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Why Are the Wealthiest So Wealthy? New Longitudinal Empirical Evidence and Implications for Theories of Wealth Inequality*

Joachim Hubmer† ⓡ Elin Halvorsen‡ ⓡ Sergio Salgado§ ⓡ Serdar Ozkan¶

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Abstract

We study the lifecycle dynamics of wealth inequality using 1993-2019 Norwegian administrative panel data on wealth and income. Employing a novel budget-constraint approach, we decompose the excess wealth of the top 0.1% households relative to the median between ages 45 and 64 into higher saving rates (36%), inheritances (31%), returns (28%), and labor income (5%). One-quarter of the wealthiest—the "New Money"—start with negative wealth on average but accumulate rapidly through high labor income and exceptionally high saving rates and returns. The "Old Money" inherit substantial wealth and grow it through above-average though more modest saving and returns. We use these dynamic facts to evaluate five standard wealth inequality models. Although these models match cross-sectional wealth concentration, they fail to reproduce the distinct dynamics of New and Old Money. A heterogeneous entrepreneurship model with decreasing returns to scale technology and nonhomothetic preferences is consistent with the observed dynamics.

Keywords: Wealth inequality, lifecycle wealth dynamics, rate of return heterogeneity, bequests, saving rate heterogeneity
JEL codes: D14, D15, E21

*See Online Supplemental Material in Hubmer, Halvorsen, Salgado and Ozkan (2025) for additional empirical results. The "ⓡ" symbol indicates certified random order for authors' names (Ray and Robson (2018)). Halvorsen acknowledges support from the European Research Council under the European Union's Horizon 2020 research and innovation program (grant agreement No. 851891). Ozkan acknowledges financial support from the Canadian Social Sciences and Humanities Research Council. We thank three anonymous referees, numerous conference and seminar participants, and Jess Benhabib, Alberto Bisin, Corina Boar, Chris Carroll, Mariacristina De Nardi, Andreas Fagereng, Fatih Guvenen, Greg Kaplan, Virgiliu Midrigan, Kurt Mitman, Ben Moll, Luigi Pistaferri, and Kjetil Storesletten for helpful comments. The views expressed herein are those of the authors and do not reflect the ones of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Board of Governors. Click here for the latest version.

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1 Introduction

Wealth concentration is increasingly at the center of academic and public discourse, prompting active debate on issues such as wealth taxation (e.g., Piketty (2014)). To study these questions, however, cross-sectional evidence alone is insufficient; understanding how the wealthiest accumulate fortunes over the life cycle is essential as different mechanisms imply different policy prescriptions. Do they inherit their wealth (De Nardi (2004))? Or do they build it up by consistently investing in high-return assets (Cagetti and De Nardi (2006); Benhabib *et al.* (2019)), by saving a higher portion of their income due to lower discount rates (Krusell and Smith (1998)), or by saving more as a result of temporarily extremely high earnings (Castañeda *et al.* (2003))? We shed light on these questions by empirically investigating the joint *dynamics* of wealth and income over the life cycle using Norwegian administrative *panel* data between 1993 and 2019. We then use these dynamic facts to test leading theories of wealth inequality.

Because of data limitations, the earlier literature has mostly analyzed wealth concentration using quantitative models calibrated with cross-sectional survey data (see De Nardi and Fella (2017) for a survey).[1] Instead, we exploit a long panel dataset to document long-term wealth accumulation patterns empirically. Its administrative nature with third-party reporting ensures minimal measurement error or attrition. Thanks to its richness, we can study the joint dynamics of all household budget constraint variables such as wealth, labor and capital income, taxes and transfers, as well as inheritances (including inter vivos transfers). Finally, its large sample size enables precise estimates for narrowly defined groups, including households at the very top of the wealth distribution.

In our empirical analysis, we leverage the completeness of our data to quantify

[1] For example, in the US, the main data source on wealth, the Survey of Consumer Finances (SCF), is a triennial cross-sectional survey. The Panel Study of Income Dynamics (PSID) also collects wealth data since 1999 but does not sample the top 1% households well (Insolera *et al.* (2021)), even though they own more than one-third of total wealth. Finally, Saez and Zucman (2016) impute household wealth from administrative tax records by capitalizing income from different assets, but this method requires strong assumptions on returns (Smith *et al.* (2023)).

the contribution of each budget constraint component to wealth inequality employing a novel dynamic accounting decomposition based on household's intertemporal budget constraint. We start with documenting the underlying heterogeneity by retrospectively tracking wealth, return and saving rates, labor earnings, and inheritances by following the same individuals for the *past* 26 years, conditional on the *terminal* wealth quantile and age group.[2] We then employ our accounting method to decompose the wealth gap between the top and median households into these components.

First, on average, the wealthiest households begin adult life substantially richer than others in their cohort. For instance, the richest 0.1% of households aged 50–54 hold, on average, 124.3 times the economy-wide average wealth ($434,000 in 2019; hereafter referred to as "AW"). The same households already owned around 7×AW in their mid-20s. Moreover, the top 0.1% group owns around 8-9 times as much wealth as those in the next 0.9%—a gap that remains roughly stable over the life cycle. However, within-cohort wealth concentration declines over the life cycle as bottom-half households steadily accumulate housing wealth and converge to the median.

Second, the wealthiest 0.1% have maintained substantially higher equity shares (85%-90% of their portfolios), particularly in private businesses, starting from very young ages—even compared with cohort peers of similar wealth. They also maintain moderate leverage throughout life, hovering around 50%, primarily through private businesses. For households below the 90th percentile, in contrast, housing constitutes around 90% of gross wealth over the life cycle. Consistent with their higher equity shares, wealthier households persistently earn significantly higher returns (see also Fagereng *et al.* (2020a); Bach *et al.* (2020)). Among 50- to 54-year-olds, long-term annual returns on net wealth rise monotonically from 1.4% for the bottom 50% to 9.1% for the top 0.1% , with differences most pronounced among younger households.

Third, among the same households, lifetime annual labor income rises from $0.2 \times AW$ for the bottom 50% to $0.6 \times AW$ for the top 0.1%, while annual inheritances jump from negligible amounts to $0.4 \times AW$ for the wealthiest. Despite higher labor income

[2]This backward-looking approach, of course, conditions on an endogenous variable (e.g., households reaching the top). We complement this analysis with a forward-looking investigation documenting the same features over the *subsequent* 26 years, conditional on the *initial* wealth quantile. These two approaches jointly paint a complete picture of lifecycle wealth dynamics.

and inheritances, these sources constitute a small share of total lifetime resources for the top 0.1%, with equity income dominating. Furthermore, while the wealthiest receive inheritances earlier in life—allowing longer compounding periods—their labor income advantages emerge more gradually.

Finally, we compute the past 26-year saving rate out of gross (Haig-Simons) income. Consistent with previous evidence (e.g., Fagereng *et al.* (2019)), saving rates rise steeply with wealth from around 10% in the bottom half to 35%-85% for the top 0.1% across age groups. Importantly, this positive correlation is not merely mechanical (i.e., higher saving rates moving households up the wealth distribution); the next 26-year saving rate also increases with initial wealth, as do returns.

As our primary empirical contribution, we quantify each factor's importance in explaining the wealth gap between the wealthiest and median households. We simulate counterfactual wealth profiles by sequentially replacing each variable in the budget constraint—such as the saving rate or return on net wealth—with its age-specific average for the reference group, the middle 50% of households. Since wealth accumulation is dynamic and nonlinear, the order of replacement matters; we therefore employ a Shapley-Owen (S-O) decomposition that averages the marginal effect of each component across all possible permutations (Shorrocks (2013)). Our approach ignores behavioral responses and thus has to be understood as an accounting exercise capturing the first-order effects of each dimension of heterogeneity. Yet, we view its simplicity and transparency—avoiding any behavioral assumptions—as an advantage enabled by the completeness of our data. Moreover, we use these novel descriptive moments to benchmark structural models of wealth inequality.

Among households aged 50–54, the wealth gap between the top 0.1% and the median is mainly accounted for by higher saving rates (39.1%), higher inheritances (32.8%), and higher return rates (24.7%), with higher labor income explaining only a small remainder (3.4%). Three conclusions follow. First, higher labor income and higher returns on wealth, commonly viewed as central, jointly account for less than a third of the gap. Second, heterogeneity in saving rates is more important than heterogeneity in rates of return and labor income for top wealth accumulation. Third, after correcting for underreporting and accounting for the compounding of inheritances and inter vivos transfers received earlier in life, we find a substantially

larger role for intergenerational transfers than previous empirical work suggests (e.g., Charles and Hurst (2003); Black *et al.* (2022)).

We find similar patterns across all age groups from 45 to 64, reinforcing our benchmark results. Furthermore, moving up the wealth distribution within the top 10%, higher inheritances and returns become increasingly important in explaining excess wealth relative to median households. Conversely, the relative importance of saving rates and labor income declines at the very top of the distribution. Finally, the importance of each component is robust to alternative assumptions, including imputing market values for private firms, more aggressively inflating intergenerational transfers, and removing remaining time-series nonstationarity. Although these adjustments can change the level of top wealth, the S-O shares remain remarkably stable.

As our second major empirical contribution, we document significant heterogeneity among top wealth owners. One quarter of the top 0.1% aged 50–54 were already in the top 0.1% in their mid-20s, with average net wealth of $26 \times AW$—the Old Money—while another quarter of them start with an average negative net wealth of $-0.1 \times$ AW and receive minimal intergenerational transfers. This latter group, the New Money, rapidly grows their wealth early in life, as they earn even higher returns and save at higher rates than the Old Money, and progressively shift their portfolio from housing to private businesses. After 26 years, their portfolio allocation resembles that of the Old Money, although their net worth remains somewhat lower.

Applying the S-O decomposition, we find that by age 50 the wealth gap between the New Money and mid-wealth households is driven by higher saving rates (50.1%) and higher returns on net wealth (37.6%), with higher labor income (13.3%) also contributing significantly. Inheritances contribute slightly negatively (-1.1%), reflecting that the New Money start out with below-average initial wealth. In contrast, the fortunes of the Old Money by age 50 are mostly due to higher inheritances (42.2%), higher saving rates (31.4%), and higher returns (25.9%), with higher labor income contributing little (0.6%). These results highlight that wealthy households are far from homogeneous: they include both self-made entrepreneurs and businesses heirs.

As our third major contribution, we use the empirical dynamic decomposition results to test five competing quantitative theories of wealth inequality, each tied to a specific component of the household budget constraint. We begin with a *basic* lifecycle

Bewley model with accidental bequests and non-Gaussian idiosyncratic labor income risk estimated with our data. We then add, one at a time, the leading mechanisms proposed in the literature: a *superstar* earnings state (Castañeda *et al.* (2003)), heterogeneity in the *rate of return* (Benhabib *et al.* (2019)), heterogeneity in the *discount rate* (Krusell and Smith (1998)), and a nonhomothetic *warm-glow bequest motive* (De Nardi (2004)). All augmented models replicate the targeted cross-sectional inequality moments; only the basic model falls short, as is well known (Aiyagari (1994)). In the absence of dynamic evidence, each augmented model would therefore appear to be a plausible explanation for top wealth concentration. Applying the S-O decomposition to simulated data reveals a very different picture. In all models, except the *superstar* specification, inheritances explain 53%-107% of the wealth gap between the top 0.1% and median households. Therefore, these models generally do not feature the observed rapid rise of the New Money. Instead, top wealth accumulates gradually across generations. Furthermore, the Old Money do not grow their inheritances as much as our data show. The *superstar* model, in contrast, loads excessively on labor income (57%) and minimally on inheritances (7%), failing to capture the Old Money dynamics observed in the data. These features of the data are crucial for the design of optimal tax policies (Guvenen *et al.* (2019); Boar and Midrigan (2022)).

Motivated by these findings, we develop and estimate a sixth model that directly targets the dynamic S–O moments for the top 0.1%, the New Money, and the Old Money. This *full* model combines two empirically essential mechanisms: (i) heterogeneous entrepreneurial returns that are nonmonotone with wealth, arising from decreasing returns to scale production and financial frictions (Quadrini (2000); Cagetti and De Nardi (2006)), and (ii) nonhomothetic consumption-saving preferences (Carroll (1998)). In the stationary distribution, entrepreneurial productivity—thereby the average realized return—is positively correlated with wealth, but conditional on productivity, returns decline with wealth due to decreasing returns to scale. This allows highly productive New Money entrepreneurs to accumulate wealth rapidly early in life while keeping the fortunes of the Old Money bounded. In addition, the nonhomothetic saving motive helps generate the high saving rates observed at the top of the distribution—especially for the Old Money, whose returns are above average though modest, therefore, insufficient on their own to explain their high saving rate. The

model successfully reproduces the lifecycle wealth accumulation patterns of both the New Money and the Old Money.

2 Longitudinal Data on Wealth and Income

We use data from a combination of administrative tax and income records, which contain detailed information on assets, income, taxes, transfers, and demographic information for the entire Norwegian population from 1993 to 2019. These registers include annual tax records, a shareholder registry, firm balance sheets, the inheritance tax registry, and the central population register. Most information is third-party reported to the tax authorities, ensuring accuracy and reliability.[3] Figure 1 summarizes the main variables used in our analysis. Similar data have been used by other work (e.g., Fagereng *et al.* (2020a, 2019)), so, for brevity, we relegate the details on the data sources and the description of variables to Appendix B as well as the online supplemental material in Hubmer *et al.* (2025) (OSM hereafter).

Our measure of household net wealth accounts for all financial assets (e.g., stocks, mutual funds, bonds, cash and deposits), real estate, and private business wealth. Liabilities comprise both personal debt (e.g., credit card debt, student debt, and mortgages) and private firm liabilities. Bank accounts, bonds, mutual funds, listed shares and other securities in the Norwegian Central Security Depository, and personal debt are third-party reported in tax records, ensuring high accuracy. Housing values are imputed annually from contemporaneous transactions data using a machine-learning method (Fagereng *et al.* (2020b)).

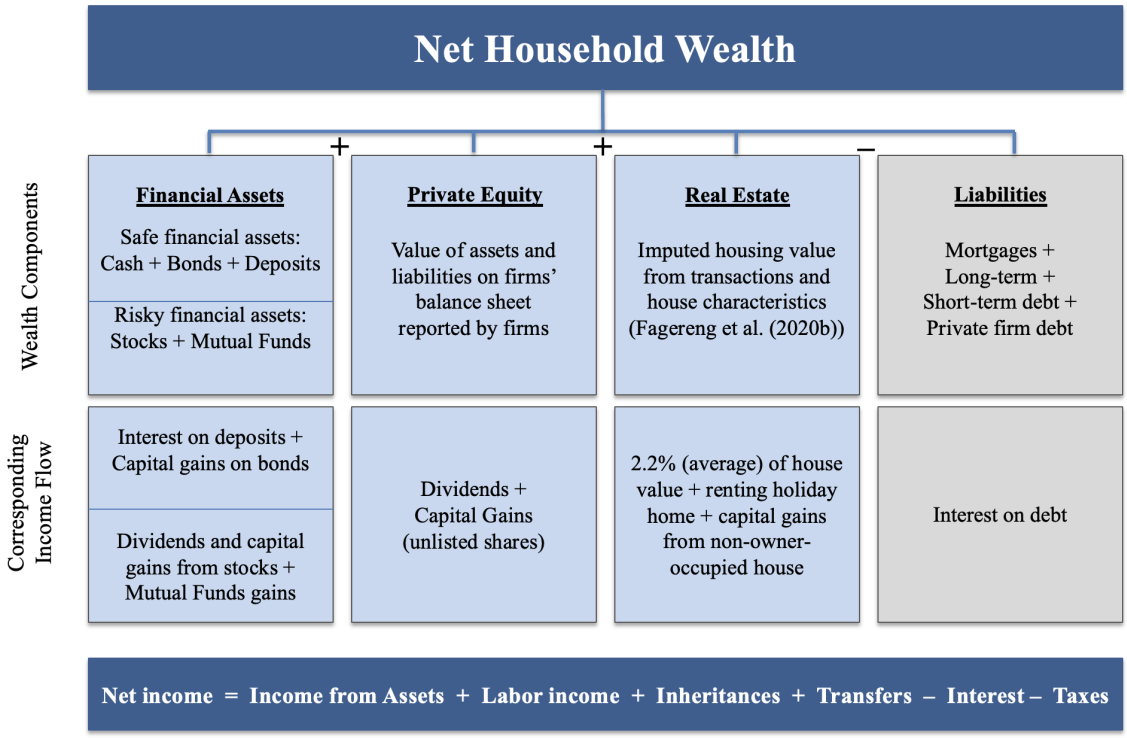
The value of equity owned by the household is primarily derived from personal tax records, supplemented with detailed information on individuals' ownership of publicly traded stocks and tax values of private firms.[4] Tax values follow standardized rules , designed to measure assets at current market values rather than historical cost.[5]

[3]Both wealth and income are taxed in Norway. Norwegians are asked to report all of their assets and liabilities, even if they do not meet the tax threshold. All variables are measured as of December 31 of each year, so our data represent an end-of-year snapshot of individuals' balance sheets.

[4]We trace indirect ownership of public equity through private holding companies back to ultimate individual owners. This adjustment has minimal impact: on average, only 2.5% of private equity is reclassified, with negligible variation across wealth groups or time.

[5]Tax authorities regularly audit private firms to assess their value and compare it with reported

FIGURE 1 – SUMMARY OF VARIABLES



Notes: See Appendix B for measurement of these variables and additional details.

These valuations account for depreciation, pension obligations, and value of inventories. In practice, however, tax values correlate highly with book values (Fagereng *et al.* (2020a)), which generally exclude intangible assets and may understate true economic values. Importantly, the measured firm values align well with the entrepreneurs' business wealth in the model in Section 6, ensuring consistency between our empirical and quantitative approaches. Furthermore, in Section 5.1.1 we report the sensitivity of our S–O decomposition to imputing market values for private firms using time-varying multipliers estimated from publicly listed firms.

Most income components are precisely reported in tax records, comprising labor earnings (including self-employment income), interest income and expenses, transfers, and taxes. Rental income from real estate is directly observed. Following the rental-equivalence approach, annual owner-occupied housing income is imputed on average

tax forms. Although not all firms are audited, firms with revenues over around $500,000 are required to have their balance sheets audited by an approved auditing entity.

at 2.2% of property value (Eika *et al.* (2020)), adjusted for changes in the price-to-rent ratio over our sample period (Appendix SM.2 in OSM).

Measuring equity income (including unrealized capital gains) is more complicated. A 2006 dividend tax reform triggered a shift from dividends to retained earnings (capital gains).[6] Following previous studies using Norwegian data (Alstadsæter *et al.* (2016); Fagereng *et al.* (2020a, 2019)), we obtain both dividends and retained earnings by linking individuals' equity ownership—both direct and indirect through holding companies—to companies' balance sheets using the shareholder registry from 2005 onward, when the registry became complete. This approach captures total returns to equity ownership regardless of payout form, ensuring our measures are not distorted by tax-motivated payout timing.

Prior to 2005, we impute dividends and capital gains by training a gradient boosting regression with around 30 individual and aggregate predictors using post-2005 information. This method can capture complex nonlinear relationships without requiring explicit feature engineering. Out-of-sample predictions successfully replicate both the level of returns and their variation across the wealth distribution. See Appendix B.6 for details.

Inheritance data are available through 2013, when the inheritance tax was abolished. This registry contains all inter vivos transfers and inheritances—including those below the tax threshold—with information on donors, recipients, and taxes paid. Assets in the inheritance registry are substantially undervalued but subsequently appear at full value in recipients' wealth, raising measured saving rates and potentially distorting measured return rates. Thus, we correct for this undermeasurement by reversing statutory discount rates. Private equity transfers received a 70% discount on assessed values below NOK 10 million ($\sim$ \$1.5 million) until 2009 and 40% thereafter. For real estate, we infer a 45% discount. We proxy unobserved estate composition with the recipient's portfolio shares.

Adjusted inheritances closely match heirs' share of donors' end-of-life estate across all years, providing strong validation. For the wealthiest 0.1%, they remain about 30% below estate shares, possibly reflecting pre-death donations, end-of-life health

[6] First, large dividends were paid out immediately before the reform, with minimal distributions afterward. Second, holding companies were created to defer or avoid dividend taxation.

expenditures, and estate transfer costs. We implement a robustness check for this discrepancy in Section 5.1.1.

For post-2013 years, we impute inheritances by assigning each child an equal share of the deceased's estate—motivated by the strong fit between adjusted inheritances and estate shares pre-2014. For inter vivos transfers, we first estimate a probit model for receipt (extensive margin), then employ a rich gradient boosting regression to predict amounts conditional on receipt (intensive margin). Out-of-sample validation confirms accurate predictions of both the frequency and magnitude of transfers across wealth groups. Finally, we further augment our measurement of inter vivos transfers by using data on intergenerational equity transfers from the shareholder registry after 2005, replacing their values when shareholder-registry values are larger.[7] See Appendix B.5 for details.

Our data exclude pension wealth. Over 80% of Norwegian pensions are pay-as-you-go, with most of the rest covered by employer-provided plans. Only 0.3% of total pension wealth is held in personal plans reported on tax returns. Given our focus on the wealthiest households, pension wealth likely constitutes a minor fraction of their net wealth.

Our data also exclude offshore wealth not reported to Norwegian tax authorities. Alstadsæter *et al.* (2018) show that accounting for hidden wealth increases the share of the top 0.1% of households by 1 percentage point (p.p.) of total wealth. Finally, our data exclude assets with difficult-to-measure value (e.g., art or jewelry).

Sample selection. The main variable of interest in our analysis is net wealth, for which the natural decision-making unit is a household. Furthermore, the Norwegian government taxes the wealth of individuals in a household jointly. Therefore, we measure all variables—assets, liabilities, and income—at the household level. In our baseline sample, we consider all individuals who are at least 20 years old with nonmissing net wealth. This leaves us with a sample of 74.4 million individual-year observations and an average of 2.75 million households per year. We convert all nominal values to 2018 prices using the Norwegian Consumer Price Index.

Cross-sectional wealth distribution over the life cycle. Before delving into longitudinal dynamics, we briefly describe the evolution of the cross-sectional wealth

[7] Only about one-third of parent–child equity transfers appear in the inheritance registry.

distribution over the life cycle. The average wealth displays a hump-shaped profile over the life cycle (Figure A.1a), rapidly increasing from 0.15 × AW to 1 × AW between ages 25 and 45, after which wealth accumulation slows down before peaking at 1.6 × AW at age 65. The median wealth grows faster than the average, indicating a steeper wealth profile in the bottom half of the distribution (Figure A.1b). Thus, wealth concentration declines over the life cycle (Figure A.1c), with the share of total net worth held by the top 1% declining sharply from close to 50% at age 25 to less than 20% at age 50, as opposed to the fanning out of earnings inequality (e.g., Ozkan *et al.* (2023)). We find similar patterns in the SCF (despite the significantly higher wealth concentration in the US). This suggests that similar economic forces are in play behind lifecycle wealth dynamics in both countries.

3 Lifecycle Wealth Dynamics

As a first step toward our dynamic decomposition, we describe how each household budget constraint component evolves differently across the wealth distribution. We organize the empirical analysis around the intertemporal budget equation

$$W_{i,t} = W_{i,t-1} + (R_{i,t}W_{i,t-1} + L_{i,t} + H_{i,t}) \times S_{i,t}, \tag{1}$$

where $W_{i,t}$ denotes household i's net worth in year t. The return on net wealth $R_{i,t}$ includes income from equity (including unrealized capital gains), safe assets, and real estate, net of interest payments and wealth and capital income taxes. After-tax labor earnings $L_{i,t}$ include wage and salary income, self-employment income, and government transfers (such as unemployment and disability benefits). Inheritances and inter vivos transfers net of taxes are captured by $H_{i,t}$. Finally, $S_{i,t}$ represents the gross saving rate from total income, so that consumption equals $(1 - S_{i,t}) \times (R_{i,t}W_{i,t-1} + L_{i,t} + H_{i,t})$.

To understand the heterogeneity underlying our decomposition results, we examine these variables over the life cycle across wealth groups using two complementary approaches. Our main approach retrospectively traces these variables over the *preceding* 26 years, stratified by the *terminal* wealth quantile and age group. For example, we identify wealthy households in 2019 and follow their trajectories back to 1993.

Although intuitive, this *backward-looking* approach suffers from a "survivorship bias"—focusing exclusively on successful households may obscure critical information about those who failed to accumulate wealth. To address this limitation, we complement it with a *forward-looking* approach that tracks the same variables *prospectively* over 26 years, conditional on initial wealth and age.

3.1 Methodology

Retrospective Analysis. For each conditioning year $\tau \leq 2019$, we group household heads aged 45—whom we can follow back to age 19 in 1993—and older into 5-year age bins, $h \in \{45-49, ..., 75-79, 80+\}$. Within each age group h, we rank them with respect to their average net wealth between τ and $\tau-1$, $\overline{W}^h_{i,\tau} \equiv 0.5 \times (W_{i,\tau} + W_{i,\tau-1})$, which mitigates transitory fluctuations.

We partition households into nine wealth groups denoted by BW^h_j. The first two contain households with negative average net wealth ($\overline{W}^h_{i,\tau} < 0$) and those with minimal positive wealth, $\overline{W}^h_{i,\tau} \in \left[0, W^{\min}_t\right)$, where $W^{\min}_\tau$ is 9,000 NOK in 2019. These groups comprise 21.5% and 3.4% of our sample in 2019, respectively. The remaining households are then ranked into the following seven quantiles: $j \in \left\{\left[W^{\min}_\tau, P50\right), [P50, P75), [P75, P90), [P90, P95), [P95, P99),\right.$
$\left.[P99, P99.9), \geq P99.9\right\}$, where Px denotes the xth percentile of the $\overline{W}^h_{i,\tau}$ distribution.

For each age-wealth group BW^h_j, we compute moments of all budget constraint variables, denoted $\mathbb{M}^\tau_{h,j}$. To control for year effects, we repeat this analysis across 10 conditioning years $\tau \in \{2010, 2016, ..., 2019\}$ and average the resulting moments: $\overline{\mathbb{M}}_{h,j} = \frac{1}{10}\sum_{\tau=2010}^{2019} \mathbb{M}^\tau_{h,j}$.[8] Restricting to $\tau \geq 2010$ ensures a minimum 17-year panel window for all households.

Forward-looking Analysis. We also group household heads aged 20+ into five-year age bins (h) for each $\tau \in \{1993, 1994, ..., 2002\}$. Within each age group h, households are ranked by their average net wealth $\overline{W}^h_{i,\tau}$ and assigned to the same nine wealth categories (j) defined previously. These forward-looking wealth groups, denoted FW^h_j, trace wealth accumulation paths conditional on initial economic positions. As before, we report moments averaged across all conditioning years.

[8] While this approach smooths out short- and medium-term time effects, our 1993–2019 sample period necessarily reflects a specific historical context that includes the information technology revolution, globalization, and institutional evolution.

Unit of Analysis and Household Composition. We measure wealth and income at the household level—where saving decisions are made— while tracking *individuals* who are household heads in conditioning year τ. These individuals may belong to different households over time (e.g., due to marriage or divorce). Although family formation can affect wealth accumulation (Fagereng *et al.* (2022)), our results are robust when restricting the analysis to a balanced panel of compositionally stable households (see Appendix SM.2 in OSM).

3.2 Dynamic Average Wealth Profiles

We start by presenting the average net worth ($W_{i,t}$) over the life cycle. Figure 2a shows that the richest 0.1% of households aged 50–54 ($BW^{50-54}_{\geq P99.9}$) own 124.3×AW. The same households were already quite wealthy 26 years prior, owning 6.9 × AW, indicating a substantial degree of persistence at the top of the wealth distribution. The next 0.9% wealth group has seen average wealth increasing from 1.1 × AW to 11.9 × AW over the same period. Similarly, $FW^{20-24}_{\geq P99.9}$—those in the top 0.1% of households aged 20–24—own 18.8 × AW in the beginning of the sample period. Instead of seeing any mean reversion, their wealth increased to 40 × AW by their mid-40s (Figure 2b). In fact, the top group's wealth growth is similar to that of the other groups in the top 5%; consequently, wealth concentration in the right tail of the distribution remains mostly unchanged over the life cycle.

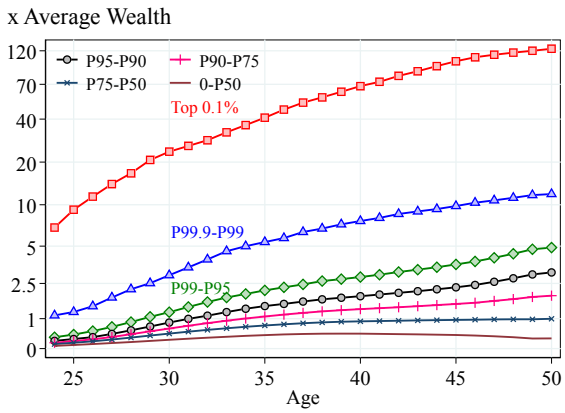
Consistent with these patterns, 24.0% of $BW^{50-54}_{\geq P99.9}$ were already in the top 0.1% quantile of their cohort initially (Figure D.1a). We later refer to these households, who started their lives rich and have remained rich, as part of the "*Old Money*" and investigate them in more detail. Yet, about 24% of those who reach the top 0.1% of the distribution started below the 90th percentile. This group of households broadly belongs to the "*New Money*" who start with average initial wealth of $-0.1 \times AW$, and we contrast their wealth dynamics with that of the Old Money in Section 4.

Despite the substantial persistence at the top of the wealth distribution over the life cycle, the bottom half of the distribution converges to the median. Young households with little wealth experience steep wealth growth, especially between ages 25 and 35. Therefore, the decline in wealth inequality is mainly because of the bottom half of the distribution converging toward the median.

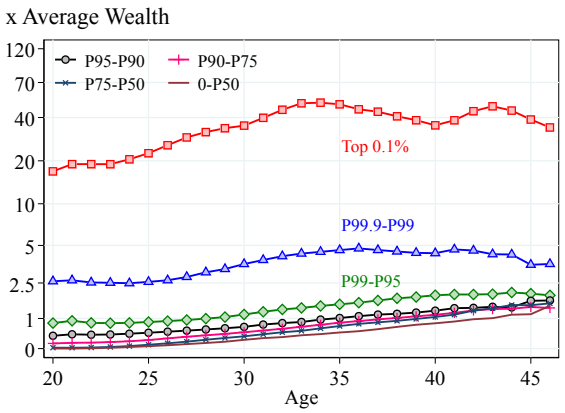
Given our research question—why are the wealthiest so wealthy?—we focus pri-

FIGURE 2 – AVERAGE WEALTH PROFILES

(A) Backward-Looking Wealth Profile



(B) Forward-Looking Wealth Profile



Notes: Figures 2a and 2b show the backward-looking and forward-looking average wealth profiles, respectively. The vertical axis displays wealth in units of AW, re-scaled using the inverse hyperbolic sine (IHS) transformation (IHS, Pence (2006)) given by $\ln\left(\theta W_{it} + \sqrt{\theta^2 W_{it}^2 + 1}\right)$ with $\theta = 0.5$.

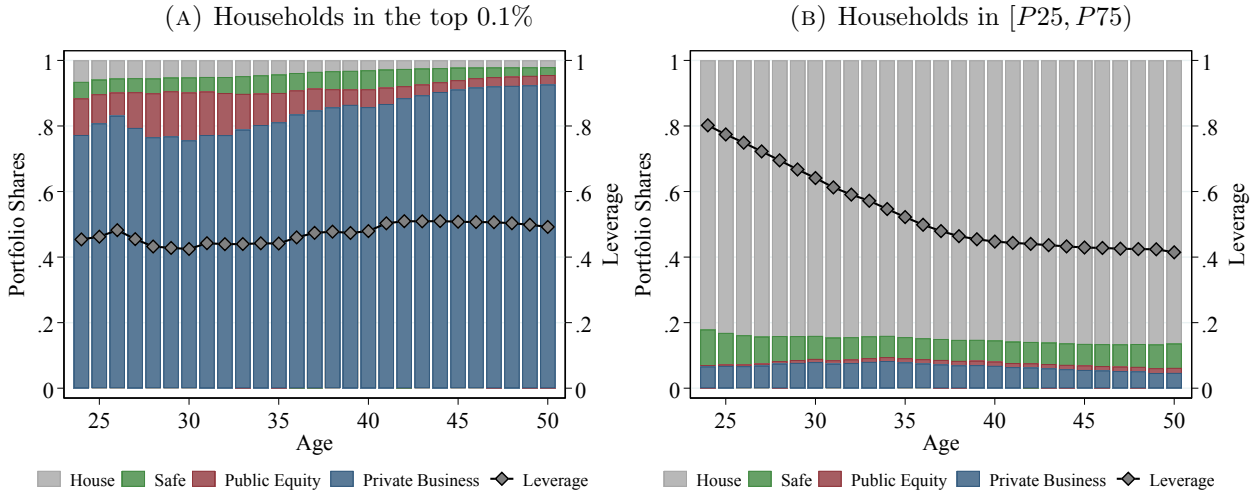
marily on the retrospective approach, highlighting differences with the forward-looking approach where relevant. This approach allows us to quantify the mechanisms—high saving rates, returns, inheritances, labor income—that characterize actual top wealth accumulation, rather than ex ante expected paths that may or may not lead to the top. We concentrate on prime-age households (50–54 years old) in the main text (i.e., BW_j^{50-54}), discussing age variation where relevant. See OSM for the results from the forward-looking approach and for other age groups.

3.3 Portfolio Composition and Long-term Returns

We now analyze differences in rates of return by focusing on four broad asset categories—housing, safe assets, public equity, and private business wealth—as well as liabilities (including both personal debt and private firm liabilities).

As has been documented in cross-sectional data (e.g., Carroll (2000)), wealthy households tend to hold most of their wealth in equity, particularly in private businesses. For the top 0.1% group ($BW_{\geq P99.9}^{50-54}$), the average equity share of the portfolio over the previous 26 years hovers above 90%, almost all of it invested in private businesses (Figure 3a). Exploiting our longitudinal data further, we show that households reaching the top 0.1% invested in equity significantly more heavily starting earlier in life, even compared with those of similar wealth and age (Appendix F). Therefore, their large equity shares do not just reflect the cross-sectional correlation. They have

FIGURE 3 – BACKWARD-LOOKING PORTFOLIO SHARES



Notes: Figure 3 shows the portfolio shares (left y-axis) and leverage (right y-axis) for households aged 50–54, weighted by gross assets. Private business share is defined as the ratio of private business assets to gross household wealth and leverage includes both personal debt and private business liabilities.

small shares of safe assets and housing, which remain roughly constant over the life cycle. Finally, they are moderately levered throughout life, primarily through private businesses, with liabilities hovering around 50% of total assets (including firm assets).[9]

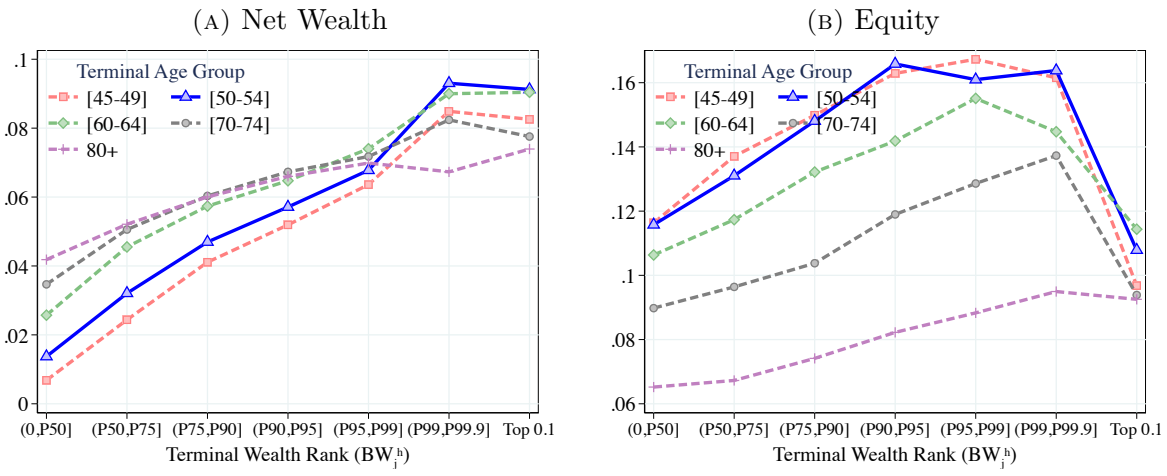
In contrast, for households below the 95th percentile of the wealth distribution, housing is the single most important asset in their portfolios. For example, for median-wealth households ($BW^{50-54}_{[P25,P75)}$) housing constitutes around 90% of their gross wealth throughout the sample period (Figure 3b).[10] They also start their lives with much higher leverage (80% of total assets), mostly in the form of long-term debt, and reduce it to 40% of total assets by age 50.

Lifecycle Returns. Consistent with recent empirical evidence (Fagereng *et al.* (2020a); Bach *et al.* (2020)), Figure 4a shows large differences in *life cycle average*

[9]Excluding firm liabilities, the top 0.1%'s direct household leverage is only 1.8%.

[10]The public equity share in Norway is significantly lower than in the US and other OECD countries, while real estate wealth is higher. This is because, first, the Norwegian tax policies promote homeownership (80%+ ownership rate vs. 65% in the US). Second, tax incentives favor private business ownership over public equity. Third, Norway's public pension system owns roughly one-third of all public equity (see Fagereng *et al.* (2019)).

FIGURE 4 – LONG-TERM AVERAGE RETURNS ACROSS THE WEALTH DISTRIBUTION



Notes: 26-year average of asset value-weighted mean annual returns within terminal age and wealth groups, averaged across different conditioning years.

returns.[11] For households aged 50–54, the average annual return over the previous 26 years increases monotonically from 1.4% for those below median ($BW^{50-54}_{[W_t^{\min},P50)}$) to 9.1% for the top 0.1% ($BW^{50-54}_{\geq P99.9}$). These differences are more pronounced among younger cohorts: There is only a 3.5 p.p. difference among households aged 80 and above versus 7.5 p.p. for those aged 50–54. Finally, the wealthiest earn more volatile and more positively skewed returns (Figure A.4).

Equity returns are substantially higher but hump-shaped across the wealth distribution. They rise from 12% for below-median households to above 16% in the top 10% of the wealth distribution, then decline to 11% for the top 0.1% group, $BW^{50-54}_{[\geq P99.9)}$ (Figure 4b).[12] This pattern aligns with standard models of entrepreneurs facing decreasing returns to scale and collateral constraints (e.g., Cagetti and De Nardi (2006)), as discussed in Section 6. These findings indicate that the top 0.1%

[11] In our analysis, we follow Fagereng *et al.* (2020a), in calculating the ex post return as the ratio of annual income (including unrealized capital gains) generated from the asset to its value at the beginning of each year, which we adjust for intra-year asset purchases and sales à la Dietz (1968). Life cycle average returns are weighted averages of returns over the life cycle, across households within wealth groups, across conditioning years. For details of our method, see Appendix E.

[12] Fagereng *et al.* (2020a) find a positive correlation between net wealth and equity returns. Our differing results stem from using weighted versus unweighted measures (Figure E.1). Boar *et al.* (2022) similarly document declining equity returns by firm value in Spain.

earn higher returns on net worth primarily through their larger equity allocation.

Examining returns on safe assets and housing, we find that the first generates the lowest returns, ranging from below 1% for below-median wealth households to 3.5% for the top 0.1% (Figure A.3a). Housing returns increase from around 5% for below-median households to about 8% above the 95th percentile (Figure A.3b).

Although backward-looking measures mechanically reflect selection—since households with high past returns are more likely to end up at the top—our forward-looking analysis shows similar patterns when households are ranked by initial wealth. Households starting wealthy earn persistently higher returns (Figure A.5a), largely driven by higher equity portfolio shares (Figure SM.2.27 in OSM). Thus, selection alone does not explain the strong portfolio and return differences we observe.

3.4 Labor Income and Inheritance Heterogeneity

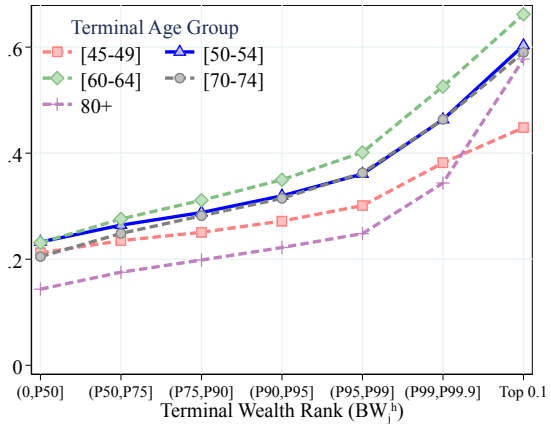
Among 50- to 54-year-olds, average annual labor income ($L_{i,t}$) over the past 26 years rises from above $0.2 \times AW$ for below-median-wealth households to $0.6 \times AW$ for the top 0.1% (Figure 5a). While economically meaningful, mechanically accumulating these differences explains only a modest fraction of the wealth gap, and their contribution depends critically on how long income differences compound and on associated differences in saving and return rates. Moreover, the gradient is noticeably flatter for younger age groups, limiting the scope for compounding early in life. Our S-O decomposition in Section 5 provides a disciplined way to quantify these forces.

Although labor income exceeds inheritances ($H_{i,t}$) for most age and wealth groups (Figure 5b), the inheritance gradient is much steeper in relative terms. Inheritances are nearly zero for below-median wealth households but rise to above $0.4 \times AW$ annually for the top 0.1%. Unlike labor income, top wealth owners receive inheritances earlier in life, allowing longer compounding. The steep relative gradient and earlier timing highlight inheritances' distinctive role at the top.

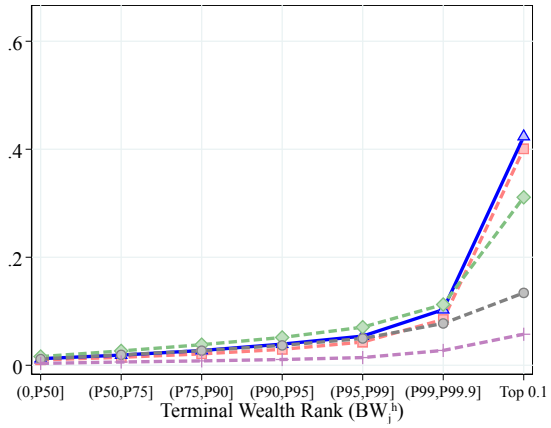
Despite higher labor income and inheritances, these sources constitute only a small share of lifetime resources—the noncompounded sum of all income plus initial wealth in 1993—for the top 0.1% (see Appendix G for details). For the top 0.1%, labor income and inheritances account for less than 13% of lifetime resources, while equity income constitutes around 88% (consistent with high returns and large initial wealth). In contrast, the bottom 90% derive 80%-90% of their lifetime resources from labor

FIGURE 5 – LABOR INCOME AND INHERITANCES BY WEALTH

(A) Lifetime Labor Income



(B) Lifetime Inheritances



Notes: Average annual after-tax, after-transfer labor income (including self-employment income) and after-tax inheritances (including inter vivos transfers) in the last 26 years.

(see also Black *et al.* (2020)).

3.5 Lifecycle Saving Rate Heterogeneity

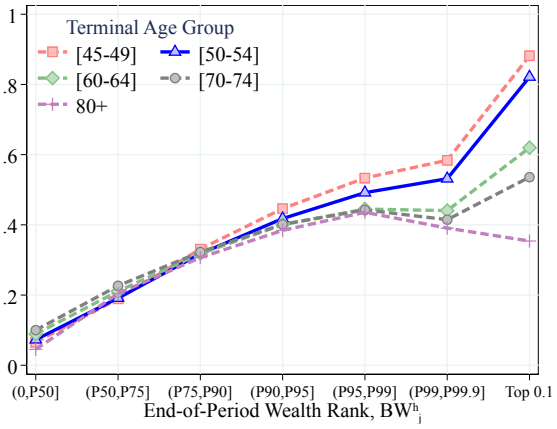
Several papers show that saving rates increase with wealth and income (e.g., Fagereng *et al.* (2019), Bach *et al.* (2017), Carroll (1998), and Dynan *et al.* (2004)). We confirm this finding holds true from a lifecycle perspective. We define individual i's lifetime saving rate as $S_i = (W_{i,\tau} - W_{i,1993}) / Y_{i,\tau}$, where $Y_{i,\tau}$ is lifetime income—the sum of income from all sources between 1994 and τ. For each age h and wealth group j, we compute the average saving rate weighted by the lifetime income $Y_{i,\tau}$, then average across base years τ.

The lifetime saving rate increases with wealth, from around 10% for the bottom half of the wealth distribution to 35%-85% for the top 0.1% across age groups, with a steeper gradient for younger age groups (Figure 6a). By age 50–54, the richest households have saved around 80% of lifetime income, while the middle class, (P50-P75], have saved around 20% of their lifetime income. These patterns align with those in Fagereng *et al.* (2019).[13]

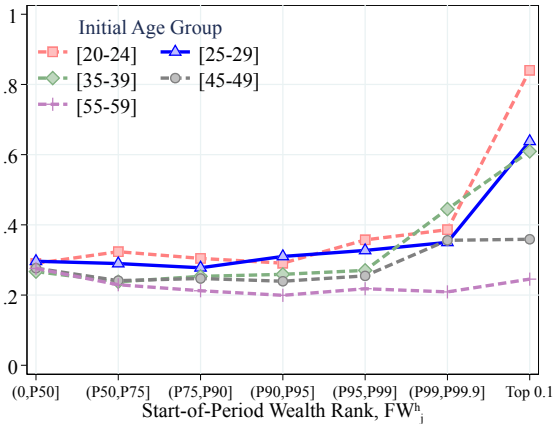
[13] Fagereng *et al.* (2019) emphasize that higher gross saving rates among the wealthy are driven by capital gains, which we observe for the wealthiest primarily as retained earnings from private businesses. To treat business income symmetrically regardless of payout form, we use the gross saving rates in our analysis.

FIGURE 6 – LIFETIME GROSS SAVING RATE ACROSS THE WEALTH DISTRIBUTION

(A) Backward Looking



(B) Forward Looking



Notes: Lifetime saving rate, defined as the ratio of cumulated savings to cumulated gross income, by terminal and initial age and wealth groups.

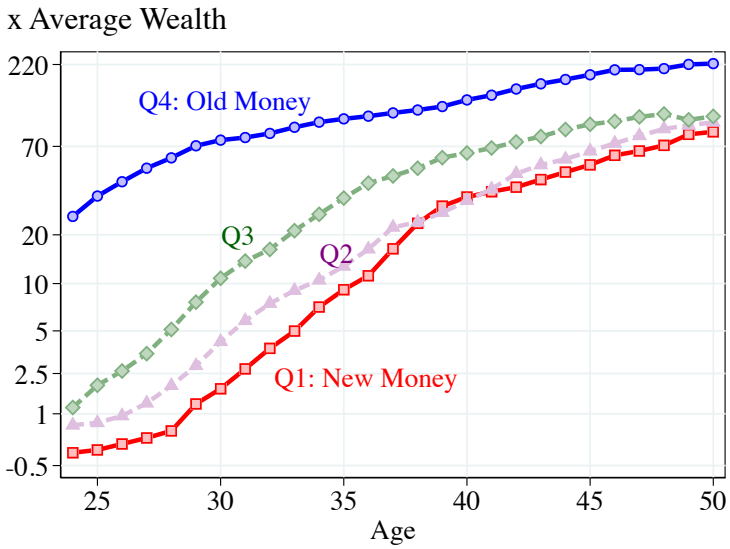
Again, a potential concern is that the wealth-saving correlation is mechanical, as higher saving rates move households up the distribution. However, Figure 6b shows that lifetime saving rates remain strongly increasing in initial wealth (FW_h^j), though the relationship is quantitatively weaker. Households starting below $P75$ save around 25%-30% of their lifetime income, while those in the top 0.1% save up to 80%.

4 New Money versus Old Money

While the wealthiest *on average* start their working lives very rich, at least a quarter of them start with minimal wealth (Section 3.2). This section examines within-group heterogeneity among the wealthiest aged 50–54 $\left(BW_{\geq P99.9}^{50-54}\right)$ by ranking them into quartiles based on the sum of initial wealth $\left(\overline{W}_{i,1994}\right)$ and the net present value of all future net inheritances discounted at the average net wealth return of 3.3%.[14] Bottom quartile households—the "New Money"—start with little wealth and receive minimal intergenerational transfers but eventually reach the top of the wealth distribution. Top quartile households—the "Old Money"—are already wealthy when young and remain in the top wealth group. We confirm that the New Money actually come from modest backgrounds with limited resources, whereas the Old Money are

[14] See Appendix SM.2.3 in OSM for similar patterns for other age groups.

FIGURE 7 – AVERAGE WEALTH PROFILE: OLD MONEY AND NEW MONEY



Notes: Retrospective average wealth profile of four groups within the top 0.1% group aged 50–54, which are ranked by the sum of their initial average wealth ($\overline{W}_{i,1994}$) and the present value of all inheritances net of taxes. The y-axis is re-scaled using the IHS transformation.

substantially more likely to have wealthy parents.[15]

4.1 Average Wealth Profiles

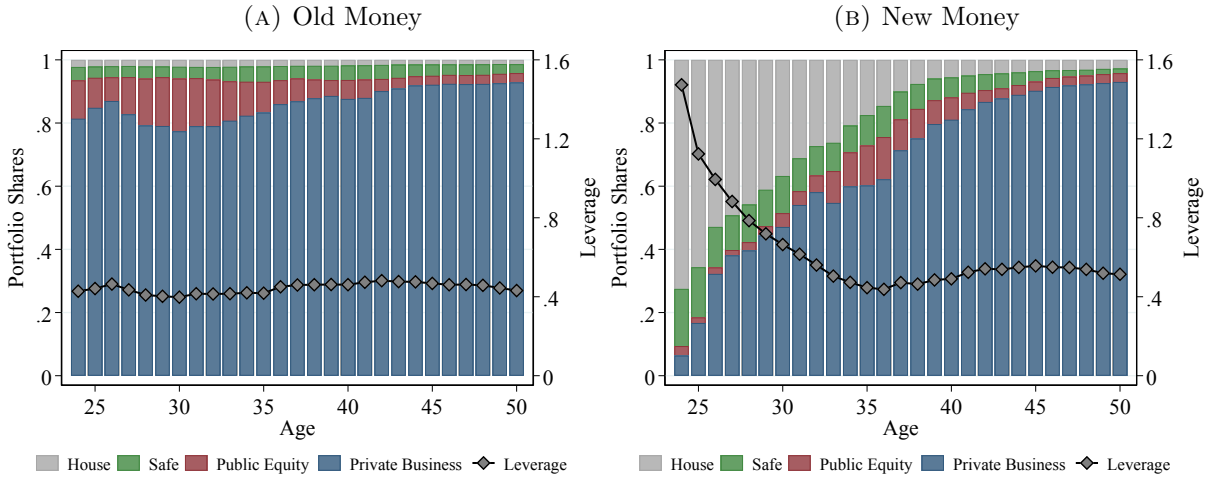
The Old Money have an average net worth of 25.9 × AW in 1993 in their early 20s versus a negative −0.1 × AW for the New Money (Figure 7). The New Money then experience rapid wealth growth, especially between their late 20s and age 40, after which growth slows down. By contrast, the Old Money see their wealth grow steadily. As a result, while the gap between the Old Money and New Money shrinks significantly, it remains quite large even after 26 years. The two middle quartiles are closer to the New Money than to the Old Money, in terms of their initial wealth and lifecycle wealth dynamics.[16]

Where does the initial wealth of the Old Money come from? Although we do not have data on inter vivos transfers and inheritances prior to 1994, we

[15] 6.2% and 26.5% of the Old Money have parents in their cohorts' top 0.1% and top 1%, respectively, versus only 1.1% and 6.8% for the New Money, with 75% of the New Money parents being in the bottom 90%. (see Figure A.2)

[16] Smith *et al.* (2019) also find that in the US, more than 75% of top earners are self-made and unlikely to receive large financial inheritances or inter vivos gifts.

FIGURE 8 – PORTFOLIO SHARES: OLD MONEY AND NEW MONEY



Notes: Portfolio shares and leverage for the Old Money (left) and New Money (right) aged 50–54.

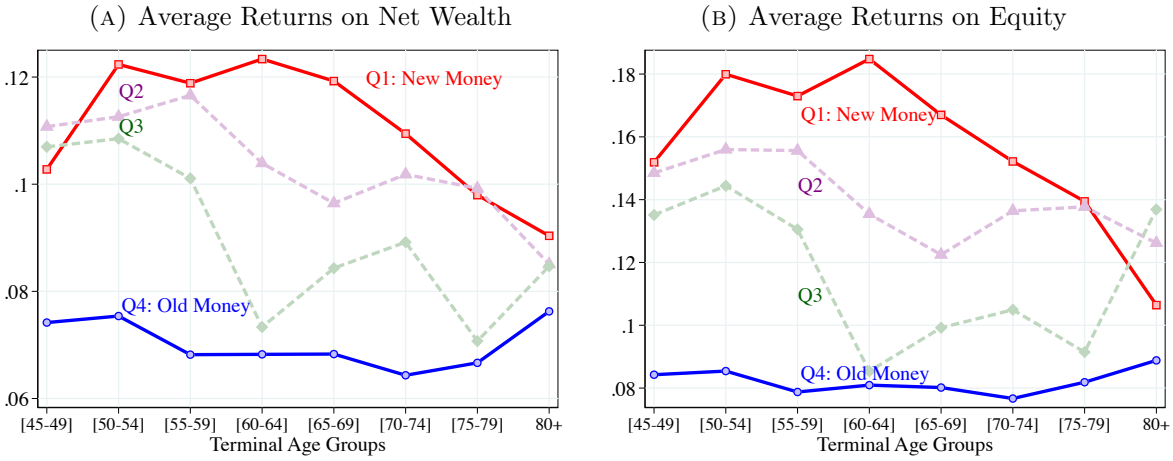
use data on post-tax and transfer labor earnings since 1967 to argue that the Old Money's vast majority of initial wealth should be thought of as having originated from intergenerational transfers. First, the simple sum of earnings until age 24 amounts to only 1.19 × AW, or 4.6% of initial Old Money wealth. Second, instead of simply summing up all labor income, we capitalize it before 1993 using the average saving rate and return on wealth observed between 1993 and 2019 for this group. By this metric, they would have accumulated 0.98 × AW from their labor income prior to 1993, which again accounts for only 3.8% of their initial wealth. Finally, in Section 5 we extend the S-O decomposition back to age 20 by finding younger "twins" of the Old Money to show that the fundamental source of their wealth in their mid-20s is intergenerational transfers.

4.2 Portfolio Composition and Long-term Returns

Because the Old Money hold the majority of wealth within the top 0.1%, their portfolios closely mirror the weighted average for the group shown in Section 3.3: They have invested heavily in equity, particularly private business, and maintain moderate leverage mainly through their firms. Total liabilities hover above 40% of total assets, similar to the leverage of their businesses (Figure 8a).

In contrast, the New Money start their working lives with only 9.5% of their portfolios in equity (Figure 8b). As their wealth grows, its composition shifts from housing to private business, reaching 95.4% of their portfolio by their 50s—similar to

FIGURE 9 – LONG-TERM AVERAGE RETURNS: OLD MONEY AND NEW MONEY



Notes: 26-year value-weighted average returns for four quartiles within the top 0.1% group aged 50–54.

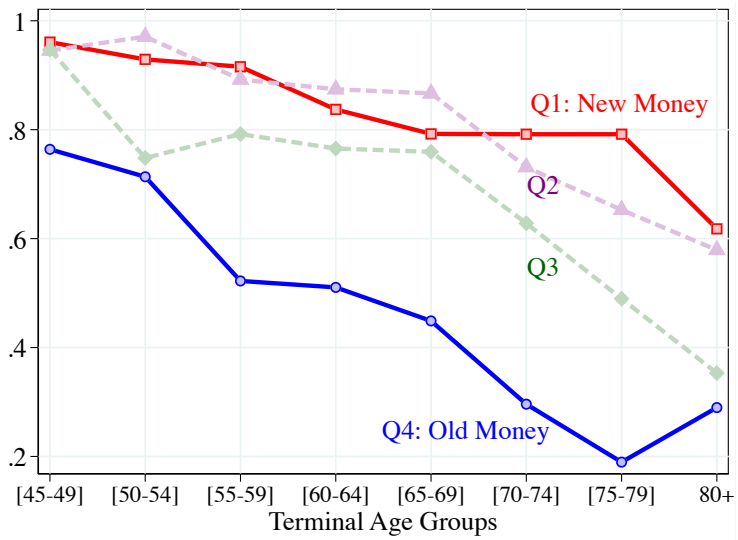
Old Money's private business share. Notably, the New Money start highly indebted—with a 1.47 debt-to-asset ratio (thereby starting with negative average net wealth)—but quickly reduce leverage to around 45% until age 35. Consistent with their portfolio evolution, the liabilities shift from personal debt to private business debt, which decline from above 60% of firm assets to about 50% by age 50.[17] Thus, New Money businesses are somewhat more levered than those owned by Old Money.

Lifecycle Returns. The New Money earn substantially higher returns on net wealth across age groups, with generally more pronounced differences for younger cohorts (Figure 9a). For those aged 50–54, the average return on net wealth is 12.2% for the New Money versus 7.5% for the Old Money. This finding is perhaps surprising because the New Money initially hold less equity—the highest-returning asset class. We therefore investigate average returns for each asset class individually.

Early in life, the New Money are mostly invested in housing, earning returns similar to those of the Old Money. We also do not find significant differences in safe asset returns between the groups (see Figure A.6). Instead, differences in net wealth

[17] Only 10% of both New Money and Old Money hold law or medical degrees, while 38% and 48% respectively have a high school education or less. Wealth accumulation dynamics are similar across professions. Thus, unlike what Smith *et al.* (2019) show for the US, highly educated entrepreneurs (e.g., lawyers, physicians, and so on) neither drive New Money–Old Money differences nor dominate top wealth groups, partly reflecting Norway's public health care system and civil law tradition.

FIGURE 10 – SAVING RATE: OLD MONEY AND NEW MONEY



Notes: Lifetime saving rate (see Section 3.5) for four quartiles within the top 0.1% group aged 50–54 .

returns stem mainly from large disparities in equity returns (Figure 9b). Among 50- to 54-year-olds, the New Money earn a high 18.0% annual average return on their equity versus 8.5% for the Old Money. Thus, although the New Money hold smaller equity shares, substantially higher returns from these investments yield higher long-term returns on net wealth relative to the Old Money.

Higher equity returns for the New Money, however, come with higher volatility. For instance, among 50- to 54-year-olds, the P90-P10 gap of the returns on net wealth is around 58% for the New Money versus 49% for the Old Money (Figure A.7). Furthermore, this higher dispersion is mainly driven by more volatile yet more positively skewed equity returns for the New Money relative to the Old Money.

Labor Income and Inheritance Heterogeneity. By construction, the Old Money receive substantially higher intergenerational transfers after age 24. The Old Money households aged 50–54 receive an average of $1.2 \times AW$ in inheritances annually, compared with nearly zero for the New Money. Labor earnings show no significant differences between these groups.

4.3 Lifetime Saving Rate

The large differences in rates of return help explain the closing wealth gap between the New Money and Old Money over the life cycle. However, saving behavior also

plays a major role. As Figure 10 shows, the New Money save at substantially higher rates than the Old Money across age groups. Among 50- to 54-year-olds, the New Money's lifetime saving rate—defined in Section 3.5— is roughly 20 percentage points higher than that of the Old Money. In the next section, we quantify the importance of these channels (e.g., saving rate, rate of return, and so on) for wealth accumulation differences between the New Money and Old Money.

5 Why Are the Wealthiest So Wealthy?

So far, we have shown that wealthy households differ systematically from the rest of the population in their initial wealth, portfolio composition, return rates, sources of income, and saving rates. In this section, we combine these results to provide a set of counterfactuals to quantify the importance of these factors. We focus on five main sources of heterogeneity in the budget constraint: rates of return, saving rates, labor income, inheritances (including inter vivos transfers), and initial wealth.

The decomposition begins with the budget constraint in equation 1, from which we derive the path of net worth between 1994 and τ as a function of five sequences of factors, $\{W_{i,t}\}_{t=1994}^{\tau} = f\left(W_{i,1993}, \{L_{i,t}, H_{i,t}, R_{i,t}, S_{i,t}\}_{t=1994}^{\tau}\right)$.[18] We use this function to simulate counterfactual wealth profiles by iteratively replacing these factors with values from the reference group.[19] We use the middle 50% (households between the 25th and 75th percentiles of wealth) in the same age group and conditioning year, $BW^h_{[P25,P75)}$, as the reference group. For any wealth group BW^h_j, we start with the budget constraint in the initial year and simulate the counterfactual wealth evolution consecutively for the following years by replacing some or all factors with their corresponding values for the reference group.

For example, to assess how the wealth profile of the top 0.1% of wealth owners ($BW^{50-54}_{\geq P99.9}$) in 2019 would differ had they earned the same return as the middle 50%, we construct a counterfactual average wealth profile by assigning them the after-tax

[18]The budget equation can be defined using alternative saving rates. For example, defining saving rate out of cash on hand (i.e., $\tilde{S}_{it} = W_{i,t}/\left(W_{i,t-1} + L_{i,t} + H_{i,t} + R_{i,t}W_{i,t-1}\right)$) yields similar conclusions (see Appendix SM.2 in OSM).

[19]To be precise, to smooth out the noise in the data, we implement this exercise at the age-wealth group level by aggregating the budget constraint in equation 1 within each BW^h_j.

return of median households in the same cohort ($\bar{R}_t$) while holding all other factors fixed at their actual values—that is, $f\left(W_{i,1993}, \left\{L_{i,t}, H_{i,t}, \bar{R}_t, S_{i,t}\right\}_{t=1994}^{\tau}\right)$. We repeat this construction for each conditioning year $\tau \in \{2010, 2011, ..., 2019\}$ and average over τ. See Appendix C for details.

These counterfactual wealth profiles abstract from behavioral responses and thus capture only first-order effects of each dimension of heterogeneity. Replacing labor income, for instance, may also affect saving rates, portfolio composition, or realized returns. While such interactions could matter quantitatively, our dynamic accounting decomposition offers a simple and transparent empirical benchmark that quantifies the first-order contribution of each component. Moreover, the resulting dynamic moments provide disciplined targets for evaluating and estimating structural models of wealth inequality in Section 6.

Expanding panel dimension. Our 26-year panel allows us to trace households aged 50–54 back to age 24 (in 1993). While this approach already captures most of their wealth accumulation, it is more restrictive for older cohorts and for the Old Money, who possess substantial initial wealth. To extend the analysis back to age 20, we supplement wealthy households in the baseline sample with younger "twins."

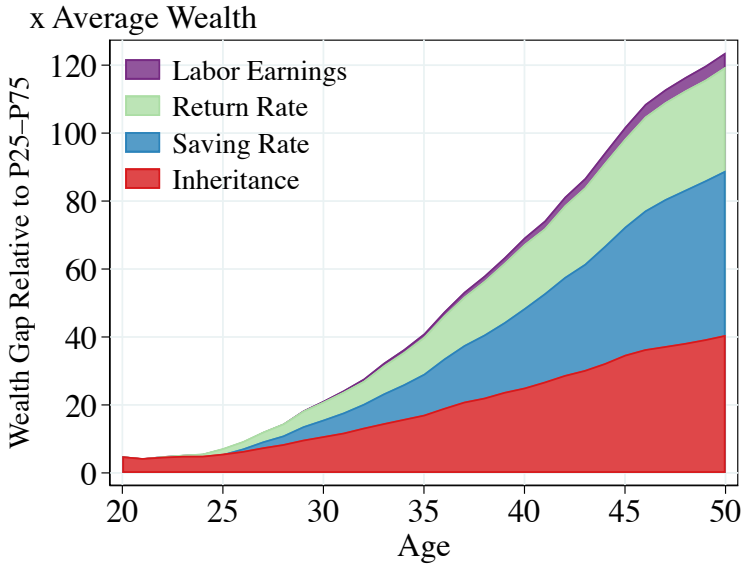
We identify younger twins of the wealthiest households in our baseline sample (i) whose wealth profiles between ages 24 and 33 closely resemble those of the original top 0.1% households and (ii) who are age 20 or younger in 1993. Similarity is measured using the Mahalanobis (1936) multivariate distance metric. For each original household, we select the closest match, choosing as many twins as there are original wealthy households (additional details in Appendix C). Average wealth profiles of twins and originals align closely between ages 24 and 33 (Figure C.1).

Because the decomposition begins at age 20, we interpret initial wealth at that age as intergenerational transfers. For parsimony and consistency with the structural model in Section 6, we combine initial wealth and inheritances into a single category in the decomposition, although we discuss their individual roles below.

5.1 Decomposing Top Wealth Inequality

Before turning to the S-O decomposition, we begin with a simple counterfactual exercise that changes only one factor at a time while keeping others unchanged (see Figure A.8). This "single-factor" decomposition isolates the importance of each com-

FIGURE 11 – DETERMINANTS OF THE TOP 0.1% WEALTH ACCUMULATION



Notes: The S-O decomposition for top 0.1% households aged 50–54.

ponent independent of changes in other contributing factors; therefore, the resulting effects do not sum to 100%.

Replacing the high returns of the top 0.1% among households aged 50–54 ($BW^{50-54}_{\geq P99.9}$) with average returns of mid-wealth households sharply reduces their terminal wealth from 124 × AW to 31 × AW—a decline of about 90 × AW. Similarly, substituting their initial wealth at age 20 with those of median households lowers wealth at age 50 by about 85 × AW, while inheritances received after age 20 contribute only 21 × AW, underscoring the importance of longer compounding time.

Substituting the labor income of mid-wealth households has only a small effect (9 × AW), consistent with the low share of lifetime resources the top 0.1% derive from labor and the smaller labor income gaps earlier in life. By contrast, replacing their high saving rate with that of mid-wealth households reduces wealth at 50 by a staggering 115 × AW, reflecting the central role of saving behavior for accumulating large fortunes.

Shapley-Owen Decomposition.

The previous results quantify each factor's importance holding others fixed at their actual values. For instance, we find that high returns are very important for the high net worth of the wealthiest by simulating a counterfactual wealth path with mid-

wealth households' rate of return while keeping their actual high inheritances. The importance of a high return on wealth, however, would be diminished if the wealthiest received the (lower) inheritances of mid-wealth households. More generally, because the budget constraint is jointly nonlinear in the respective components, summing the marginal effects in the previous section adds up to more than 100% of the wealth gap. Relatedly, the order in which the respective components of the budget constraint are replaced matters.

To address these concerns, we employ a Shapley-Owen decomposition, which cycles through all possible permutations of the order in which different components of the budget constraint are replaced ($5! = 120$ combinations for five variable sets). Furthermore, the resulting average marginal effects exactly add up to account for the entire wealth between any given group and the reference group of mid-wealth households (Shorrocks (2013)). See Appendix C for details.

Figure 11 summarizes the results for households in the top 0.1% at age 50-54. Inheritances (including those at age 20 and afterward) account for a large share of the wealth gap, declining from 100% of the gap in the beginning (by construction) to 32.8% of the gap by age 50. As individuals age, the relative importance of inheritances declines—even though individuals receive inheritances later in life as well—while the roles of saving rates and rates of return rise. By age 50, higher saving rates explain 39.1% of the gap and higher returns account for 24.7%. Together, these three components account for 96.6% of the total wealth gap. The small remainder (3.4%) is accounted for by higher labor earnings.

We conclude that, first, higher labor income and higher returns, which are typically regarded as the main drivers of wealth inequality, jointly explain less than one-third of the wealth gap. Second, differences in saving rates are at least as important a factor. As demonstrated in Section 6, these differences are difficult to attribute to precautionary saving motives or higher expected returns, and instead necessitate nonhomothetic preferences.

Lastly, while previous research has found a minor role for intergenerational transfers in perpetuating wealth inequality, we show that inheritances account for at least one-third of the top wealth gap.[20] For example, Black *et al.* (2022) also use Norwegian

[20]Several studies find intergenerational transfers reduce wealth concentration (Boserup *et al.*

data to argue that transfers are not the primary source of wealth, even among the very wealthy.[21] Our contrasting findings reflect differences in the measurement of inheritances as well as that the wealthiest receive transfers earlier in life and compound them at significantly higher rates through elevated returns and saving rates relative to the rest of the population.

5.1.1 Additional Results and Robustness

Other age groups. For brevity, our main analysis focused on households aged 50–54. The top panel of Table I extends the S-O decomposition to other age groups ranging from 45—the oldest age for which we can track households back to age 20 without relying on the twin-matching procedure—to 64, the final pre-retirement age group. Across these age groups, the excess wealth of top 0.1% households relative to median households is consistently explained by three primary factors: higher saving rates (35%–39%), inheritances received at age 20 and afterward (30%–33%), and higher returns (25%–29%). Higher labor income accounts for the residual (3%–6%). The contribution of each factor varies only marginally across age groups (and compared to our benchmark 50- to 54-year-old group), and this stability reinforces our main finding.

Other wealth groups. Given the large wealth concentration at the top of the distribution, our main analysis focused on the wealthiest 0.1% of households. Panel II of Table I presents the S-O decomposition for other wealth groups within the top 10% of the distribution.[22] Moving up the wealth distribution, we see several patterns emerge. First, inheritances play an increasingly important role in explaining excess wealth rel-

(2016) for Denmark; Wolff (2002) for the US) or explain little intergenerational wealth persistence (Charles and Hurst (2003)). Exceptions include Nekoei and Seim (2023), who show Swedish wealth inequality increases post-inheritance as only wealthy heirs preserve transfers, and Boserup *et al.* (2018), who find initial wealth at age 18 matters for later Danish wealth inequality.

[21] However, they find transfers constitute a large proportion of resources for a small number of people who have wealthy parents, consistent with our Old Money findings.

[22] We do not employ the twin-matching approach here and instead track profiles from age 24 onward only, because twin matching becomes less relevant for wealth groups closer to the median as their early life wealth profiles are similar (for instance, the $[P90, P95)$ have initial wealth of $0.25 \times AW$ at age 24, closely resembling the $0.12 \times AW$ of median households at that age). As a result, for the top 0.1%, the contribution of inheritances increases from 32.8% to 42.4% because all

ative to median households at the very top, reflecting both the greater concentration of inheritances among the wealthiest (Figure 5b) and stronger compounding through higher saving and return rates. Second, while saving rates increase monotonically in household wealth (Figure 6), their relative contribution declines in the far right tail. Third, the relative importance of differential returns on net wealth increases monotonically in household wealth, mirroring the pattern for lifetime average rates of return (Figure 4) and that the wealthiest possess larger initial wealth (Figure 2) to compound over time. Finally, the contribution of labor income declines at the top of the wealth distribution, consistent with our findings on sources of lifetime income (Appendix G).

Robustness under alternative assumptions. Panel III of Table I reports the sensitivity of our baseline S–O decomposition to alternative assumptions (see Figure A.9 for corresponding age profiles). Scenario 1 (S1) replaces private-firm tax values with imputed market values using time-varying market-to-tax value multipliers estimated from publicly listed firms.[23] This adjustment mechanically raises the net wealth of the top 0.1% from $124 \times AW$ to $215 \times AW$—reflecting an average multiplier of about 1.8 and the high private-equity share of top portfolios—and generates corresponding capital gains and savings. However, the S-O shares change little because initial wealth, capital income, and savings all rise roughly proportionally.

S2 imputes additional intergenerational transfers by marking up observed inheritances and inter vivos transfers after age 20 by 30% for the top 0.1%. The 30% factor comes from linking children to parents and comparing parental wealth at death to our adjusted registered inheritance measure; for the top 0.1%, this ratio averages 1.3 (Figure B.1). We view this as an upper bound, since not all parental wealth is necessarily transferred. Even so, the inheritance share in the S–O decomposition increases only slightly, reflecting that most of the inheritance contribution arises through initial wealth at age 20 and its compounded effect over the life cycle.

S3 removes remaining aggregate time-series trends beyond those already elimi-

initial wealth at age 24 is interpreted as inheritance.

[23] We rely on estimates from Andresen and Bø (2022), shown in Figure C.2. We view these imputed market values as upper bounds for private firm valuations because publicly listed firms are presumably positively selected.

TABLE I – SHAPLEY-OWEN DECOMPOSITION: ADDITIONAL RESULTS

	2019 Wealth ($\times AW$)	Inheritance	Saving	Return	Labor
I. Terminal age groups for the top 0.1%, wealth dynamics from age 20					
Age 45–49	98.0	31.2%	33.9%	29.2%	5.7%
Age 50–54	124.3	32.8%	39.1%	24.7%	3.4%
Age 54–59	126.7	29.7%	37.3%	27.8%	5.1%
Age 60–64	122.0	30.8%	35.1%	29.2%	4.9%
II. Wealth groups among aged 50–54, wealth dynamics from age 24					
$[P90, P95)$	3.1	22.7%	62.2%	6.3%	8.9%
$[P95, P99)$	4.9	27.4%	53.9%	8.4%	10.3%
$[P99, P99.9)$	11.9	36.7%	40.7%	13.0%	9.6%
Top 0.1%	124.3	42.4%	37.4%	16.5%	3.7%
III. Robustness: Top 0.1% aged 50–54, wealth dynamics from age 20					
Baseline	124.3	32.8%	39.1%	24.7%	3.4%
S1. Market value private firms	215.4	33.3%	36.0%	28.4%	2.3%
S2. Marking up inheritances	124.3	33.5%	38.9%	24.0%	3.5%
S3. Stationary distribution	119.8	32.1%	37.1%	28.4%	2.3%

Notes: Each row reports average wealth in 2019 together with the S-O decomposition shares. Panel I reports results for the top 0.1% at different terminal ages, tracking wealth dynamics from age 20 (twins are added to extend profiles back to age 20, except for the 45–49 group). Panel II reports results for different wealth groups within the terminal age group 50–54, tracking wealth dynamics from age 24 without twin matching. Panel III reports robustness exercises for the baseline group of the top 0.1% aged 50–54, including alternative assumptions on private-firm valuation (S1), intergenerational transfers (S2), and the construction of stationary age-specific distributions (S3).

nated by normalizing by calendar-year average wealth (AW) as well as averaging over 10 conditioning years. For each budget variable—net wealth, labor income, capital income, and inheritances— in each age we create a time-independent distribution by averaging their quantile functions across all years (see Appendix C.1 for details). Thus, someone at P99 of the age-50 wealth distribution in any year owns the same time-averaged wealth value, while her labor income or capital income are replaced with values from corresponding age-specific time-invariant distributions. This yields a synthetic stationary panel that preserves lifecycle and cross-sectional heterogeneity within each variable while removing all remaining time-varying shifts. Our S-O decomposition results under this exercise remain close to the benchmark, suggesting little role for nonstationarity in our data. The terminal wealth level of the top 0.1% decreases slightly, from $124.3 \times AW$ to $119.8 \times AW$, reflecting that wealth inequality at the end of our sample was slightly above the sample average.

5.2 Decomposing the New Money–Old Money Wealth Gap

The importance of each variable in the budget constraint for wealth accumulation differs sharply between the Old Money, who begin adulthood with substantial wealth, and the New Money, who start with very little wealth. To quantify these differences, we apply the S-O decomposition separately to each subgroup of the top 0.1%. Figure 12 reports the decomposition of each group's lifetime wealth gap relative to the P25–P75 reference households.

Old Money. Figure 12a shows that inheritances dominate as the source of the Old Money's wealth advantage. Higher saving rates are the second-largest contributor, while higher returns also matter but to a smaller degree. By age 50, 42.2% and 31.4% of the wealth gap of the Old Money is explained by higher inheritances and higher saving rates, respectively. A higher return on wealth represents 25.9%, whereas only 0.6% is accounted for by relatively higher labor income.

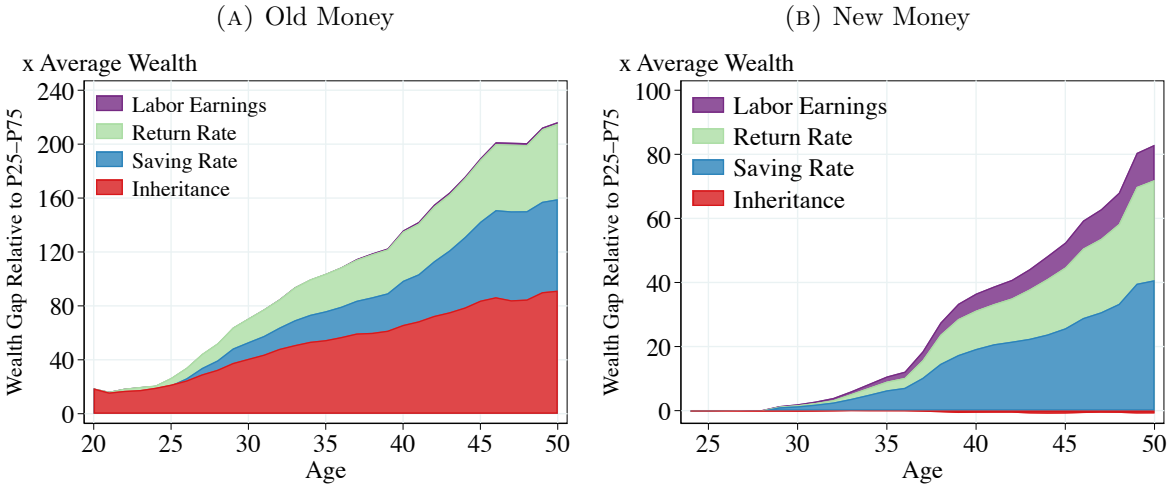
New Money. The New Money tell a different story (Figure 12b). High saving rates account for 50.1% of their excess wealth relative to mid-wealth households, followed by high returns on wealth (37.6%) and high labor income (13.3%). In contrast, inheritances contribute close to zero—indeed, they are slightly negative at -1.1%—consistent with these households starting with slightly negative initial wealth, below the average of the middle wealth group.

This contrasting evidence highlights the distinct economic forces that propel different households into the top of the wealth distribution: inherited wealth and saving behavior for the Old Money, versus aggressive saving, strong returns, and high labor income for the New Money. We use these insights in the next section to distinguish between competing theories of top wealth inequality.

6 Theories of Wealth Inequality

We now connect our dynamic empirical findings to theories of wealth inequality. We proceed in two steps. First, we *evaluate* a set of standard "single-channel" models, each calibrated to match cross-sectional wealth inequality through one mechanism at a time—such as superstar income, heterogeneous returns, stochastic discount factors, or nonhomothetic bequest motives. While these models can fully rationalize cross-sectional inequality moments, we show that they fail to capture key dynamic features

FIGURE 12 – SHAPLEY-OWEN DECOMPOSITION: NEW MONEY AND OLD MONEY



Notes: S-O decomposition for the New and Old Money households aged 50–54.

revealed by our empirical decomposition. Second, we show how our new dynamic moments can be used constructively to *discipline* structural models. We calibrate a richer model that embeds several mechanisms simultaneously, directly targeting the dynamic decomposition. This exercise illustrates how our new evidence can identify the forces behind wealth accumulation.

6.1 Evaluating Theories of Wealth Inequality

Basic model. We start from a baseline heterogeneous agents lifecycle model à la Aiyagari-Bewely-Huggett-Imrohoroglu with log consumption utility, $u(c) = \ln c$. Agents live for a finite number of periods, divided into working and retirement years, and die stochastically with an age-specific conditional probability ψ_{h+1}. During working years, households face a labor income process estimated to match lifecycle patterns and non-Gaussian features in Norwegian data (Halvorsen *et al.* (2022)); in retirement, they receive pension income. The labor income process contains a fixed type ($\bar{e}$), a first-order Markov persistent component (η) whose innovations are drawn from a mixture of normal distributions, and fully transitory non-Gaussian shocks (ξ). Hence, for a given idiosyncratic exogenous state, $\Theta = (\bar{e}, \eta, \xi)$, the household problem can be

written as

$$V_h(w,\Theta) = \max_{c,a'\geq 0} \left\{ u\left(c\right) + \beta(1-\psi_{h+1}) E\left[V_{h+1}(w',\Theta') \mid \Theta\right] \right\},$$
$$\text{s.t. } c + w' = w - \tau^a(w) + (1-\tau^k)\cdot r \cdot w + l_h(\Theta),$$

where w, τ^a, and τ^k denote household wealth, the progressive wealth tax, and the flat capital income tax, respectively. Furthermore, $l_h\left(\Theta\right)$ represents post-tax-and-transfer earnings. All taxes and transfers (including pensions) are calibrated to the Norwegian data (see Appendix H for the externally calibrated parameter values). Finally, the baseline model features accidental bequests.

We calibrate a single parameter, the discount factor $\beta = 0.975$, to match the empirical aggregate wealth-to-labor income ratio of 6.4. As in Aiyagari (1994), the baseline fails to generate sufficient top wealth concentration, even when paired with a realistic non-Gaussian earnings process (Guvenen *et al.* (2024)). In our calibration, the top 0.1% wealth share at age 50 is just 0.8%, far below the 9.3% observed in the data (see column (1) of Table II).

Building on the baseline, we examine four augmented models (columns (2)–(5) of Table II), each corresponding to a prominent theory of wealth inequality with a counterpart in our empirical decomposition. We calibrate all of them to match cross-sectional wealth inequality in the spirit of this literature.

Superstars. Column (2) introduces a *superstar* income state into the labor income process, following Castañeda *et al.* (2003). Similarly to their calibration strategy, we calibrate the value (108.2 × average labor income) and persistence (0.644) of this shock to match two key cross-sectional statistics at age 50: the top 0.1% wealth share (9.3%) and the top 0.1% total income share (6.6%).[24]

Heterogeneous returns. Column (3) augments the basic model with heterogeneous returns to wealth (e.g., Benhabib *et al.* (2019); Hubmer *et al.* (2021)). We replace capital income in the budget constraint of the household with $(1-\tau^k)\cdot(r+$

[24] We target a population fraction of superstars of 0.04%, borrowing from Castañeda *et al.* (2003), and assume that only the highest labor type ($\bar{e}$) can enter the superstar state. Given the calibrated superstar state exit probability of $1-0.644 = 35.6\%$, the implied entry rate into the superstar state, among the highest labor type workers (6% of the population), equals 0.25%.

$z+\zeta)\cdot w$, where z is a fixed type and ζ a transitory shock. We calibrate the dispersion of z (0.048) and of ζ (0.186) to again match the top 0.1% wealth and income shares.[25]

Stochastic-β. Column (4) introduces fundamental heterogeneity in saving behavior via heterogeneity in the discount factor, following Krusell and Smith (1998). We model β_i as a fixed type that remains constant within a generation but follows an AR(1) process across generations. We fix the persistence of this process to the one of permanent labor ability (0.24) and calibrate the dispersion (0.113) to match again the top 0.1% wealth share.

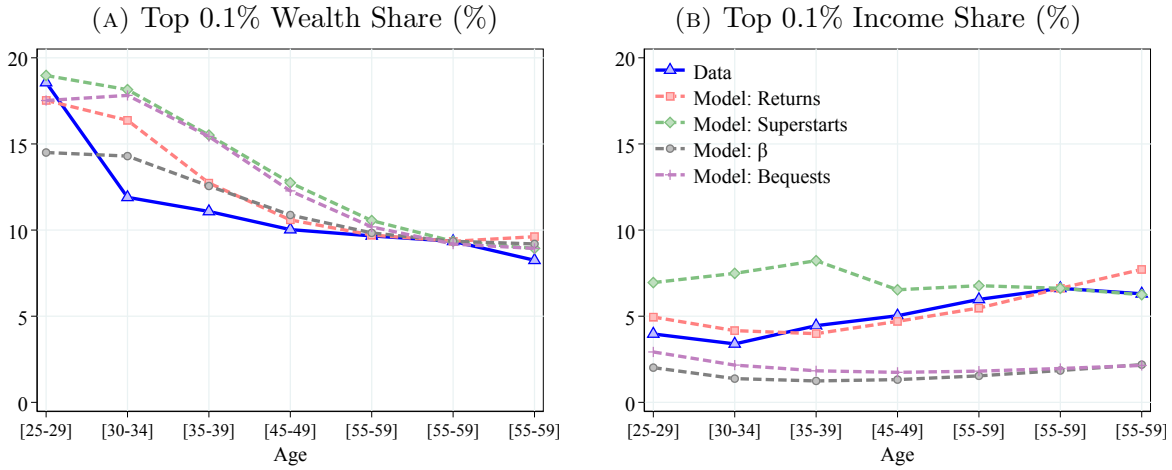
Nonhomothetic bequests. Finally, column (5) augments the basic model with a nonhomothetic bequest motive (e.g., De Nardi (2004)). We add a warm-glow bequest utility term $\nu(b) = \chi \ln(b + \bar{b})$, weighted by the death rate ψ_{h+1}. We calibrate the nonhomotheticity parameter $\bar{b} = 10.0 \times$ AW and the weight $\chi = 40.8$ to match the top 0.1% wealth share and average wealth at death ($0.8 \times$ AW).

Evaluation of augmented models matched to cross section. Each of these four augmented models in columns (2)–(5) successfully replicates top wealth concentration at age 50–54 (Panel A of Table II). Figure 13 assesses their broader performance against cross-sectional inequality moments. The left panel shows that all models reproduce the declining lifecycle profile of top wealth shares. The right panel compares top income concentration: while all models generate less income than wealth inequality—as in the data—only the heterogeneous-returns and superstar models match observed levels. The stochastic-β and nonhomothetic bequest models fall short, as they are theories of wealth, not of top income.

We conclude that, based on cross-sectional data alone, all four models remain viable candidate explanations for top wealth concentration. To evaluate the fit of these models to the dynamics of wealth accumulation, we apply the same empirical procedure to simulated data and compute the S-O decomposition for households aged 50–54 in the model's stationary equilibrium. Results are shown in Panel B of Table

[25] We fix the intergenerational persistence of z to the one of permanent labor ability (0.24). As a result, the lifetime average return exhibits intergenerational persistence of 0.17, close to the estimate reported in Fagereng *et al.* (2020a). Alternatively, we have disciplined the return process by directly matching the cross-sectional return standard deviation (10.2 p.p.). The results, available on request, are very similar.

FIGURE 13 – MODEL FIT TO CROSS-SECTIONAL INEQUALITY MOMENTS



Notes: The fit of each of the four single-channel models to cross-sectional data on top wealth (left) and top income (right) concentration over the life cycle.

II for the full top 0.1% group, while Panels C and D provide the S-O decomposition for the New Money and Old Money subgroups.

Compared to the data, these models place too much weight on inheritances and too little on return and saving rate heterogeneity, generating excessive intergenerational persistence in wealth. This pattern appears not only for the full top 0.1% group but also when we split that group into quartiles by initial wealth, Q1–Q4. In the data, New Money households start out poor and rise rapidly through high returns and high saving rates. In most models, however, Q1 households start out already wealthy because inheritances dominate their dynamics, so they produce too few self-made households and too little early-life wealth growth. Likewise, the Q4 group (Old Money in the data) relies disproportionately on inherited wealth in the models, exhibiting far less active accumulation than in the data, where Old Money households continue to earn high returns and save at elevated rates.

Among these single-channel models, the superstar model comes closest to generating New Money–type dynamics. Superstar income can be interpreted as entrepreneurial income from both labor and capital. Yet, this model still places too much weight on the joint labor and capital returns contributions (56.9% vs. 28.1% in the data) and far too little on inheritances (6.6% vs. 32.8%). Q4 households fail to compound their initial wealth as their returns and saving rates are too low. In

TABLE II – QUANTITATIVE MODELS AND DYNAMICS MOMENTS

		(1)	(2)	(3)	(4)	(5)	(6)
	Data	Basic	Superstar	Returns	β	Bequest	Full model
Target cross-section			✓	✓	✓	✓	✓
Target dynamics							✓
A. Cross-Sectional Moments							
Wealth/Lab.Inc. ratio	6.4	**6.4**	**6.4**	**6.4**	**6.4**	**6.2**	**6.2**
Top 0.1% wealth (%)	9.3	0.8	**9.3**	**9.3**	**9.3**	**9.2**	**9.2**
Top 0.1% income (%)	6.6	0.8	**6.6**	**6.6**	1.8	2.0	**6.8**
Business owners (%)	7.2						**7.2**
Debt-to-equity (%)	1.49						**1.49**
B. Dynamics: Top 0.1% Wealth Decomposition							
Initial wealth (AW)	6.9	2.7	5.5	31.8	57.7	124.8	8.8
Wealth at 50-54 (AW)	124.3	11.2	124.3	124.3	124.3	122.2	122.5
Inheritance (%)	32.8	33.3	6.6	53.3	68.6	106.9	**32.3**
Labor income (%)	3.4	50.1	57.1	0.0	0.2	0.0	**5.1**
Returns (%)	24.7	-0.1	-0.2	20.3	-0.2	0.0	**27.1**
Saving rate (%)	39.1	16.7	36.5	26.4	31.4	-6.8	**35.5**
C. Dynamics: Q1 (Data: New Money) Wealth Decomposition							
Initial wealth (AW)	-0.1	0.0	0.0	6.9	25.5	112.9	0.0
Wealth at 50-54 (AW)	83.7	10.9	108.3	74.5	78.7	110.1	83.4
Inheritance (%)	-1.1	-1.4	-0.1	36.1	55.6	107.1	**0.0**
Labor income (%)	13.3	72.3	61.2	0.4	2.7	-0.1	**13.7**
Returns (%)	37.6	-0.1	-0.1	28.4	-0.3	0.0	**38.9**
Saving rate (%)	50.1	29.2	39.0	35.1	41.9	-7.0	**47.4**
D. Dynamics: Q4 (Data: Old Money) Wealth Decomposition							
Initial wealth (AW)	25.9	9.0	20.6	74.0	113.5	139.5	33.5
Wealth at 50-54 (AW)	217.0	10.7	133.9	214.8	204.6	136.9	213.6
Inheritance (%)	42.2	110.1	21.0	60.0	74.7	106.7	**44.6**
Labor income (%)	0.6	4.2	49.1	0.0	-0.1	0.0	**1.9**
Returns (%)	25.9	-0.1	-0.2	18.6	-0.2	0.0	**22.9**
Saving rate (%)	31.4	-14.1	30.1	21.4	25.5	-6.7	**30.6**

Notes: Columns 2–6 report the model counterparts to the moments in the data (column 1). In each column, targeted moments are in **bold**. Cross-sectional wealth and income shares are computed at age 50-54. The dynamic wealth decompositions are computed using the backward-looking Shapley–Owen method at age 50–54. For Panels C and D, households in the top 0.1% at age 50–54 are divided into quartiles based on their initial wealth in the first period (age 23). We refer to Q1 as New Money and Q4 as Old Money when describing the data.

sum, although all models replicate the cross-sectional concentration of wealth, none matches the dynamic processes that underpin top-wealth accumulation in the data.

6.2 Disciplining Theories of Wealth Inequality

These findings point to two key ingredients needed to match the dynamic features of the data. First, heterogeneous returns, nonmonotone in wealth, are essential to generate New Money households who start with little or no wealth yet accumulate rapidly. Second, a mechanism is needed to ensure that high-wealth households already save at higher rates *early in life*, and to transmit wealth across generations so as to generate Old Money households—without overstating the role of inheritances as the previous models do. We incorporate both elements in the full model (column (6) of Table II), augmenting the basic model in two ways. First, households may invest in a decreasing returns to scale production technology with heterogeneous returns to a fixed factor (à la Quadrini (2000); Cagetti and De Nardi (2006)). Second, we introduce nonhomothetic preferences via wealth in the utility function (e.g., Gaillard *et al.* (2023); Carroll (1998); Straub (2019)). We discipline the strength of these mechanisms by directly targeting our dynamic S-O decomposition facts.

Model details and calibration. We choose nine parameters to target fourteen moments in the data. The targeted moments are the five cross-sectional statistics in Panel A of Table II—the wealth–labor income ratio, the top 0.1% wealth and income shares, the share of business owners, and the aggregate debt-to-equity ratio—together with the S–O wealth decomposition shares for the full top 0.1% group and for the New Money and Old Money subgroups in Panels B–D.[26] While the nine parameters are jointly identified, we describe below the moment to which each parameter is most closely tied. With fourteen moments and nine parameters, five moments act as over-identifying restrictions.

First, households may invest in a stochastic production technology that uses capital to generate additional income: $\pi(w, z, \zeta) = \max\{0, \max_{k \leq \lambda w}\{(e^{z+\zeta} \cdot k)^{\mu} - (\delta + r) \cdot k - c_f\}\}$, where w is net worth, k is entrepreneurial capital subject to a collateral constraint parametrized by λ, z is the entrepreneurial type (constant over the life cycle), and ζ is an i.i.d. shock. We fix the returns to scale parameter at

[26] Each decomposition contains four entries that sum to 100% and therefore provides three independent moments.

$\mu = 0.8$, consistent with the literature (e.g., Guvenen *et al.* (2023)). Decreasing returns are crucial to match high returns to equity early in life for new entrepreneurs, enabling fast wealth accumulation while preventing excessive divergence as wealth grows. We allow the fixed type z to be correlated with the permanent labor type $\bar{e}$: $z = \sqrt{1-\rho_{ez}^2}\tilde{z} + \rho_{ez}\frac{\sigma_z}{\sigma_{\bar{e}}}(\bar{e} - \mathbb{E}[\bar{e}])$, where the latent type $\tilde{z}$ follows an independent AR(1) Gaussian process with cross-sectional dispersion σ_z and intergenerational persistence ρ_z. Under this formulation, σ_z is the standard deviation of the effective entrepreneurial type z and ρ_{ez} is its correlation with labor type.

The dispersion of (i) the fixed type ($\sigma_z = 0.527$)) and (ii) the i.i.d. shock ($\sigma_\zeta = 0.774$)) jointly shape the cross-sectional top 0.1% income and wealth shares at age 50. (iii) The correlation $\rho_{ez} = 0.473$ primarily affects the labor income contribution to New Money wealth accumulation, while (iv) the persistence $\rho_z = 0.721$ controls intergenerational propagation of high entrepreneurial returns and hence the return component of Old Money.[27] (v) The fixed cost $c_f = 0.138 \times AW$ controls the 7.2% share of entrepreneurs in the population, and (vi) the leverage constraint $\lambda = 2.93$ the aggregate debt-to-equity ratio of 1.49.[28]

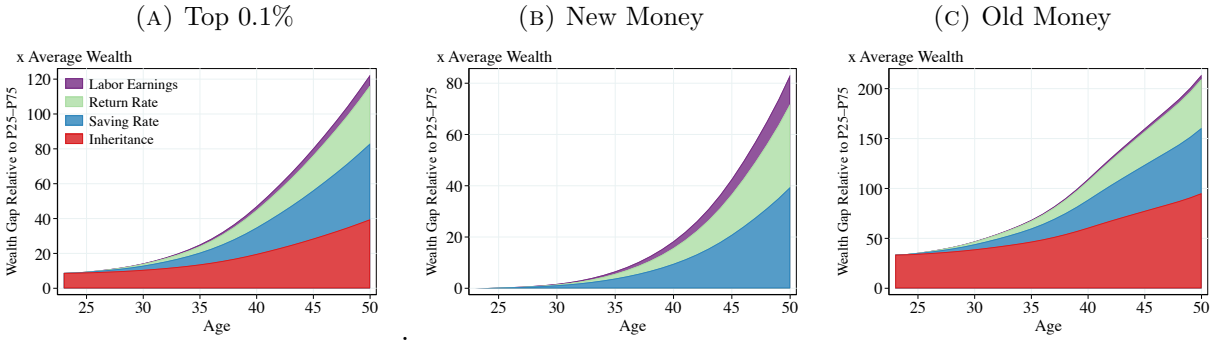
Second, we modify period utility to $\ln c + \chi \ln(a + \bar{a})$, interpreting the latter as "capitalist spirit" motive. This preference for wealth mirrors the warm-glow bequest motive, except that it is not multiplied by the death rate and, therefore, already important early in life. For comparison, the warm-glow bequest model in column (5) loads way too much on inheritances and even features a negative saving rate contribution (since wealthy heirs initially deplete their wealth).[29] (vii) The weight $\chi = 0.68$ and (viii) the nonhomotheticity parameter $\bar{a} = 10.3 \times$ AW affect primarily the inheritance and saving rate contributions in the S-O decomposition. Finally, as

[27] In simulated data, the persistence of the return fixed effect computed as in Fagereng *et al.* (2020a) is lower at 0.171, close to their empirical estimate of 0.16, because the persistence of effective entrepreneurial ability z is a convex combination of ρ_z and the one of $\bar{e}$ (0.24), interacts with decreasing returns to scale, and is attenuated by the substantial i.i.d. shock ζ.

[28] The implied weighted average firm leverage is about 60%, consistent with the household-level firm-leverage patterns shown in Sections 3.3 and 4.2.

[29] Benhabib *et al.* (2019) use a quantitative model targeted to US data to find that return heterogeneity contributes to top wealth concentration but is not sufficient. In addition, a luxury bequest motive is quantitatively important in accounting for top wealth inequality.

FIGURE 14 – SHAPLEY-OWEN WEALTH DECOMPOSITION IN THE FULL MODEL



Notes: Panel (A) shows the contribution of each component in the S-O decomposition to the wealth gap between the top 0.1% and the control group (P25-75), in the full model. Panels (B) and (C) show model results for the New and Old Money.

in all model versions, (ix) $\beta = 0.934$ controls the wealth-labor income ratio.[30]

This leaves several of the S-O shares, in particular for New and Old Money, as overidentifying restrictions. In addition, Table II also reports the starting and end points of each group's lifecycle wealth profiles as additional validation.

Findings. Column (6) of Table II shows that the full model provides a close joint fit to both the cross-sectional moments and the dynamics of wealth accumulation. At age 50, the model replicates the empirical S–O decomposition for the top 0.1%, matching the relative importance of inheritances, labor income, returns, and saving behavior. Figure 14a further shows that the model captures the lifecycle patterns of these components: inheritances dominate early in life but gradually decline in importance, while differences in saving rates and realized returns increasingly account for the widening wealth gap as households age.

The model also replicates the rapid wealth accumulation of the New Money. As in the data, they start with zero wealth and reach 83.4 × AW by age 50. Their fast rise is driven primarily by high saving rates and high returns, with a nontrivial contribution from high labor income. As in the data, the New Money in this model earn even higher returns than the Old Money, who themselves enjoy above-average returns. This result arises from decreasing returns to scale technology; conditional on

[30] We remove accidental bequests as these overstate the importance of inheritances, even when $\chi = 0$. We relegate non-essential calibration details to Appendix H, which also shows results for the deterministic lifecycle versions of single-channel models.

productivity, returns decline with wealth. Therefore, the New Money operate highly productive but capital-constrained start-ups that grow rapidly. Figure 14b shows the resulting lifecycle S-O decomposition.

The model also matches the finding that while the Old Money start with substantial inherited assets ($33.5 \times AW$), they continue to grow their fortunes to $213.6 \times AW$. The Old Money own mature, well-capitalized firms with healthy returns that, combined with the nonhomothetic consumption-saving motive, sustain persistent wealth accumulation. Figure 14c shows the corresponding lifecycle S-O decomposition.

These findings have important implications for the design of capital income and wealth taxation, as the equity-efficiency trade-off depends critically on the nature of wealth dynamics among the wealthiest—dynamics our analysis helps to illuminate.

7 Conclusions

The earlier literature has offered several explanations for the observed high concentration of wealth, such as the intergenerational transmission of bequests and human capital (De Nardi (2004)) and the heterogeneity in rates of return (Cagetti and De Nardi (2006); Benhabib *et al.* (2019)), saving rates (Krusell and Smith (1998)), and labor earnings (Castañeda *et al.* (2003); Kaymak *et al.* (2020)). In this paper, we used a rich administrative dataset from Norway between 1993 and 2019 to quantify the importance of each of these channels for the wealth accumulation of the richest households. We find that, between ages 45 and 64, the excess wealth of the top 0.1% relative to mid-wealth households is accounted for by higher saving rates (36%), higher inheritances (31%), and higher returns (28%), whereas higher labor income accounts for the small residual (5%).

Furthermore, we find significant heterogeneity among the wealthiest: Around one-fourth of these households, the New Money, start below the median wealth yet achieve rapid wealth growth. Their fast ascent to the top is accounted for by a higher saving rate (50%) and by higher returns on net wealth (38%), with higher labor income (13%) also contributing significantly. In contrast, the Old Money are mainly characterized by higher inheritances (42%) and to a lesser extent by higher saving rates (31%) and higher returns (26%).

Our empirical findings shed light on mechanisms underlying wealth accumula-

tion, especially for the richest. Compared with our new empirical evidence, standard models of wealth inequality—whether emphasizing bequests, return heterogeneity, or stochastic discount factors—put too much emphasis on inheritances and too little on return and saving rate heterogeneity in accounting for top wealth concentration. They generate too few New Money households and insufficient wealth growth for Old Money. The superstar model exhibits the opposite problem, producing too few Old Money households. However, a heterogeneous entrepreneurship model with decreasing returns to scale technology—yielding nonmonotone wealth-dependent returns—and nonhomothetic preferences successfully replicates both cross-sectional inequality as well as our novel evidence on the dynamics of wealth inequality.

These quantitative findings reveal that our novel dynamic empirical facts indeed help us quantify the role of different economic forces behind top wealth concentration. As different mechanisms imply different economic policy prescription, we hope our findings will further feed back into economic research and policy analyses.

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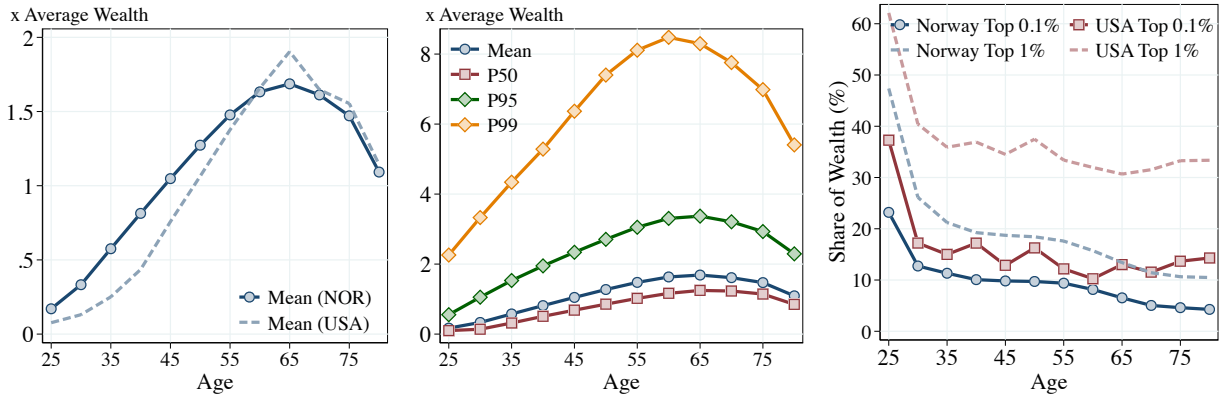
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Online Appendix for "Why Are the Wealthiest So Wealthy? New Longitudinal Empirical Evidence and Implications for Theories of Wealth Inequality"

A Additional Figures

FIGURE A.1 – AVERAGE WEALTH AND CONCENTRATION OVER THE LIFE CYCLE

(A) Average Net Worth (B) Selected Percentiles for Norway (C) Wealth Concentration



Notes: Panel A shows the within-age-group average. Panel B shows selected percentiles of the wealth distribution in Norway averaged across years. All values are expressed relative to the average wealth in the economy (AW). Panel C shows the within-age-group share of wealth averaged across years.

FIGURE A.2 – INTERGENERATIONAL TRANSITION MATRIX

(A) Age 50/54

Children Wealth Rank in 1993	Parents Life Time Wealth Rank [0,50]	(50-75]	(75-90]	(90-95]	(95-99]	(99-99.9]	Top 0.1%
Q1	20.8	22.8	27.2	9.6	12.7	5.7	1.1
Q2	17.2	24.5	28.3	8.4	14.6	5.5	1.5
Q3	12.1	28.0	23.6	10.4	15.7	8.4	1.8
Q4	6.4	15.7	18.7	11.2	21.6	20.3	6.2

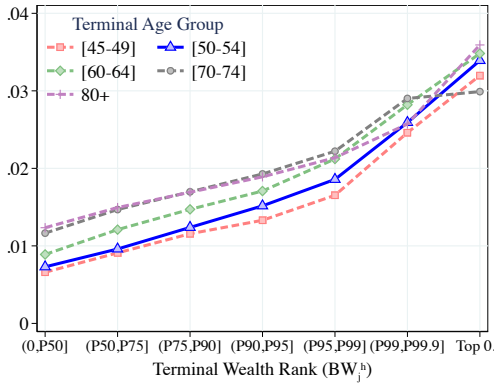
(B) Age 55/59

Children Wealth Rank in 1993	Parents Life Time Wealth Rank [0,50]	(50-75]	(75-90]	(90-95]	(95-99]	(99-99.9]	Top 0.1%
Q1	18.4	37.9	19.2	12.4	7.4	3.7	1.1
Q2	15.7	30.6	27.5	9.2	12.6	3.9	0.5
Q3	11.3	24.7	19.2	13.6	17.8	10.8	2.6
Q4	7.8	17.0	17.2	8.6	23.5	19.6	6.3

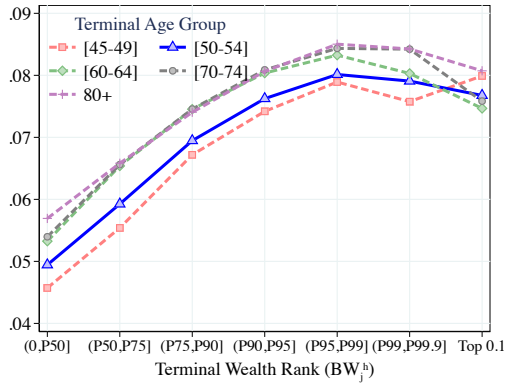
Notes: Figure A.2 shows an intergenerational transition matrix between household wealth in 2015 and their parental household wealth for households in different age groups. Each cell represent the fraction of households in different percentiles of the parents wealth distribution (columns), conditional on their percentile of the wealth distribution in the conditioning year, BW_j^h (rows). Each row sums to 100. The Parents Life Time Wealth Rank is calculated as the rank of the average wealth adjusted for an age- and year-specific mean.

Figure A.3 – Long-Term Average Returns on Assets the Wealth Distribution

(a) Safe Assets



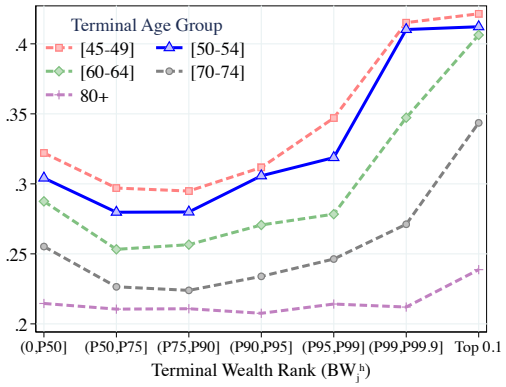
(b) Housing



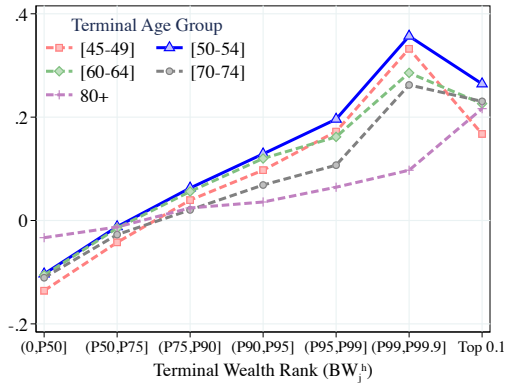
Notes: Figure A.3 shows the asset value-weighted cross-sectional mean of annual returns within age and wealth groups averaged across different conditioning years.

Figure A.4 – Dispersion and Skewness of Returns

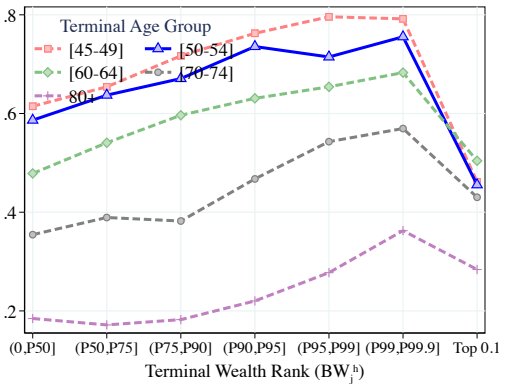
(a) Net Wealth Returns: Dispersion



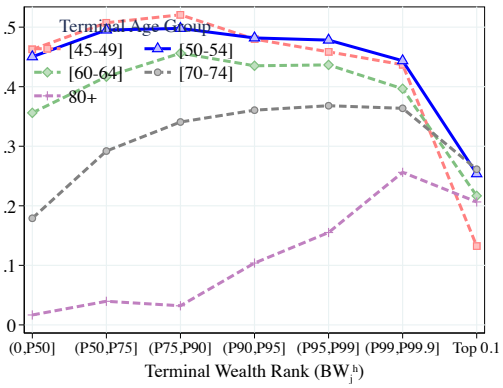
(b) Net Wealth Returns: Skewness



(c) Equity Returns: Dispersion

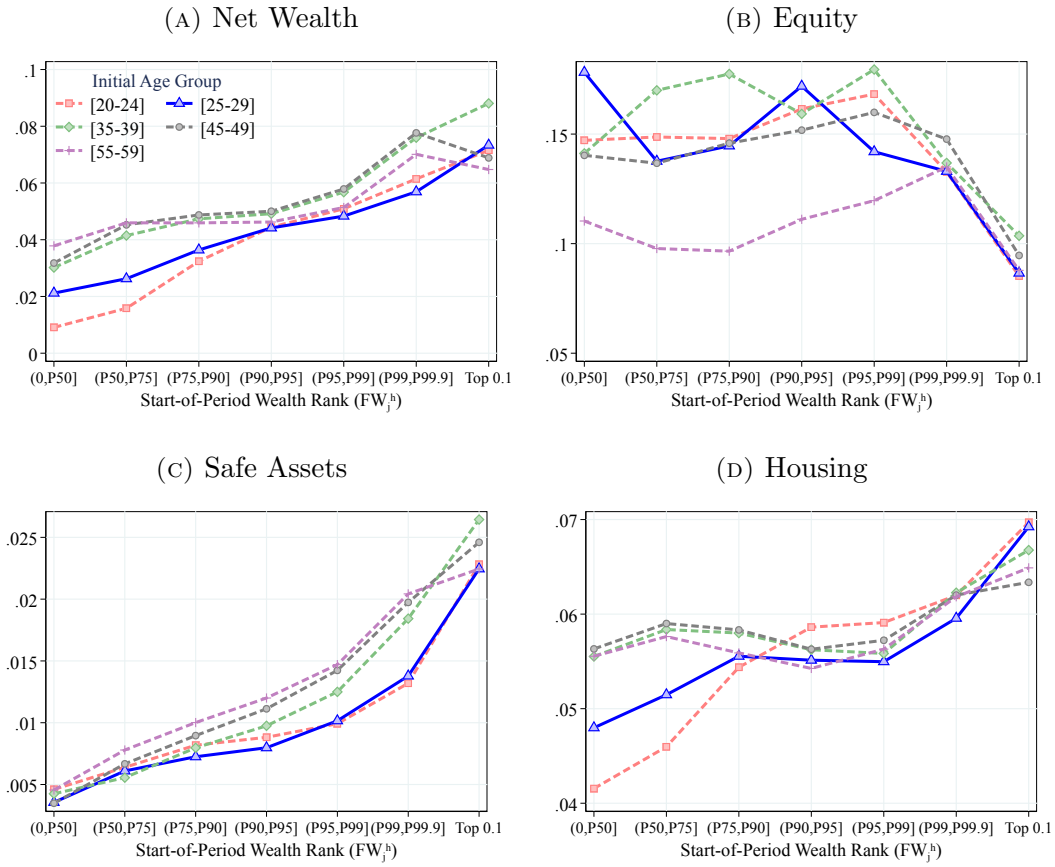


(d) Equity Returns: Skewness



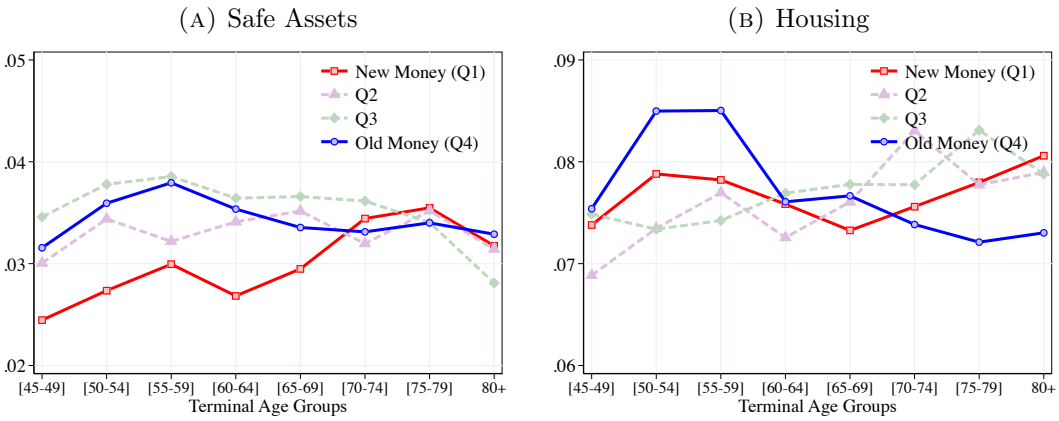
Notes: Figure A.4 shows the asset value-weighted, 15-year average of the P90-P10 and Kelley skewness $\left(\mathcal{S}_{\mathcal{K}} = \frac{P90-P50}{P90-P10} - \frac{P50-P10}{P90-P10}\right)$ of annual returns within age and wealth groups averaged across different conditioning years. We only use calendar years 2005–2019 for higher-order moments to avoid using imputed equity returns.

Figure A.5 – Long-term Average Returns: Forward Approach



Notes: Figure A.5 shows the asset value-weighted, 26-year average mean of annual returns within age and wealth groups averaged across different conditioning year for households in the FW_j^h wealth group.

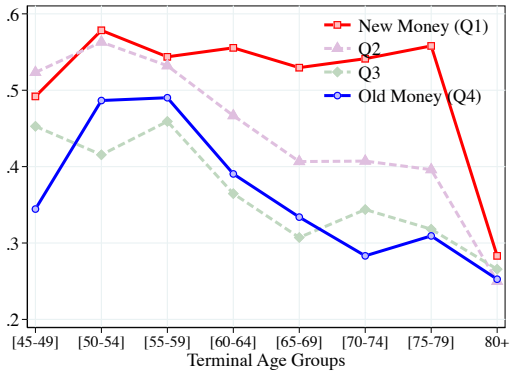
Figure A.6 – Long-Term Average Returns: Old Money and New Money



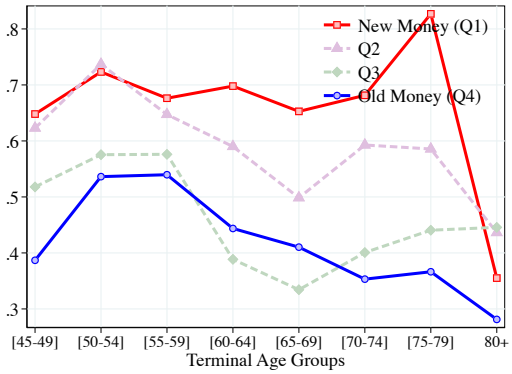
Notes: Figure A.6 shows the 26-year mean of the value-weighted average returns for households in the $BW^h_{\geq P99.9}$ wealth group, which are ranked in quartiles according to the sum of their initial average wealth $\left(\overline{W}_{i,1994}\right)$ and the present value of all future inheritances net of taxes.

Figure A.7 – Dispersion and Skewness of Returns: Old Money and New Money

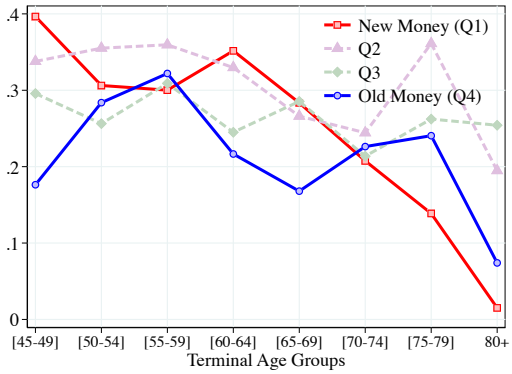
(a) Net Wealth Returns: Dispersion



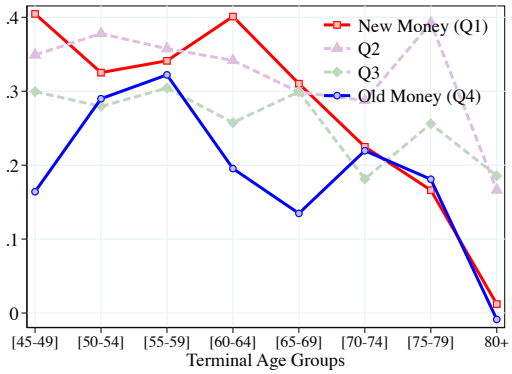
(b) Equity Returns: Dispersion



(c) Net Wealth Returns: Skewness

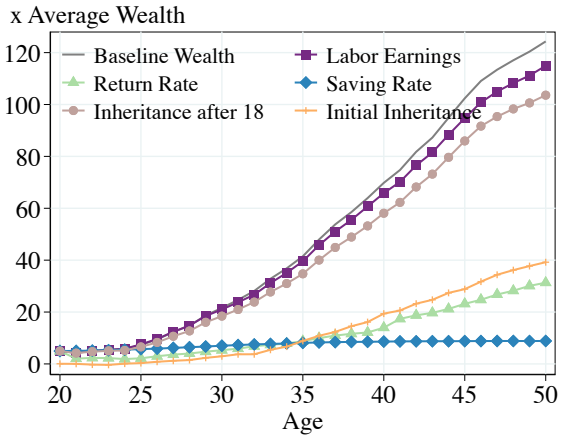


(d) Equity Returns: Skewness



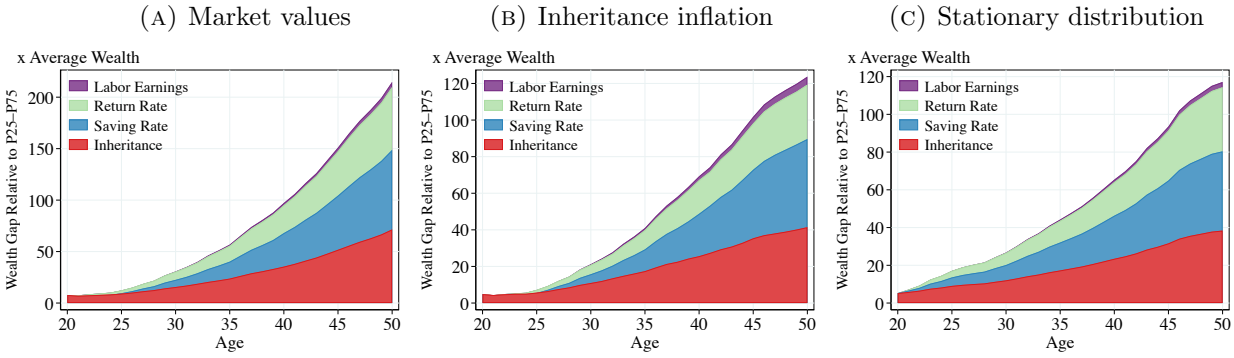
Notes: Figure A.7 shows the asset value-weighted, 15-year average of the P90-P10 and Kelley skewness $\left(\mathcal{S}_{\mathcal{K}} = \frac{P90-P50}{P90-P10} - \frac{P50-P10}{P90-P10}\right)$ of annual returns for households in the $BW^{h}_{\geq P99.9}$ wealth group, ranked in quartiles according to the sum of their initial average wealth $\left(\overline{W}_{i,1994}\right)$ and the present value of future inheritances net of taxes. We only use calendar years 2005–2019 for higher-order moments to avoid using imputed equity returns.

Figure A.8 – Single-Factor Decomposition for Baseline Group



Notes: Figure A.8 shows the S-O decomposition changing one component of the budget constraint at the time.

FIGURE A.9 – S-O DECOMPOSITION TOP 0.1%: ROBUSTNESS



Notes: Figure A.9 displays robustness scenarios for top 0.1%, 50–54 terminal age group, S-O decomposition. Corresponds to Table I, Panel III. Panel A uses imputes market values for private firms (S1), Panel B inflates intergenerational transfers by 30% (S2), and Panel C transforms the data to stationary age-specific distributions (S3).

B Data Appendix

B.1 Data sources

Tax returns (TAX). The main data source is tax returns for all persons in Norway from 1993 to 2019. The tax system is residence based (excluding Norwegians living abroad). Income is taxed individually, but wealth is taxed jointly for married couples. Cohabitant couples are taxed separately, even if they own assets jointly. For housing, the division of jointly owned assets follows formal ownership shares, whereas mortgage division is chosen freely. For most households, this division has little consequence, as only a fraction pay wealth taxes due to exemption thresholds. All values are measured as of December 31. We revert items reported with discounted tax values to their initial market value (see Table B.1). Records rely primarily on third-party reporting from employers and financial intermediaries (e.g., banks, brokers, or the Norwegian Central Securities Depository (VPS)). Items not provided by third parties (e.g., foreign income) are self-reported and checked by the tax authority, which also utilizes automatic routines to flag and audit extreme fluctuations in income or wealth.

Shareholder register (SHR). All private companies must submit shareholder information to the Norwegian Tax Administration. The register is available partially from 2001 and completely from 2004. We calculate a person's ownership fraction by combining individually owned shares with the total number of shares. While some companies are held directly, many are owned indirectly through other firms. We trace indirect ownership back to the ultimate individual owner through up to four layers.

Including additional layers does not change our results in any material way.

Firm balance sheet and tax return. For equity in unlisted firms, we rely on assessed values derived from balance sheets and book values reported to tax authorities. Balance sheets include total equity, assets, debt, retained earnings, revenue, and profits. Tax authorities use routines to identify underreporting. Additionally, firms with turnover above USD 500,000 are required to have their balance sheets audited.

Housing wealth. We use housing wealth based on an ensemble machine-learning method on transaction data for the period 1993–2019. This imputation covers owner-occupied housing, secondary housing, and cabins. Wealth is allocated to individuals according to ownership shares. Our construction of housing wealth extends the methodology in Fagereng *et al.* (2020b) from 2015 to 2019.

Central population registry and Norwegian educational database. The annual national register, available since 1964, contains individual identification numbers, residence, marital status, and highest completed education. Each individual has a unique personal ID number, and marital status is recorded as single, married/cohabitant, widowed, divorced, or separated. We create a household ID using spousal IDs and marital status; a change in status (e.g., marriage or divorce) generates a new household ID. The head of household is defined as the eldest person. A household's "year of death" is defined as the maximum year of death associated with that household ID. If a spouse is still alive, this value is set to missing.

Inheritance tax records. These records include information about inheritances and inter vivos gifts as derived from Inheritance tax records from 1995 to 2013. The inheritance tax in Norway was abolished in 2014.

B.2 Income Sources

Labor income, self-employment income, and transfers. Source: *Tax records and Social Security Administration records* [annual, 1993-present].

- **Labor income**: Labor income includes wages and salaries, bonuses and other irregular payments. The information is third-party reported by employers
  Tax codes: TAX 2.1.

- **Labor income from self-employment**: Norway employs a dual-income tax system where capital taxation is proportional and labor taxation is progressive.

To ensure neutrality between wage earners and entrepreneurs, income from self-employment and small companies is split: an imputed return to capital is taxed as capital income, while the residual is taxed as labor income.
Tax codes: TAX 1.6, TAX 1.7 and TAX 2.7).

- **Transfers**: Transers includes unemployment benefits, sickness benefits, paid parental leave, disability benefits, public pensions, and other social welfare payments.
Tax codes: TAX 2.1.7, TAX 2.2, sykepenger, foreldrepenger, dagpenger, arbeid-savklaringspenger, tidbegrenset uførestønad, bostøtte and *sosialhjelp* from the Social Security Administration.

Interest income. Source: *Tax records* [annual, 1993-present]. Interest income is the sum of interest income on bank deposits in Norway (TAX 3.1.1), other interest income (TAX 3.1.2), interest on loans to companies (TAX 3.1.3), yields and disbursements from endowment insurance (TAX 3.1.4), and interest income on bank deposits abroad (TAX 3.1.11). Following Fagereng *et al.* (2020a), we impute interest on outstanding claims and private loans using the average rate charged by Norwegian banks on corporate loans and capital gains on bond funds. Interest payments on debt at home and abroad (TAX 3.3.1 + TAX 3.3.2 + TAX 3.3.4).

Dividends. Source: *Tax records* [annual, 1993-present] , *Shareholder registry* [annual, 2001-present], *Firm balance sheet and tax return* [annual, 1995-present]. Tax records contain taxable dividends received from stocks and shares registered in the VPS (TAX 3.1.5), from mutual funds (TAX 3.1.6), from private equity, and foreign shares or unit trusts not registered with the VPS (TAX 3.1.7).

From 2004, dividends received from non-listed companies can be obtained by combining a person's share in a company with the company's dividend payout. Using the fraction of an unlisted company (k) that an individual (i) owns (as measured in the SHR, and including indirect ownership), s_{it}^k, and multiplying with dividends from an unlisted company, D_t^k, gives us an alternative measure of dividend income as $\sum_k s_{it}^k D_t^k$. These provide two sources of information for dividends. In practice, 92% of observations are equal in the two datasets, whereas 8% have a positive value in tax records (TAX) and zero in the shareholder registry (SHR) or vice versa. When there is a discrepancy, we use the non-zero value. Otherwise, we use tax values (TAX) up to and including 2003, and shareholder registry (SHR) from 2004.

Capital gains from housing. Source: *Imputed housing values* [annual, 1994-2019]. Capital gains from housing are calculated as the annual change in imputed house value in years with no transactions, winzorized at +/- 2%. In years with market transactions, capital gains from housing are set to zero since net transactions are measured directly from housing transaction data (i.e., net saving in housing is calculated based on net transactions at market value in a given year), while capital gains are imputed, and therefore, it would not add up if we tried to decompose the two parts. Capital gains from housing are also set to zero in period t if the housing value is zero in either t or $t-1$.

Income from housing. Source: *Tax records, imputed housing values* [annual, 1993-2019]. Following the rental-equivalence approach, annual owner-occupied housing income is imputed on average at 2.23% of property value (Eika *et al.* (2020)), adjusted for changes in the price-to-rent ratio over our sample period calculated by the OECD. Total housing income is thus the sum of imputed rental income, income from ownership of real assets from tax returns (TAX 2.8.2), and taxable income from renting out a holiday home or property abroad (TAX 2.8.3 + TAX 2.8.5).

Capital gains from private equity. Source: *Shareholder registry* [annual, 2001-present], *Firm balance sheet and tax return* [annual, 1995-present]. Capital gains on private equity are obtained by linking individual and firm data using SHR. Balance sheets contain information about total equity (total assets minus total debt), earned capital, dividends, total revenue, profits before tax, and profits after tax. We measure unrealized capital gains as the individual's share of their company's retained earnings. Retained earnings in year t is the part of earned capital that is not paid out as dividends. Using the fraction of a company (k) that an individual (i) owns (as measured in the SHR), s_{it}^k, we allocate these earnings to ultimate owners.

Capital gains from mutual funds. Source: *Tax records* [annual, 1993-present]. Following Fagereng *et al.* (2019), we obtain capital gains from mutual funds by assuming that mutual funds investors own a composite index fund representative of the Oslo Stock Exchange (OSE) market (80%) and the MSCI World (20%) with price q_{t-1}^{mf} as measured on December 31 of year $t-1$, which we take from the OSE price database. We estimate the shares of mutual funds owned at the end of $t-1$ as $s_{it-1}^{mf} = w_{it-1}^{mf}/q_{t-1}^{mf}$. Subsequently, yields on mutual funds are calculated as

$y_{it}^{mf} = (q_t^{mf} - q_{t-1}^{mf})s_{it-1}^{mf} + ((q_t^{mf} - \bar{q}_t^{mf})(s_{it}^{mf} - s_{it-1}^{mf}))$ if $s_{it-1}^{mf} \neq s_{it}^{mf}$, where $\bar{q}_t^{mf}$ is the geometric average of the composite index fund price in year t.

B.3 Assets and Liabilities

Safe assets. Source: *Tax records* [annual, 1993-present]. Safe assets are sum of bank deposits in Norwegian banks (TAX 4.1.1) + cash (TAX 4.1.3) + deposits in foreign banks (TAX 4.1.9), bond funds and money market funds (TAX 4.1.5), bonds (TAX 4.1.7.2), and other financial assets such as outstanding claims/loans to friends and family (TAX 4.1.6).

Public equity. Source: *Tax records* [annual, 1993-present]. Public equity includes mutual funds/stock market funds (TAX 4.1.4) and shares/stocks and shares listed in VPS (TAX 4.1.7).

Private equity. Source: *Tax records* [annual, 1993-present], *Shareholder registry* [annual, 2001-present], *Firm balance sheet and tax return* [annual, 1995-present]. The value of private equity assets in tax records is the firm-assessed tax value of shares in non-listed Norwegian firms plus non-listed bonds and options (TAX 4.1.8). A private business is a company that is not listed on a stock exchange. These firms are typically small- to medium-sized businesses or holding companies. In 2006, Norway introduced a dividend tax at the personal level as part of a major tax reform. One response to this reform was that the number of holding companies increased, as owners would retain their earnings in firms to avoid paying dividend tax. These holding companies are therefore common, especially at the top of the wealth distribution. It is important to account for indirect ownership so that we are able to allocate capital gains to the ultimate owner. The approach is similar to other papers using Norwegian data (Alstadsæter *et al.* (2018), Fagereng *et al.* (2020a, 2019)). Using the fraction of an unlisted company (k) that an individual (i) owns (as measured in the SHR and including indirect ownership), s_{it}^k, and multiplying with the equity value of an unlisted company (V_t^k), gives us an alternative measure of the overall value of unlisted shares owned as $\sum_k s_{it}^k V_t^k$. The correlation between equity values in TAX and book values is 0.98 for non-zero values in both registers. We compute indirect ownership up to four layers. For more than four layers, it becomes difficult to avoid a degree of cross-ownership. We use equity values from balance sheets to ensure a consistent measure of returns but adjust totals to equity values in the tax return to ensure a

consistent measure over time, since we use the tax return until 2003 and balance sheet information from 2004. In addition, we use information from SHR and balance sheets in 2001-2003 if possible.

Housing. Source: *Imputed housing values from Fagereng, Holm and Torstensen (2020b)* [annual, 1993-2019]. We use imputed values of housing based on ensemble machine-learning methods on housing transaction data, as described in detail in Fagereng, Holm and Torstensen (2020b). The imputation includes not only owner-occupied housing, but also secondary housing and cabins (holiday homes). Housing wealth is allocated to individuals according to their ownership shares. That is, if a married couple has reported that the wife owns 30% and the husband 70%, these ownership shares are used when allocating household values to individuals.

Household Liabilities. Source: *Tax records* [annual, 1993-present]. Household liabilities include total household debt; That is, the sum of mortgages, student loans and consumer debt (TAX 4.8).

B.4 Taxes

Total taxes. Source: *Tax records* [annual, 1993-present]. Total taxes include those paid on labor income, capital income and wealth.

Labor income tax. Source: *Tax records* [annual, 1993-present]. Tax on labor income, T^l, is derived from other tax components and approximated as $T_t^l = \left[1 - \tau_t^c \left(\frac{Y_t^c}{Y_t^c + Y_t^l}\right)\right] \times (T_t - T_t^w)$, where T^l and Y^c are labor and capital income (as defined in tax records), respectively, T is total taxes, T^w is wealth tax, and τ^c is the flat tax rate on capital income.

Capital income tax. Source: *Tax records* [annual, 1993-present]. Capital tax is approximated as $T_t^c = \tau_t^c *$(interest income + dividends), where τ^c is the flat tax rate on capital income, which was 28% until 2014. From 2014 to 2019, the tax rate on capital was gradually reduced downward to 22%.

Wealth tax. Source: *Tax records* [annual, 1993-present]. During our sample period, wealth taxation has become more lenient, both through a reduced rate and through specific valuation concessions. Table B.1 shows the evolution of the wealth tax over our sample period.

Table B.1 – The wealth tax 1993-2015

			Tax Value (%)					Tax Value (%)	
Year	Rates	Allow-ances	Primary home*	Pub. stock/ priv. equity**	Year	Rates	Allow-ances	Primary home*	Pub. stock/ priv. equity**
1993	1/1.3	120/235	20-25	100(75)/30	2011	1.1	700	25	100
1994-97	1.1/1.4/1.5	120/235/530	20-25	100(75)/30	2012	1.1	750	25	100
1998-04	0.9/1.3	120/540	20-25	100(65)/65	2013	1.1	870	25	100
2005	0.9/1.3	151/540	20-25	65	2014	1.0	1000	25	100
2006	0.9/1.3	200/540	20-25	80	2015	0.85	1200	25	100
2007	0.9/1.3	220/540	20-25	85	2016	0.85	1400	25	100
2008	0.9/1.3	350/540	20-25	100	2017	0.85	1480	25	90
2009	1.1	470	20-25	100	2018	0.85	1480	25	80
2010	1.1	700	25	100	2019	0.85	1500	25	75

Allowances in 000s of NOK. * Prior to 2010, tax values were based on construction cost and adjusted irregularly, but on average kept at a level corresponding to 20%-25% of market value. Not shown in the table are the values of other real estate, such as secondary housing, holiday homes, and business property. These were also reported by their set tax values until 2010, when they were replaced by 40% of market value. This discount has been reduced in recent years. ** In 1994-2004, there was no tax discount on shared traded on the stock exchange, except for small to medium sized businesses (in parentheses). After 2004, the same discount applies to both public and private stocks.

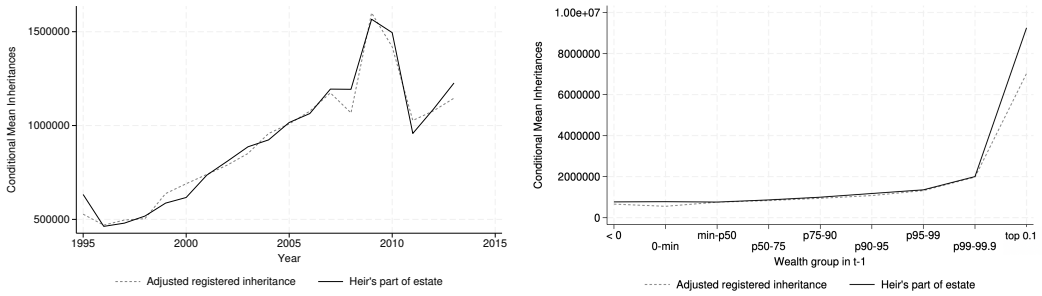
Inheritance tax. Source: *Inheritance tax records* [annual, 1995-2013]. Norway taxed inheritances for most of the study period. Records were digitized in 1995 through the tax's 2014 abolition, limiting our observation window. We observe the exact inheritance taxes paid by each heir.

B.5 Inheritances and Inter vivos Transfers

Intergenerational transfers (IGT)—inheritances and inter vivos—are an important component of household wealth dynamics. Norway provides detailed administrative registers on these transfers, but the data have two key limitations. First, the inheritance and gift tax was abolished in 2014, after which no information on transfers is collected. Second, even prior to 2014, statutory valuation discounts imply that both inheritances and gifts are systematically undermeasured. This appendix describes how we correct for undermeasurement pre-2014 and how we impute transfers for the period 2014–2019.

Institutional Background Through 2013, Norway levied a recipient-based inheritance and gift tax, with exemptions (NOK 470,000 per donor; NOK 940,000 from two parents in 2013) and marginal tax rates ranging from 6% to 15% depending on kinship and size of transfer. Transfers were reported to tax authorities irrespective of tax liability, and the register records both inheritances and gifts, linked to donors and recipients. Norway also has strict heirship rules, guaranteeing children a minimum statutory share (two-thirds of the estate). Surviving spouses could hold an undivided

FIGURE B.1 – ADJUSTED REGISTERED INHERITANCE VERSUS HEIRS' ESTATE



Note: Averages (in 2018 NOK) by year (left) and recipient wealth group (right). Comparison shown only for matched observations (i.e., when reported inheritances can be linked to a deceased parent with children).

estate until death.

Correcting for undermeasurement of inheritances pre-2014 Before 2014, inheritances on private business equity and real estate were recorded at discounted values. We correct all reported inheritances by reversing these statutory discounts. For private equity, inheritances received a 70% discount on assessed values below NOK 10 million (approximately $1.5 million) until 2009 and a 40% discount thereafter. For real estate there was no formal discount, but undervaluation practices were common. By exploiting differences between registered inheritances and an heir's share of a deceased person's wealth, we infer a 45% discount for real estate. We proxy for unobserved inheritance composition with the observed recipient's portfolio shares.

Figure B.1 shows that the resulting adjusted registered inheritances closely match heirs' share of the donor's end-of-life estate, both in levels and in year-to-year variation, providing strong validation for the correction procedure. The only systematic deviation arises for the wealthiest top 0.1%, where adjusted inheritances remain about 30% below heirs' estate shares. It is unclear whether this reflects residual undermeasurement or genuinely lower transfers to children at the top (e.g., end-of-life expenditures, donations). To bracket this uncertainty, we report a robustness check inflating top 0.1% IGT by 30% in Section 5.1.1 (Table I, Panel III, S2).

Imputing inheritances post-2014 For the period 2014–2019, we impute inheritances by assigning each child an equal share of a deceased parent's estate (using the longest-living parent if the parents were still married, or dividing each parent's estate separately if divorced). By construction, these imputed inheritances exactly match

heirs' share of the estate in each year. The excellent fit between adjusted inheritances and heirs' estate shares in the pre-2014 period (right panel of Figure B.1) provides reassurance that this post-2014 imputation is accurate.

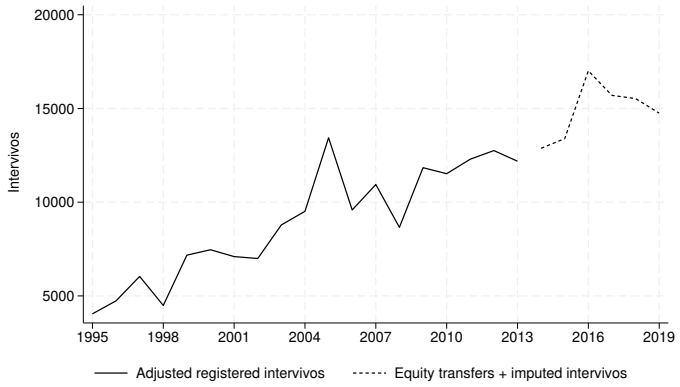
Correcting for undermeasurement of inter vivos transfers pre-2014 Inter vivos gifts recorded in the registry are systematically undermeasured for the same reasons as inheritances: statutory valuation discounts. We correct these amounts by reversing the relevant discounts using the same procedure as for inheritances, and by proxying for the asset composition of transfers using the recipient's portfolio shares.

A second source of undermeasurement is that many transfers of private business equity are not reported as gifts in the inheritance registry. By linking the inheritance registry to the shareholder registry, we find that only about one-third of parent–child equity transfers appear in the inheritance registry. To address this underreporting, we augment inter vivos transfers by replacing the corrected gift value with the shareholder-registry value whenever the latter is larger. This procedure ensures that substantial private-equity transfers, which are common among wealthier households, are incorporated even when not formally reported as gifts. The augmented series provides a consistent and comprehensive measure of inter vivos transfers until 2013, capturing both valuation adjustments and transfers that bypass the inheritance reporting system.

Imputing inter vivos transfers post-2014 After 2013, inter vivos gifts are no longer recorded in the inheritance and gift registry. We therefore construct inter vivos transfers for the period 2014–2019 using two sources of information. First, for households with observed private-equity transfers in the shareholder registry, we treat these transactions as inter vivos gifts and use their recorded values directly. Second, for households without such transfers, we impute inter vivos gifts using a model trained on pre-2014 data.

To obtain imputed values, we use a two-stage machine-learning procedure. In the first stage, we estimate the probability that a household receives an inter vivos gift as a function of observable characteristics such as age, own and parental wealth, and immigrant status. In the second stage, we predict the conditional value of a gift—again using pre-2014 data—based on a flexible gradient-boosting regression (Friedman (2001)) that incorporates demographics, parental characteristics, and wealth and in-

Figure B.2 – Adjusted and imputed household inter vivos transfers



Note: Averages (in 2018 NOK) by year.

come measures. The final imputed transfer equals the predicted probability times the predicted conditional value, ensuring that imputed gifts align with both the extensive and intensive margins observed historically. This approach preserves the key empirical relationships between inter vivos transfers, household characteristics, and parental wealth.

This procedure extends the inter vivos transfer series beyond 2013 in a way that maintains continuity with the administrative data. Figure B.2 displays the resulting time series, combining adjusted observed transfers before 2014 with equity-based and imputed transfers thereafter (see Appendix SM.4 in Hubmer *et al.* (2025) (OSM hereafter)).

B.6 Imputing Equity Income Prior to 2005

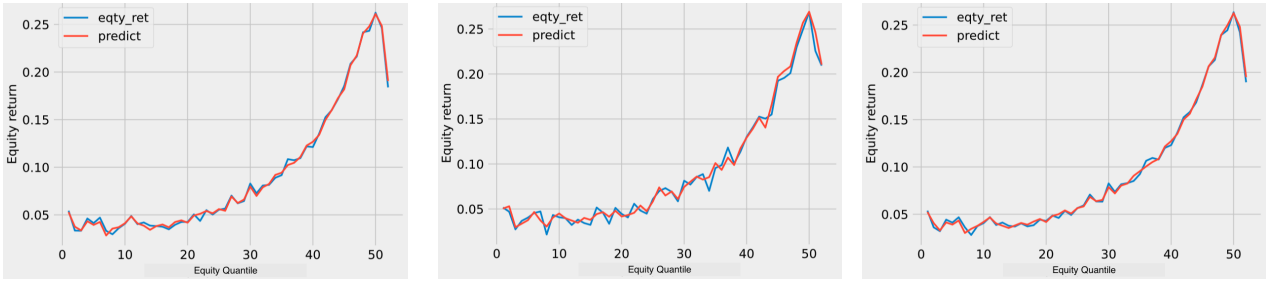
Following previous studies using Norwegian data (Alstadsæter *et al.* (2016); Fagereng *et al.* (2020a, 2019)), we obtain both dividends and retained earnings by linking individuals' equity ownership—both direct and indirect through holding companies—to companies' balance sheets using the shareholder registry from 2005 onward. We impute equity income for 1994–2004 using a machine-learning model trained on post-2004 data.[1]

To ensure reliable return calculations, we exclude individuals with financial wealth

[1]Although the shareholder registry starts in 2001 but, records are only complete from 2004 onward. We use actual data when available.

FIGURE B.3 – AVERAGE RETURNS OVER THE EQUITY DISTRIBUTION

(A) Training Sample (B) Test Sample (C) Whole Sample Sample



Notes: Panel A shows the average equity returns across the equity distribution (among those that hold equities) for the actual values in the data (eqty_ret) and its corresponding predicted value. Panels B and C show the same figure for test and entire samples, respectively.

below NOK 9,000 (approximately $1,000), consistent with (Fagereng *et al.* (2020a)). We winsorize equity returns at the 0.5th and 99.5th percentiles to mitigate the influence of outliers. We compute equity returns by summing capital gains on private equity, capital gains on stocks, and dividend income, divided by average equity (public and private) holdings between the current and previous year (à la Dietz (1968)).

Similar to our imputation of inter vivos transfers, the capital income imputation employs a gradient-boosting regression incorporating more than 30 variables on demographics, wealth and income measures and changes in them, portfolio composition, returns on other assets, and macroeconomic indicators. This rich feature set captures the diverse factors influencing equity returns, including individual financial circumstances, portfolio decisions, position in the wealth distribution, and broader economic conditions. See Appendix SM.3 in OSM for details.

Figure B.3 shows that the predictive model successfully captures the heterogeneity of equity returns across the equity distribution. The predicted returns (red lines) closely track actual returns (blue lines) across training, test, and full samples, validating the model's ability to generalize effectively. This maintained heterogeneity in returns is essential for our empirical investigation of lifecycle wealth accumulation.

C Shapley-Owen Decomposition

This appendix provides details on the S-O decomposition of wealth gaps (Shorrocks (2013)) used in Section 5.

Step 1: Obtaining profiles for target and reference groups. We follow our retrospective approach to define a target (e.g., in the baseline, the top 0.1% aged 50–54 in 2019, or corresponding Old Money households) and a reference group (always P25–P75 of the same age group). Let $\mathcal{G}$ denote a group.

Step 2 (optional): Expanding panel dimension ("twins"). Because the panel begins in 1993, the youngest observable age for some groups may be older than 20 (i.e., $h^{\mathcal{G}}_{1993} > 20$, where $h^{\mathcal{G}}_t$ denotes the age of $\mathcal{G}$ in year t). To construct their complete profiles from age 20 onward, we supplement such groups with matched younger "twins" for some exercises (including our baseline): In particular, for group $\mathcal{G}$ we find twins aged $h^{\mathcal{G}}_{1993}$ in the middle of our sample, which can be followed back until age 20. To find these twins, we minimize the Mahalanobis distance (Mahalanobis (1936)) between households in $\mathcal{G}$ and their twins over two variables: i) wealth level at age $h^{\mathcal{G}}_{1993}$ and ii) nine-year wealth growth between $h^{\mathcal{G}}_{1993}$ and $h^{\mathcal{G}}_{1993}+9$ (e.g., 24 to 33).[2] The nine-year window maximizes the number of years we can use in our analysis and captures the fast wealth growth observed in the early years of the life cycle among some groups, such as the New Money. We select as many twins as there are original households in $\mathcal{G}$. Figure C.1 shows average wealth for the top 0.1% aged 50–54 group and their twins. Combining these series, we construct backward profiles from age 50 to 20.

Step 3: Computing the S-O decomposition. To smooth out noise in the data, we implement the S–O decomposition at the group level, aggregating the budget constraint in equation 1. For each $\mathcal{G} = (h, p)$, where h denotes the age group and j the wealth group:

$$W_t(h,j) = W_{t-1}(h,j) + \left(R_t(h,j)\, W_{t-1}(h,j) + L_t(h,j) + H_t(h,j)\right) \times S_t(h,j)\,. \quad (2)$$

Here, $W_t(h,j)$ denotes average wealth in group (h,j) at time t. $L_t(h,j)$ is average labor income, $H_t(h,j)$ is average inheritances and inter vivos transfers, and

[2] Mahalanobis distance measures a point's distance from a multivariate distribution, accounting for correlations between variables. This distance is defined as $D^2 = (\mathbf{x}-\mathbf{m})^T \mathbf{C}^{-1} (\mathbf{x}-\mathbf{m})$, where $\mathbf{x}$ is a vector of observations, $\mathbf{m}$ is the mean of each vector, and $\mathbf{C}$ is the covariance matrix. If variables are uncorrelated, this measure reduces to the normalized Euclidean distance.

$R_t(h,j)W_{t-1}(h,j)$ is average capital income, each measured after taxes and transfers. We denote as $R_t(h,j)$ the average rate of return on wealth (weighted by $W_{i,t-1}$) and as $S_t(h,j)$ the average gross saving rate (weighted by total income $R_{i,t}W_{i,t-1} + L_{i,t} + H_{i,t}$). We treat the wealth profile as a function of five components, $x \in X \equiv \{L, H, R, S, W_{20}\}$, where W_{20} is wealth at age 20, interpreted as inherited wealth, which we therefore combine with inheritances H in our results.

To isolate the contribution of component x, we recompute the wealth path of the target group replacing x with the age-specific values of the reference group, denoted by $\bar{x}_t(h)$. Because the mapping from components to wealth is nonlinear, the order of replacement matters. The S-O averages the marginal effect of replacing a component on the wealth gap, over all $5! = 120$ permutations.

Formally, denote by $\tilde{W}_t^Z(h,j)$, for $Z \subseteq X$, the counterfactual wealth profile of group (h,p) when replacing components Z with the values of the reference group, denoted by an overbar. For instance, after replacing both the saving rate and the return rate, the counterfactual wealth profile is computed as

$$\tilde{W}_t^{\{R,S\}}(h,j) = \tilde{W}_{t-1}^{\{R,S\}}(h,j) + \left[L_t(h,j) + H_t(h,j) + \bar{R}_t(h)\,\tilde{W}_{t-1}^{\{R,S\}}(h,j)\right]\bar{S}_t(h).$$

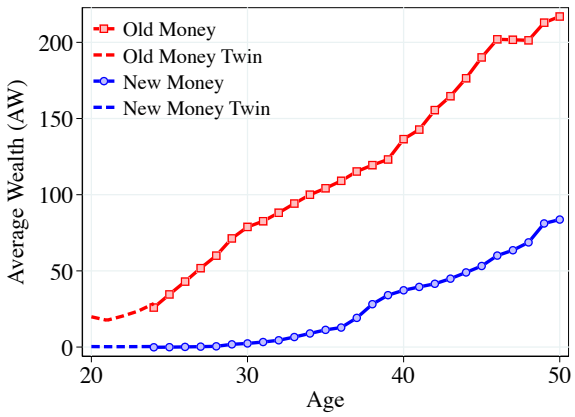
Hence, the contribution of a component $x \in X$ to the wealth gap between group (h,p) and the reference group in year t is

$$C_t^x(h,j) = \sum_{Z \subseteq X \setminus \{x\}} \frac{|Z|! \times (5 - |Z| - 1)!}{5!} \left[\tilde{W}_t^Z(h,j) - \tilde{W}_t^{Z\cup\{x\}}(h,j)\right],$$

where $\tilde{W}_t^Z(h,j)$ is the counterfactual wealth path after replacing a subset Z of the components but not x, and $\tilde{W}_t^{Z\cup\{x\}}(h,j)$ is the same after replacing x as well. Note that after replacing all five components, counterfactual wealth equals the one of the reference group by construction, $\tilde{W}_t^X(h,j) = \bar{W}_t(h)$. Hence, the total wealth gap $W_t(h,j) - \bar{W}_t(h)$ equals the sum of the contributions $\sum_{x\in X} C_t^x(h,j)$, and we compute the S-O share of component x as $Share_t^x(h,j) = C_t^x(h,j) \,/\, \sum_{x'\in X} C_t^{x'}(h,j)$.[3]

[3] A minor adjustment is applied when saving or return rates become ill-defined due to near-zero denominators (in the early years of the New Money). In these cases, we replace age-specific rates with life-time averages to compute marginal changes in the S–O. This affects only a handful of observations.

FIGURE C.1 – COMPARISON GROUP AND TWINS USED IN S-O DECOMPOSITION

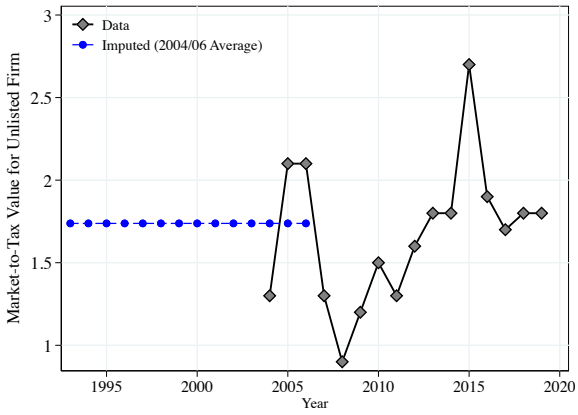


Notes: Figure C.1 shows the average wealth profile of the baseline group of top 0.1% separated in New and Old Money and for the their "twins", averaged across all conditioning years.

C.1 Details of Robustness for S-O Decomposition

Scenario 1. Figure C.2 shows the ratio of market values to tax values for private firms used in Section 5.1.1.

FIGURE C.2 – MARKET-TO-TAX MULTIPLIER



Notes: Estimated market-to-tax value multiplier used in robustness scenario to inflate private equity tax values. Based on Andersen and Bo (2022).

Scenario 3. Scenario 3 removes remaining aggregate time-series trends beyond those already eliminated by normalizing by calendar-year average wealth (AW) as well as averaging over 10 conditioning years. We construct a time-invariant distribution for each variable in each age. For each budget constraint variable x we observe in our data (wealth, labor income, inheritance, and capital income), we:

1. Compute its quantile function (inverse CDF) in each year t and for each age h,

with each variable normalized by average wealth in year t, AW_t .

2. Create a time-invariant distribution by taking an average of quantile functions across years, $\bar{F}^{-1}_{x,h}(p) = \frac{1}{26}\sum_{t=1994}^{2019} F^{-1}_{x,t,h}(p)$.

3. Replace each observation i in year t at age h $x_{t,h,i}$ by its corresponding time-invariant value using this stationary distribution $\tilde{x}_{h,i} = \bar{F}^{-1}_{x,h}(F_{x,t,h}(x_{t,h,i}))$.

We replicate our S-O decomposition using these variables from corresponding time-invariant distributions. Thus, someone at the 99th percentile of the age-50 wealth distribution in any year owns the same time-averaged wealth value, while her labor income or capital income are replaced with values from corresponding age-specific time-invariant distributions. This yields a synthetic panel that preserves life cycle and cross-sectional heterogeneity within each variable while removing all remaining time-varying shifts.

D Long-term Transition Matrix

We examine intragenerational wealth mobility using backward- and forward-looking transition matrices. Figure D.1a shows where households aged 50–54 in each wealth group originated from in 1994, while Figure D.1b tracks 25 to29-year-olds forward to 2018-2019. These matrices, averaged over 10 conditioning years, represent roughly the same cohort. For additional age groups, see Section SM.2.2 in OSM.

Among the top 0.1% of households, 48% were already in the top 1% in 1994, with 24% maintaining top 0.1% status throughout (the "Old Money"). Remarkably, 24% rose from the bottom 90%—the "New Money".

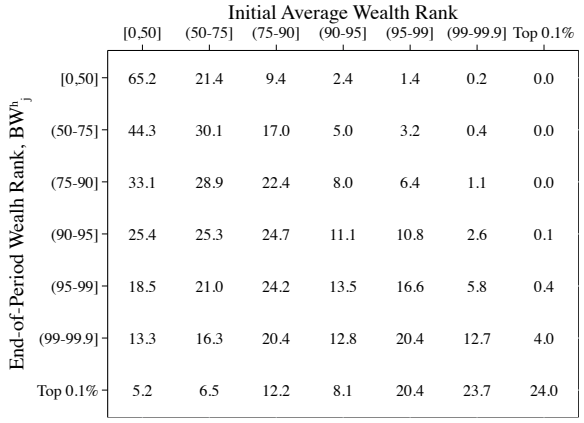
Wealth persistence is strong at both extremes: 80% of initial the top 0.1% households remained above the 95th percentile by 2019, with only 2.4% falling below median wealth. Similarly, most households starting below the 75th percentile maintained their relative position, though a small fraction climbed above the 90th percentile.

E Calculation of Returns

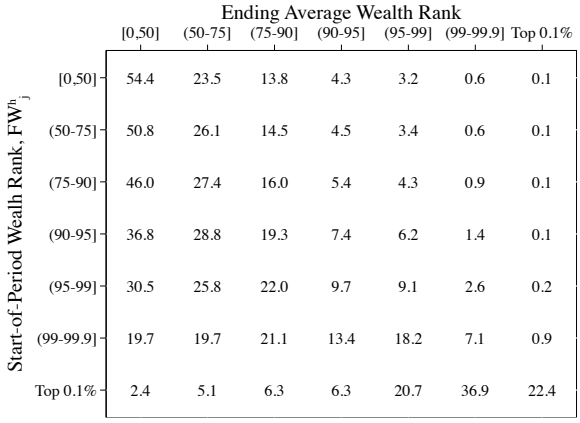
We calculate returns for total net worth, safe assets, equity (private and public), and housing at the household level. As in Fagereng *et al.* (2020a), we define returns on assets as $r^n_{it} = \frac{y^s_{it}+y^e_{it}+y^h_{it}-y^b_{it}}{w^g_{it}+F^g_{it}/2}$, where y^s_{it}, y^e_{it}, and y^h_{it} correspond to income from financial assets (interest income), equity (dividends plus unrealized capital gains from stocks

Figure D.1 – Long-term Intragenerational Transition Matrix

(A) Backward-Looking Transition



(B) Forward-Looking Transition



Note: Figure D.1a shows the fraction of households in different percentiles of the wealth distribution in $\overline{W}_{i,1994}$ (columns), conditional on their percentile of the wealth distribution in the conditioning year, BW_j^{50-54} (rows). Each row sums to 100. Figure D.1b shows similar results by initial wealth, FW_j^{25-29} (rows), and the wealth distribution in $\overline{W}_{i,2019}$ (columns).

Table E.1 – Wealth Returns

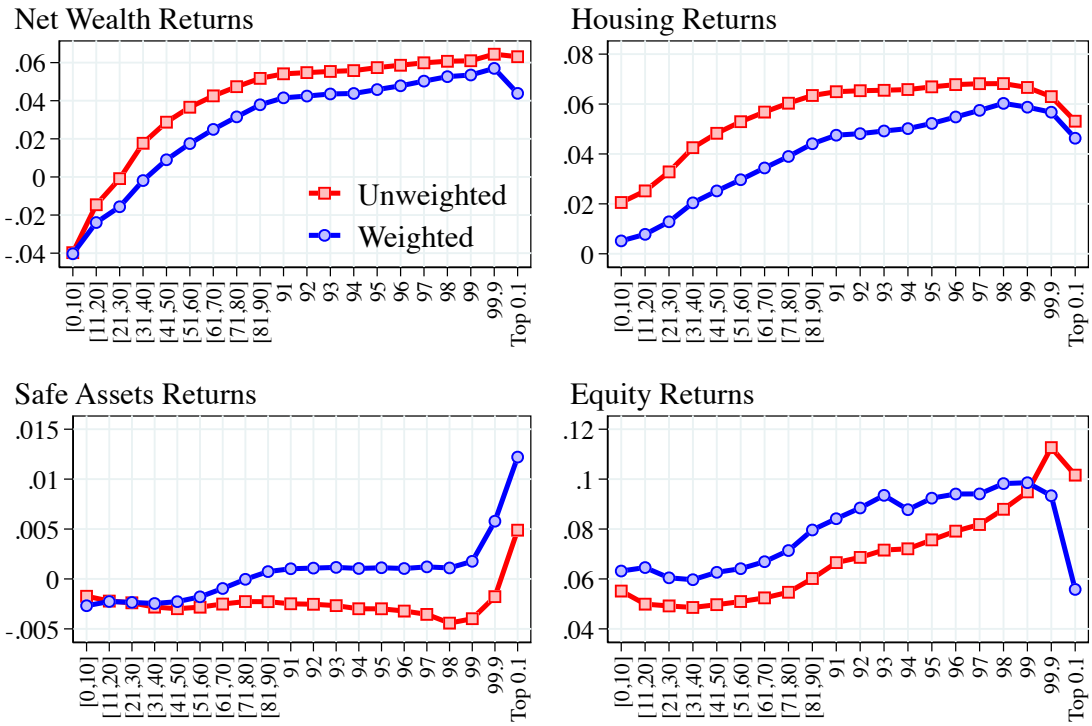
	N 000s	Mean	SD.	Skew.	Kurt.	P1	P5	P10	P50	P90	P95	P99
All	17,807	0.030	0.123	0.701	15.120	-0.376	-0.129	-0.060	0.018	0.141	0.205	0.431
Equity	8,508	0.070	0.239	4.007	37.861	-0.407	-0.154	-0.100	0.031	0.263	0.415	1.030
Housing	17,723	0.040	0.131	0.804	16.300	-0.405	-0.134	-0.046	0.024	0.152	0.219	0.481
Safe	17,675	0.001	0.022	2.687	25.537	-0.032	-0.027	-0.022	-0.001	0.026	0.034	0.068

Notes: Table E.1 shows cross-sectional statistics of the returns distribution for different asset classes based on a pooled sample of households between 2005 and 2019.

and private equity), and housing (imputed rental income plus capital gains), and y_{it}^b is interest paid, respectively. We define w_{it}^g as the stock of wealth at the beginning of the period. Finally, F_{it}^g is net flows of gross wealth during period t (asset yields happen during the year, and households add/subtract from assets). We calculate similar returns for safe assets, equity, and housing. Table E.1 shows assets-weighted cross-sectional moments of the distribution of returns in our sample, which are relatively close to those in Fagereng *et al.* (2020a) (for a more direct comparison, see Appendix SM.1 in OSM).

The average annual return on net wealth increases with wealth, from -4.0% for the first decile to 6% for the top 0.1% (Figure E.1). Returns on safe assets also rise with net wealth but only above the 40th percentile. The return on housing shows a hump-shaped pattern. The weighted and unweighted average returns for net wealth, safe assets, and housing are similar in shape. However, returns on equity

FIGURE E.1 – CROSS-SECTIONAL AVERAGE RETURNS



Notes: Figure E.1 shows the average returns within different quantiles of the household net worth distribution. To construct this figure, we pool household observations between 2005 and 2019. Weighted averages are weighted using the value of the corresponding asset. Negative or missing asset values are assigned a weight of 0.

differ significantly: Unweighted returns rise from 6% for the bottom decile to 11.0% for the top 1%, then drop to 10% for the top 0.1%. The weighted average returns are hump-shaped relative to wealth, peaking at 10% around the 99th percentile and falling to 6% for the top 0.1%. This indicates strong decreasing returns to scale for equity at the top of the wealth distribution, consistent with empirical evidence from Spain (Boar *et al.* (2022)).

F Portfolio Composition

In Section 3.2 we show that the wealthiest invest in equity more heavily from early in life. We now show that the current wealthiest invested in equity more heavily in the past even compared with those of similar wealth and age. We regress the portfolio equity share in every year t between 1993 and 2013 on dummies for $\overline{W}^h_{i,2015}$. We find

TABLE F.1 – EQUITY PORTFOLIO ACROSS WEALTH GROUPS, $\overline{W}^h_{i,2015}$

	Total Equity	Public	Private
$\overline{W}^h_{i,2015} \geq P99.9$	0.124***	0.0090***	0.115***
	(0.0007)	(0.0005)	(0.0005)
$P99 \leq \overline{W}^h_{i,2015} < P99.9$	0.0882***	0.0127***	0.0756***
	(0.0002)	(0.0002)	(0.0002)
$P95 \leq \overline{W}^h_{i,2015} < P99$	0.0316***	0.0098***	0.0218***
	(0.0001)	(0.0001)	(0.0001)

Notes: Table F.1 shows the coefficients of a panel regression of equity shares on $\overline{W}^h_{i,2015}$ dummies. We control for the highly nonlinear contemporaneous relationship between wealth and portfolio shares by including 28 dummies of net worth in every year t ($W_{i,t}$) as well as year and age effects. The dummy for $\overline{W}^h_{i,2015} < P95$ is omitted. We control for age and year dummies, as well as dummies for current wealth for the following 28 wealth groups $\{< 0, [0, 0.5], (0.5, 1], (1, 2], (2, 3], ..., (24, 25], +25\}$. Standard errors are in parentheses (*** $p < 0.01$).

that even conditional on contemporaneous wealth and age, those households that end up in the top 0.1% have invested on average 4 p.p. and 12 p.p. more in equities compared with those that end up in the next 0.9% and those below the 95th percentile, respectively (Table F.1). These differences mostly stem from a larger portfolio share of private businesses, which are also very important for wealth concentration in the US (Cagetti and De Nardi (2006)).

G Sources of Lifetime Income

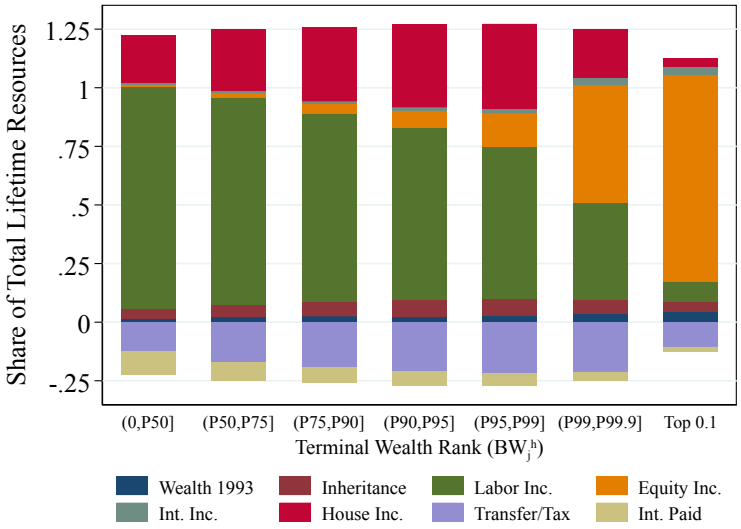
In this appendix, we perform a static accounting decomposition of total life time resources without compounding. Consider the sum of yearly budget constraints between 1993 and a conditioning year τ:

$$W_{i,\tau} = \underbrace{W_{i,1993} + \sum_{t=1994}^{\tau} \left[\tilde{L}_{i,t} + \tilde{H}_{i,t} + \tilde{R}^E_{i,t} + \tilde{R}^S_{i,t} + \tilde{R}^H_{i,t} + T_{i,t} - I^L_{i,t}\right]}_{\text{Total life-time resources: } \overline{Y}_{i,\tau}} - \sum_{t=1994}^{\tau} C_{i,t}. \quad (3)$$

where $W_{i,t}$ is household i's net wealth at the end of year t, $\tilde{L_{i,t}}$ and $\tilde{H}_{i,t}$ are labor income (includingself-employment income) and inheritances (incl. inter vivos transfers), pre-tax. The terms$\tilde{R}^E_{i,t}$, $\tilde{R}^S_{i,t}$, and, $\tilde{R}^H_{i,t}$ denote income from equity, safe assets, and real estate, all pre-tax. The terms $T_{i,t}$ and $I^L_{i,t}$ represent public transfers net of taxes and interest payments for liabilities. We denote the sum of these flows between 1993 and τ , and initial wealth $W_{i,1993}$, as the life time resources of i, $\bar{Y}_{i,\tau}$.

For each age h and wealth group j, we compute each component's share out of

Figure G.1 – Decomposition of Total Lifetime Resources



Notes: Figure G.1 shows the shares of lifetime resources across the BW_j^{50-54} distribution. Lifetime resources are calculated as the sum of all sources of income within an age and wealth group. Therefore, the average share of each income source is weighted by lifetime resources. Shares are calculated separately for each conditioning year and then averaged across all conditioning years.

lifetime resources, e.g., $\left(\sum_{t=1994}^{\tau} L_{it}\right)/\bar{Y}_{i,\tau}$ for labor income, as a weighted average, averaged across base years, $\tau \in \{2010, 2011, ..., 2019\}$. Figure G.1 reports these. The most important source—88.4%—of lifetime income for the top 0.1% 50-to-54-year-old wealth owners ($BW_{\geq P99.9}^{50-54}$) is equity income. In contrast, for households below the 99th percentile of the wealth distribution, labor income constitutes the majority of their resources.

H Details of Quantitative Exercises

A household's efficiency units of labor supply e_{ih} are given by

$$\ln e_{ih} = \underbrace{\kappa_h}_{\text{life cycle}} + \underbrace{\bar{e}_i}_{\text{permanent}} + \underbrace{\eta_{ih}}_{\text{persistent stochastic}} + \underbrace{\xi_{ih}}_{\text{transitory stochastic}},$$

where κ_h is a life cycle component—common for all households—assumed to be a quadratic function of age, and $\bar{e}_i$ denotes a household's fixed labor efficiency type, which is inherited imperfectly across generations: $\bar{e}_{child} = \rho_e \bar{e}_{parent} + \varepsilon^e_{child}$. The parameter ρ_e captures the inter generational correlation of labor efficiency, and $\varepsilon^e \sim N(0, \sigma_e)$ is an i.i.d. shock. The stochastic component of labor efficiency comprises a persistent component, denoted by η_{ih}, and a transitory component, denoted by ξ_{ih}. The per-

sistent component is modeled as a first-order autoregressive process with innovations drawn from a mixture of normally distributed random variables:

$$\eta_{ih} = \rho_\eta \eta_{i,h-1} + \varepsilon^\eta_{ih}, \text{ where } \quad \varepsilon^\eta_{ih} = \begin{cases} N(\mu_{\eta,1}, \sigma_{\eta,1}) & \text{with probability } p^\eta. \\ N(\mu_{\eta,2}, \sigma_{\eta,2}) & \text{with probability } 1 - p^\eta. \end{cases}$$

The transitory component is also modeled as a mixture of normals:

$$\xi_{ih} = \begin{cases} N(\mu_{\xi,1}, \sigma_{\xi,1}) \text{ with probability } p^\xi, \\ N(\mu_{\xi,2}, \sigma_{\xi,2}) \text{ with probability } 1 - p^\xi. \end{cases}$$

The mixture of normal distributions is crucial in matching the negative skewness and excess kurtosis that characterize the typical earnings process (Guvenen *et al.* (2021)). Without loss of generality, we normalize η and ξ to have zero mean (e.g., $\mu_{\eta,1}p^\eta + \mu_{\eta,2}(1-p^\eta) = 0$) and assume $\mu_{\eta,1} < 0$, $\mu_{\xi,1} < 0$ for identification. Finally, we assume an age-dependent probability of drawing shocks given by

$$p^x = p^x(t) = \frac{e^{\zeta^i_{x,t}}}{1 + e^{\zeta_{x,t}}}, \text{ where } \zeta_{x,t} \equiv a_x + b_x\,(t/10) + c_x\,(t/10)^2\,, x \in \{\eta, \xi\}\,.$$

We estimate this income process using data on household labor income after tax and transfers. We employ the method of simulated moments, targeting the following sets of moments: (i) the standard deviation, skewness, and kurtosis of one-year earnings growth and (ii) five-year earnings growth; (iii) auto-correlation matrix of log income, and (iv) average earnings and variance of log income over the life cycle. Following Guvenen *et al.* (2021), we minimize in our estimation the (weighted) sum of squared arc-percent deviations between the data and simulated moments. Using the same data, Halvorsen *et al.* (2022) estimate an inter-generational correlation of income of $\rho_e = 0.24$, which we use in our calibration. Table H.1 shows parameter values for our income process.

We set the interest rate $r = 5.5\%$, corresponding to the equilibrium interest rate under a Cobb-Douglas production function, $r = \alpha K^{\alpha-1} - \delta$, given $\delta = 0.05$, $\alpha = 0.4$, the normalization $L = 1$, and a targeted wealth-labor income ratio $\frac{K}{wL} = \frac{K^{1-\alpha}}{1-\alpha}$ of 6.37.

TABLE H.1 – INCOME PROCESS PARAMETERS

ρ_e	σ_e	ρ_η	$\sigma_{\eta,1}$	$\sigma_{\eta,2}$	$\mu_{\eta,1}$	$\sigma_{\xi,1}$	$\sigma_{\xi,2}$	$\mu_{\xi,1}$
0.24	0.332	1.00	0.539	0.057	–0.395	0.316	0.082	–1.899
	p^η						p^ξ	
a_η	b_η	c_η				a_ξ	b_ξ	c_ξ
-3.008	-0.379	-0.179				-1.884	-2.896	0.543

Note: Table shows the parameter estimates of the labor income process.

Role of Accidental Bequests. In Section 6, we assume accidental bequests in model versions (1)-(5). Here, we remove this assumption by imposing a deterministic life cycle. We re-estimate all five models using the same calibration strategy. Except in the warm-glow bequest model of column (5), initial wealth is zero, and consequently the contribution of inheritances to the wealth gap is zero (Panel B of Table H.2). The stochastic-β model in (4) has trouble even generating enough wealth inequality by age 50 without differences in initial wealth. The other single-channel models can generate sufficient wealth inequality, but neither model captures the dynamics of wealth at the top well.

TABLE H.2 – RE-ESTIMATED MODELS WITHOUT ACCIDENTAL BEQUEST

		(1)	(2)	(3)	(4)	(5)
	Data	Basic	Superstar	Returns	β	Bequest
Target cross section			✓	✓	✓	✓
A. Cross-Sectional Moments						
Wealth/Lab.Inc. ratio	6.4	**6.4**	**6.4**	**6.3**	**3.2**	**6.4**
Top 0.1% wealth (%)	9.3	0.8	**9.3**	**9.0**	**4.8**	**9.3**
Top 0.1% income (%)	6.6	0.8	**6.6**	**6.9**	0.9	1.3
B. Dynamics: Top 0.1% Wealth Decomposition						
Initial wealth (AW)	6.9	0.0	0.0	0.0	0.0	189.6
Wealth at 50-54 (AW)	124.3	10.9	124.1	119.2	63.7	124.3
Inheritance (%)	32.8	0.0	0.0	0.0	0.0	117.3
Labor income (%)	3.4	77.1	68.5	6.1	31.7	-0.1
Returns (%)	24.7	-0.1	-0.1	41.8	-0.9	0.4
Saving rate (%)	39.1	23.0	31.6	52.1	69.2	-17.7

Note: In each column, targeted moments are in **bold**.