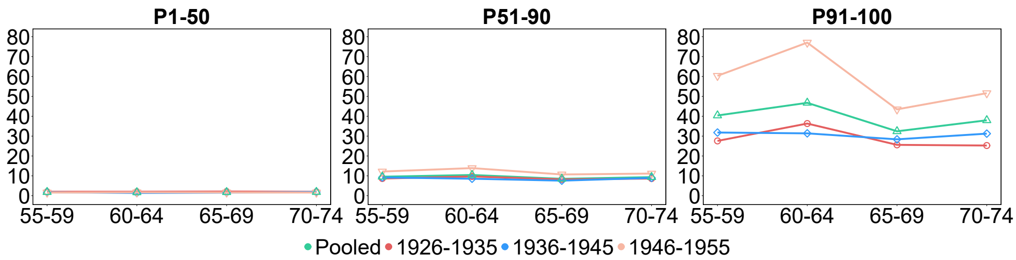
While the structure of the data does not allow for a comprehensive accounting decomposi-

Figure 7: Wealth-to-income ratios θ_b across lifecycle stages for age cohorts $\in \Upsilon^{WL}$ and $\in \Upsilon^{OA}$ based on actual wealth levels w^{Ψ}.

Working life: ages 30-54



Older age: ages 55-74



Note: these plots show the within-cohort wealth-to-income ratios for the bottom 50%, middle 50%-90% and top 10% wealthiest at each lifecycle stage per age cohort. The ratios are calculated using working life and older age samples for actual wealth ranks. Income is computed as average annual labor income. Given that the working life and older age samples contain different individuals, the ratios are not directly comparable across the upper and lower panel. The pooled wealth-to-income ratio is computed as the average of the wealth-to-income ratios across the age cohorts per lifecycle stage.

tion, it demonstrates that family wealth plays a critical role in determining the within-cohort wealth distribution at ages 30-34: wealthy individuals at the start of working life tend to belong to wealthy families and are the most likely to have received an inter-vivos transfer or inheritance. This overlap in individuals' wealth ranks at ages 30-34 with family wealth and inter-generational transfer receipts aligns with evidence from Boserup et al. (2018): these authors find a similar overlap in Denmark, albeit for much younger individuals (at age 18). In what follows, I quantify these findings in more detail.

Of the individuals in the within-cohort top 10% at ages 30-34, 55% have parents that belong to the top 30% of their own cohort at that time. Furthermore, close to 30% of individuals in the top 10% have already received an inter-vivos transfer or inheritance. This is higher than for the middle 50%-90% (15%) and bottom 50% (8%). Total transfer receipts of the top 10% by ages 30-34 make up around 50% of the total cumulative transfers received by individuals at that stage. Instead, of the individuals in the within-cohort bottom 20% at ages 30-34, only 15% have parents that belong to the top 30% of their own cohort at that time. Moreover, only 6% of individuals in the within-cohort bottom 20% at the start of working life have received an inter-vivos transfer or inheritance at that point.

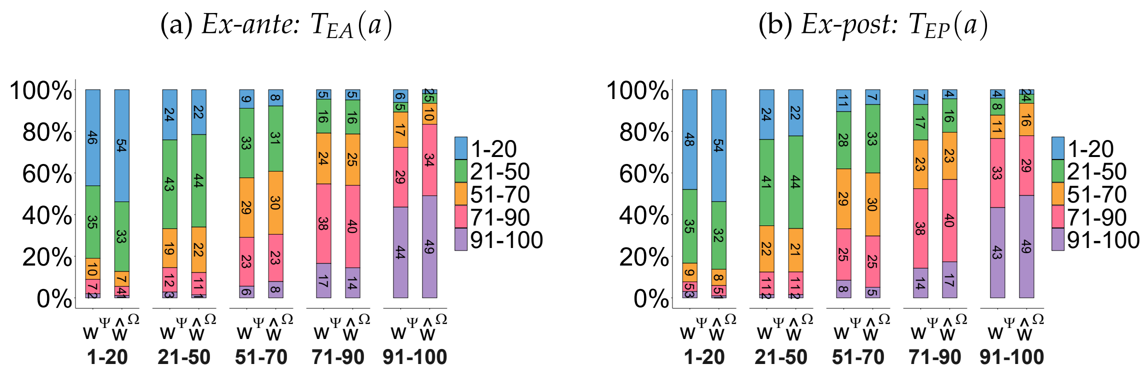
5.3 Wealth mobility during working life

While wealth growth rates over the working lifecycle (ages 30-54) are broadly similar across wealth brackets (Section 5.1), this conceals intra-generational mobility of individuals across the within-cohort wealth distribution. That is, the within-cohort bottom 50%, middle 50%-90% and top 10% are not fixed groups: there takes place significant turnover over the lifecycle. In what follows, I quantify the degree of wealth mobility during working life at the individual level.

Overall mobility The rank-rank coefficient (based on κ^{Ψ}) in the pooled dataset between ages 30-34 and 50-54 equals 0.56 (Table 2). This finding is in line with Shiro et al. (2022), who obtain a rank-rank estimate of 0.59 for the United States using a PSID-sample over the same age span (30-54). The minor difference to my estimate likely follows from sample differences: while I use the SRC-subsample in the PSID (as detailed in Appendix A), Shiro et al. (2022) use this SRC-subsample in combination with the SEO-subsample and two immigrant subsamples. Furthermore, Conley & Glauber (2008) produce a log-log estimate of 0.47 using a PSID sample that spans twenty years. However, these authors' sample constitutes of individuals across a broad spectrum of initial age levels, and is therefore not directly comparable to mine.

Two conclusions can be drawn. First, intra-generational wealth mobility in the United States is significantly lower compared to the Nordic countries. Specifically, over the same age span as this paper (30-54), Audoly et al. (2024) find a rank-rank coefficient slightly in excess of 0.20 for Norway. Moreover, Boserup et al. (2018) obtain a β-estimate of 0.22 for Denmark in a study where individuals' wealth ranks at age 45 are regressed on those at age 18. Second, in

Figure 8: Ex-ante and ex-post transition matrices during working life (ages 30-54) for the pooled dataset.



Note: these transition matrices compare the within-cohort wealth ranks of individuals in the working life sample at ages 30-34 and ages 50-54. The ex-ante matrix shows individuals' wealth ranks at ages 50-54 given their initial wealth rank at ages 30-34 (shown on the x-axis). Instead, the ex-post matrix shows individuals' initial wealth ranks at ages 30-34 given their final wealth rank at ages 50-54 (shown on the x-axis). The usage of the pooled dataset indicates that individuals across all selected age cohorts are included in the sample.

line with the inter-generational analysis, rank-rank coefficients based on proxy wealth ranks under-estimate the actual degree of intra-generational wealth mobility: the β-estimate based on $\hat{\kappa}^{\Omega}$ equals 0.65 (compared to the actual value of 0.56).

Mobility at the bottom & top Rank-rank coefficients provide insight into intra-generational wealth mobility across the entire wealth distribution, but do not show how broad-based mobility over the lifecycle is. Next, I therefore report transition probabilities and hierarchical clustering outcomes.

The pooled ex-ante transition matrix $T_{\mathrm{EA}}(a)$, ex-post $T_{\mathrm{EP}}(a)$ transition matrix (Figure 8) and discretionary groups (Table 2) based on actual wealth ranks κ^{Ψ} reveal that[10]:

- At the bottom: 46% (54%) of individuals in the bottom 20% of their cohort at ages 30-34 still belong to the bottom 20% at ages 50-54 (steady poor, 9% of the sample). Conversely, 54% (46%) of the individuals in the bottom 20% at age 30-34 displayed upward mobility during their working life, with 19% (12%) migrating to the top 50% of the distribution. The latter comprise close to 4% of the sample (the past poor). Finally, 17% (14%) of the individuals that end the working lifecycle in the bottom 20% originate from the within-cohort top 50% at ages 30-34. This corresponds to approximately 3% of the individuals in the sample (the new poor).
- At the top: 44% (49%) of individuals in the top 10% at ages 30-34 have remained in this wealth bin by ages 50-54. These individuals account for approximately 4% of the sample

[10]The transition probabilities based on proxy wealth $\hat{\kappa}^{\Psi}$ are reported in parentheses.

(the steady wealthy). Conversely, 56% (51%) of the top 10% wealthiest at ages 30-34 exhibit downward wealth mobility, with 28% (16%) falling to the bottom 70% (the past wealthy, 3% of the sample). Last, among those individuals in the top 10% at ages 50-54, 23% (22%) started working life in the bottom 70% (the new wealthy, around 2% of the sample). 12% (6%) of the top 10% individuals at ages 50-54 began their working life in the bottom 50% wealthiest.

These results have two key implications. First, overall mobility during working life is induced by both wealth mobility at the bottom and at the top of the wealth distribution. Second, the proxy wealth series' bias in estimating wealth mobility relates both to the bottom and to the top: the proxy ranks over-estimate the persistence at the bottom (56% versus 46%), as well as the persistence at the top (49% versus 44%).

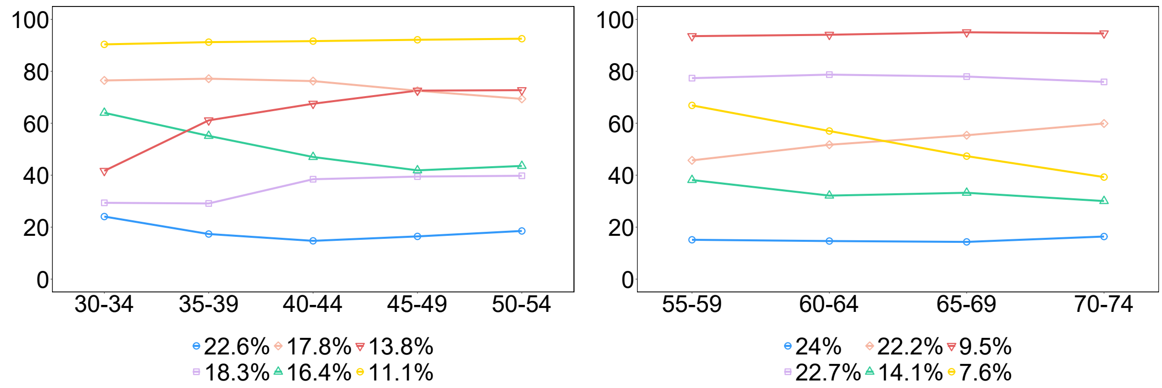
Complementary evidence to the transition matrices and discretionary groups is provided by the hierarchical clustering algorithm. Its application to the actual wealth series κ^{Ψ} for working life is presented in Figure 9 (panel a). Unlike for the discretionary groups, all individuals in sample Ψ have been categorized into one of the six benchmark clusters. I report the proportion of individuals in each cluster in parentheses. That is:

- Two immobile clusters at the bottom (41%): akin to the steady poor group, the steady bottom cluster (23%) contains individuals that spend their entire working life in the vicinity of the 20th wealth percentile. Instead, the steady supra-bottom cluster (18%) include individuals that display a minor rise in their wealth ranks from slightly above the 30th wealth percentile to close to the 40th wealth percentile.
- Two mobile clusters (30%): akin to the new wealthy group, the average individual in the strong risers cluster (14%) starts off around the 30th wealth percentile, exhibits a drastic rise to the 60th wealth percentile by ages 40-44, and a slight further increase to above the 70th wealth percentile thereafter. Instead, individuals in the middle decline cluster (16%) experience a slight drop in their wealth ranks from the 70th to somewhat below the 50th wealth percentile.
- Two immobile clusters at the top (29%): the steady sub-top cluster (18%) contains individuals that spend their entire working lifecycle between the 70th and 80th wealth percentiles. Instead, akin to the steady wealthy group, the individuals in the steady top cluster (11%) maintain a stable wealth rank around the 90th wealth percentile throughout their working lifecycle.

Only a relatively small fraction of individuals (30%) displays significant wealth mobility over working life. The remainder of individuals in the sample (70%) is relatively immobile. This fraction of mobile individuals in the United States (30%) is lower than in Norway: Audoly et al. (2024) find that 36% of the individuals in their sample display substantial upward or downward mobility between ages 30 and 54. As a result, intra-generational wealth mobility

Figure 9: Hierarchical clustering wealth rank trajectories for working life and older age for the pooled dataset based on actual wealth ranks κ^{Ψ}.

(a) *Working life (ages 30-54)* (b) *Older age (ages 55-74)*



Note: the plots report the average within-cohort wealth rank trajectories of the individuals in the six hierarchical clusters. The clusters have been computed through the hierarchical clustering algorithm described in the Online Supplement using actual wealth ranks κ^{Ψ} as input. I report cluster outcomes based on proxy wealth ranks in the Online Supplement.

in the United States is lower than in Norway, which aligns with the conclusion based on rank-rank coefficients.

5.4 Wealth mobility during older age

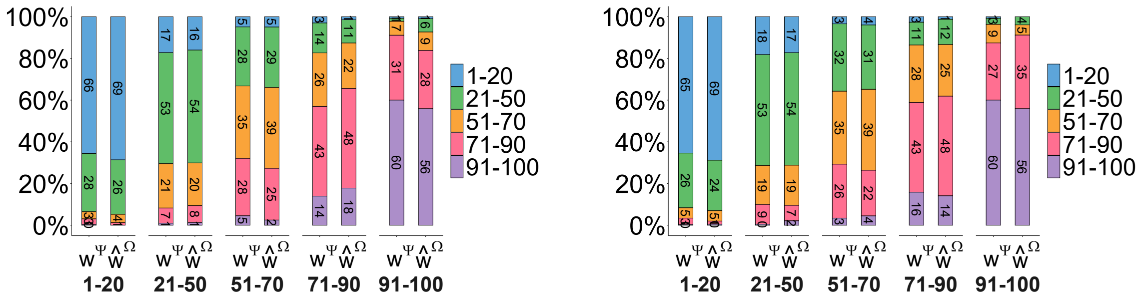
Having discussed wealth mobility during working life, I now move to the discussion of intra-generational wealth mobility during older age (ages 55-74). This paper is the first to explicitly study wealth mobility during this lifecycle phase.

Intra-generational wealth mobility during older age is found to be lower than intra-generational wealth mobility during working life: the rank-rank coefficient estimate in the pooled dataset equals 0.76 between ages 55 and 74 (Table 2), compared to 0.56 for working life (Section 5.3). This finding holds also when accounting for the disparity in lifecycle time span: the estimated rank-rank coefficients for a 20-year working lifecycle span equal 0.59 (for ages 30-49) and 0.66 (for ages 35-54), which are still significantly lower than the estimate for older age (0.76).

These findings should be approached with caution, however: the sample restrictions (see introduction to Section 5) imply that older age wealth mobility moments are computed based on a sample of individuals that are still alive by ages 70-74. This may introduce a selection bias: individuals that have poor health and face death prematurely (and are thus not included in the sample) could face downward wealth mobility due to high healthcare expenditures or as a result of voluntary bequests. As this downward mobility will not be captured, the estimated

Figure 10: Ex-ante and ex-post transition matrices during older age (ages 55-74) for the pooled dataset.

(a) *Ex-ante:* $T_{EA}(a)$ (b) *Ex-post:* $T_{EP}(a)$



Note: these transition matrices compare the within-cohort wealth ranks of individuals in the old age sample at ages 55-59 and ages 70-74. The ex-ante matrix shows individuals' wealth ranks at ages 70-74 given their initial wealth rank at ages 55-59 (shown on the x-axis). Instead, the ex-post matrix shows individuals' initial wealth ranks at ages 55-59 given their final wealth rank at ages 70-74 (shown on the x-axis). The usage of the pooled dataset indicates that individuals across all selected age cohorts are included in the sample.

rank-rank coefficient (0.76) may under-estimate the actual degree of wealth mobility during older age.

The lower wealth mobility during older age compared to working life holds both at the bottom and top of the wealth distribution. More precisely, the ex-ante $T_{\text{EA}}(a)$ and ex-post $T_{\text{EP}}(a)$ transition matrices (Figure 10) reveal that[11]:

- At the bottom: 66% (69%) of the individuals in the bottom 20% at ages 55-59 still belong to this bin by age 70-74 (the steady poor, 13%). Of those displaying upward mobility, only 6% (5%) migrated to the top 50% wealthiest. These comprise a little over 1% of the individuals in the sample (the past poor). Around 8% (6%) of the individuals in the bottom 20% at age 70-74 started the older age phase in the top 50%, constituting close to 2% of the individuals (the new poor).
- At the top: 60% (56%) of the individuals in the top 10% at the start of older age still belong to this bin by age 70-74. These steady wealthy make up around 6% of the sample. 9% (16%) of the individuals starting at the top drop to the bottom 70% of the wealth distribution, making up close to 1% of the sample (past wealthy). New wealthy during older age constitute a little over 1% of the sample: 13% (9%) of the individuals ending older age in the top 10% started off in the bottom 70%.

The hierarchical clustering procedure underscores that wealth mobility during older age is lower than during working life (Figure 9, panels a and b): while the older age cluster types

[11]Results based on the proxy wealth data are reported in parentheses.

overlap with those from working life, the strong risers cluster is replaced by a middle risers cluster whose wealth ranks rise only moderately from slightly above P40 to around P55. The relative occurrence of the cluster types also differs: in older age compared to working life, the steady bottom make up 24% (versus 23%), the steady supra-bottom 14% (versus 18%), the middle risers 22% (versus 14% of strong risers), the middle decline 8% (versus 16%), steady sub-top 23% (versus 18%), and the steady top 10% (versus 11%).

Finally, the proxy wealth series approximates actual wealth mobility during older age more accurately than during working life and across generations: the rank-rank coefficient estimate based on proxy wealth (0.77) lays very close to the one based on actual wealth (0.76). Moreover, the degree of persistence at the bottom and top align a lot more closely (66% versus 69% and 60% versus 56% respectively) than in previous sections of the paper. This better approximation during older age may relate to the lower importance of hard-to-capture variables such as business returns and non-mortgage indebtedness during older age.

5.5 Timing effects

In this section, I investigate timing effects in intra-generational wealth mobility: is within-cohort wealth rank mobility stronger at specific points of the lifecycle? The analysis relies primarily on Figure 11, which presents rank-rank coefficients from a rolling window analysis.

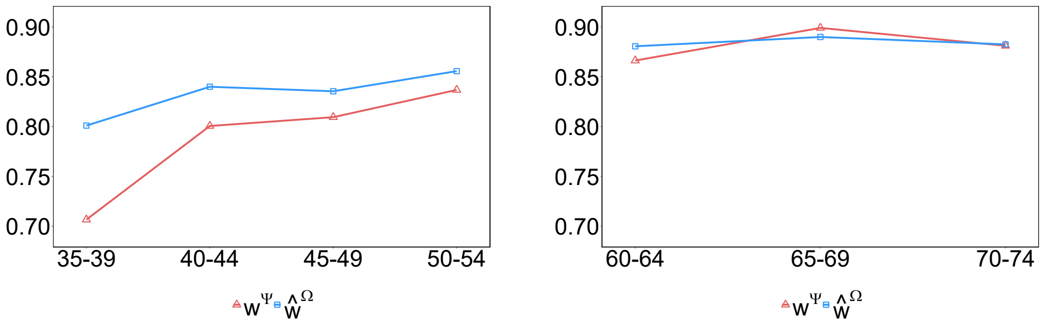
Two key findings persist. First, cumulative intra-generational wealth mobility rises consistently as individuals progress through working life: rank-rank coefficients are persistently below one in the rolling window analysis. In other words, individuals' wealth rank position at ages 30-34 is increasingly less predictive of their current wealth rank as these individuals progress through their lifecycle. Second, the majority of wealth mobility over the lifecycle occurs between ages 30 and 39: the rolling analysis based on w^{Ψ} reports a β-estimate of around 0.70 for the transition from stage 30-34 to 35-39. This is significantly lower than the $0.80-0.85$ estimates for the other transitions during working life and $0.85-0.90$ for the transitions during older age. The timing effect is corroborated by Figure 9 (panel a): the middle decline and strong risers clusters for working life exhibit the majority of their mobility during the earlier stages of the working lifecycle, particularly between ages 30 and 39. Additionally, the middle decline and strong risers clusters for older age display gradual rather than abrupt shifts in wealth rank trajectories (Figure 9, panel b). The timing effect of intra-generational wealth mobility aligns with evidence for Norway in Audoly et al. (2024).

The higher intra-generational wealth mobility between ages 30 and 39 holds both at the bottom and top of the wealth distribution (Figure 23, Appendix H)[12]. At the bottom, an individual in the bottom 20% at stage 30-34 has a 56% probability of remaining in the bottom 20% by ages 35-39 (steady poor). This probability increases to above 60% in the subsequent stages. Moreover,

[12] The patterns shown here are even more pronounced when using age group 25-29 as starting point, as shown in the Online Supplement.

Figure 11: Rolling window analysis for rank-rank coefficient β.

(a) *Working life: ages 30-54.* (b) *Older age: ages 55-74*



Note: the rank-rank coefficient β is computed with Ξ_{k-1} as initial stage and Ξ_k as final stage, where Ξ denotes working lifecycle stages and $k \in \{1, 2, 3, 4\}$. The reported data for stage k gives an indication of wealth mobility outcomes between this stage k and the previous stage $k-1$. For example, when $k = 3$, the cross-section of individuals' within-cohort wealth ranks at ages 45-49 is regressed on the cross-section at ages 40-44.

the likelihood of moving from the bottom 20% to the top 50% between stages 30-34 and 35-39 equals 13% (past poor). It drops to below 10% for later transitions. Finally, the probability of dropping to the bottom 20% when starting from the top 50% remains relatively stable at 8%-9% throughout the working lifecycle (new poor). At the top, an individual in the top 10% at stage 30-34 has a 53% probability of still belonging to the top 10% by ages 35-39 (steady wealthy). For later transitions, this probability consistently exceeds 60%. Furthermore, an individual belonging to the top 10% at ages 30-34 has a 15% probability of dropping to the bottom 70% by ages 35-39, which declines to below 8% for later transitions (past wealthy). Last, the probability of rising from the bottom 70% to the top 10% declines from around 6% to 4% (new wealthy).

What are potential theoretical mechanisms underlying the timing effects in intra-generational wealth mobility? First, absolute differences in wealth levels between individuals are significantly smaller at the start of working life (Section 5.1). This implies that given additive shocks (labor income, inter-generational transfers, household formation) are expected to generate more substantial wealth mobility early in working life. Second, idiosyncratic investment risk-taking is slightly stronger between ages 30 and 39, which follows from the peak observed for conditional business portfolio shares at these ages (see Online Supplement). Third, equity market participation is at its lowest at the start of the working lifecycle, which makes it more likely that an individual will have heterogeneous aggregate investment risk exposures relative to its wealth rank neighbors (Figure 18, Appendix G).

Table 2: Fraction of individuals belonging to each of the discretionary groups (in %) and rank-rank coefficients β across cohorts $\in \Upsilon^{WL}$ based on actual wealth ranks κ^{Ψ}.

Cohort	Poor Groups (%)			Wealthy Groups (%)			β
	Steady	Past	New	Steady	Past	New	
Pooled	9.2	3.8	3.3	4.4	2.8	2.4	0.56
1946–55	9.8	3.6	2.6	3.7	3.7	3.9	0.56
1956–65	9.4	3.2	3.7	4.3	2.6	1.7	0.56
1966–75	8.1	5.7	3.5	5.5	1.8	1.5	0.57

Note: this table reports the fraction of individuals in the sample belonging to each of the discretionary groups (in %). Moreover, it reports rank-rank coefficients β. These metrics are calculated with within-cohort wealth ranks at stage 50-54 as dependent variable.

5.6 Cross-cohort differences

To investigate the time trend in intra-generational wealth mobility, I compare rank-rank coefficients β across age cohorts based on actual wealth ranks κ^{Ψ} (Table 2). Given that most wealth mobility occurs during working life and because of the lower sample size for the older age phase, I present only the results for the working life phase.

While overall intra-generational wealth mobility has dropped slightly, intra-generational wealth mobility at the top has declined substantially over time. Specifically, β-estimates are only marginally higher in the 1966-75 age cohort compared to earlier cohorts (0.57 versus 0.56), but this conceals contrasting dynamics at the bottom and top of the wealth distribution. At the top, wealth consolidation during working life has increased significantly: the fraction of steady wealthy has risen from close to 4% in the 1946-55 cohort to close to 6% in the 1966-75 cohort. This has coincided with a strong drop in downward mobility from the top (the fraction of past wealthy has declined from 4% to below 2%) and a decrease in upward mobility to the top (the fraction of new wealthy has dropped from 4% to below 2%). Instead, wealth consolidation at the bottom during working life has declined, as evidenced by the declining fraction of steady poor from close to 10% to around 8%. This was accompanied by a strong increase in upward mobility from the bottom (the fraction of past poor has risen from over 3% to close to 6%), and a small increase in downward mobility to the bottom (the fraction of new poor has risen from around 3% to 4%).

Together with the findings from Section 5.1, the data therefore points towards a negative correlation between within-cohort wealth inequality and mobility at the top of the wealth distribution: the higher within-cohort wealth inequality in recent cohorts (Section 5.1) has coincided with stronger wealth consolidation (and thus weaker mobility) among the top 10% wealthiest. Instead, at the bottom, intra-generational persistence is found to have slightly declined over time.

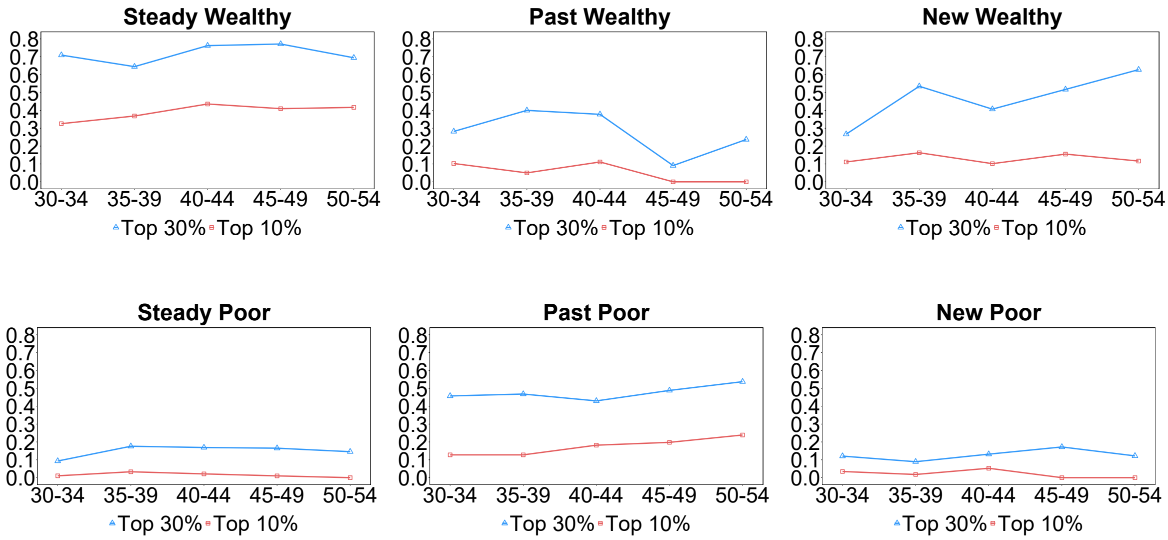
6 Within-family interdependence in intra-generational wealth mobility

I have established that there exists significant inter-generational persistence in within-cohort wealth ranks of parents and their children at identical points in their lifecycles (Section 4.1). Moreover, individuals' within-cohort wealth ranks at the start of working life overlap significantly with their parents' within-cohort wealth ranks at that time: the wealthiest individuals at age 30-34 are the most likely to have wealthy parents (Section 5.2). In this section, I build on these findings to investigate the third research question of this paper: does there exist inter-dependence between the within-cohort wealth rank trajectories of individuals and those of their parents (conditional on these being alive) as these individuals' progress through working life?

In short, the answer is yes: there seems to be inter-dependence between individuals' wealth rank trajectories and those of their parents. Individuals that face upward mobility from the bottom and to the top in their cohort (past poor, new wealthy) are likely to have parents that face upward mobility in their own cohort as well. Furthermore, individuals that experience downward mobility from the top (past wealthy) are prone to having parents that encounter downward wealth mobility also. Last, individuals that consolidate their position at the top of the wealth distribution are the most likely to have wealthy parents throughout their entire working life. These findings are quantified in Figure 12:

- Steady poor: throughout their working life, individuals that start and end working life in the bottom 20% (the steady poor) face a slightly increasing probability (from 9% to 18%) of having parents that belong to the top 30% of their within-cohort wealth distribution. Instead, the probability of having top 10% parents remains close to 0%.
- Past poor: individuals that display upward mobility from the bottom 20% to the top 50% of the within-cohort wealth distribution (the past poor) face a rising likelihood of having wealthy parents: the likelihood of having top 30% parents rises from 45% to 54%, while the probability of having top 10% parents increases from 13% to 24%.
- New poor: for individuals that drop from the within-cohort top 50% to the bottom 20%, there is little inter-dependence with parental wealth ranks: the likelihood of having top 30% parents remains relatively stable around 10%, and the probability of having top 10% parents fluctuates between 0% and 4%.
- Steady wealthy: throughout their working life, individuals that start and end working life in the top 10% (the steady wealthy) have a 70% to 80% probability of having parents in the top 30% of their own within-cohort wealth distribution. Instead, the probability of having top 10% parents rises slightly from 33% to above 40% between ages 30 and 55 for these individuals.

Figure 12: Inter-dependence between individuals' and their parents' wealth rank trajectories based on actual wealth ranks κ^{Ψ}.



Note: this plot uses the individuals from the working life sample defined in Section 5 of the paper. For a given discretionary group, it computes (for each lifecycle stage) the fraction of individuals in that group that have parents belonging to the top 10% and top 30% of their within-cohort wealth distribution at that historical point in time. Individuals that have no parents are excluded from the sample.

- Past wealthy: individuals starting working life in the top 10% but dropping to the bottom 70% (the past wealthy) face a declining likelihood of having wealthy parents: the probability of having top 30% parents first rises slightly from 28% to 40%, but then drops to between 10% and 20% by late working life. Furthermore, the likelihood of having top 10% parents initially remains steady at 10%, but declines towards 0% by late working life.
- New wealthy: individuals that display upward mobility from the bottom 70% to the top 10% over working life (the new wealthy) face a strongly rising likelihood of having top 30% parents as these individuals' working life progresses: the likelihood of having top 30% parents rises from 26% at ages 30-34 to 63% at ages 50-54. The probability of having top 10% parents displays a relatively flat lifecycle profile between 10% and 16%.

Of course, this analysis does not take an explicit stance on causality. For example, it may be that new wealthy individuals (who accumulate a lot of wealth during working life despite starting in the bottom 70%) share part of their newly accumulated wealth with their parents via inter-vivos transfers (channel 1 in Section 2.3). On the contrary, it may be that the strong wealth accumulation of new wealthy individuals relates to a reversal in their parents' fortunes that is transmitted to them through inter-vivos transfers or other channels (see Section 2.3). Moreover, the inter-dependence could instead be driven by exposures to identical sources of idiosyncratic risk, for instance a family business or a highly concentrated portfolio of stocks. A causal decomposition of the importance of these effects is left to future research.

7 Sources of mobility: composition analysis

As a final step in this paper, this section conducts a composition analysis to investigate the inter-generational transfer receipts and socio-economic characteristics of individuals across the discretionary groups and clusters. The composition analysis should be interpreted as an exploratory exercise: it does not disentangle the causal driving forces behind wealth mobility dynamics, nor does it draw conclusions regarding the quantitative importance of the variables under consideration. The infeasibility of causal and quantitative identification follows from the presence of type and scale dependencies in families' and individuals' behavioral parameters. These create endogeneity between wealth accumulation and individuals' socio-economic characteristics (see Section 2.3). As an example, suppose one observes in the data high business ownership rates among the wealthiest individuals. This could relate to the easier access to business financing that wealth enables (a scale dependence). However, it could also reflect that only a subset of individuals hold valuable entrepreneurial ideas, generating higher wealth positions for these individuals over time (a type dependence).

The analysis is conducted on the intra-generational working life sample and therefore focuses on the sources of intra-generational (individual-level) wealth mobility over the working lifecycle. However, the Online Supplement demonstrates that the intra-generational findings extend to two-generational (family-level) mobility: the sources of inter-generational wealth mobility are found to be equivalent to those of intra-generational wealth mobility. This observation makes sense intuitively: as individual wealth ranks at ages 30-34 overlap to a large extent with family wealth ranks (Section 5.2), reversals in individual's fortunes over the lifecycle generate similar reversals from an inter-generational perspective (at the family level). Furthermore, the Online Supplement shows that families consolidating their position at the bottom or top over two generations exhibit highly similar socio-economic characteristics between parents and children at the same age. Only for families with high (upward or downward) inter-generational wealth mobility do children's composition metrics diverge from those of their parents. This aligns with a literature documenting inter-generational persistence in socio-economic characteristics (e.g. Adermon et al., 2021; Charles & Hurst, 2003; Fagereng et al., 2021; Lindquist et al., 2015)[13].

In what follows, I first define the individual-level composition metrics used, and subsequently present the key findings with respect to inter-generational transfers and socio-economic characteristics. The latter are visualized in Appendix G. Given the top wealth bias of the PSID (see

[13]Some of the papers papers in this literature also disentangle the role of pre- versus post-birth factors using data for adoptees. In the PSID, such strategy is hard to implement due to the lack of extensive adoptee data.

Section 3.1), the findings in this section relate to the entire wealth distribution and have little say on the wealth accumulation dynamics of the very top wealthiest (top 1% and beyond). The composition of these very top wealthiest are the focus in for instance König et al. (2023) for Germany and Hubmer et al. (2024) for Norway.

Composition metrics The composition analysis is executed based on various individual-level metrics, detailed in Appendix F. The metrics are organized into four categories. First, a labor income and saving category calculates within-cohort labor income ranks, gross saving rates, non-mortgage debt participation and non-mortgage debt-to-income ratios (conditional on holding non-mortgage debt). Second, an asset ownership and allocation category computes homeownership, equity ownership, unincorporated business ownership, incorporated business ownership and mortgage participation rates. In addition, it calculates housing, equity, business and mortgage allocations relative to total assets (conditional on participation in the respective asset or debt market). Third, the health and household status category calculates whether an individual belongs to a household where at least one member has poor health and whether the individual is single, in a relationship or married. Fourth, the inter-vivos transfers and inheritances category assesses whether the individual has received an inter-generational transfer at any point in its lifecycle, and computes the ratio of its cumulative (capitalized) transfer receipts to its lifetime resources, in line with Black et al. (2022). Lifetime resources are defined as the cumulative sum of (capitalized) labor income[14]. These individual-level measures are summarized over the set of individuals in a discretionary group or cluster, as outlined in Appendix F.

Inter-generational transfers Inter-vivos transfers and inheritances are associated with wealth persistence at the top during working life. At ages 30-34, the wealth and cumulative transfer distributions overlap: top 10% individuals have received substantial transfers already, while the bottom 50% have hardly received any (see Section 5.2). Over their lifecycle, individuals consolidating their position at the top (steady wealthy, steady top) receive additional transfers: the proportion of recipients among these individuals rises to 60%-65% by ages 50-54, and their receipts make up around 11%-16% of lifetime resources at these ages. Instead, among the individuals stuck at the bottom (steady poor, steady bottom), the proportion of recipients rises to at most 20% by ages 50-54, and their receipts constitute a mere 4%-6% of lifetime resources.

The association between inter-generational transfers and upward wealth mobility is weaker. In comparison to the median American, past poor and new wealthy individuals are more likely to receive transfers (40%-45% by ages 50-54), which additionally comprise a more significant fraction of their lifetime resources (13%-14% by ages 50-54). It is therefore possible that these two groups include individuals that belong to wealthier families, but received inter-generational

[14]Unlike in Black et al. (2022), I do not include government transfers as part of lifetime resources. This assumption may induce an upward bias in the inter-generational transfers to lifetime resources variable for poorer individuals.

transfers only later in life relative to the steady money and steady top. Alternatively, these individuals' parents may have experienced favorable reversals in their fortunes only later in their lifecycle. On the contrary, the strong risers cluster is not linked with unusually high transfer receipts (approximately 6% of resources by ages 50-54).

Of course, these arguments do not by definition imply that these inter-vivos transfers and inheritances (their relative absence) are critical in consolidating individuals' position at the top (at the bottom). In fact, the inverse conclusion prevails: even for the wealthiest individuals their cumulative receipts constitute a limited fraction of lifetime resources (at most 16%). However, the comparatively high inter-generational transfer receipts of the consistently wealthy do indicate that these individuals are more likely to belong to wealthier families (in line with the finding in Section 6). They may therefore have benefited from their parental wealth through other channels (channels 2-5 in section 2.3). The apparent minimal importance of inter-vivos transfers and inheritances in generating inter-generational wealth persistence (the first channel in Section 2.3) aligns with other evidence for the United States (Charles & Hurst, 2003; Pfeffer & Killewald, 2018) and with results for Norway (Audoly et al., 2024). However, it contradicts findings for Sweden (Adermon et al., 2018).

Nonetheless, this conclusion regarding the minimal importance of inter-generational transfers warrants caution. There are two reasons for this. First, the PSID contains survey data, and is therefore prone to under-reporting of inter-generational transfers. On top of that, the transfer variable in the PSID likely suffers from a significant downward bias due to the irregular structure of the PSID survey waves (see Appendix F for a detailed explanation). Second, the timing of inter-generational transfers matters if there exist scale dependencies in individuals' behaviour. For example, an early receipt of transfers may enable individuals to allocate higher fractions of their assets to high-return assets such as housing or businesses (e.g. Lee et al., 2020). In expectation, such early receipt of inter-generational transfers may therefore generate higher wealth accumulation over these individuals' lifecycle. Whether there actually exists heterogeneity in the timing of transfer receipts across individuals in the United States and whether such timing affects individuals' wealth rank trajectories over the lifecycle are questions that I leave to future research.

Socio-economic characteristics Persistence at the top (steady wealthy, steady top, steady subtop) is linked to high labor income, with individuals in these groups and clusters consistently belonging to the top 40% highest labor income earners over working life. High labor income is also associated with upward wealth mobility (past poor, new wealthy), although the evidence does not extend to the strong risers cluster. Instead, persistence at the bottom (steady poor, steady bottom, steady supra-bottom) and downward mobility to the bottom (new poor) are linked with low and declining ranks in the labor income distribution throughout working life. These results relate to Charles & Hurst (2003), who find that inter-generational income persistence explains half of the inter-generational persistence in wealth in the United States.

Their results are in line with those for the United Kingdom (Davenport et al., 2021; Levell & Sturrock, 2023). For the Nordic countries, Audoly et al. (2024) find human capital to be the main predictor of individuals' falling and rising over the wealth distribution (for Norway). Instead, Adermon et al. (2018) obtain that earnings and education only account for a quarter of two-generational wealth persistence (for Sweden).

Business ownership is linked to consolidation at the top (steady wealthy, steady top) and to significant downward mobility (past wealthy, middle decline, new poor). This suggests that business ventures can sustain or break individuals' and families' positions in the wealth distribution. The association between business ownership and upward wealth mobility is inconclusive, however: business ownership is clearly linked with the new wealthy, but not particularly with past poor or strong risers individuals. Matching evidence is provided for Norway: even though Audoly et al. (2024) do not find a marked role for business ownership in generating upward wealth mobility during working life, their results do show a clear correlation with consolidation at the top and downward wealth mobility. For the United States, both Charles & Hurst (2003) and Pfeffer & Killewald (2018) establish that business ownership has a non-negligible impact on inter-generational wealth persistence.

Individuals that are wealthy over the lifecycle (steady wealthy, steady top, steady subtop) or rise to the top (new wealthy, strong risers) display higher equity ownership rates compared to poor individuals. This relates to Charles & Hurst (2003), who find that equity ownership contributes significantly to inter-generational wealth persistence. Moreover, while homeownership and wealth ranks are positively correlated, wealthier individuals display lower conditional housing allocations. The disparity between the wealthy and poor is less pronounced for conditional equity allocations. Finally, persistence at the bottom (steady poor, steady bottom) and downward wealth mobility (new poor, past wealthy) are associated with poor and deteriorating health, a high likelihood of belonging to single households, and elevated and increasing non-mortgage indebtedness over the lifecycle.

8 Conclusion

Even though there exists an extensive body of research on social and income mobility, research on wealth mobility over the past decades is very limited. In this paper, I fill this gap for the United States by studying inter- and intra-generational wealth mobility using data from the Panel Study of Income Dynamics (PSID). I formulate and provide insight into three research questions.

First, I study inter-generational (family-level) wealth mobility from a static perspective, comparing individuals' within-cohort wealth ranks to those of their parents and grandparents at specific lifecycle stages. In addition to providing a rich set of empirical moments and contrasting these to existing studies, I show that two-generational wealth mobility has declined over time between ages 35 and 44. Moreover, wealth mobility across three generations exceeds the mobility across two generations, but this effect is stronger for mobility at the top than for mobility at the bottom. Finally, wealth rank resemblance between parents and their children increases with age (parent-child lifecycle bias), while wealth rank resemblance between grandparents and their grandchildren is higher when grandchildren are older than 35 years (grandchild lifecycle bias).

Second, this paper investigates intra-generational (individual-level) wealth inequality and mobility given the initial wealth rank distribution at ages 30-34. Within-cohort wealth inequality is found to be roughly stable over the lifecycle. Next, having provided a broad set of empirical moments, I show that intra-generational wealth mobility at the top has declined over time, and that the majority of wealth mobility occurs between ages 30 and 39. Moreover, the composition analysis based on the intra-generational sample during working life shows that persistence at the top is associated with the most substantial inter-vivos transfers and inheritances receipts. However, even for the wealthiest, these receipts make up only a relatively limited fraction of their lifetime resources. Individuals that are stuck at the bottom stand out by an overall absence of inter-generational transfers. Business ownership is linked with persistence at the top and downward mobility, while its association with upward mobility is inconclusive. Last, consistently poor and new poor individuals earn little labor income in combination with poor and deteriorating health as well as elevated non-mortgage indebtedness. At the top, labor incomes and asset ownership are high.

Third, this paper is the first to show that there exists inter-dependence between the within-cohort wealth rank trajectories of individuals and those of their parents (conditional on these being alive) over the same time period as individuals progress through working life. Specifically, individuals that face upward mobility from the bottom and to the top in their cohort are likely to have parents that encounter upward mobility in their own cohort as well. Furthermore, individuals that experience downward mobility from the top are likely to have parents facing downward wealth mobility also. Last, individuals that consolidate their position at the top are the most likely to have wealthy parents. These findings suggest the presence of altruism across generations and/or the exposure of parents and their children to identical sources of idiosyncratic risk.

In addition, the paper provides two key methodological contributions. First, I harmonize and validate the PSID-dataset. I argue that the PSID can be effectively used to study wealth-related questions, in particular those that relate to wealth mobility. Second, I construct a proxy wealth rank series using a gradient-boosting machine learning model that improves the naive proxies used in the literature. Throughout the paper, it is demonstrated that these proxies provide a useful tool for extending wealth mobility analyses across generations. Nonetheless, these proxies under-estimate the actual degree of wealth mobility (apart from the intra-generational mobility observed during older age).

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A Data

A.1 Waves & samples

This paper uses data from the Panel Study of Income Dynamics (PSID), which was conducted annually between 1968 and 1997, and bi-annually from 1999 until 2021. All waves infer about households' gross main housing value, gross main housing mortgage debt and rents paid. The waves in 1984, 1989, 1994 and 1999-2021 add to this questions about other assets and debts, allowing to define households' wealth.

The original 1968 PSID-sample consists of two independently drawn subsamples: (1) the SRC-subsample (Survey Research Center): a nationally representative sample of households, and (2) the SEO-sample (Survey of Economic Opportunities): an over-sample of low-income families. In 1990, a Latino subsample was added to the PSID, but this sample was dropped again from 1995 onwards. In 1997 and 2017, the PSID was permanently augmented with two representative immigrant subsamples to reflect the changing composition of the US population. For each of these four subsamples, the PSID tracks over time the individuals belonging to the original set of households. In addition, it tracks individuals that descended from these original individuals, as well as non-sample individuals that entered the PSID through their connection to the former (e.g. a relationship or marriage).

The default in economic research using PSID-data is to focus on the SRC-subsample (e.g. Cooper et al., 2019; Heathcote et al., 2010; Kaplan et al., 2014; Straub, 2019). The SEO-subsample and the immigrant sub-samples are thus typically excluded from the analysis. In this paper, I follow this approach. As a robustness, I include the two representative immigrant samples from 1997 and 2017 onwards. The results for this alternative sample are presented in the Online Supplement. It shows that the conclusions of this paper are robust to the inclusion of these two immigrant samples.

Let us define the two core samples used in this paper. Denote N as the total number of households that to have responded to the PSID-questionnaires in at least one year between 1969 and 2021. Moreover, let us denote a specific household by subscript i. We have:

$$\mathcal{T}_\Omega = \{1969, 1970, \ldots, 1997, 1999, 2001, \ldots, 2021\} \tag{3}$$

$$\Omega = \{\mathbf{I}_i^\Omega(t) \mid i = 1, 2, \ldots, N,\ t \in \mathcal{T}_\Omega\} \tag{4}$$

where $\mathcal{T}_\Omega$ is the set of years corresponding to full sample Ω and $\mathbf{I}^\Omega$ denotes the vector of PSID variables that are available over $\mathcal{T}_\Omega$. 1968 is excluded from the sample due to the high number of outliers for this year. In addition, we can write:

$$\mathcal{T}_\Psi = \{1984, 1989, 1994, 1999, 2001, \ldots, 2021\} \tag{5}$$

$$\Psi = \{\mathbf{I}_i^\Psi(t) \mid i = 1, 2, \ldots, N,\ t \in \mathcal{T}_\Psi\} \tag{6}$$

where $\mathcal{T}_\Psi$ is the set of years corresponding to reduced sample Ψ and $\mathbf{I}_i^\Psi$ the vector of PSID variables that are available over $\mathcal{T}_\Psi$. It holds that $\mathbf{I}^\Psi = [\mathbf{I}^\Omega, \mathbf{I}^\Phi]$, where $\mathbf{I}^\Phi$ is defined as the vector of additional variables exclusive to sample Ψ.

A.2 Definitions

Unit of analysis The unit of analysis in the PSID-questionnaires is the family unit. Pfeffer et al. (2016) argue that the family unit may not always be equivalent to the household unit. For example, when an adult child that previously lived outside of the parental home moves back into the parental home, it will still be considered as a separate family unit even though its financial decisions, financial flows and wealth levels may be intertwined with the parents' ones. Still, this is more often than not a temporary situation, and it seems likely that at least some independence in financial decision-making, flows and wealth levels is maintained. For that reason, I do equate family units to households.

Wealth & wealth ranks In full sample Ω, the wealth categories are limited to gross main housing (h) and main housing mortgages outstanding (m). Non-homeowners are asked to report their rental payments (r). In contrast, reduced sample Ψ extends the PSID by including questions about a broader range of assets and debts. Beyond gross main housing, the asset categories encompass business holdings, equity holdings, fixed-income holdings, pension wealth, and gross other housing. On the liabilities side, besides main housing mortgages outstanding, households report the value of other housing debt and non-mortgage debt. I define household wealth w as the total of all asset categories minus the total of all debt categories. For a household i at time t, wealth is computed only if values are reported for every asset and debt category. If any category is missing, the household is considered a non-respondent at t.

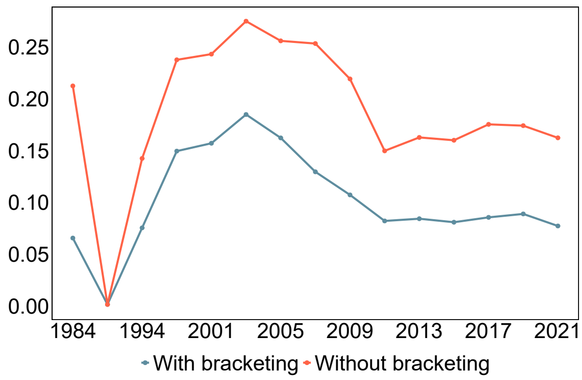
To study wealth mobility, the ultimate interest lays in households' wealth ranks, denoted as κ. Let $N(t)$ represent the total number of responsive households at time t, with their wealth levels given by $w_1(t), w_2(t), \ldots, w_{N(t)}(t)$. I define the wealth rank $\kappa_i(t)$ for household i at time t as:

$$\kappa_i(t) = \left\lceil \frac{100 \times \left(1 + \sum_{k=1}^{N_t} \mathbf{1}(w_k(t) < w_i(t))\right)}{N_t} \right\rceil \tag{7}$$

where $\mathbf{1}(w_k(t) > w_i(t))$ is an indicator function equal to 1 if $w_k(t) > w_i(t)$ and 0 otherwise. $\lceil \cdot \rceil$ denotes a ceiling function, which ensures the rank is placed into an integer bin from 1 to 100. Since the wealth variable w is defined exclusively in sample Ψ ($w \in \mathbf{I}^\Phi$) the same applies to κ: $\kappa_i \in \mathbf{I}^\Phi$.

Outliers & non-response The wealth-related sections of the PSID face two primary challenges. First, there is significant non-response, as shown in Figure 13. This issue is partially mitigated through the use of bracketing. Given that such bracketing effectively reduces non-response

Figure 13: Fraction of non-respondent households with and without bracketing applied.



Note: this plot displays the fraction of households in each year that responded to the PSID-survey but displayed non-response for at least one wealth category. As a result, their total wealth for that year is undefined. The fraction of non-responsive households is shown for the dataset without bracketing applied and the dataset with bracketing applied. In 1989, non-response was close to zero.

(Figure 13), I apply it whenever available. The details of the bracketing procedure are provided in Appendix B. Second, asset- and debt-related variables in Ψ are not harmonized over time, and both the reduced sample Ψ as the full sample Ω exhibit measurement errors. To address this, I have carefully aligned wealth categories across time periods, as discussed in Appendix B. Moreover, I have applied different outlier-correction procedures. These include on the one hand variable-specific outliers (see Appendix B) and on the other hand general outlier-correction procedures (see Online Supplement).

A.3 PSID-validation

In what follows, I validate the PSID by comparing its time trajectories for aggregate wealth (and its underlying components) to the trajectories for these variables in the top-wealth-adjusted Survey of Consumer Finances (SCF) (Figure 14). Furthermore, I set side by side the wealth shares observed in the PSID to those seen in the SCF (Figure 15).

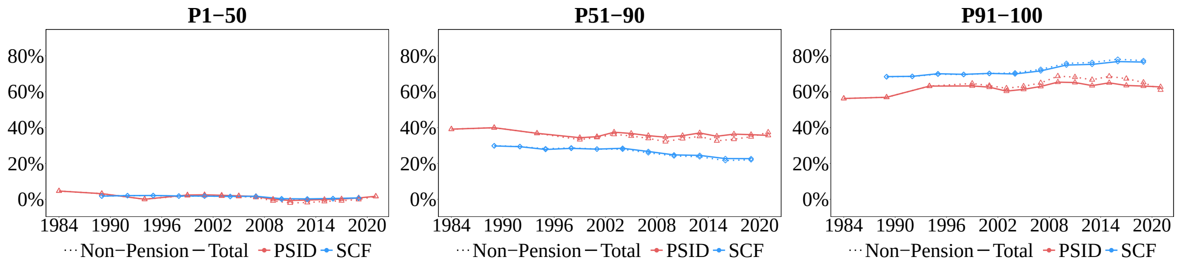
With respect to aggregate wealth, the PSID systematically under-estimates all wealth categories compared to the SCF (Figure 14). This is consistent with previous findings (e.g., Pfeffer et al., 2016; Insolera et al., 2021). The under-estimation is particularly strong for net business holdings. However, crucially given this paper's focus on wealth mobility, the PSID does accurately capture the time evolution of wealth and its underlying categories.

In addition, the evolution of wealth shares in the PSID aligns closely with those of the SCF: both databases indicate a slight increase in overall wealth inequality since the early 1980s (Figure 15). However, as noted in previous studies (e.g., Pfeffer et al., 2016; Cooper et al., 2019), the PSID underestimates top wealth inequality. For instance, in 2019, the top 10% wealth share

Figure 14: Average wealth levels per household (for total wealth and its underlying categories).

Note: these plots report the aggregate holdings of wealth and its different underlying categories, averaged across households. The outcomes are compared across the PSID and SCF databases over time.

Figure 15: Wealth shares (in %) in the PSID and SCF databases.



Note: these plots report the share of three commonly used wealth brackets (the bottom 50%, middle 50%-90% and top 10%) in aggregate wealth over time. I report outcomes both for non-pension wealth and for total wealth (consisting of non-pension and pension wealth). The wealth shares in the PSID are set side to side to those in the SCF.

(including pension wealth) equaled 62% in the PSID, compared to 77% in the SCF. The same top-wealth bias is observed when comparing the fraction of low- and high-wealth households in the PSID versus the SCF (see Online Supplement).

What explains this discrepancy between the PSID and SCF? While the SCF adjusts its nationally representative sample by oversampling at the top of the wealth distribution, the PSID does not. To address this, the PSID could in principle be supplemented with data from the Forbes 400 to better approximate top wealth (as is done for the distributional national accounts of Saez & Zucman (2016)). However, there are two key reasons against this approach. First, the composition of the Forbes 400 changes annually. Incorporating rich-list data into a wealth mobility study across the entire wealth distribution would therefore require making assumptions about the households that entered or exited the Forbes 400 during the period under consideration. This would introduce significant uncertainty into the wealth mobility analysis. Second, the primary focus of this paper is wealth mobility rather than wealth inequality. For wealth mobility measures, the number of households across the wealth distribution serves as the key calculation input. Excluding a small number of high-wealth households has a minimal impact on these outcomes. In contrast, wealth inequality metrics rely on the total wealth owned by households as the main calculation input. In such setting, excluding a small number of high-wealth households disproportionately skews the results downward. Therefore, correcting for top wealth is less critical in the context of this paper's focus on wealth mobility.

B Data definitions, outliers & non-response

B.1 Bracketing

Responding families in the PSID are occasionally unaware of the exact value of their wealth variables. In that case, for some years and variables, bracketing questions are provided. As an example, let x be the variable of interest, and let x_1, x_2 denote the thresholds, where it holds that $x_1 < x_2$. Using the answers to the bracketing question, I allocate x to one of the following three intervals: $[0, x_1[$, $[x_1, x_2[$ and $[x_2, +\infty[$. For the first two brackets, the actual x-value is estimated using the average of the lower and upper bound. For the last bracket, the estimate is calculated as $x_2 + \frac{1}{2}x_2$. When available, I apply this bracketing procedure for missing observations. In the Online Supplement, I have verified that the findings of this paper are robust to whether or not the bracketing procedure is applied.

B.2 Variable-specific definitions & outliers

B.2.1 Housing-related wealth categories

Main housing & rent Main housing mortgages outstanding are not reported in the years 1973-1975 and 1982. These are interpolated as follows. First, for all non-missing years in Ω, I compute the mortgage ratio as $\frac{h_i(t)}{m_i(t)}$. Second, a distance-weighted interpolation procedure (specified in the Online Supplement) is applied to the mortgage ratio over the missing years in Ω. Third, given the observed $h_i(t)$, the interpolated value for $\frac{h_i(t)}{m_i(t)}$ is used to trace out $m_i(t)$ for the missing years in Ω.

For the period 1969-1992, rental payments by renter households are reported on an annual basis. Instead, for the period 1993-2021, they are disclosed on a monthly basis. I define rents r on an annual basis, and therefore annualize the values for the latter period. In addition, rental payments are not provided for the years 1988-1989. These missing values are interpolated using a distance-weighted linear interpolation (specified in the Online Supplement). Furthermore, in 1970, reported rents for a select subset of homeowners takes on the value '768'. These outliers are set to their correct value of zero.

Other housing For the period 1984-2011, other housing is reported net of mortgage debt. Instead, for the period 2013-2021, gross other housing and mortgage debt on other housing are reported separately. To compute portfolio allocations (in Appendix F), our interest lays in the gross representation. I therefore calculate the average mortgage ratio on other housing conditional on ownership using data from the Survey of Consumer Finances (SCF) from 1989 to 2019. This mortgage ratio is found to equal 52 percent. I then use this ratio to trace out approximations for gross other housing and mortgages outstanding on other housing for the period 1984-2011.

B.2.2 Non-housing wealth categories

Business & equity For the period 1984-2011, business holdings are reported net of business debts. Instead, for the period 2013-2021, gross business assets and debts are reported separately. Between 2013 and 2021, I therefore compute the net measure. Additionally, there exist a handful of observations for net business holdings that take on unrealistically large negative values (for one survey wave only). These outliers are set equal to zero.

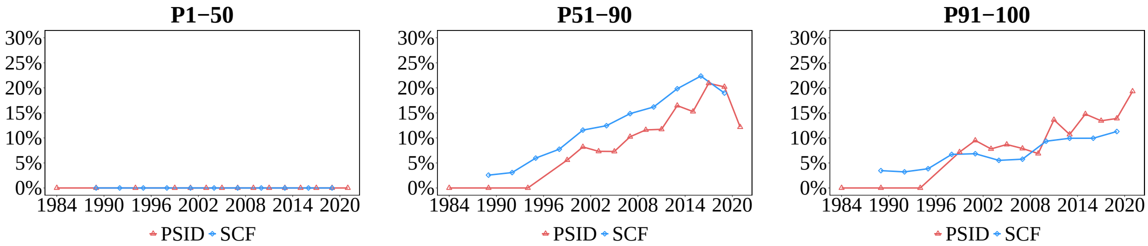
Equity holdings are defined as the cumulative value of stocks in publicly-traded corporations, stock market mutual funds or investment trusts. However, in the period 1984-1997, this variable also includes holdings of stocks in IRAs. Similar to business holdings, there are a handful of observations that take on unrealistically large negative values for one survey wave only. These values are corrected to zero.

Fixed income For the period 1984-1997, fixed income is computed as the sum of two survey questions. In a first question, labeled as 'baseline fixed income' in the variable codes in the Online Supplement, households report the cumulative value of their checking accounts, saving accounts, money market fund holdings, certificates of deposits, government savings bonds and Treasury bills, including those held in IRAs. In a second question, labeled as 'other' in the Online Supplement, the household is asked about the cumulative value of any other assets, including bond funds and cash value of lifecycle insurance values. For the period 1999-2017, there exists a minor difference: the questions are the same as for the 1984-1997 period, but fixed income IRAs are now inferred about in a separate question and are therefore excluded from the fixed income variable. This shows up as a minor trend-change for the fixed income variable in 1999 (Figure 14). Finally, for the period 2019-2021, the 'baseline fixed income' question is split up into two separate questions: on the one hand a question on checking accounts, saving accounts and money market funds, and on the other hand a question on certificates of deposits, government bonds and treasury bills. The 'other' question remains unchanged. For the period 2019-2021, fixed income is then computed as the sum of the reported values over the three questions (two baseline fixed income questions and the other question).

B.2.3 Pension wealth

Pension wealth is calculated as the sum of (1) defined contribution plans, and (2) IRAs and private annuities. On the one hand, defined contribution account values are reported only from 1999 onwards and equal the sum of the reported values in defined contribution accounts held by the reference person and by the partner. These comprise not only the plans held with the current employer, but also those held with the two previous employers from both individuals. On the other hand, as noted earlier, IRA-and private annuity wealth are inferred about in a separate question from 1999 onwards. This structure implies that pension wealth prior to 1999 will equal zero (Figure 14). Also for pension wealth, in some years, there are one-off outliers that take on a negative value of multiple billions. These are set equal to zero.

Figure 16: Ratio of pension to total wealth across the non-pension wealth distribution.



Note: these plots display the ratio of pension wealth to total wealth across three wealth brackets: the bottom 50%, middle 50%-90% and top 10%. Households have been allocated to the one of the three brackets based on their rank in the non-pension wealth distribution. For the PSID, pensions equal zero prior to 1999 given that pensions are not inquired about in the PSID-questionnaire for these years.

There exist two difficulties related to the measurement of pension wealth. First, IRA wealth is included in equity and fixed income questions prior to 1999, and inferred about in a separate question from 1999 onwards. There does not exist a straightforward method of separating the IRA-proportion of the equity and fixed income questions prior to 1999, nor a reliable method of allocating IRA wealth to equity and fixed income afterwards. Therefore, I keep IRA wealth as part of the equity and fixed income variables prior to 1999, and include it in pension wealth from 1999 onwards. As this discrepancy affects only the portfolio share calculations and not households' total wealth levels or ranks, its impact on the findings in this paper is minimal. Second, from 1999 onwards, defined contribution plan wealth is included in the calculation of w, while it is not in the years prior. As our ultimate interest lays in wealth ranks κ, this shift may be problematic insofar as there exists heterogeneity in pension wealth across the non-pension wealth distribution. Figure 16 shows that this heterogeneity is relatively limited: the share of pension to total wealth displays roughly similar levels and time-trajectories across the wealth bins. Nevertheless, as a robustness, in the Online Supplement I show that the main conclusions of the paper continue to hold when restricting the wealth variable to non-pension wealth.

B.2.4 Non-mortgage debt

In the period 1984-2009, the PSID captures non-mortgage debt through a variable 'other debt'. In 2011, the 'other debt' variable is subdivided into credit card debt, student loan debt, medical debt and debt to relatives. I then calculate non-mortgage debt as the sum of these four categories. In the period 2013-2021, a residual debt category is added to the four categories from the 2011-wave. I include it as part of non-mortgage debt. This shift in definitions implies that the underlying non-mortgage debt variable may be slightly different across the three periods. In particular, the absence of a residual category in 2011 might imply a minor under-estimation of non-mortgage debt compared to the other years. However, the impact of this exclusion is marginal, as evidenced by the absence of a major trend-shift for non-mortgage debt in 2011 (Figure 14).

C ML-proxies over the full sample Ω

C.1 Framework

Data on wealth w is available over the reduced sample $\mathcal{T}_\Psi$, which begins only in 1984. This leads to two limitations. First, it restricts a comparison of wealth mobility outcomes across age cohorts. Second, it limits the feasibility of an inter-generational wealth mobility analysis, particularly in examining grandparent-grandchild wealth linkages (across three generations). However, gross main housing value h (for homeowner households) and rental payments r (for renter households) are available over the full period $\mathcal{T}_\Omega$. To approximate wealth over the entire period $\mathcal{T}_\Omega$, it is therefore common to estimate wealth based on h or r:

$$\hat{w}_i^\Omega(t) = \begin{cases} \hat{f}_h(\mathbf{x_h})h_i^\Omega(t) & \text{if } h_i(t) > 0 \\ \hat{f}_r(\mathbf{x_r})r_i^\Omega(t) & \text{if } h_i(t) = 0 \end{cases} \tag{8}$$

where $\hat{w}_i^\Omega(t) = \hat{w}_i(t) \mid t \in \mathcal{T}_\Omega$ represents the predicted wealth level over $\mathcal{T}_\Omega$. For homeowners, wealth is approximated by multiplying the observed main housing value $h_i^\Omega(t)$ (available for $t \in \mathcal{T}_\Omega$) by a scaling factor $\hat{f}_h$. For renters, wealth is approximated in parallel using observed rental payments $r_i^\Omega(t)$ and a scaling factor $\hat{f}_r$.

While $h_i^\Omega(t)$ and $r_i^\Omega(t)$ constitute variables that are directly observable, the scaling factors $\hat{f}_h$ and $\hat{f}_r$ need to be estimated as a function of some vector of input variables available over $\mathcal{T}_\Omega$. Let us define these input vectors as $\mathbf{x_h} = \mathbf{x_{h,i}^\Omega(t)} = \mathbf{x_{h,i}(t)} \mid t \in \mathcal{T}_\Omega$ for homeowners and $\mathbf{x_r} = \mathbf{x_{r,i}^\Omega(t)} = \mathbf{x_{r,i}(t)} \mid t \in \mathcal{T}_\Omega$ for renters.

C.2 Common assumptions

Existing literature (e.g. Chetty et al., 2020; Pfeffer & Killewald, 2018) makes the assumption that $\hat{f}_h = C$ and $\hat{f}_r = 0$, where C is some fixed number such as the average or median wealth-to-gross main housing value ratio in the sample. Mathematically:

$$\hat{w}_i^\Omega(t) = \begin{cases} Ch_i^\Omega(t) & \text{if } h_i(t) > 0 \\ 0 & \text{if } h_i(t) = 0 \end{cases} \tag{9}$$

implying that total wealth is approximated as main housing value for homeowners, while renters are assumed to have zero wealth. When studying wealth mobility $-$ where the interest lays in wealth ranks rather than absolute wealth levels $-$ the correctness of this approach hinges on the assumptions of (1) main housing values being positively correlated with wealth levels, (2) this relationship being stable over time, and (3) renters having zero wealth.

For the first assumption, the Pearson correlation coefficient in the PSID between gross main housing value and wealth over Ψ equals 0.66. However, there exists substantial heterogeneity in the homeowner scaling factors across households: the standard deviation of this variable equals 2.23. This suggests that the constant C constitutes a strong simplification. For the second assumption, while the median renter scaling factor indeed equals 0, a non-negligible proportion of renter households reports positive wealth levels. Furthermore, there exists significant heterogeneity in wealth levels among renters: the standard deviation for the renter scaling factor equals 10.03.

As a result, the proxy in Equation 9 can be improved by accounting for household heterogeneity in homeowner and renter scaling factors. To address this, in Section C.3, I estimate two machine learning (ML-models) that incorporate additional household-level information available in the PSID-dataset in full sample Ω. In Section C.4, I define four naive proxies, which represent variations to Equation 9. These serve as benchmarks against which the performance of the ML-models can be compared in Section C.5. The results demonstrate that the ML models significantly outperform the naive proxies.

C.3 ML-models

In what follows, I construct and estimate a gradient-boosting (GB)-model to predict scaling factors $\hat{f}_h$ and $\hat{f}_r$. Additionally, in the Online Supplement, I develop an alternative ML-model $-$ a multi-layer perceptron (MLP) model $-$ to which the performance of the GB-model can be compared. Both ML-models are trained and tested on observable sample Ψ, and estimated for homeowners and renters separately. Their inputs $\mathbf{x_h}$ and $\mathbf{x_r}$ consist of household-level variables available over the full sample period $\mathcal{T}_\Omega$. The models can then be used to make predictions over $\mathcal{T}_\Omega$.

The construction of the ML-models proceeds in three steps. First, I define the inputs $\mathbf{x_h}$ and $\mathbf{x_r}$ used by the models. Second, I outline the equations of the (homeowner and renter) GB-model, with a detailed derivation provided in the Online Supplement. Cross-validation is employed to determine the optimal hyperparameters. Thereafter, the GB-model is estimated. The full development of the (homeowner and renter) MLP-model is presented in the Online Supplement also. Third, I perform a series of diagnostic tests on ML-model outcomes, with the procedures and results again described in the Online Supplement.

Input variables The selection of the input variables $\mathbf{x_h}$ and $\mathbf{x_r}$ occurs according to two criteria. A first criterion is availability: the variable should be available over the full period $\mathcal{T}_\Omega$, or equivalently $x \in \mathbf{I}^\Omega(t)$. Due to the limited number of variables in $\mathbf{I}^\Omega(t)$, this criterion imposes a relatively strong restriction. A second criterion is relevance: the variable should contribute to the predictive performance of the ML-models. Based on these two criteria, and defining $A, B, C \in \mathbb{R},\ A, B, C < \infty$, the following input variables are selected for the homeowner and renters ML-models:

1. Labor income $\frac{y_i(t)}{\bar{y}(t)}$: the household's labor income $y_i(t)$ normalized by the average labor

income across all households $\bar{y}(t)$.

2. Capital income $\frac{\gamma_i(t)}{\bar{\gamma}(t)}$: the household's capital income $\gamma_i(t)$ relative to the average capital income income across all households $\bar{\gamma}(t)$.
3. Household size $h_i^n \in [1, A]$: the number of individuals living in household i, comprising the reference person, partner, and children.
4. Household status $h_i^s \in \{0, 1, 2\}$: indicates whether the reference person is single (0), in a relationship with the partner (1), or married to the partner (2).
5. Age $h_i^a \in [1, B]$: the age of the oldest individual in the household (between the reference person or the partner).
6. Business ownership $n_i^b \in \{0, 1, 2\}$: indicates whether the household does not own a business (0), owns an unincorporated business (1), or owns an incorporated business (2).
7. Health status $h_i^h \in [0, 1]$: the proportion over the past four years in which at least one of the core household members was unable to work due to poor health.
8. Cars per adult $\frac{h_i^c}{\bar{h}(t)}$, with $h_i^c \in [1, C]$: the number of cars per adult owned by the household, normalized by the sample median at time t.

Different outlier correction procedures are applied to these input variables. For cars per adult, data is missing for years 1973-1974 and 1987-1997. To address this, I apply to this variable the distance-weighted interpolation procedure outlined in the Online Supplement. The PSID-questionnaire codes for the input variables are provided in the Online Supplement as well.

In addition to variables (1)-(8), the inputs for the homeowner ML models ($\mathbf{x_h}$) include normalized gross main housing values $h_i(t)/\bar{h}(t)$ and the mortgage ratio $m_i(t)/h_i(t)$. For the renter models, the inputs ($\mathbf{x_r}$) also include normalized rental payments $r_i(t)/\bar{r}(t)$. These additional variables allow for scale dependence between the scaling factors ($\hat{f}_h$ and $\hat{f}_r$) and the value of the household's residence. For instance, as households accumulate more wealth, they may transition to more valuable houses, but the value of the house or corresponding rental payments might constitute a declining proportion of their total wealth over time.

Estimation & cross-validation The homeowner and renter GB-model is estimated over sample $\mathcal{T}_\Psi$. Observations over $\mathcal{T}_\Psi$ are divided into a randomly generated training set and testing set. I use a mean squared error (MSE) loss function, which is the benchmark in the literature. The predictions for the scaling factors over full sample $\mathcal{T}_\Omega$ of the GB-model are given by:

$$\hat{f}_h^{\text{GB}} = \hat{f}_h^{M_h^*}(\mathbf{x_h}) = \hat{f}_h^{(0)} + \sum_{m=1}^{M_h^*} \lambda_h^* g_h^{(m)}(\mathbf{x_h}) \tag{10}$$

$$\hat{f}_r^{\text{GB}} = \hat{f}_r^{M_r^*}(\mathbf{x_r}) = \hat{f}_r^{(0)} + \sum_{m=1}^{M_r^*} \lambda_r^* g_r^{(m)}(\mathbf{x_r}) \tag{11}$$

where a detailed derivation is provided in the Online Supplement. $\hat{f}^{(0)}$ denotes the initial guesses and $g^{(m)}$ is the weak learner at iteration m. The hyperparameters include the optimal number of boosting rounds M^*, the optimal learning rate λ^*, and the optimal maximum depth of a tree d^*. Predictions for $\hat{w}_i^{\Omega}(t; \mathcal{M}_{\text{GB}})$ are obtained by substituting $\hat{f}_h^{\text{GB}}$ and $\hat{f}_r^{\text{GB}}$ into Equation 8.

To optimize the hyperparameters, a k-fold cross-validation is performed separately for the homeowner and renter GB-model. Using the MSE loss function $\mathcal{L}_{\text{CV}}$, the average cross-validation losses are defined as:

$$\mathcal{L}_{\text{CV}}(M_h, d_h, \lambda_h) = \frac{1}{k} \sum_{j=1}^{k} \mathcal{L}^{(j)}(M_h, d_h, \lambda_h) \tag{12}$$

$$\mathcal{L}_{\text{CV}}(M_r, d_r, \lambda_r) = \frac{1}{k} \sum_{j=1}^{k} \mathcal{L}^{(j)}(M_r, d_r, \lambda_r) \tag{13}$$

where I set $k = 10$, consistent with standard practices. The optimal hyperparameters are obtained by minimizing the cross-validation loss:

$$(M_h^*, d_h^*, \lambda_h^*) = \arg\min \mathcal{L}_{\text{CV}}(M_h, d_h, \lambda_h) \tag{14}$$

$$(M_r^*, d_r^*, \lambda_r^*) = \arg\min \mathcal{L}_{\text{CV}}(M_r, d_r, \lambda_r) \tag{15}$$

For the homeowner GB-model, the resulting optimal hyperparameters equal $M^* = 140$, $d^* = 9$ and $\lambda^* = 0.045$. Those for the renter GB-model are given by $M^* = 90$, $d^* = 6$ and $\lambda^* = 0.06$. In the Online Supplement, I compute summary metrics of the SHAP-values for the homeowner and renter GB-model across all observations.

C.4 Naive measures

I aim to evaluate whether the predictions of the GB and MLP models outperform proxies that neither rely on an optimization procedure nor utilize all available information in the sample Ω, as is typically the case in the existing literature (e.g. Chetty et al., 2020; Pfeffer & Killewald, 2018). In the following, I define four such proxies, referred to as naive proxies.

A first naive proxy, denoted as $\hat{w}_i^{\Omega}(t; \mathcal{M}_{\text{NP1}})$, is defined by Equation 9. It assumes that homeowners' wealth equals C-times their main housing value, while renters' wealth is zero. Since we are ultimately interested in wealth rankings, the value of C is irrelevant as long as $C > 0$. The second naive proxy $\hat{w}_i^{\Omega}(t; \mathcal{M}_{\text{NP2}})$, third naive proxy $\hat{w}_i^{\Omega}(t; \mathcal{M}_{\text{NP3}})$ and fourth naive proxy $\hat{w}_i^{\Omega}(t; \mathcal{M}_{\text{NP4}})$ attempt to refine the estimation of renters' wealth.

The second naive proxy is defined as:

$$\hat{w}_i^{\Omega}(t; \mathcal{M}_{\text{NP2}}) = \begin{cases} C h_i^{\Omega}(t) & \text{if } h_i(t) > 0 \\ C \frac{r_i^{\Omega}(t)}{v(t)} & \text{if } h_i(t) = 0 \end{cases} \tag{16}$$

where C is again a fixed number, and $v(t)$ the rental yield, which is taken from Jordà et al. (2019). This proxy (1) assumes that rental yields are uniform across houses, (2) approximates the value of renters' residence as the inverse of the rental yield, and (3) assumes that renters' wealth corresponds to the value of the house they occupy. However, given that the median wealth of renters equals zero, the latter assumption seems particularly strong. To address this, a third naive proxy is introduced:

$$\hat{w}_i^{\Omega}(t; \mathcal{M}_{\text{NP3}}) = \begin{cases} \bar{C}_h h_i^{\Omega}(t) & \text{if } h_i(t) > 0 \\ \bar{C}_r \frac{r_i^{\Omega}(t)}{v(t)} & \text{if } h_i(t) = 0 \end{cases} \tag{17}$$

where $\bar{C}_h$ is the average scaling factor to gross main housing value for homeowners, and $\bar{C}_r$ is the average scaling factor for renters' estimated housing values. Both are calculated over the sample $\mathcal{T}_{\Psi}$. That is:

$$\bar{C}_h = \frac{1}{n} \sum_{i=1}^{n} \frac{w_i^{\Psi}(t)}{h_i^{\Psi}(t)} \qquad \text{if } h_i(t) > 0 \tag{18}$$

$$\bar{C}_r = \frac{1}{n} \sum_{i=1}^{n} \frac{w_i^{\Psi}(t)}{r_i^{\Psi}(t)} v(t) \qquad \text{if } h_c(t) = 0 \tag{19}$$

Finally, to mitigate the influence of outliers in scaling factors, a fourth naive proxy is defined as:

$$\hat{w}_i^{\Omega}(t; \mathcal{M}_{\text{NP4}}) = \begin{cases} \tilde{C}_h h_i^{\Omega}(t) & \text{if } h_i(t) > 0 \\ \tilde{C}_r \frac{r_i^{\Omega}(t)}{v(t)} & \text{if } h_i(t) = 0 \end{cases} \tag{20}$$

where $\tilde{C}_h$ and $\tilde{C}_r$ are defined analogously to Equations 18 and 19, but calculate the medians instead of the averages.

C.5 Performance comparison

Given the wealth predictions from the optimal ML models and the four naive proxies, the approximated wealth rank series can be determined. These ranks represent the ultimate objects of interest and are defined as:

$$\hat{\kappa}_i^{\Omega}(t;\chi) = \left\lceil \frac{100 \times \left(1 + \sum_{k=1}^{N_t} \mathbf{1}(\hat{w}_k^{\Omega}(t;\chi) < \hat{w}_i^{\Omega}(t;\chi))\right)}{N_t} \right\rceil \tag{21}$$

where $\chi = \{\mathcal{M}_{\text{GB}}, \mathcal{M}_{\text{MLP}}, \mathcal{M}_{\text{NP1}}, \mathcal{M}_{\text{NP2}}, \mathcal{M}_{\text{NP3}}, \mathcal{M}_{\text{NP4}}\}$.

To evaluate the performance of the two ML models and the four naive measures, I compare the proxy wealth ranks ($\hat{\kappa}$) to the actual ones (κ) over the testing set. Performance metrics include the mean squared error (MSE), mean absolute error (MAE), and the proportion of wealth rank predictions that deviate by more than 25 and 50 ranks to actual ones. These metrics are summarized using two approaches. In a first approach, the performance metric $\mathcal{M}$ is calculated for each year and averaged across years:

$$\mathcal{M}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} m(a_{i,t}, p_{i,t}), \quad \mathcal{M} = \frac{1}{T} \sum_{t=1}^{T} \mathcal{M}_t \tag{22}$$

In a second approach, the performance metric $\mathcal{M}$ is computed for each household and averaged across all households:

$$\mathcal{M}_i = \frac{1}{T_i} \sum_{t \in \mathcal{V}_i} m(a_{i,t}, p_{i,t}), \quad \mathcal{M} = \frac{1}{I} \sum_{i=1}^{I} \mathcal{M}_i \tag{23}$$

where $\mathcal{V}_i$ denotes the set of valid time points for individual i. $m(a, p)$ represents the specific calculation for the chosen metric, such as $(a - p)^2$ for MSE or $|a - p|$ for MAE.

The performance results are displayed in Table 3. Two key findings persist. First, across the naive proxies, the third naive proxy consistently displays superior performance. Second, the naive proxies' performance does not come close to those of the ML-models. Moreover, between the ML-models, it is the GB-model that outperforms the MLP-model. Therefore, in the following sections, I use the GB-model predictions as a proxy for wealth and wealth ranks over the sample $\mathcal{T}_{\Omega}$. To simplify notation, I define:

$$\hat{w}_i(t) = \hat{w}_i^{\Omega}(t; \mathcal{M}_{\text{GB}}), \quad \hat{\kappa}_i(t) = \hat{\kappa}_i^{\Omega}(t; \mathcal{M}_{\text{GB}}) \tag{24}$$

Despite the superior performance of the GB model, a significant number of predictions remains inaccurate (Table 3). On average, 9% of wealth rank predictions deviate by more than 25 ranks from their actual values in any given year, while approximately 1% of the predictions diverge by more than 50 ranks. Additionally, 21% of households in the sample experience a wealth rank misallocation of at least 25 ranks at some point during their lifecycle. When the misallocation threshold is raised to 50 ranks, this proportion drops to 3%.

Table 3: Model performance for naive and machine learning wealth proxies.

Across years

Proxy	MSE	MAE	≥ 25	≥ 50
NP1	453.88	15.58	0.20	0.04
NP2	909.32	23.57	0.41	0.10
NP3	429.09	15.42	0.19	0.03
NP4	528.38	17.53	0.26	0.04
MLP	238.51	11.02	0.10	0.01
GB	195.67	10.00	0.08	0.01

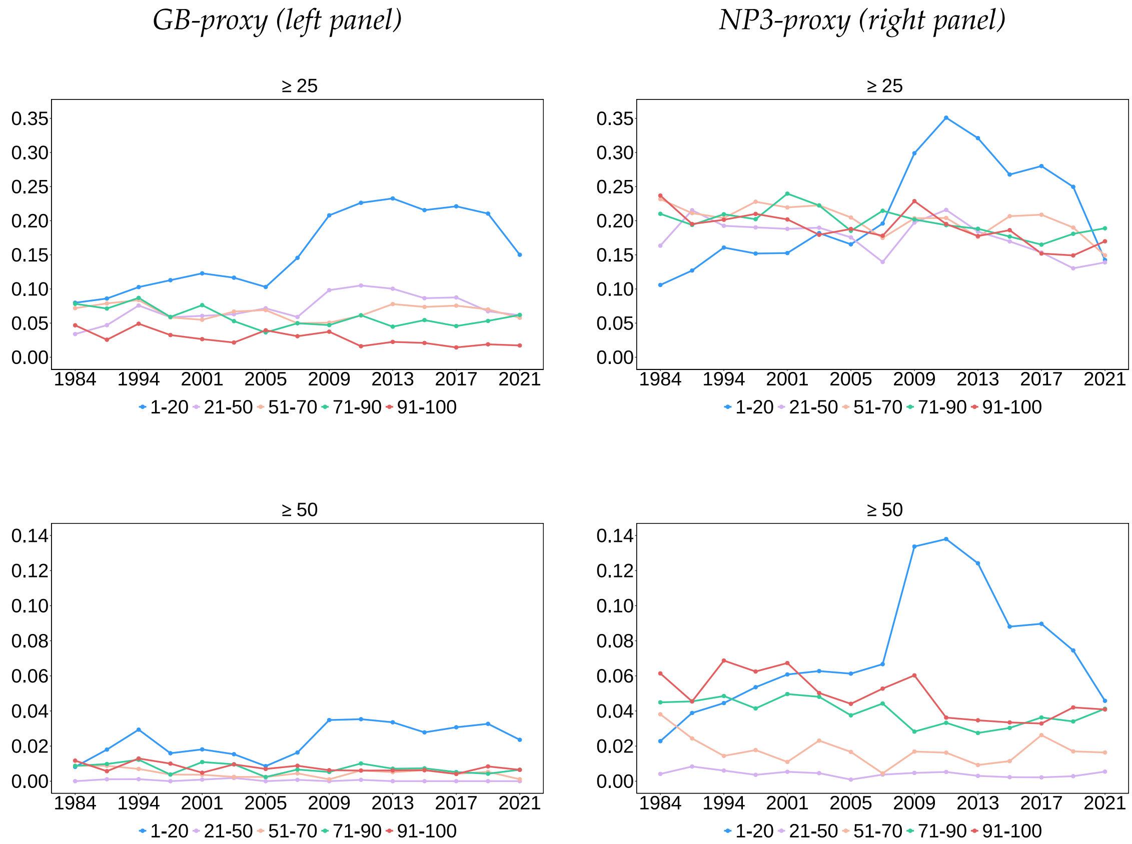
Across households

Proxy	MSE	MAE	≥ 25	≥ 50
NP1	438.17	15.10	0.37	0.09
NP2	925.15	23.58	0.61	0.21
NP3	410.61	14.87	0.36	0.08
NP4	510.56	17.00	0.44	0.09
MLP	235.76	10.68	0.23	0.03
GB	196.15	9.80	0.19	0.02

Note: panel (a) computes the performance metrics per year and averages across time. For example, in the average year, 8% of households have their wealth ranks misallocated by at least 25 units based on the GB-proxy. Instead, in panel (b), the performance metrics are calculated per household and are averaged across households. For example, 19% of households have their wealth rank misallocated by at least 25 wealth rank units at some point in this household's existence based on the GB-proxy.

Figure 17 highlights the timing of misallocations and its distribution over actual wealth. Three key observations emerge. First, the GB-proxy series outperforms the naive proxy series in all time periods and across all actual wealth levels. Second, for both the GB- and naive proxy, misallocations are more common among poor households (those belonging to the bottom 20%). This makes sense: wealth levels near the bottom of the distribution are closer to zero, so that small errors in estimated scaling factors disproportionately affect wealth ranks. Third, for the poor households, there exists time variation in the likelihood of misallocation: the degree of misallocation was significantly higher during and in the aftermath of the global financial crisis of 2008. This effect holds for both the GB-proxy and naive proxy, but is significantly stronger for the latter.

Figure 17: Proportion of misallocated households per wealth bin (according to actual wealth) for the GB-proxy and the third naive proxy.



Note: this plot reports the fraction of households that is misallocated by at least 25 wealth rank units (upper panel) or 50 wealth rank units (lower panel) for each year. The left panels report the outcomes for the GB-proxy series (GB), while the right panel does so for the third naive proxy (NP3). Households are allocated to wealth bins according to their actual wealth levels.

D Empirical strategy

D.1 Individual-level

Notation & eligibility Ultimately, our focus is on the mobility of individuals, rather than households. This requires taking into account that individuals may switch households over time. For instance, an individual living alone may begin cohabiting with a partner or get married, causing the original household (e.g. $i = 1$) to dissolve and a new household with different characteristics (e.g. $i = 2$) to be formed. Such transitions might influence the individual's wealth positively or negatively. Let us write variable z of an individual j belonging to household i at t as $z_j(t, i)$, where i may vary over time.

I restrict the analysis to individuals that have at least some control over their finances, and $-$ consequently $-$ influence the decisions of the household to which they belong. Therefore, I limit the PSID-sample to individuals identified as either the reference person or the partner within their household i. I designate an individual as partner if its relationship to the reference person is classified in the individual-level PSID file as legal spouse, partner, uncooperative legal spouse, or other non-relatives (which primarily includes same-sex partners).

Wealth levels & rankings A key question regarding individual-household linkages is how to allocate household-level wealth categories and total wealth w_i to the individual level. This allocation is performed using the household status variable h_i^s, which was defined in Section C.3. I use the following allocation rules:

1. Single individual ($h_i^s = 1$): when the household consists of a single financially-independent individual, the entire household-level wealth $w(i)$ is allocated to this individual: $w_j(i) = w_i$.
2. Non-married couple ($h_i^s = 2$): when the household comprises a non-married couple, the household-level wealth level $w(i)$ is allocated in proportion to each individual j's contribution (averaged over the past three survey waves) to the household's labor income: $w_j(i) = \frac{y_j(i)}{y(i)} w(i)$.
3. Married couple ($h_i^s = 3$): when the household consists of a married couple, the household-level wealth level $w(i)$ is divided equally between both individuals: $w_j(i) = \frac{1}{2}\, w(i)$.

Once w_j is defined for j in $1, 2, \ldots, N_j$ $-$ with N_j defined as the number of eligible individuals $-$ I compute both the individual-level actual wealth ranks $\kappa_j(t, i)$ and proxy wealth ranks $\hat{\kappa}_j(t, i)$. The individual-level wealth ranks are calculated as in Equation 7, with the household subscript

i replaced by the individual subscript j:

$$\kappa_j(t,i) = \left\lceil \frac{100 \times \left(1 + \sum_{k=1}^{N_t^j} \mathbf{1}(w_k(t,i) < w_j(t,i))\right)}{N_t^j} \right\rceil \tag{25}$$

$$\hat{\kappa}_j(t,i) = \left\lceil \frac{100 \times \left(1 + \sum_{k=1}^{N_t^j} \mathbf{1}(\hat{w}_k(t,i) < \hat{w}_j(t,i))\right)}{N_t^j} \right\rceil \tag{26}$$

where N_t^j represents the number of eligible individuals at time t, w is the actual wealth level, and $\hat{w}$ is the estimated wealth level using the GB-model from Appendix C.

D.2 Cohorts & lifecycle stages

Definitions To structure the analysis, each individual j is assigned to a time-invariant age cohort a and time-varying lifecycle stage s. A variable z at time t of individual j belonging to household i, age cohort a and lifecycle stage s is then defined as $z_j(t,i,s;a)$. Here, i and s vary with t, while a remains time-invariant. Age cohorts Y are defined over ten-year intervals, beginning with 1866-1975 up until 2006-2015. Lifecycle stages Ξ are based on age brackets and defined as 0-24, 25-29, 30-34, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74 and 75+, determined by the individual's age $a_j(t)$.

Within-cohort wealth ranks In the literature, wealth rank outcomes are typically calculated across the entire population. However, since older individuals tend to have accumulated more wealth, they naturally occupy higher positions in the overall wealth distribution. To address this, I define individual-level within-cohort wealth ranks, using the previously introduced age cohorts. These ranks are calculated for both actual wealth (using observed values) and proxy wealth (using GB-model estimates). The within-cohort ranks are derived by applying the ranking formula to the subset of individuals belonging to a specific age cohort a:

$$\kappa_j(t,i,s;a) = \left\lceil \frac{100 \times \left(1 + \sum_{k=1}^{N_t^a} \mathbf{1}(w_k(t,i,s;a) < w_j(t,i,s;a))\right)}{N_t^a} \right\rceil \tag{27}$$

$$\hat{\kappa}_j(t,i,s;a) = \left\lceil \frac{100 \times \left(1 + \sum_{k=1}^{N_t^a} \mathbf{1}(\hat{w}_k(t,i,s;a) < \hat{w}_j(t,i,s;a))\right)}{N_t^a} \right\rceil \tag{28}$$

where N_t^a is the number of eligible individuals in cohort a at time t, w denotes the actual wealth level, and $\hat{w}$ represents the wealth level predicted by the GB-model. These within-cohort wealth ranks serve as the primary input of the wealth mobility analyses conducted in this paper.

Summary across stages Finally, I summarize each variable for an individual j over their lifecycle stages. For a given variable z of individual i during lifecycle stage s, the summarized value, denoted as $z_j(s;a)$, is defined as the median of all observations of z for individual j across the years t within the lifecycle stage s:

$$z_j(s;a) = \tilde{z}_j(t,i,s;a) \quad \forall t \in \mathcal{T}_s \tag{29}$$

where $\tilde{z}_j(i,s;a)$ represents the median value of z for individual i, belonging to age cohort a, during the lifecycle stage s. The set $\mathcal{T}_s$ includes all years t that correspond to the lifecycle stage s for individual j. This approach allows us to drop the time indicator t. The key objects $\kappa_j(s;a)$ and $\hat{\kappa}_j(s;a)$ are then defined as the median actual and proxy wealth ranks of individual j over their lifecycle stage s, with $s \in \Xi$.

This summary over multiple observations per lifecycle stage offers four key advantages. First, any remaining transitory measurement errors − even after the application of outlier correction procedures − are likely to be smoothed out. Second, the formulation reduces the impact of occasional non-response, helping to preserve sample size in wealth mobility analyses. Third, aggregating data by lifecycle stage helps minimizing noise arising from household transitions, such as marriage or divorce. These might otherwise distort wealth mobility estimates. Fourth, it circumvents the non-uniform timing of PSID survey waves, in particular for the reduced sample Ψ.

D.3 Proxy wealth & wealth ranks over Ψ

In earlier appendices and sections, I have defined actual wealth $w_j(s;a) = w_j^{\Psi}(s;a)$ and within-cohort wealth ranks $\kappa_j(s;a) = \kappa_j^{\Psi}(s;a)$. Additionally, I introduced proxy wealth $\hat{w}_j(s;a) = \hat{w}_j^{\Omega}(s;a)$ and proxy within-cohort wealth ranks $\hat{\kappa}_j(s;a) = \hat{\kappa}_j^{\Omega}(s;a)$. These take values over reduced sample $\mathcal{T}_{\Psi}$ and full sample $\mathcal{T}_{\Omega}$ respectively.

Let us now define proxy wealth and within-cohort wealth ranks, summarized per lifecycle stage s, restricted to the reduced sample Ψ:

$$\hat{w}_j^{\Psi}(s;a) = \hat{w}_j^{\Omega}(s;a)\Big|_{\mathcal{T}_{\Psi}}, \quad \hat{\kappa}_j^{\Psi}(s;a) = \hat{\kappa}_j^{\Omega}(s;a)\Big|_{\mathcal{T}_{\Psi}} \tag{30}$$

where $|_{\mathcal{T}_{\Psi}}$ indicates that the values are restricted to the time frame $\mathcal{T}_{\Psi}$.

Equation 30 covers the same time-frame and individuals as actual wealth $w_j^{\Psi}(s;a)$ and wealth ranks $\kappa_j^{\Psi}(s;a)$. Therefore, a comparison of the outcomes of $\hat{w}_j^{\Psi}(s;a)$ to those of $w_j^{\Psi}(s;a)$ provides insight into the validity of the GB-model predictions and the accurateness of $\hat{w}_j^{\Omega}(s;a)$ and $\hat{\kappa}_j^{\Omega}(s;a)$. As argued in Section 3.2, throughout the mobility analyses, the outcomes based on $\hat{w}_j^{\Psi}(s;a)$ align more closely to those based on $\hat{w}_j^{\Omega}(s;a)$ than those based on $w_j^{\Psi}(s;a)$. This indicates that differences in the results between $w_j^{\Psi}(s;a)$ and $\hat{w}_j^{\Omega}(s;a)$ relate to the usage of the proxy ($\hat{\kappa}$ versus κ) rather than sample differences (Ω versus Ψ).

For future reference, I define the relevant sets of actual and proxy within-cohort wealth and wealth ranks as:

$$W = \{w_j^{\Psi}(s;a),\ \hat{w}_j^{\Omega}(s;a),\ \hat{w}_j^{\Psi}(s;a)\} \tag{31}$$

$$K = \{\kappa_j^{\Psi}(s;a),\ \hat{\kappa}_j^{\Omega}(s;a),\ \hat{\kappa}_j^{\Psi}(s;a)\} \tag{32}$$

D.4 Inter-generational linkages

The PSID enables the construction of family trees, allowing individuals to be linked to their parents and grandparents. I focus on biological and adoptive parents, excluding step-parenting. An individual can thus have at most two parents and four grandparents. Parent indices are denoted as $p_1(j)$ and $p_2(j)$, so that $p(j) = \{p_1(j), p_2(j)\}$. The set of grandparent indices is then defined as:

$$g(p(j)) = \{g_1(p_1(j)), g_2(p_1(j)), g_1(p_2(j)), g_2(p_2(j))\} \tag{33}$$

while a variable z associated with the k-th parent of individual j is expressed as $z_{p_k(j)}$. Similarly, a variable z of the first grandparent of the k-th parent of individual j is denoted as $z_{g_1(p_k(j))}$.

D.5 Intra-generational lifecycle phases

For the intra-generational analyses, individuals' wealth rank trajectories are investigated over two lifecycle phases: working life (ages 30-54) and older age (55-74). For completeness, I define the lifecycle stages relevant to working life and older age as Ξ^{WL} and Ξ^{OA} respectively. The distinction in two lifecycle phases offers two main advantages. First, not a single individual has data points spanning the entire lifecycle. By separating the analysis into two phases, it becomes possible to examine intra-generational mobility across the entire lifecycle, albeit using data from different age cohorts. Second, this approach aligns with both theoretical and empirical literature, which frequently differentiates between models of wealth dynamics during working life and during older age.

E Inequality & mobility metrics

In this section, I define the outcome measures used in the inter- and intra-generational wealth mobility analyses. These include (i) metrics related to wealth inequality and accumulation over the lifecycle, (ii) rank-rank coefficients, (iii) a squared mobility metric, (iv) transition probabilities, (v) discretionary groups and (vi) hierarchical clustering. For intra-generational analyses, all six measures are calculated and reported. The inter-generational analyses are restricted to measures (ii), (iii), (iv) and (v).

Outcome metrics (ii) to (vi) compare two cross-sections of wealth ranks. Specifically, for the inter-generational analyses, different individuals (parent-child or grandparent-grandchild) of the same family are compared at the same lifecycle stage (if available) or different lifecycle stages (otherwise). In the intra-generational analyses, the same individuals are evaluated at an initial and a final lifecycle stage.

E.1 Wealth dynamics over the lifecycle

For each wealth bin b, I calculate their wealth shares and wealth-to-average labor income ratios across the lifecycle stages $s \in \Xi^{\mathrm{WL}}$ or $s \in \Xi^{\mathrm{OA}}$:

$$\lambda_b(s;a) = \frac{\sum_{j \in b} w}{\sum_j w}, \quad \theta_b(s;a) = \frac{\sum_{j \in b} w}{|b| \cdot \bar{y}(t)} \tag{34}$$

where $|b|$ denotes the number of individuals in wealth bin b, $w \in W$ represents wealth, and $\bar{y}(t)$ is the average labor income across all individuals at time t. Depending on the lifecycle phase under consideration, $a \in \Upsilon^{\mathrm{WL}}$ or $a \in \Upsilon^{\mathrm{OA}}$, and $s \in \Xi^{\mathrm{WL}}$ or $s \in \Xi^{\mathrm{OA}}$. In addition to these measures, I compute the proportion of low-wealth and high-wealth individuals for each lifecycle stage s. These groups are defined as individuals with wealth levels below $\bar{y}(s;a)$ and in excess of twenty times $\bar{y}(s;a)$ respectively:

$$\vartheta^l(s;a) = \frac{1}{|a|} \sum_j^{j \in a} w < \bar{y}(s;a), \quad \vartheta^h(s;a) = \frac{1}{|a|} \sum_j^{j \in a} w > 20 \cdot \bar{y}(s;a) \tag{35}$$

where $|a|$ denotes the number of individuals in age cohort a, and $w \in W$.

E.2 Overall mobility

Rank-rank coefficients I calculate a rank-rank coefficient β, obtained by regressing wealth ranks in a final stage ($s = f$) on wealth ranks in the initial stage ($s = i$) using Ordinary Least Squares (OLS). It is defined as:

$$\kappa_k(s = f) = \alpha + \beta \kappa_k(s = i) + \epsilon_k, \tag{36}$$

where α denotes the intercept, β the regression coefficient capturing the degree of wealth persistence, and ϵ_k the error term for an individual, parent-child pair or grandparent-grandchild pair k.

Squared mobility To attach higher weight to large wealth rank fluctuations, I define a squared mobility measure η as:

$$\eta(a) = \frac{\sum_k [\kappa_k(\text{s = f}) - \kappa_k(\text{s = i})]^2}{|a|} \tag{37}$$

where $|a|$ denotes the number of individuals in age cohort a, and i and f denote the initial and final lifecycle stages under consideration. Across all analyses, the squared mobility metric yields identical findings to the rank-rank coefficient β. I therefore do not report this squared mobility metric in the main text.

E.3 Mobility at the bottom and top

Transition matrices Transition matrices summarize the probability of individuals moving from a wealth bin b_i to a wealth bin b_f from an initial stage $s = i$ to a final stage $s = f$.

After categorizing individuals into wealth bins b based on $\kappa \in K$, the transition probability from b_i to b_f is calculated for a given cohort a as:

$$P(b_\text{i} \to b_\text{f})(a) = \frac{n_a(b_\text{i}, b_\text{f})}{\sum_{b_\text{f}} n_a(b_\text{i}, b_\text{f})} \tag{38}$$

where $n_a(b_\text{i}, b_\text{f})$ represents the number of individuals in cohort a transitioning from bin b_i to bin b_f. The total number of individuals in the initial bin b_i is given by $\sum_{b_\text{f}} n_a(b_\text{i}, b_\text{f})$. The ex-ante and ex-post transition matrices $T_\text{EA}(a)$ and $T_\text{EP}(a)$ for cohort a are then defined as:

$$T_\text{EA}(a) = [P(b_\text{i} \to b_\text{f})(a)]_{b_\text{i}, b_\text{f}}, \quad T_\text{EP}(a) = [P(b_\text{i} \to b_\text{f})(a)]_{b_\text{f}, b_\text{i}} \tag{39}$$

where each element of $T_\text{EA}(a)$ and $T_\text{EP}(a)$ represents the probability of transitioning between two wealth bins b for age cohort a. While the underlying calculations are identical, the interpretation of the columns differs between the two matrices. In the ex-ante matrix $T_\text{EA}(a)$, a column represents the probability of moving to wealth bins b given the initial wealth bin b_i. In the ex-post matrix, a column represents the probability of originating from wealth bins b given the final wealth bin b_f.

Discretionary groups Using Equation 38, I calculate the relative occurrence of six discretionary groups that focus on wealth mobility at the bottom 20% and top 10% of the wealth distribution. The groups include the steady poor (SP), past poor (PP), new poor (NP), steady wealthy (SW), past wealthy (PW) and new wealthy (NW). At the bottom, (i) the steady poor include those families or individuals that start and end in the bottom 20%, (ii) the past poor the families or individuals that display upward wealth mobility to the top 50% originating from the bottom 20%, and (iii) the new poor start off in the top 50% but experience downward mobility to the bottom 20%. At the top, (iv) the steady wealthy start and end in the top 10%, (v) the past wealthy begin in the top 10% but display downward mobility to the bottom 70%, and (vi) the new wealthy experience upward mobility to the top 10% after starting off in the bottom 70%.

Hierarchical clusters The transition matrices and discretionary groups have the advantage of being intuitive and easily interpretable. They also facilitate cross-cohort comparisons. However, these methods may be considered somewhat ad hoc, as they require defining thresholds for wealth bins and discretionary groups prior to the analysis. Additionally, only a fraction of the sample is allocated to one of the six discretionary groups.

To complement these approaches, I employ hierarchical clustering, a method from the machine learning literature. This technique groups individuals' wealth rank trajectories into clusters, providing an alternative perspective to the discretionary groups. The four-step procedure used for this clustering is adapted from Audoly et al. (2024) and is detailed in the Online Supplement. As it requires wealth rank trajectories as input, it is used only for the intra-generational analyses.

The clustering process ultimately results in a set of k clusters, where each cluster c contains the wealth rank trajectories of the individuals assigned to it. All individuals in the sample are allocated to a specific cluster. Each cluster c is summarized by its average wealth rank trajectories $\bar{\kappa}_c(s)$, with $s \in \Xi^{\mathrm{WL}}$ or $\in \Xi^{\mathrm{OA}}$. Denoting $|C_\mathrm{c}|$ as the number of individuals in a specific cluster, we have:

$$\bar{\kappa}_\mathrm{c}(s) = \frac{1}{|C_\mathrm{c}|} \sum_{i \in C_\mathrm{c}} \kappa_i(s) \tag{40}$$

F Composition metrics

In Appendix E, I have defined different outcome measures to assess the degree of inter -and intra-generational wealth mobility. As part of this, I defined six discretionary groups (steady poor, past poor, new poor, steady wealthy, past wealthy and new wealthy), as well as a set of hierarchical clusters. In this Appendix, I define a set of variables that can be used to compare the composition of the individuals within a sample or across different discretionary groups or hierarchical clusters.

F.1 Labor income, saving rates & non-mortgage indebtedness

To assess heterogeneity in labor incomes, I define the within-cohort labor income rank $\delta_j(t,s,i;a)$, which is computed by applying the ceiling function to labor income $y_j(t,s,i;a)$ for an age cohort a:

$$\delta_j(t,i,s;a) = \left\lceil \frac{100 \times \left(1 + \sum_{k=1}^{N_t^a} \mathbf{1}(y_k(t,i,s;a) < y_j(t,i,s;a))\right)}{N_t^a} \right\rceil \tag{41}$$

where N_t^a is the number of individuals in age cohort a. $\delta_j(t,s,i;a)$ is then summarized into lifecycle stages as $\delta_j(s;a)$ according to the procedure described in Appendix D. In addition, I calculate the non-mortgage debt-to-income ratio $v_j(t,s,i;a)$ − summarized over s as $v_j(s;a)$ − as the ratio of non-mortgage debt to total household income. It is equated to the level of the household i individual j is linked with. These variables are aggregated over a sample, group or cluster g by taking the median observation across the relevant individuals.

F.2 Asset ownership & allocation

With respect to asset ownership and allocation, I formalize two types of measures. First, I define a homeownership dummy variable $d_j^h(s;a)$ which equals one whenever individual j belonged more often than not to a household i owning at least one house during lifecycle stage s. Additionally, two dummy variables $d_j^{bu}(s;a)$ and $d_j^{bi}(s;a)$ equal one whenever individual j was linked to a household i that respectively owned an unincorporated or incorporated business more often than not throughout lifecycle stage s. These variables are aggregated across the sample, group or cluster by calculating the fraction of individuals with dummies equal to one. Second, I define the conditional equity, housing and mortgage portfolio shares at the individual level as $\alpha_j^e(s;a)$, $\alpha_j^h(s;a)$ and $\alpha_j^d(s;a)$. These are equated to their household-level counterparts. They are aggregated across the sample, group or cluster by computing the median.

F.3 Inter-vivos transfers & inheritances

The PSID contains two variables that could possibly capture inter-vivos transfers and inheritances. For the first variable $-$ available over sample Ω $-$ households are asked how much they have received in lumpsum payments (comprising inheritances and payouts from insurance) since the previous survey wave. Prior to 1982, this lumpsum-question provides a bracketing response only. Summary statistics for this lumpsum variable provide highly non-robust outcomes, however. For example, the lumpsum variable suggests that the cumulative proportion of individuals having received a payment remains more or less constant over working life, which strongly contradicts empirical evidence (e.g. Black et al., 2022). For that reason, I do not proceed with this variable. For the second variable $-$ defined over sample Ψ $-$ households are asked how much they have received in gifts or inheritances since the previous survey wave. For $\mathcal{T}_\Psi[1] = 1984$, the gifts or inheritances inferred about are those that have been received overall prior to 1984. For the 1984-1990 survey waves, the respondent can provide two separate inheritances or gifts, while this number was raised to three from 1994 onwards. I apply bracketing to the responses if necessary and available, link the household-level responses to individual-level ones based on the procedure described in Appendix D, and define the received gifts or inheritances at t as $l_j(t, s, i; a)$.

For an individual j, I then compute at each t the cumulative value of the inter-vivos transfers and inheritances it has received up until that that point in time. This allows to define two composition metrics. First, I calculate a dummy variable $\iota_j^d(t, s, i; a)$ which indicates whether the individual j has received any transfer in its lifetime up until t. It is summarized per lifecycle stage s to obtain $\iota_j^d(s; a)$, and aggregated by calculating the fraction of individuals in the sample, group or cluster that has received a transfer. Second, I define the individual's cumulative transfer receipts to its lifetime resources (Black et al., 2022), defined as $\iota_j(t, s, i; a)$. Lifetime resources are computed as the cumulative sum of capitalized labor income. $\iota_j(t, s, i; a)$ is then summarized over lifecycle stage s to obtain $\iota_j^s(s; a)$. Finally, $\iota_j^s(s; a)$ is aggregated across the individuals in the group or cluster by taking the mean.

There are three remaining issues with $\iota_j^s(t, s, i; a)$. First, given that it depends on the cumulative sum, the accurateness of $\iota_j^i(a)$ for a given individual j is strongly affected by the timing of non-response or the timing of an individual's entry into the dataset. For example, the 1984-question infers about inheritances and gifts ever received prior to 1984. If a household displays non-response specifically for 1984, or enters the dataset only after 1984, $\iota_j^i(a)$ may strongly underestimate actual transfers received. However, as long as the non-response is random across the different discretionary groups or clusters, it should not affect the observed relative differences between these groups or clusters. Second, as noted, gifts and inheritances are allocated from the household to the individual level according to the rules described in Appendix D. For gifts and inheritances, which are mostly intertwined with the family of a specific individual in the household, these allocation rules may be suboptimal. Nevertheless, given the data, there is no straightforward option to execute the linkages more appropriately. Third, the gift and inheritance questions are self-reported, and may thus suffer from a downward bias. This holds specifically at the top of the inter-generational transfer distribution.

F.4 Health & household composition

Regarding health and household composition, I delineate two measures[15]. First, to assess an individual's health level, I define a dummy health variable $d_j^h(t,s,i;a)$, which is summarized per lifecycle stage s as $d_j^h(s;a)$. The dummy variable uses a question in the household PSID-dataset which categorizes the household's reference person's and partner's health. Whenever an individual j belongs to a household where at least one of the two core members is stated to have poor health, variable $d_j^g(t,s,i;a)$ is set to one. It is aggregated as the fraction of individuals in a sample, group or cluster that are part of a household with a poor health member. Second, the individual's household status variable, $s_j^h(t,s,i;a)$ and $s_j^h(s;a)$, is equated to the status variable of the household it belongs to (see Appendix C). It is aggregated across a sample, group or cluster by computing the fraction of individuals that is co-habiting with a partner or married (i.e. is non-single).

[15]In addition, I have considered the number of children in the household and the integration of the household. The results indicate that these two variables are not clearly associated with wealth rank combinations or trajectories. I therefore do not report their outcomes in this paper.

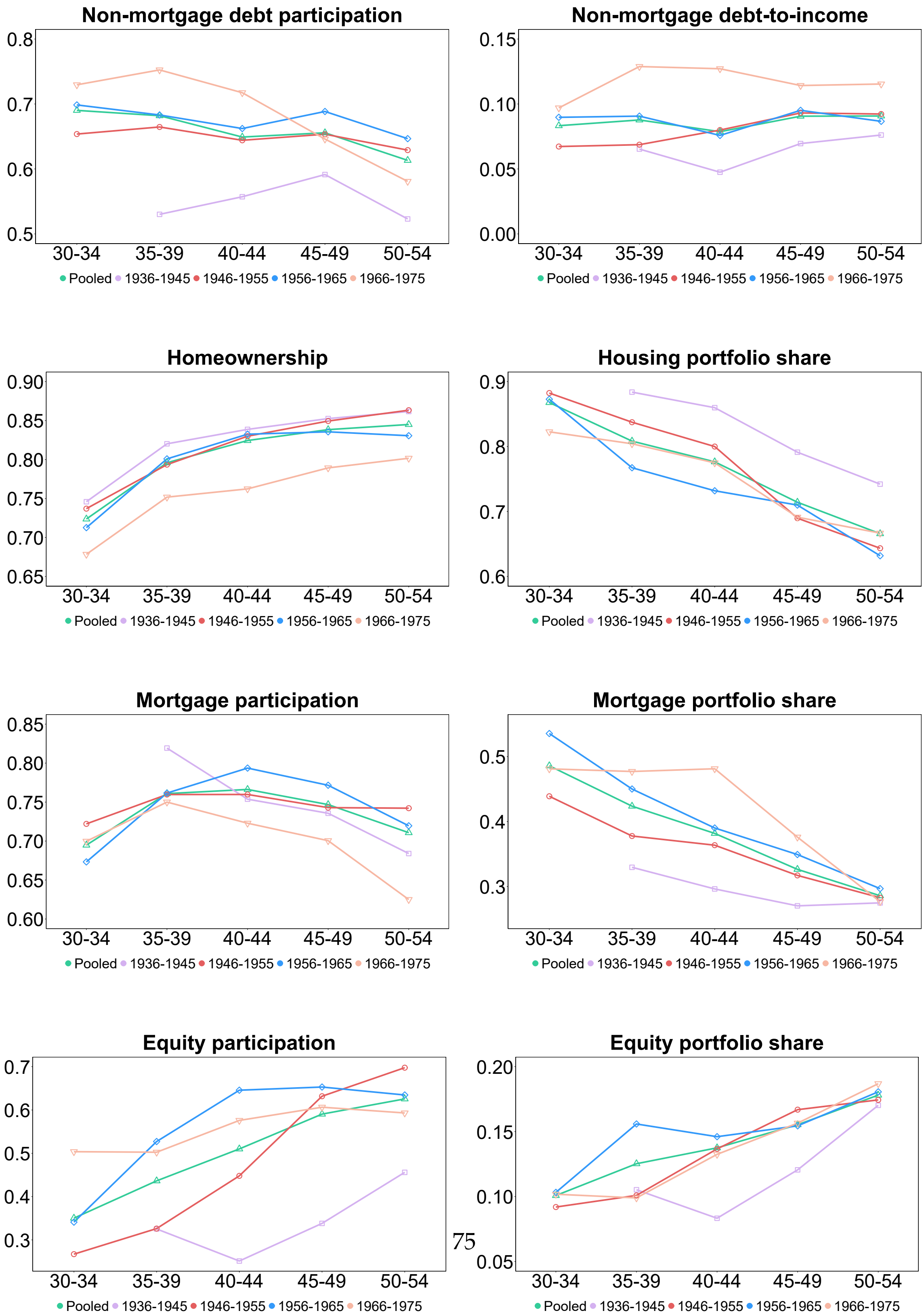
G Composition analysis: intra-generational wealth mobility during working life

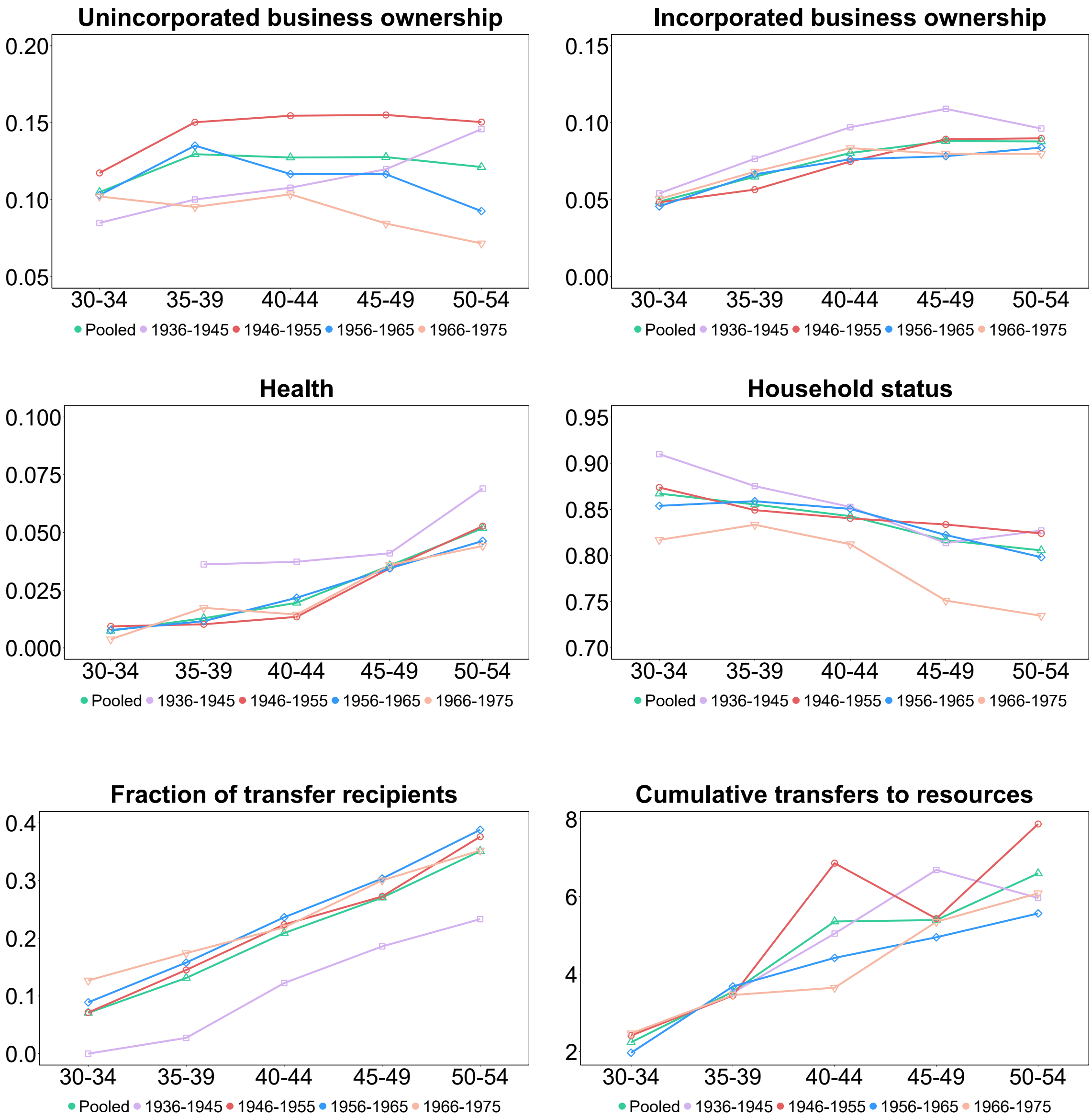
In this Appendix, I present the results of the composition analysis for working life. Specifically, Section G.1 provides the composition outcomes for the entire working life sample per lifecycle stage. Instead, Sections G.2 and G.3 compute the outcome metrics for the individuals in each of the discretionary groups and clusters. The composition metrics reported in these sections have been defined in Appendix F. Moreover, in the same Appendix, I have discussed how the individual-level metrics are aggregated across the sample or across the individuals in a specific group or cluster.

G.1 Composition across the entire sample

Figure 18 presents the composition metrics per age cohort for all individuals in the working life sample. Four findings persist. First, non-mortgage debt participation and non-mortgage debt-to-income ratios are relatively stable over working life. Overall, non-mortgage indebtedness has increased over time: more recent cohorts have higher participation rates and higher non-mortgage debt-to-income ratios. Second, homeownership rises over the working lifecycle, while the conditional share of housing in individuals' portfolios follows a downward trajectory. Homeownership is lower in the most recent (1966-75) cohort, while the conditional housing share was higher in the oldest (1936-45) cohort. Mortgage participation displays an inverse U-shaped pattern (peaking at ages 40-44), while conditional mortgage-to-total assets ratios decline over the working lifecycle. Moreover, equity market participation and the conditional equity portfolio share rise with age, and were significantly lower for the 1936-45 cohort compared to more recent cohorts. Instead, business ownership rates are roughly stable over the working lifecycle and across cohorts. Third, individuals are more likely to belong to a poor health household and more likely to be part of a single household as the working lifecycle progresses. The fraction of single individuals is higher in the most recent (1966-75) cohort. Fourth, the fraction of inter-generational transfer recipients and the size of their cumulative receipts increases strongly over working life. Figure 18 suggests that the fraction of inter-generational transfer recipients lays significantly lower for the 1936-45 cohort. However, this is likely related to a measurement error: the 1936-45 age cohort is likely to have received significant transfers prior to 1984, which may not be accurately captured in the PSID-data (see Appendix F for a detailed explanation).

Figure 18: Socio-economic characteristics and inter-generational transfers of individuals in the working life sample.

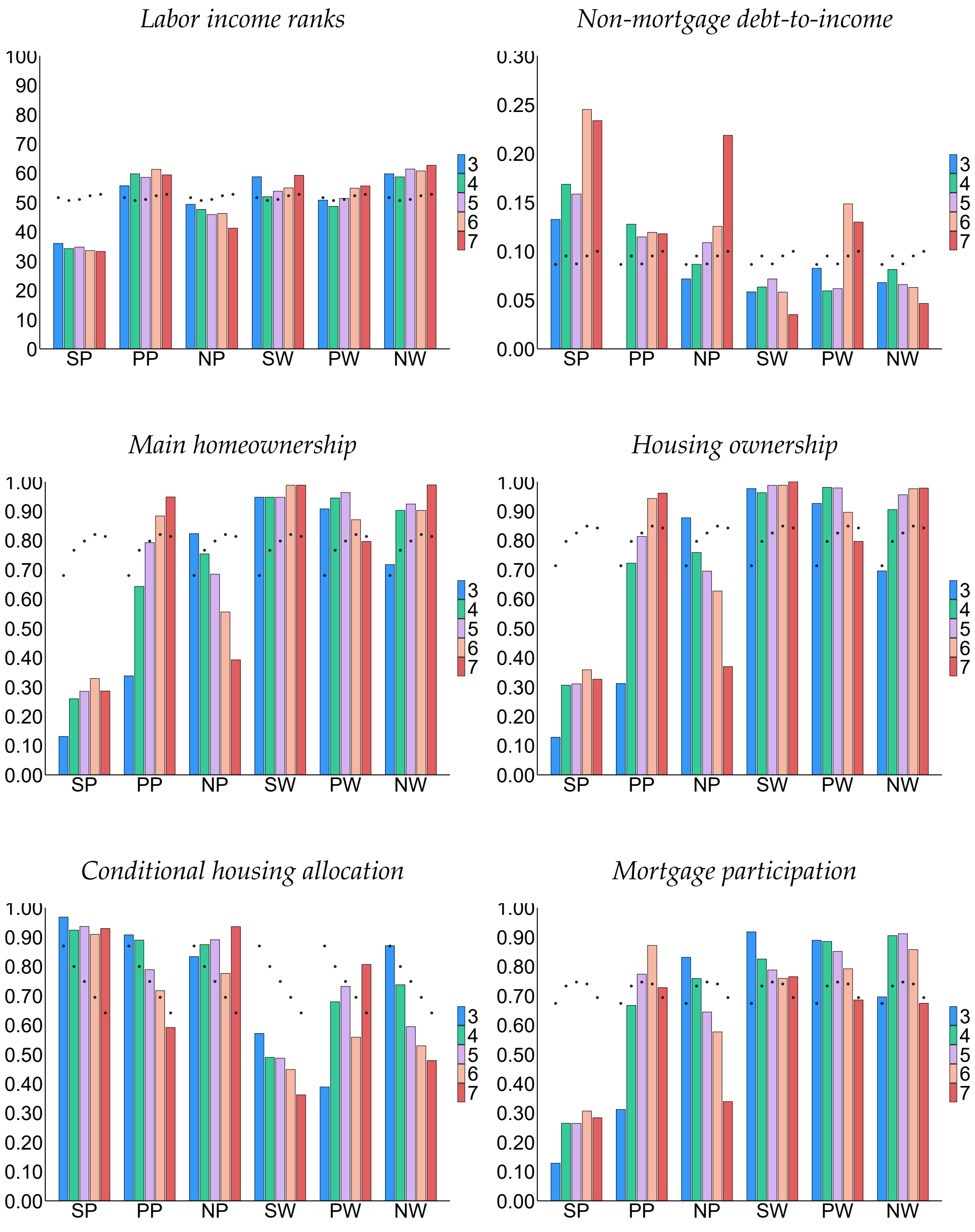


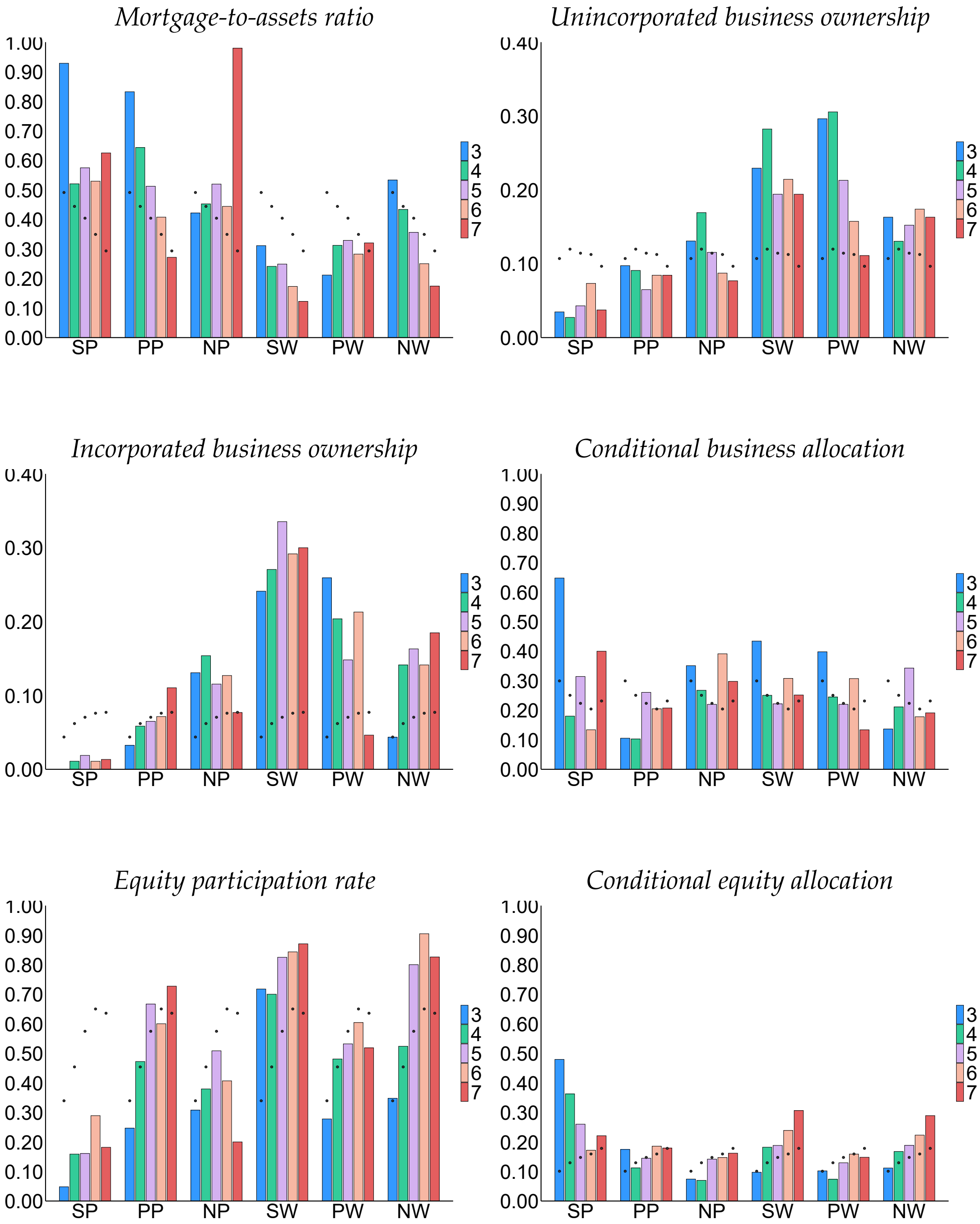


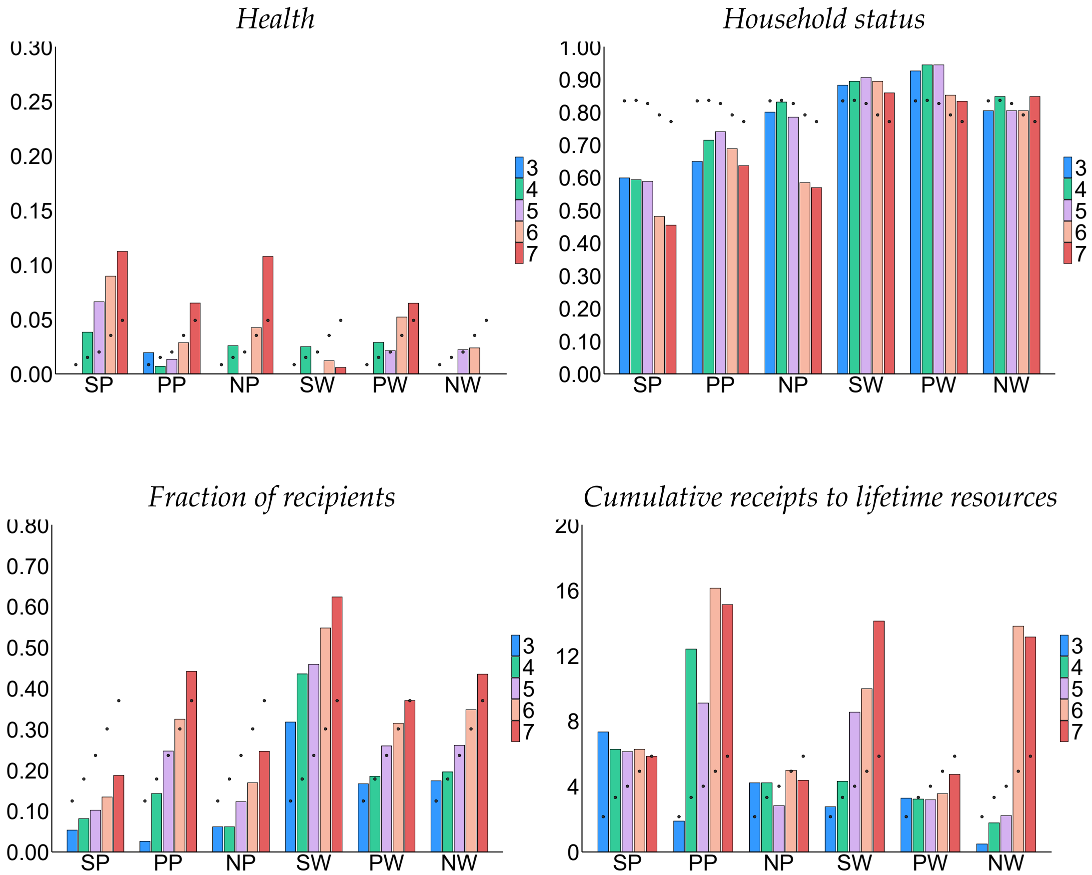
Note: this figure summarizes the key composition metrics across all individuals in the working life sample per lifecycle stage. The composition metrics and their aggregation method are defined in Appendix F.

G.2 Composition discretionary groups

Figure 19: Composition metrics for the individuals per discretionary group across the working lifecycle stages.



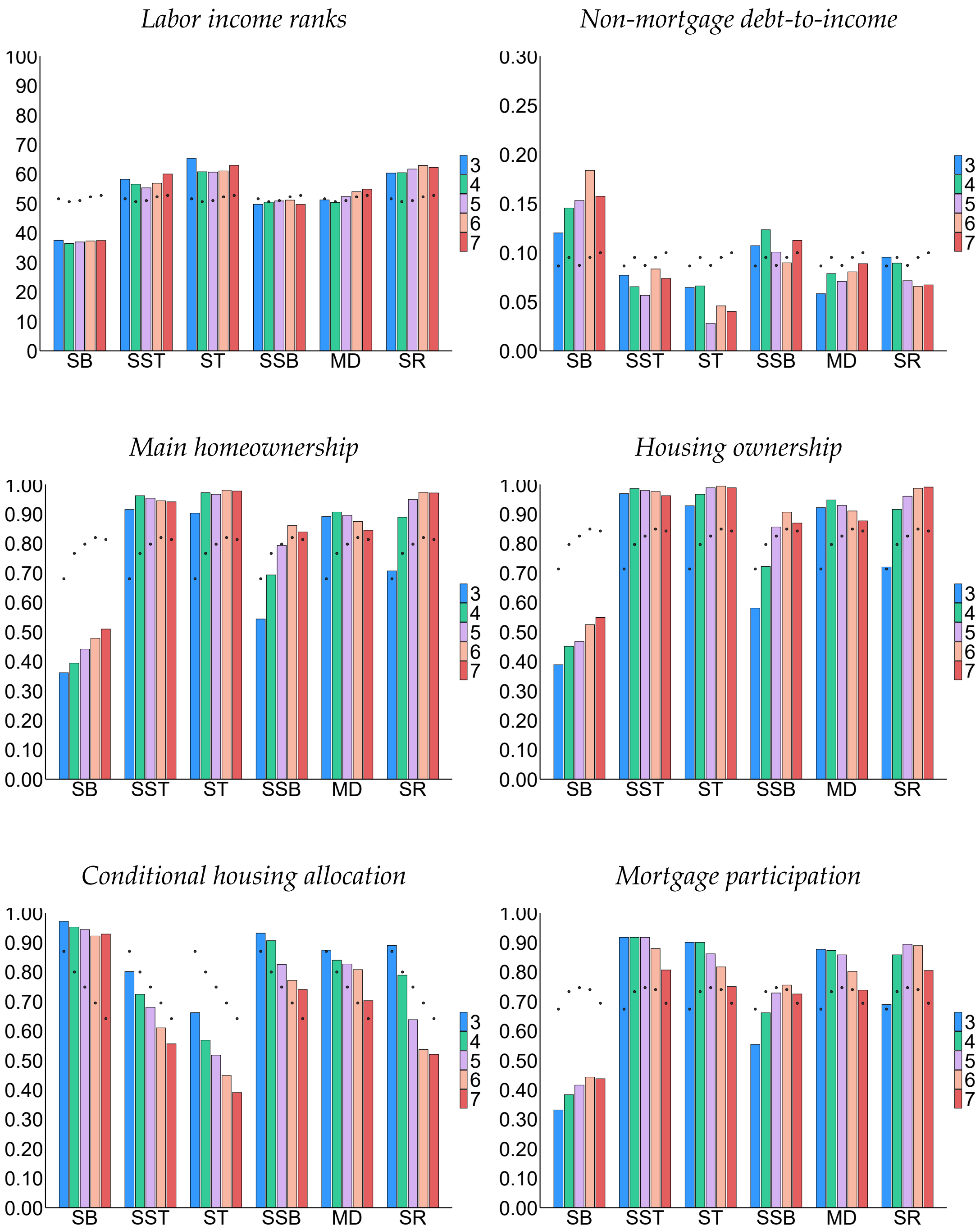

Mortgage-to-assets ratio
Unincorporated business ownership
Incorporated business ownership
Conditional business allocation
Equity participation rate
Conditional equity allocation
SP PP NP SW PW NW
3 4 5 6 7
0.00 0.10 0.20 0.30 0.40 0.50 0.60 0.70 0.80 0.90 1.00

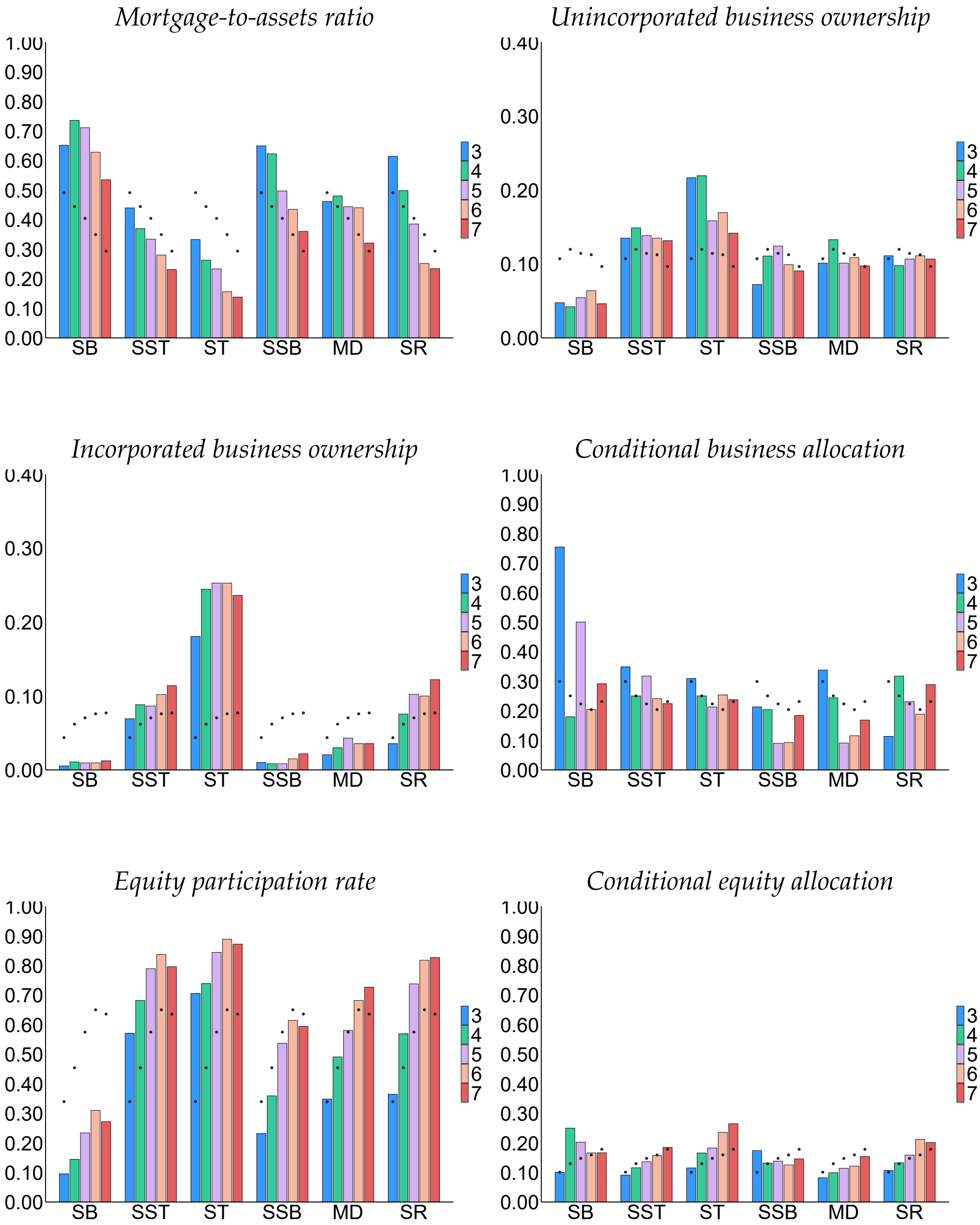


Note: this figure summarizes the key composition metrics across all individuals in each of the discretionary groups per lifecycle stage. The composition metrics and their aggregation method are defined in Appendix F.

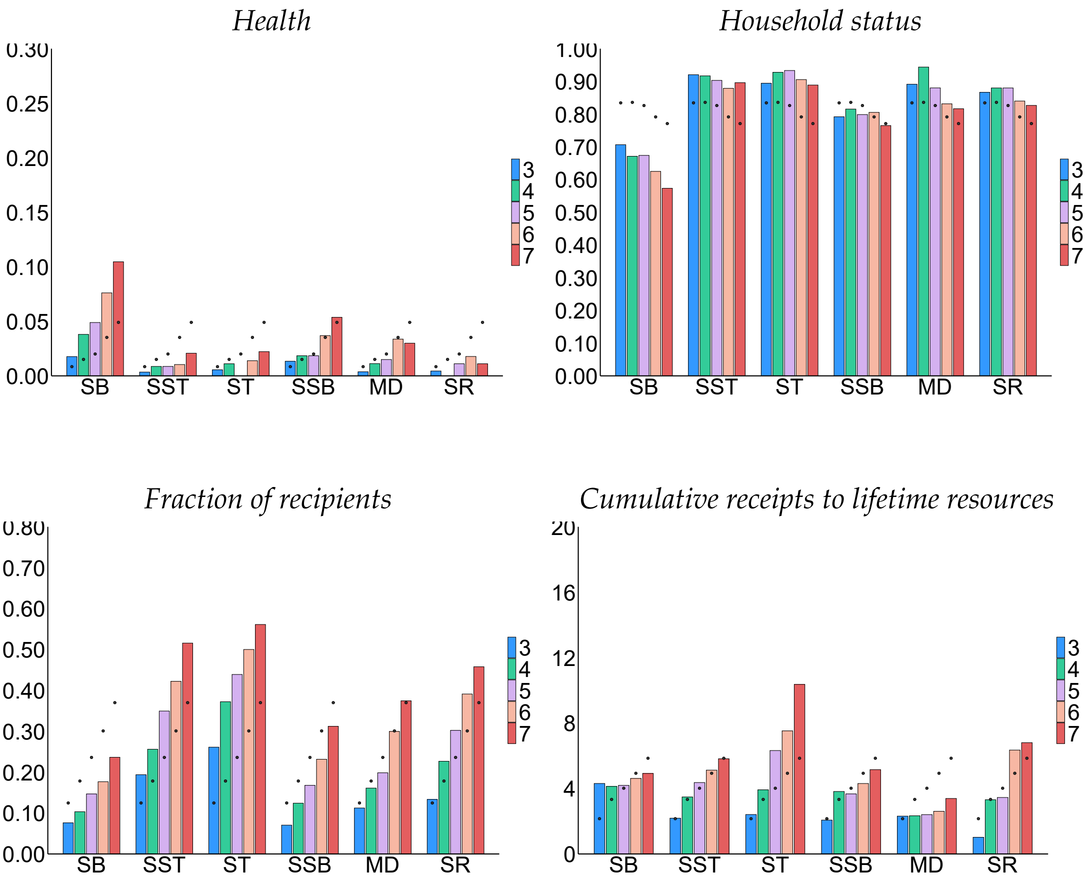
G.3 Composition hierarchical clusters

Figure 20: Composition metrics for the individuals per hierarchical cluster across the working lifecycle stages.





Mortgage-to-assets ratio
Unincorporated business ownership
Incorporated business ownership
Conditional business allocation
Equity participation rate
Conditional equity allocation
SB
SST
ST
SSB
MD
SR
3
4
5
6
7



Note: this figure summarizes the key composition metrics across all individuals in each of the discretionary clusters per lifecycle stage. The composition metrics and their aggregation method are defined in Appendix F.

H Additional visualizations

In this Appendix, I report additional visualizations related to inter- and intra-generational wealth mobility outcomes. The structure of the appendix follows the chronology of the main text: I first provide additional visualizations for three- and two-generational wealth mobility, and then move to intra-generational wealth mobility outcomes.

H.1 Two-generational (parent-child) wealth mobility

Table 4: Probability of consolidating in the bottom 20% over two generations, computed across children's age cohorts $\in Y^{PC}$ for parents and children at identical lifecycle stages.

Variable	Stage	1946–55	1956–65	1966–75	1976–85	1986–95	Pooled
	30–34	-	-	0.37	0.31	0.32	0.34
	35–39	-	0.31	0.37	0.39	-	0.37
	40–44	-	0.37	0.38	0.43	-	0.42
$\hat{\kappa}^{\Omega}$	45–49	0.45	0.42	0.33	-	-	0.40
	50–54	0.37	0.40	-	-	-	0.39
	55–59	0.47	0.47	-	-	-	0.47
	60–64	0.38	-	-	-	-	0.42

Note: the transition probabilities are calculated based on parents' and children's within-cohort wealth ranks at identical lifecycle stages (ranging from 30-34 to 60-64) for the proxy wealth $\hat{\kappa}^{\Omega}$ series. The values are calculated only when an age cohort has at the minimum 750 observations for the respective variable (as noted in the introduction to Section 4).

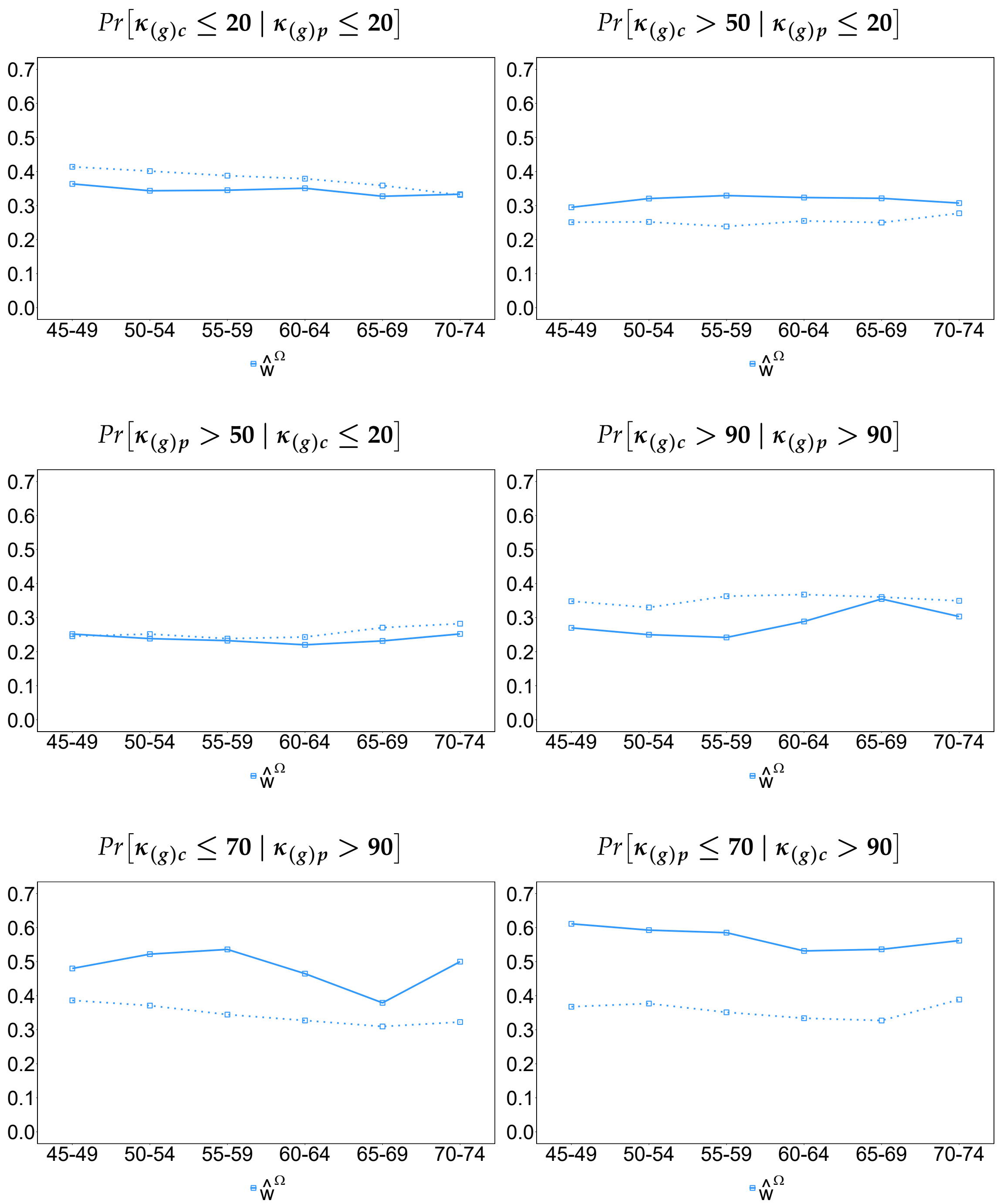
Table 5: Probability of consolidating in the top 10% over two generations, computed across children's age cohorts $\in Y^{PC}$ for parents and children at identical lifecycle stages.

Variable	Stage	1946–55	1956–65	1966–75	1976–85	1986–95	Pooled
	30–34	-	0.21	0.29	0.25	0.35	0.27
	35–39	-	0.31	0.35	0.40	-	0.36
	40–44	0.22	0.30	0.34	0.32	-	0.31
$\hat{\kappa}^{\Omega}$	45–49	0.24	0.28	0.40	-	-	0.31
	50–54	0.19	0.28	-	-	-	0.28
	55–59	0.36	0.29	-	-	-	0.31
	60–64	0.34	0.35	-	-	-	0.35

Note: the transition probabilities are calculated based on parents' and children's within-cohort wealth ranks at identical lifecycle stages (ranging from 30-34 to 60-64) for the proxy wealth $\hat{\kappa}^{\Omega}$ series. The values are calculated only when an age cohort has at the minimum 750 observations for the respective variable (as noted in the introduction to Section 4).

H.2 Three-generational (grandparent-grandchild) wealth mobility

Figure 21: Transition probabilities for grandparents and grandchildren (solid lines) and parents and children (dotted lines) when (grand)children are aged 35-39.



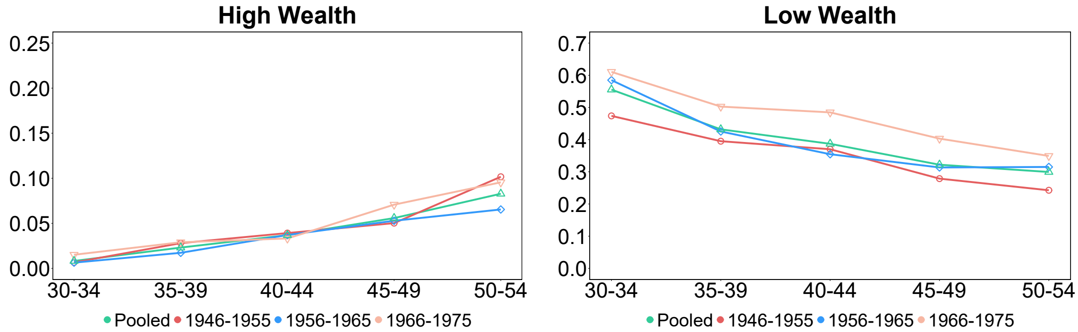
Note: these plots produce transition probabilities across specific wealth bins. These are defined in line with the discretionary groups (see Section 3.3 and Appendix E). In the notation above, $\kappa_{(g)p}$ denotes the within-cohort wealth ranks of (grand)parents, and $\kappa_{(g)c}$ the within-cohort wealth ranks of (grand)children. The transition probabilities are computed at different lifecycle stage combinations: child wealth ranks at ages 35-39 are compared to (grand)parental wealth ranks at stages between 45-49 and 70-74 (plotted on the x-axis). As an example, the values produced for the right-hand plot on the top row denote the probability of children belonging to the top 50% at stage 35-39 given that their parents belonged to the bottom 20% at any of the x-axis stages. The pooled dataset is used.

H.3 Intra-generational wealth mobility

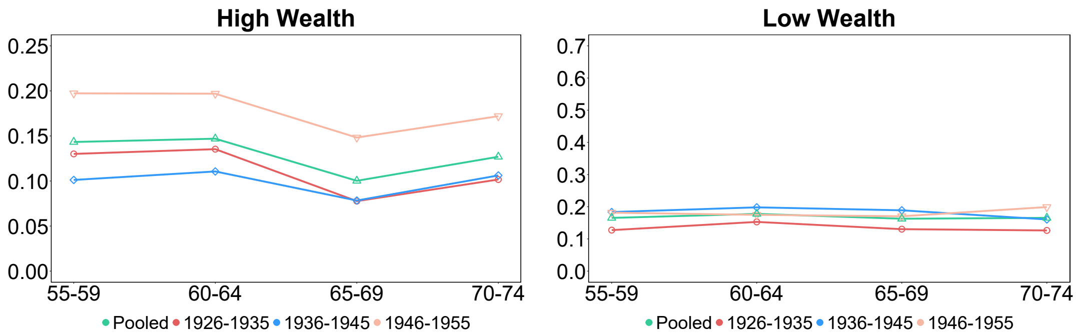
H.3.1 Wealth inequality & accumulation

Figure 22: Proportion of high-and low-wealth individuals for age cohorts $\in \Upsilon^{WL}$ and $\in \Upsilon^{OA}$ based on actual wealth levels w^{Ψ}.

Working life: ages 30-54



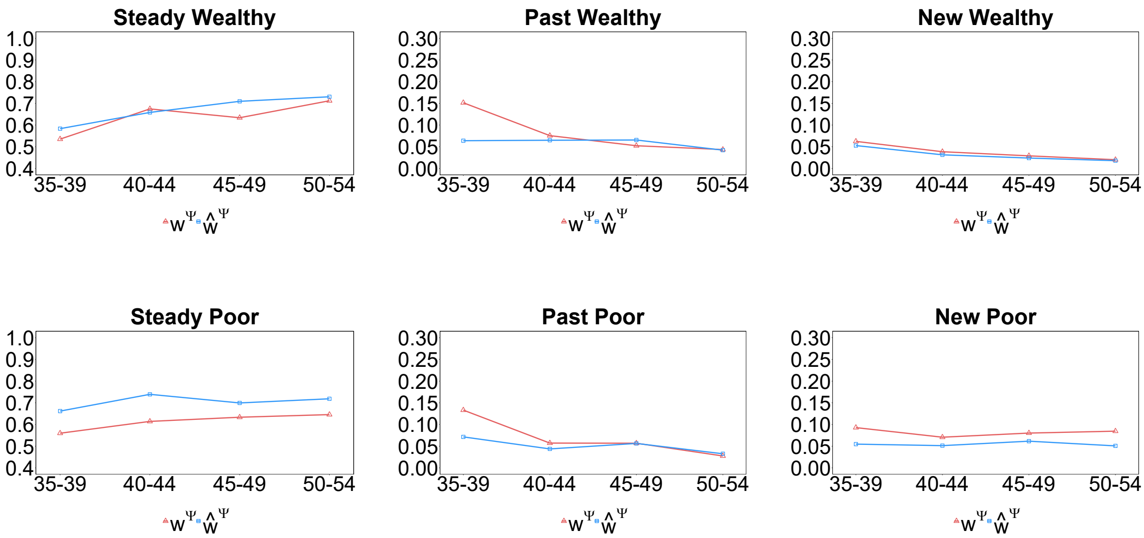
Older age: ages 55-74



Note: these plots show the fraction of high- and low-wealth individuals at each lifecycle stage per age cohort. These fractions are computed based on actual wealth levels w^{Ψ}. Given that the working life and older age samples contain different individuals, the proportion of high-and low-wealth individuals are not directly comparable across the upper and lower panels.

H.3.2 Timing effects

Figure 23: Rolling window analysis for the discretionary groups.



Note: this plot shows the probability of shifting from one wealth bin. The combination of bins considered relates to the definitions of the discretionary groups (see Section 3.3 and Appendix E). For instance, the past wealthy plot displays the probability of an individual moving from the top 10% to the bottom 70% between two lifecycle stages $k-1$ and k. The results are reported for the actual wealth w^{Ψ} and proxy wealth $\hat{w}^{\Omega}$ series.