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

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Abstract

We use 1993–2015 Norwegian administrative panel data on wealth and income to study lifecycle wealth dynamics. By employing a novel budget constraint approach, we show that at age 50 the excess wealth of the top 0.1%, relative to mid-wealth households, is accounted for by higher saving rates (38%), inheritances (34%), returns (23%), and labor income (5%). One-fourth of the wealthiest—the "New Money"—start with negative wealth but experience rapid wealth growth early in life. Relative to the "Old Money," the New Money are characterized by even higher saving rates, returns, and labor income. We use these dynamic facts to test six commonly used models of wealth inequality. Although these models can generate the high concentration of wealth seen in the cross-section, they tend to put too much weight on (accidental) bequests and fail to capture the contribution of the New Money. A model with heterogeneous returns that decrease in wealth, and non-homothetic preferences is consistent with the new facts on the dynamics of wealth accumulation.

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

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*See Online Supplemental Material 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. For helpful comments, we thank seminar participants at the 2021 NBER SI Micro Data and Macro Models Group, 2021 Barcelona GSE Summer Forum, World Inequality Conference, EEA/ESEM, HKUST-Jinan, SEA, SED, Midwest Macro, SECHI, Australasian Macro, Stanford, Wharton, EIEF, Philadelphia Fed, PUC Chile, UBC, UC Berkeley-Haas, Queen's, Central Bank of Chile, UNAB, McGill, Richmond Fed, PHBS Macro Workshop, WUSTL, NYU, and GRIPS-UT. Special thanks to 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 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); Guvenen *et al.* (2019); Boar and Midrigan (2022)). To study these questions, however, cross-sectional evidence is not enough; we also need to know how the wealthiest accumulate their fortunes over their life cycle since different mechanisms imply different policy prescriptions. For example, do they inherit their wealth from their parents (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 2015. We then use these dynamic facts to test the aforementioned 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 use a dataset with a long panel dimension to document long-term wealth accumulation patterns empirically.[2] Its administrative nature and third-party reporting mean that there is little or no measurement error or attrition. Thanks to its richness, we can study the joint dynamics of the components of the household budget constraint such as financial and non-financial wealth, labor and capital income, taxes and transfers, as well as inheritances and inter vivos transfers. Finally, its large sample size allows us to obtain precise estimates for narrowly defined groups of households, including those at the very top of the wealth distribution.

In our empirical analysis, we exploit the completeness of our data and investigate the

[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) back out household wealth from administrative tax records by capitalizing income from different assets, but this method requires strong assumptions on returns (Smith *et al.* (2023)).

[2] Recently, other studies have also utilized rich Scandinavian administrative panel datasets to document return heterogeneity (e.g., Fagereng *et al.* (2020a) and Bach *et al.* (2020)) and saving rate heterogeneity (e.g., Bach *et al.* (2017) and Fagereng *et al.* (2019)) across the wealth distribution.

role of each component of the budget constraint for the accumulation of wealth without making any behavioral assumptions. In particular, we first investigate the evolution of wealth, rates of return, labor earnings, inheritances, and saving rates by following the same individuals for the *past* 22 years, conditional on the *latest* wealth quantile and age group.[3] We then decompose the wealth gap between the top and median households into these components by employing a novel intertemporal budget constraint approach.

First, we show that, on average, the wealthiest start their lives substantially richer than other households in the same cohort. For instance, the richest 0.1% of households aged 50–54 own, on average, 125 times the economy-wide average wealth ($437,000 in 2015 and hereafter referred to as "AW"). The same households already owned 20 × AW in their late 20s.[4] Moreover, the top 0.1% group owns around 10 times as much wealth as those in the next 0.9%—a gap that roughly stays the same over the life cycle. Overall within-cohort wealth concentration, however, declines over the life cycle, especially between ages 25 and 35, mainly because the bottom half of the wealth distribution converges to the average wealth in the economy by accumulating wealth at a fast pace.[5]

Second, we study households' lifetime portfolio composition and returns. As has been documented in cross-sectional data, wealthy households own mostly equity (e.g., Carroll (2000)). In addition, we find that the current wealthiest 0.1% have invested a substantially higher share of their portfolio in equity (hovering between 85% and 90%), in particular private businesses, starting from very young ages, even compared with others in their cohort with similar wealth. For households below the 90th percentile, in contrast, housing is the single most important asset, constituting around 90% of their gross wealth over the life cycle. Consistent with these large portfolio differences, richer households persistently earn significantly higher returns (see also Fagereng *et al.* (2020a); Bach

[3]This backward-looking approach, of course, selects on an endogenous variable (e.g., we condition on those households that reach the top). Hence, we complement this analysis with a forward-looking investigation that documents the same features of the data over the *subsequent* 22 years, conditional on *initial* wealth quantile. These two approaches jointly paint a fuller picture of lifecycle wealth dynamics. In the main text we concentrate on the results from the retrospective approach and discuss the differences with those from the forward-looking approach when necessary.

[4]For a more granular investigation of wealth mobility, we construct long-term transition probability matrices for narrow wealth groups. 29% of the top 0.1% group among households aged 50–54 were also in the top 0.1% group in their late 20s, with 65% starting out within the top 5%. However, a significant fraction of them start their careers with little or no wealth. Later, we denote this group as part of the "New Money" and compare their lifecycle wealth dynamics to those who started rich, the "Old Money."

[5]This pattern is also visible in the US, where the wealth share of the top 1% declines from 60% at age 25 to about 30% at age 35 and remains relatively flat thereafter.

et al. (2020)), which are also more volatile and positively skewed. The long-term average annual return on net wealth increases monotonically from around 1.5% for the bottom 50% of the wealth distribution to about 10% for the top 0.1% group. Interestingly, these differences are more pronounced among younger households.

Consistent with their high rates of return and large initial wealth (in 1993), equity income (including capital gains) constitutes 83% of total lifetime resources—defined as the sum of all income between 1993 and 2015 and initial wealth—for top 0.1% wealth owners. Initial wealth, inheritances, and labor income account for the small remainder. These numbers represent a static decomposition that ignores compounding, thus, they do not imply that intergenerational transfers are unimportant, which we revisit soon. In contrast, households in the bottom 90% of the distribution derive 80-90% of their lifetime resources from labor (see also a contemporaneous study by Black *et al.* (2020)).

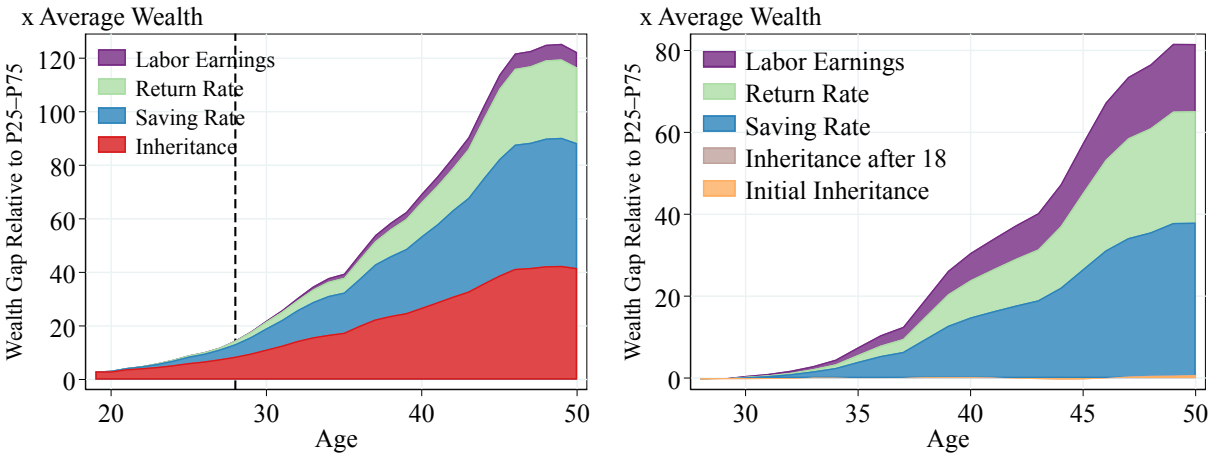
Finally, we compute the past 22-year saving rate out of gross (Haig-Simons) income for each wealth and age group. Consistent with previous evidence (e.g., Fagereng *et al.* (2019)), the saving rate is strongly increasing in wealth from around 10% in the bottom half of the wealth distribution to around 70% for the top 0.1% across age groups. Importantly, this positive correlation is not mechanical (i.e., higher saving rates moving households up the wealth distribution); we find that the saving rate over the next 22 years also increases with initial wealth.[6]

As our primary empirical contribution, we quantify the importance of each of these factors for top wealth accumulation. To do so, we simulate counterfactual wealth profiles by replacing each variable in the budget constraint (e.g., return on net wealth, saving rate, etc.) by its average value for a reference group, the middle 50% households of the same age. Since wealth accumulation is a dynamic and non-linear process, the order of replacement matters; therefore, we employ a Shapley-Owen (S-O) decomposition that averages the marginal effects across all possible permutations. Our empirical approach ignores behavioral responses and thus has to be understood as capturing the first-order effects of each dimension of heterogeneity. Yet, we view the simplicity and transparency of our method—which avoids relying on any behavioral assumptions—as an advantage that the completeness of our data allows for. Moreover, we use this set of novel descriptive moments to benchmark structural models of wealth inequality.

[6] A similar concern might arise about the positive correlation between past returns and wealth.

Figure 1 – Determinants of the Top 0.1% Wealth Accumulation

(a) Top 0.1% (b) New Money



Notes: Figures 1a and 1b decompose the excess wealth accumulation of top 0.1% households aged 50—54 and of the New Money within the top 0.1% group relative to median-wealth households, respectively. The vertical axes show the wealth gap in multiples of the economy-wide average wealth (AW). In Figure 1a, for ages to the right of the vertical line, we follow the same group of households across all ages. Because of data limitations, data to the left of the vertical black line is obtained from households with similar age, wealth, and wealth growth. Additional details in Appendix OA.2.

As discussed above, the top 0.1% of 50- to 54-year-olds already had high net worth in their late 20s (in 1993). To investigate the source of their large initial wealth, we find their younger "twins" that (i) have similar wealth profiles between ages 28 and 37 based on the Mahalanobis (1936) distance measure and (ii) are 18 years old or younger in 1993. We then employ the S-O decomposition to the excess wealth accumulation of the wealthy "twins" between ages 18 and 28 and merge it with that for the original 50- to 54-year-old top 0.1% group. Therefore, the part before age 28 (separated by the vertical dashed line) on Figure 1a corresponds to the younger "twins."

As individuals age, the relevance of inheritances declines, whereas higher saving rates and rates of return increase in their relative importance in explaining the wealth gap. By age 50, higher saving rates (38.2%), higher inheritances (34.0%), and higher returns on wealth (23.1%) account for the majority of the wealth gap. The small remainder results from higher labor income (4.7%). We conclude that, first, higher labor income and higher returns on wealth, commonly considered the primary sources of wealth inequality, jointly account for less than a third of the wealth gap. Second, heterogeneity in saving rates is more important than heterogeneity in rates of return and labor income for the wealth accumulation of the rich. Third, by correcting for underreporting of inheritances,

Again, we find that *future* average returns are positively correlated with *initial* average wealth.

as well as taking into account the compounding of intergenerational transfers received earlier in life, our findings challenge previous empirical research that found little role for inheritances in wealth concentration (e.g., Charles and Hurst (2003); Black *et al.* (2022)).

As our second major empirical contribution, we document significant heterogeneity among top wealth owners. When we rank households within the top wealth group by their initial wealth and net present value of all future inheritances, we find that the bottom quartile starts with negative average net wealth of $-0.1 \times$ AW. This group, the New Money, then rapidly grows their wealth early in life, as they earn even higher returns and save at higher rates compared with the top quartile, the Old Money, and increasingly shift their portfolio from housing to private equity. After 22 years, their portfolio allocation looks similar to that of the Old Money, although their net worth falls short of reaching the levels of the Old Money.

Applying the S-O decomposition, we find that by age 50, higher saving rates (45.6%) and higher returns on net wealth (33.3%) primarily account for the wealth gap between the New Money and mid-wealth households, with higher labor income (20.1%) also contributing significantly (Figure 1b). Higher inheritances are only a minor factor (0.9%). In contrast, the fortunes of the Old Money by age 50 are mostly due to higher inheritances (46.5%), higher saving rates (32.7%), higher returns (17.5%), and only slightly higher labor income (3.3%). These results highlight that the group of wealthy households is heterogeneous, composed of both successful self-made entrepreneurs and those that can be thought of as heirs to successful businesses.

As our third major contribution, we use the empirical dynamic decomposition results to test five competing quantitative theories of wealth inequality, each of which speaks to a component in the household budget constraint. We start from a *basic model;* that is, a lifecycle Bewley model with accidental bequests and non-Gaussian idiosyncratic labor income risk estimated with our data. The second model adds a *superstar* income state to the basic model (Castañeda *et al.* (2003)). The third and fourth models augment the basic model with heterogeneity in the *rate of return* (Benhabib *et al.* (2019)) and *discount rate* (Krusell and Smith (1998)), respectively. The fifth model adds a non-homothetic *warm-glow bequest motive* to the basic model (De Nardi (2004)). All models replicate the targeted cross-sectional inequality moments, except for the basic model, which is known to not generate enough top wealth inequality (Aiyagari (1994)). Thus, without data on

the dynamics of wealth accumulation, all four augmented models are valid candidate theories of wealth inequality. By applying the S-O decomposition to simulated data, we find that accidental bequests explain at least 61% of the wealth gap between the top 0.1% group and median households in all of these models, except for the *superstar* model, which instead loads too much on labor income. Therefore, these models generally do not feature the New Money seen in the data. Instead, the wealth of the richest accumulates gradually over multiple generations. Furthermore, the Old Money do not grow their inheritances as much as our data show. These features of the data—which these models fail to capture—are crucial for the design of optimal tax policies (Guvenen *et al.* (2019)).

Based on our findings in these models, we investigate the performance of a sixth model that features heterogeneous returns that are decreasing in wealth as, e.g., in the standard model of entrepreneurship with decreasing returns to scale production technologies, and financial frictions (Quadrini (2000); Cagetti and De Nardi (2006)). We also add non-homothetic consumption-saving preferences, as in Carroll (1998), to rationalize the importance of saving rates for the wealth accumulation of the rich. This model matches the empirical S-O decomposition very well. First, net wealth and entrepreneurial productivity—thereby average realized return—are positively correlated in the stationary distribution. However, conditional on productivity, the return is declining in wealth due to decreasing returns to scale. As a result, the highly productive New Money entrepreneurs experience rapid wealth growth early in life thanks to much higher returns, whereas the fortunes of the Old Money remain bounded. Second, the non-homotheticity in saving preferences enables the model to replicate the evidence on much higher saving rates when young at the top of the wealth distribution. In sum, this model that we estimate on the S-O decomposition accounts for both the New 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 sources, taxes, transfers, and demographic information for the entire Norwegian population from 1993 to 2015. These registers include annual tax records, a shareholder registry, firm balance sheets, the inheritance tax registry, and the central population register. Most information on households is

third-party reported to the tax authorities, ensuring accuracy and reliability.[7] Figure 2 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 the Appendix OA.1 as well as the Online Supplemental Material, OSM hereafter.

Our measure of household net wealth accounts for all financial wealth (e.g., stocks, mutual funds, and bonds), non-financial wealth (e.g., real estate), and private equity, as well as the value of short- and long-term liabilities (e.g., credit card debt, student debt, and mortgages). We rely primarily on asset values and incomes reported through tax records. Financial assets such as bank accounts, bonds, mutual funds, listed shares and other securities in the Norwegian Central Security Depository (www.euronextvps.no), and liabilities (e.g., credit card debt, student debt, and mortgages) are quite accurately reported in tax records. The value of housing in each year is imputed from contemporaneous transactions data using a machine-learning method developed by Fagereng *et al.* (2020b). For other real assets, such as farm land and real estate abroad, we use their tax values, which are usually based on purchase value net of depreciation.

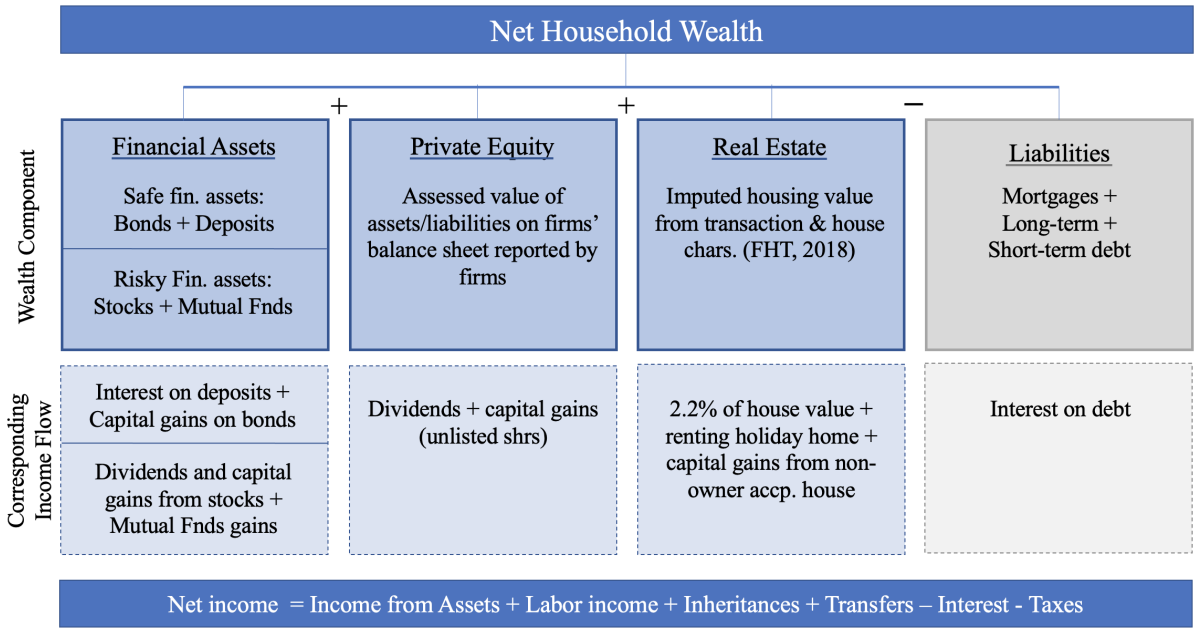
The value of equity owned by the household is primarily derived from personal tax records and supplemented with detailed information on individuals' ownership of publicly traded stocks and tax values of private firms. Tax values are recorded according to a detailed set of rules (in tax form RF-1028), that aim to measure assets at their current market values rather than at historical cost.[8] They also take into account depreciation, pension obligations, valuation of inventories, and so on. Tax values are highly correlated with book values of companies (Fagereng *et al.* (2020a)). Furthermore, neither measure includes intangible assets. Importantly, the measured firm value aligns well with the entrepreneurs' equity value in the model in Section 6. Therefore, our quantitative exercise and empirical approach are consistent.

Most income components are precisely reported in tax records, including labor earnings (comprising salaries, bonuses, earnings from self-employment, etc.), interest income

[7] Wealth and income are taxed in Norway, therefore, 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.

[8] Tax authorities regularly audit private firms to assess their value and compare it with the one reported in 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.

Figure 2 – Summary of Variables



Notes: Figure 2 summarizes the main variables used in our analysis. See Appendix OA.1 for additional details.

received, interest expenses paid, transfers, and taxes. Our data also contain information on dividends from equity. A tax reform in 2006 introduced a tax on dividends, which caused behavioral adjustments and incentivized holding private equity. First, incomes were shifted over time as large dividends were taken out prior to the reform and close to zero after. Second, holding companies were created so that dividends could be paid to the holding company from its subsidiaries, and the ultimate owner could thereby avoid (or delay) paying dividend taxes. In sum, there was an overall shift from dividends to retained earnings (capital gains) after the tax reform on 2006. Therefore, in line with previous papers using Norwegian data (Alstadsæter *et al.* (2016); Fagereng *et al.* (2020a, 2019)), we obtain both dividends and retained earnings using the link between individuals' equity ownership and companies' balance sheets given by the shareholder registry from 2005 onward. Prior to 2005, we impute dividends and capital gains using post-2005 information, which we explain in Section 3.4 (see also Appendix OA.1.4). Furthermore, because of the prevalence of holding companies at the top of the wealth distribution, we closely follow the approach in previous papers that account for indirect ownership in the calculation of returns to equity. Using the rental-equivalence approach, we impute annual income from owner-occupied housing that is equal to 2.2% of the house value.

Finally, data on inheritances are available from 1995 (when the registry was first digitalized) until 2014 (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 likely to be undervalued. For example, total bequests in the inheritance tax registry account for only 40% of the total wealth of those who die in any given year, on average. This discrepancy may reflect under-measurement of inheritances as well as donations, large health care expenditures in the year of death, and costs of transferring estate.

To correct for under measurement of inheritances, we use the statutory discount rates defined in the tax code for different asset classes. For example, transfers of private equity were given a 70% discount on assessed values below NOK 10 million (around $1.5 million) until 2009, and a 40% discount later. Since we do not observe the portfolio composition of inheritances, we use recipients' portfolio shares as a proxy. For each year we compute the average statutory discount rate for a portfolio of assets weighted by the portfolio shares, which we use to inflate measured inheritances. In 2013 our inflated value of inheritances is 2.15 times larger than the observed values. Our results are robust to inflating inheritances by 2.5 to account for the discrepancy between the total value of wealth in the last year of life and inheritances. See Appendix OA.1.3 for details.

Another shortcoming is that the data exclude the value of private or public pensions. In Norway, more than 80% of all pensions are provided through a national pay-as-you-go scheme. Almost all the rest is covered by employer-provided pension plans. And, only 0.3% of total pension wealth is held as personal pension plans, which is reported on the tax returns. Given that our focus is on the wealthiest households, pension wealth is likely to constitute a minor fraction of their net wealth.

In addition, our data exclude any wealth hidden offshore, which is not reported to the tax authorities of Norway. As shown by Alstadsæter *et al.* (2018), accounting for hidden wealth increases the share of the top 0.1% of households by 1 p.p. of total wealth. Finally, our data exclude assets whose values are difficult to measure (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 18 years old with non-missing net wealth. This leaves us with a sample of 60.2 million individual-year observations and an average of 2.6 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. We briefly describe the evolution of the cross-sectional wealth distribution over the life cycle. The average wealth displays a hump-shaped profile over the life cycle (Figure OA.5a), rapidly increasing from $0.15 \times$ AW to $1 \times$ AW between ages 25 and 45, after which wealth accumulation slows down before peaking at $1.6 \times$ 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 OA.5b). Thus, wealth concentration declines over the life cycle (Figure OA.5c) with the share of total net worth held by the top 1% declining sharply from 35% at age 25 to 18% at age 35 (as opposed to the fanning out of earnings inequality, e.g. Ozkan *et al.* (2022)). 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

We document the evolution of each component of the household budget constraint by employing two complementary approaches. In our main approach, we retrospectively investigate net wealth, rates of return, labor earnings, inheritances, and saving rates over the *previous* 22 years, conditional on the *latest* wealth quantile and age group. For example, we fix a group of households at the top of the wealth distribution in 2014 and 2015 within an age interval and follow them back to 1993 to document their wealth dynamics. Although intuitive, this *backward-looking* approach suffers from a "survival bias"; for example, by focusing on the characteristics of the households that made it to the top, we might overlook important information about the unlucky ones that did not. For this reason, we complement our retrospective approach with a *forward-looking* investigation and document the same moments from the data over the *next* 22 years, conditional on wealth quantile and age in the beginning of the sample period. Furthermore, we use our empirical findings to benchmark mechanisms behind wealth concentration using structural models.

3.1 Methodology

Backward-looking Analysis. We group households by age and wealth in the latest years of our sample and then investigate their wealth accumulation history going back to 1993. In particular, for a given base year $\tau \leq 2015$, we group heads of households into 5-year age bins, $h \in \{35-39, 40-44, ..., 75-79, 80+\}$. Here, we restrict our analysis to individuals who are 40 years and older so that we can follow them back to when they were 18 years old in 1993. Then, within each age group h, we rank individuals with respect to their average net wealth between τ and $\tau-1$, $\overline{W}^h_{i,\tau} = (W_{i,\tau} + W_{i,\tau-1})/2$, where $W_{i,\tau}$ is the net worth of household i in year τ. We use the average wealth over two years to reduce the impact of transitory wealth changes in our ranking.

We rank households into a total of nine wealth bins, BW^h_j. First, we group households with negative average net wealth, $\overline{W}^h_{i,\tau} < 0$, into one bin and define a second group of those who end up with very small but positive wealth, $\overline{W}^h_{i,\tau} \in \left[0, W^{\min}_t\right)$, where $W^{\min}_\tau$ is about \$1,500 in 2018.[9] We then partition the remaining households into the following seven bins: $\left\{\left[W^{\min}_\tau, P50\right), [P50, P75), [P75, P90), [P90, P95), [P95, P99),\right.$ $\left.[P99, P99.9), \geq P99.9\right\}$, where Px denotes percentile x of the $\overline{W}^h_{i,\tau}$ distribution.

Then, for each base year τ, for each wealth group j in each age interval h, we compute a set of moments $\mathbb{M}^\tau_{h,j}$ that are informative about the lifecycle wealth dynamics (i.e., average wealth, average saving rate, and so on). As an attempt to control for year effects, we repeat this analysis for several base years $\tau \in \{2010, 2011, ..., 2015\}$ and take an average across them $\left(\overline{\mathbb{M}}_{h,j} = \frac{1}{6}\sum_{\tau=2010}^{2015} \mathbb{M}^\tau_{h,j}\right)$.[10]

Forward-looking Analysis. We group households by their age and wealth in the initial years of our sample and investigate the wealth dynamics for these groups going forward. That is, we group heads of households at least 18 years old into 5-year age bins in each base year $\tau \in \{1994, 1995, ..., 1999\}$. Then, within each age group h, we rank households with respect to their average net wealth in τ and $\tau-1$, $\overline{W}^h_{i,\tau}$, into the previously defined wealth groups. Again, as an attempt to control for year effects, we take an average of moments over all base years within an age and wealth group. We

[9] $W^{\min}_\tau$ equals the earnings derived from working 40 hours a week for a full quarter at half the minimum wage. On average, around 7% of households in our sample have net negative wealth, and less than 1% have positive but small net wealth.

[10] In practice, we could repeat this analysis for years before 2010 at a cost of a shorter panel. Choosing 2010 as the first year ensures that we can follow individuals for at least 16 years.

denote each such forward-looking wealth j and age h group as FW_j^h. This approach allows us to uncover the heterogeneity in the wealth accumulation paths that different households expect to experience going forward.

An important detail of our approach is worth discussing. Even though we measure wealth and income at the household level, in our analysis we follow *individuals* who are heads of households in conditioning year τ. It is possible that these individuals belong to different households in different years (for example, after marriages or divorces) or that they are not identified as the heads of households in some years. As shown by Fagereng *et al.* (2022), family formation might have important implications for wealth accumulation and inequality. Our results, however, are robust to a balanced panel of stable households that remained intact during our sample period (see OSM).

3.2 Dynamic Average Wealth Profiles

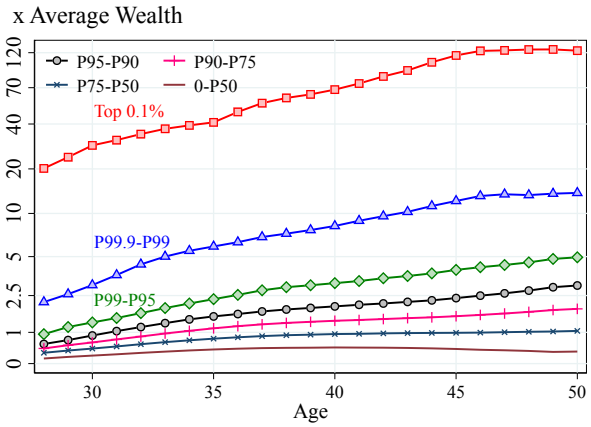
We start by documenting the evolution of households' average net worth over the life cycle for different wealth groups. We find a substantial degree of persistence, especially at the top of the wealth distribution. On average, top wealth owners already had much higher initial wealth relative to their peers 22 years prior (Figure 3a). For instance, the richest 0.1% of households aged 50–54 ($BW^{50-54}_{\geq P99.9}$) own 124.7 × AW. The same households owned 20.2 × AW when they were in their late 20s, indicating a sevenfold increase in wealth over 22 years. For the next 0.9% of the richest households, average wealth increased from 2.2 × AW to 14 × AW over the same period.

Similarly, $FW^{25-29}_{\geq P99.9}$—those in the top 0.1% of households aged 25–29—owned 28.8 × AW in the beginning of the sample period. Instead of seeing any mean reversion, this group increased their wealth to 40 × AW by their mid-40s (Figure 3b). In fact, the top group's wealth growth over the sample period is very similar to the wealth growth of the other groups in the top 10%. As a result, within-cohort wealth inequality in the right tail of the distribution remains mostly unchanged over the life cycle with relative wealth shares remaining roughly constant within the top 10% of the distribution (see OSM).

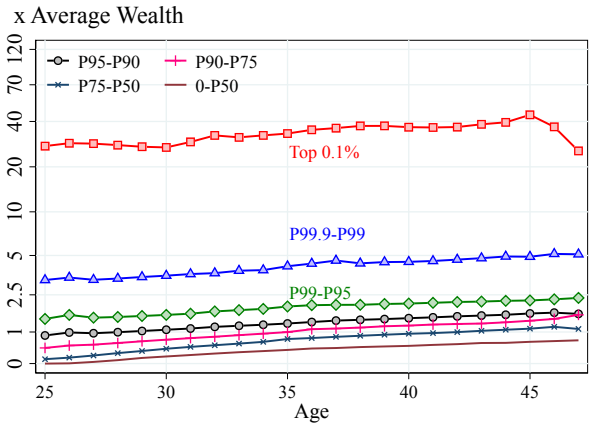
We observe a decline in wealth inequality only in the bottom half of the distribution, as young households with little wealth experience much steeper wealth growth, especially between age 30 and 40. For instance, the youngest households below the 50th percentile of the wealth distribution ($FW^{25-29}_{[W_t^{\min}, P50)}$) experience a 20-fold increase in their wealth

Figure 3 – Average Wealth Profiles

(a) Backward-Looking Wealth Profile



(b) Forward-Looking Wealth Profile



Notes: Figure 3a shows the backward-looking average wealth profile for BW_j^{50-54}. Figure 3b shows the forward-looking average wealth profile FW_j^{25-29}. The vertical axis displays the average wealth of a group in units of economy-wide average wealth (AW); it is re-scaled using the inverse hyperbolic sine (IHS) transformation (see Pence (2006)). The IHS transformation, given by $\ln\left(\theta W_{it} + \sqrt{\theta^2 W_{it}^2 + 1}\right)$ with $\theta = 0.5$, resembles a log transform but can also be applied to zero and negative values. Thus, the slopes approximate wealth growth rates.

from 0.1 × AW to 1.1 × AW (Figure 3b). Therefore, the decline in lifecycle wealth inequality (see Figure OA.5c) is mainly because of the bottom half of the distribution converging toward the median, as low-wealth households enter the working life with very little wealth and accumulate assets as they age.

Long-term Intragenerational Transition Probability Matrix

To obtain a more granular picture of wealth mobility, we construct long-term (22-year) transition probability matrices (Appendix OA.3). Consistent with our previous results, 65.4% of $BW_{\geq P99.9}^{50-54}$ were already in the top 5% of their cohort initially, and 29.2% of them were already in the top 0.1% quantile (panel A of Table I). This implies that households in $BW_{\geq P99.9}^{50-54}$ are 292 times as likely to come from the top 0.1% $\overline{W}_{i,1994}$ quantile relative to the population average. Similarly, 83.5% of $FW_{\geq P99.9}^{25-29}$ are still in the top 5% of the wealth distribution in 2015, with 23.9% being in the top 0.1% (panel B). We later refer to these households, who started their lives rich and have continued being rich, as part of the "*Old Money*" and investigate them in more detail. Yet, 21.4% of those who reach the top 0.1% of the wealth distribution started below the 75th percentile (which is about 0.5 × AW). This group of households belong to the "*New Money*" and we contrast their wealth dynamics with that of the Old Money in Section 4.

Table I – Long-term Transition Probability for the Top 0.1% Households

$< P75$	$[P75, P90)$	$[P90, P95)$	$[P95, P99)$	$[P99, P99.9)$	$\geq P99.9$
A. 1994 Wealth Quantile for $BW^{50-54}_{\geq P99.9}$ households					
21.4%	7.4%	5.9%	13.0%	23.2%	29.2%
B. 2015 Wealth Quantile for $FW^{25-29}_{\geq P99.9}$ households					
5.1%	6.3%	5.1%	22.0%	37.6%	23.9%

Notes: Panel A shows the fraction of the top 0.1% group among the 50- to 54-year-olds that come from the nth initial average wealth ($\overline{W}_{i,1994}$) quantile. Panel B shows the fraction of the top 0.1% group among the 25- to 29-year-olds that end up in the nth final average wealth ($\overline{W}_{i,2015}$) quantile.

Interestingly, few wealthy households drop below the 75th percentile even after 20 years. For example, only around 5% of the $FW^{25-29}_{\geq P99.9}$ fell to below the 75th percentile of the $\overline{W}_{i,2015}$ distribution. Thus, unlike the significant fraction of New Money—who rise through the ranks of the wealth distribution—very few wealthy households fall off from the top of the wealth distribution. In this sense, rapid wealth accumulation is more common than rapid dissaving or squandering.

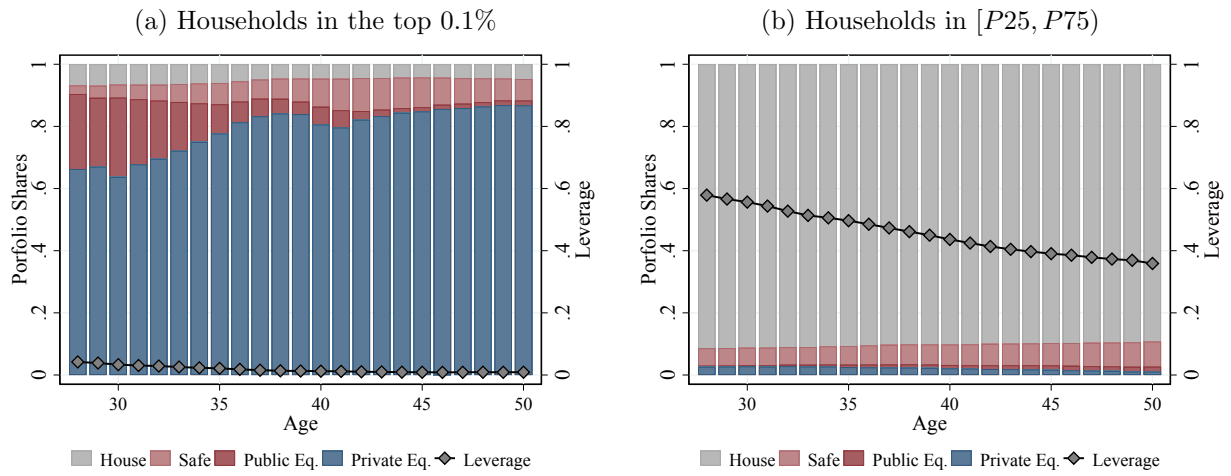
Given the similarities between the forward- and backward-looking transition matrices, for brevity, in the rest of the paper we concentrate on the results from the retrospective approach and discuss the differences with those from the forward-looking approach when necessary. For the interested reader, we present a full set of results from the forward-looking approach in OSM. Again for brevity, we focus on the wealth dynamics during prime age (up to age 50 to 54) in the main part of the paper; see OSM for results for other age groups.

3.3 Portfolio Composition and Long-term Returns

Having shown how average wealth evolves over the life cycle for different wealth groups, we now analyze differences in portfolios and rates of returns. We focus on four broad asset categories: housing (owner-occupied housing and other real estate), safe assets (bonds, cash, and deposits), public equity (directly held stock and mutual funds), and private equity. We also report leverage as the ratio of all household liabilities (mortgages, credit card debt, student debt, and others) to the sum of assets. Finally, all moments are weighted by the total value of household assets.

As has been extensively documented in cross-sectional data (e.g., Carroll (2000)), wealthy households on average hold most of their wealth in equity, particularly in private

Figure 4 – Backward-Looking Portfolio Shares



Notes: Figure 4 shows the evolution of the portfolio shares (left y-axis) and leverage (right y-axis) for households in BW_j^{50-54}. Portfolio shares are calculated as the ratio between the value of all assets in a particular category (e.g., total value of safe assets) over the total value of gross wealth (i.e., sum of wealth in housing, safe assets, public equity, and private equity) within a wealth rank and age group. Within-group leverage is the ratio between the sum of all debt (e.g., mortgages, student debt, credit card debt) and the sum of all total assets within a wealth rank and age group.

businesses. We also show that the wealthiest have invested a substantially higher share of their portfolio in private businesses starting from very young ages (Figure 4a). For the top 0.1% group of 50- to 54-year-olds ($BW_{\geq P99.9}^{50-54}$), the average share of the portfolio invested in equity over the previous 23 years hovers above 80%, of which at least three quarters are invested in private equity.[11] They have a much smaller share of safe assets and housing in their portfolios, which remain more or less constant over the life cycle. Finally, they maintain a very small amount of leverage over their lives, which never increases above 10% of total assets.

Have the current wealthiest invested in equity more heavily in the past compared with those with similar wealth and age, or do the aforementioned large portfolio shares for them reflect the cross-sectional correlation, as previously documented (e.g., Carroll (2000))? To investigate this question, we regress the portfolio equity share in every year t between 1993 and 2013 on dummies for 2014–2015 average wealth groups ($\overline{W}_{i,2015}^h$). We control for the highly nonlinear contemporaneous relationship between wealth and

[11] As discussed, our retrospective analysis may suffer from survival bias. So, it is possible that the current wealthiest are those who were lucky with their businesses and ended up at the top of the wealth distribution, thereby having a large portfolio share of private equity. However, our forward-looking analysis for the same cohort similarly shows between 60% and 70% portfolio share of equity for the wealthiest and, again, mostly in the form of private equity. Thus, survival bias is likely to be small.

Table II – 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 II shows the coefficients of a panel regression of equity shares on $\overline{W}^h_{i,2015}$ dummies. 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 (*** $p < 0.01$).

portfolio shares by including 28 dummies of net worth in every year t ($W_{i,t}$) as well as year and age effects. We find that even conditional on contemporaneous wealth and age, those households that end up in the top 0.1% invest 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 II). 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); Smith *et al.* (2019)).

In contrast, for households between the 25th and 75th percentiles ($BW^{50-54}_{[P25,P75)}$), housing is the single most important asset in their portfolios, constituting around 90% of their gross wealth throughout the sample period (Figure 4b).[12] Median-wealth households start their lives with much higher leverage (60% of total assets), mostly in the form of long-term debt and reduce it below 40% of total assets. Moreover, portfolio shares are quite similar below the 95th percentile of the wealth distribution. These differences between high- and median-wealth groups are also similar across cohorts (see OSM).

Long-Term Returns on Portfolios

Recent empirical evidence has found significant cross-sectional dispersion in returns (e.g., Fagereng *et al.* (2020a); Bach *et al.* (2020)), which has been argued to be key

[12] The share of publicly-traded stocks, owned either directly by individuals or indirectly through mutual funds, is significantly lower in Norway relative to the US and other OECD countries, and the opposite is true for real estate wealth (see OSM). This is because, first, the Norwegian government actively promotes homeownership through tax policies and housing market regulations; therefore, homeownership rates are above 80% in Norway compared to around 65% in the US. Second, the total value of public equity relative to the GDP is small in Norway relative to the US, mainly because of tax incentives favoring private equity. Third, the public pension system in Norway owns roughly one-third of the public equity (see Fagereng *et al.* (2019)).

for explaining top wealth concentration (e.g., Benhabib *et al.* (2011)). We now turn to *long-term average returns* from each asset class across different wealth and age groups.

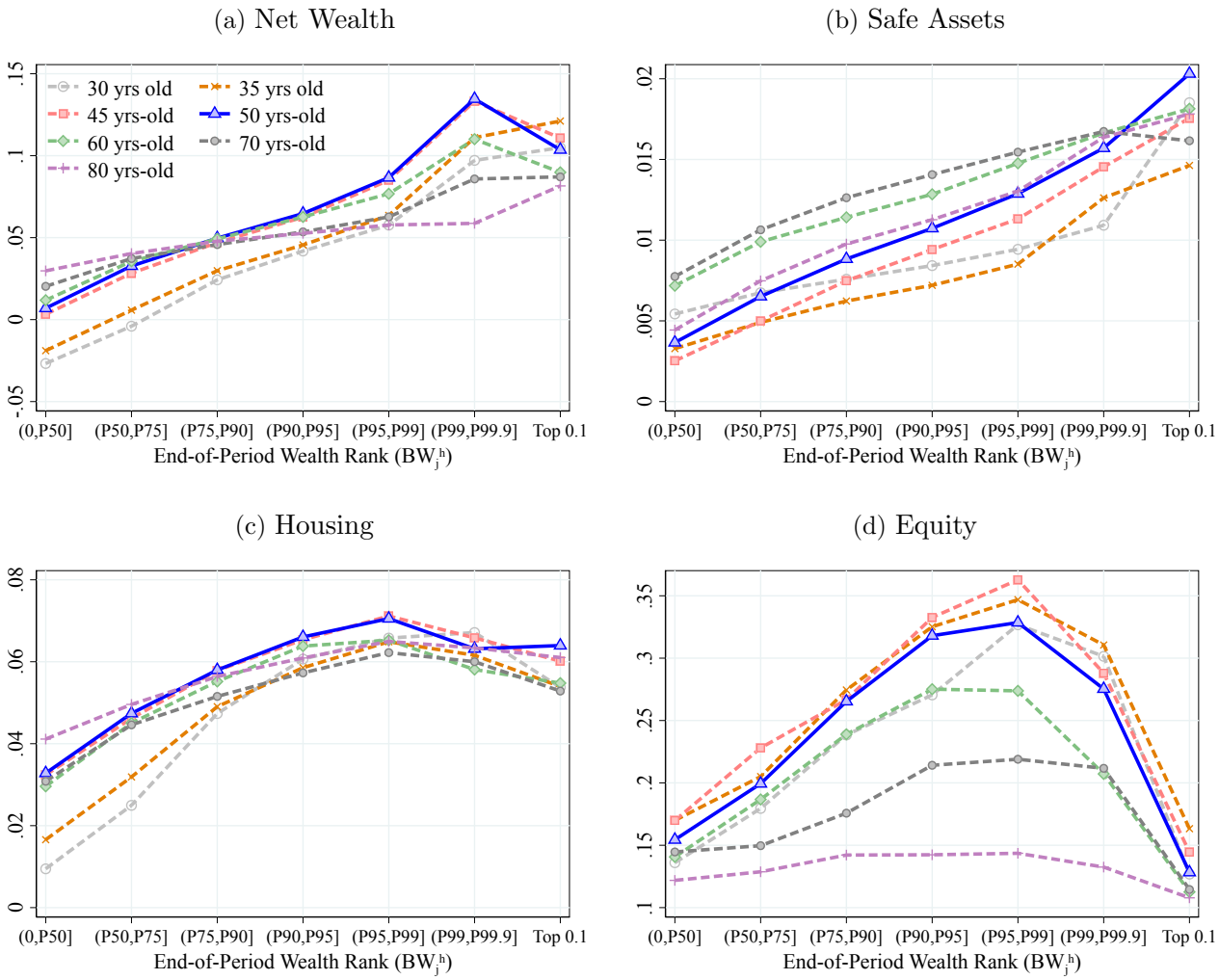
In our analysis, we follow Fagereng *et al.* (2020a), FGMP hereafter, in calculating the ex post (i.e., not the expected) return as the ratio of annual income (including unrealized capital gains) generated from the asset to its value at the beginning of each year, which we adjust for intra-year asset purchases and sales à la Dietz (1968). All moments of returns are weighted by the value of the corresponding asset. Furthermore, to compute returns on private equity we use data from shareholder registers on private companies, which is available from 2004 onward. Therefore, unlike the rest of the paper, the results in this section are computed for the latter half of the sample period. Despite a few differences between our and FGMP's methodologies, we find similar cross-sectional moments of returns, as well as similar contemporaneous positive correlation between average returns and net wealth. For details of our method and comparison with FGMP see Appendix OA.4.

Figure 5a shows large differences in the long-term average returns on net wealth across the wealth distribution. For instance, for households aged 50–54, the average annual return over the previous 10 years increases monotonically from around 0% for those below median ($BW^{50-54}_{[W_t^{\min},P50)}$) to about 10% for the top 0.1% group ($BW^{50-54}_{\geq P99.9}$).[13] Interestingly, these differences are more pronounced among the younger cohorts. There is almost a 12 p.p. difference between the highest- and lowest-return groups among 35- to 39-year-olds but only a 8 p.p. difference among households aged 75–79.

Return heterogeneity across the wealth distribution can, first, stem from differences in portfolios: Wealthier households invest a larger share of their portfolios in equity, for which the average annual return is 12.0% versus 2.6% and 4.4% for safe assets and housing, respectively. Second, wealthier households might also earn higher returns within each asset class. The long-term average return on safe assets increases from below 0.5% for those below median to 2.0% for the top 0.1% group (Figure 5b). Returns on housing and, more so, on equity instead display hump-shaped patterns over the wealth distribution, which are more pronounced for younger cohorts. The long-term average return on housing increases monotonically from around 3% for $BW^{50-54}_{[W_t^{\min},P50)}$ to about 7% for

[13] The higher-than-average returns earned by rich households are explained, in part, by relatively more dispersed returns (Figure OA.4a). However, this larger dispersion is mostly due to higher upside risk as measured by a positive Kelley skewness (Figure OA.4d). See Appendix OA.4.2 for details.

Figure 5 – Long-Term Average Returns on Assets across the Wealth Distribution

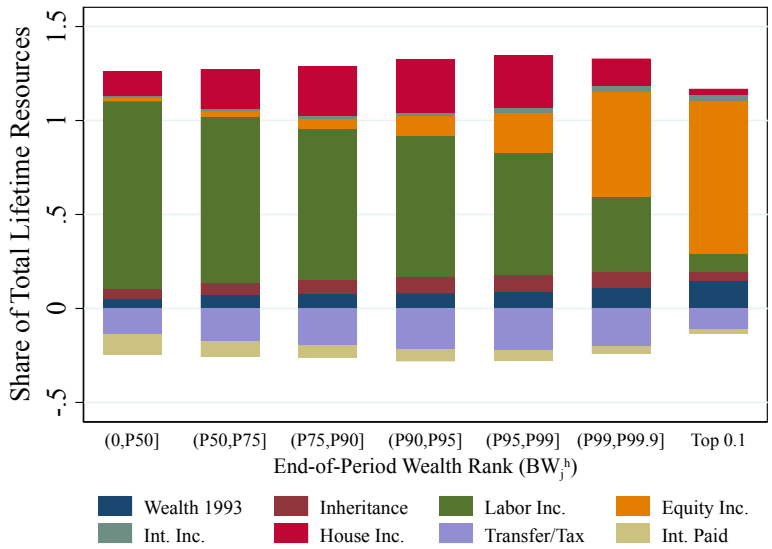


Notes: Figure 5 shows the value-weighted cross-sectional mean of annual returns within age and wealth groups averaged across different conditioning years.

those in $BW^{50-54}_{[P95,P99)}$ and then declines to 6.2% for $BW^{50-54}_{\geq P99.9}$ (Figure 5c). Similarly, equity returns increase substantially from 15% for below-median households to 32% for $BW^{50-54}_{[P95,P99)}$, and then strongly decline to 12% for the top 0.1% group (Figure 5d).[14] Therefore, we conclude that the top 0.1% group enjoys higher returns on their net worth mainly because they hold a much larger fraction of their portfolio in equity.

[14]FGMP find a positive correlation between net wealth and equity returns. Differences between our results and theirs arise from using weighted as opposed to unweighted measures (see OSM). Furthermore, as we discuss in Section 6, the hump-shaped pattern of equity returns is qualitatively consistent with standard models of entrepreneurs operating a decreasing returns-to-scale production technology and subject to a collateral constraint (Quadrini (2000); Cagetti and De Nardi (2006); Buera *et al.* (2015)). Boar *et al.* (2022) likewise document declining equity returns by firm value in Spain.

Figure 6 – Decomposition of Total Lifetime Resources



Notes: Figure 6 shows the shares of lifetime resources across the BW_j^{50-54} distribution. Total lifetime resources are calculated as the sum of all sources of income within an age and wealth group. Shares are calculated separately for each conditioning year and then averaged across all conditioning years.

3.4 Sources of Lifetime Income

So far we have documented that, on average, the current wealthiest started their working lives already quite rich and have invested their portfolio mostly in equity, which then allowed them to earn higher returns. In this section, we investigate other sources of income and quantify their importance in the long-term budget constraint. Consider the sum of yearly budget constraints between 1993 and τ:

$$W_{i,\tau} = W_{i,1993} + \underbrace{\sum_{t=1994}^{\tau} \left[L_{i,t} + H_{i,t} + R^E_{i,t} + R^S_{i,t} + R^H_{i,t} + T_{i,t} - I^L_{i,t}\right]}_{\text{Total lifetime Income:}\overline{Y}_{i,\tau}} - \sum_{t=1994}^{\tau} C_{i,t}. \quad (1)$$

In Equation (1), $W_{i,t}$ is household i's net wealth at the end of year t, and $L_{i,t}$ and $H_{i,t}$ are labor income (including self-employment income) and inheritances (including inter vivos transfers), respectively. Similarly, $R^E_{i,t}$, $R^S_{i,t}$, and, $R^H_{i,t}$ denote the income from equity (from public and private equity, including unrealized capital gains), safe assets, and real estate, respectively.[15] Finally, $T_{i,t}$ and $I^L_{i,t}$ represent public transfers net of

[15]The shareholder register on private limited companies is only available after 2004; therefore, we impute the capital income from private businesses before 2004. We have experimented with a variety of

taxes (including taxes on different sources of income, inheritances, and wealth) and total interest payments for liabilities (e.g., mortgages, student loans, credit cards, and so on), respectively. We denote the sum of these flows between 1993 and τ as the total lifetime household income of i, $\bar{Y}_{i,\tau}$. So, household i has $\bar{Y}_{i,\tau} + W_{i,1993}$ total lifetime resources at her disposal during this period, which she can split between consumption, $\sum_{t=1994}^{\tau} C_{i,t}$, and final wealth, $W_{i,\tau}$.[16]

We investigate the importance of each of these components by documenting their share out of total lifetime resources. For example, for household labor income for individual i, we compute $\left(\sum_{t=1994}^{\tau} L_{it}\right) / \left(W_{i,1993} + \bar{Y}_{i,\tau}\right)$. As before, for each τ within each age h and wealth group j, we compute the average share of each income source weighted by the total lifetime resources of individuals, $\left(W_{i,1993} + \bar{Y}_{i,\tau}\right)$, and then take an average across base years, $\tau \in \{2010, 2011, ..., 2015\}$.

Figure 6 shows these average shares across different wealth groups among households aged 50–54. The most important source—81.3%—of lifetime income for top 0.1% wealth owners is equity income (sum of dividends and capital gains). This is consistent with our previous results that top wealth owners are heavily invested in private businesses, which earn higher returns (see Figures 4a and 5a). In contrast, for households below the 90th percentile of the wealth distribution, labor income constitutes the majority of their resources with a share of 80% or more. For the top 0.1% group, initial wealth $W_{i,1993}$ (which captures the total resources available for the household at the beginning of the sample period) and labor income constitute a smaller but still significant fraction of lifetime resources (15.0% and 9.5%, respectively).[17] Inheritances (after 1994) on average account for a small share of total resources (4.3%) even for the wealthiest group (see

imputation methods that exploit the differences in wealth and equity portfolio shares. Our benchmark imputation relies on the insight that households that earn higher returns on equity increase their equity portfolio share. Therefore, we first divide our sample into groups based on household age and the growth rate of equity portfolio share. We then use the post-2004 data to calculate the average contemporaneous returns on equity (i.e., the ratio of equity income—including dividends and capital gains—to the value of equity) for each group. Finally, we apply these group-specific average returns prior to 2004. Our results from the post-2004 sample are very similar to the benchmark results. Other papers have used other methods to complete information prior to 2005. For example, Fagereng *et al.* (2019) approximate capital gains on publicly traded stock prior to 2005 using the OBXP stock price index.

[16] Our definition of total lifetime resources is similar to the measure of "Potential Wealth" in Black *et al.* (2020). However, they do not include unrealized capital gains from private equity.

[17] Naturally, initial wealth becomes more important for older cohorts who have had more time to accumulate wealth prior to 1993, increasing from 8.5% for 45- to 49-year-olds to 42.4% for those aged 75–79 (see OSM). Similarly, labor income becomes less important for older cohorts.

also Black *et al.* (2022)). Finally, taxes net of transfers reduce total lifetime resources for all wealth groups but much less so for the wealthiest group, indicating the favorable tax treatment of equity income relative to labor income in Norway.

The above analysis reveals that equity income constitutes the majority of lifetime resources for top wealth owners; however, it does not reflect the fundamental source of equity investment, whether it is inherited or saved from labor earnings. In Section 5, we perform a S-O decomposition that empirically decomposes wealth differences across groups into differences in inheritances, labor earnings, returns, and saving rates.[18]

3.5 Lifecycle Saving Rate Heterogeneity

Several papers have shown that richer households also save a larger fraction of their total resources relative to the rest of the population (e.g., Fagereng *et al.* (2019), Bach *et al.* (2017), Carroll (1998), and Dynan *et al.* (2004)). We show that this holds true from a lifecycle perspective as well and that the heterogeneity in lifetime saving rates is quantitatively significant. We define the lifetime saving rate for individual i as the ratio of cumulative savings over cumulative gross income (including capital gains). Using the notation of the budget constraint (1), the lifetime saving rate is given by $S_i = (W_{i,\tau} - W_{i,1993}) / \bar{Y}_i$. As before, for each τ within each age h and wealth group j, we compute the average saving rate weighted by the total lifetime income of individuals, $\bar{Y}_i$, and then take an average across base years τ.

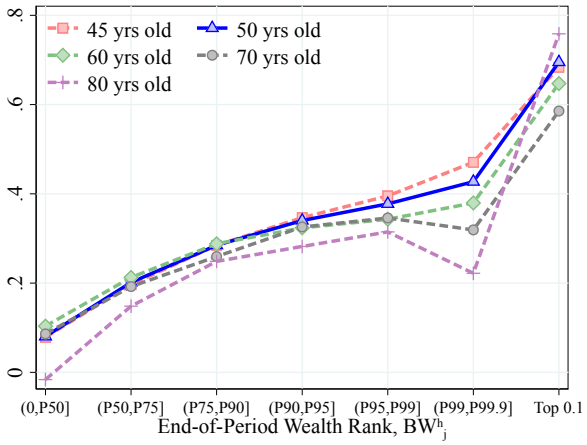
Figure 7a shows that the saving rate is increasing conditional on the end-of-period wealth group, BW_h^j, ranging from 0% to 10% for the bottom half of the wealth distribution to 60% to 75% for the top 0.1%, with relatively little variation by age. That is, the richest households save around three-quarters of their lifetime income, while the middle class (P50-P75) saves around 20% of their lifetime income. These patterns are qualitatively and quantitatively similar to those reported in Fagereng *et al.* (2019).[19] Obviously,

[18] Furthermore, in an additional accounting exercise (see OSM), we attribute income from capital to four fundamental sources of income: (i) initial wealth at the end of 1993, (ii) inheritances, (iii) labor income, and (iv) net transfers from the government. We find that the single most important fundamental component for the wealthiest group is initial wealth in 1993.

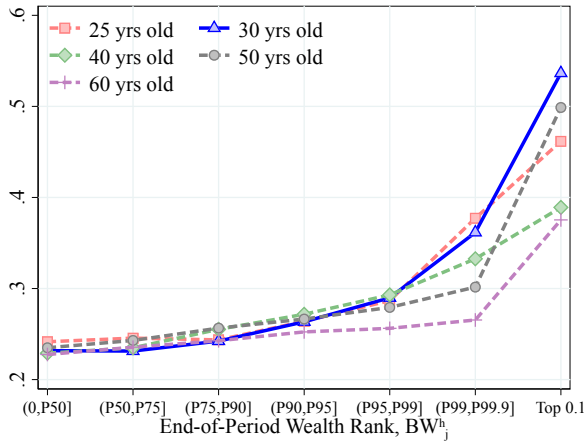
[19] Fagereng *et al.* (2019) emphasize that the increase in the gross saving rate by wealth is driven by higher capital gains, and that the net saving rate is rather flat across the wealth distribution. We confirm that a significant fraction of gross savings is coming from capital gains at the top, in particular from private businesses. However, in this paper we use the gross saving rate, which treats business income symmetrically regardless of whether profits are retained in the firm or paid out as dividends to the firm's owners.

Figure 7 – Lifetime Gross Saving Rate Across the Wealth Distribution

(a) Backward Looking



(b) Forward Looking



Notes: Figure 7 shows the lifetime saving rate by age and wealth group, defined as cumulated savings over cumulated gross income within BW_j^h and FW_j^h wealth groups.

these large differences have strong implications for the differential wealth accumulation patterns between the wealthiest and the rest of the population, which we systematically investigate (along with other possible explanations) in Section 5.

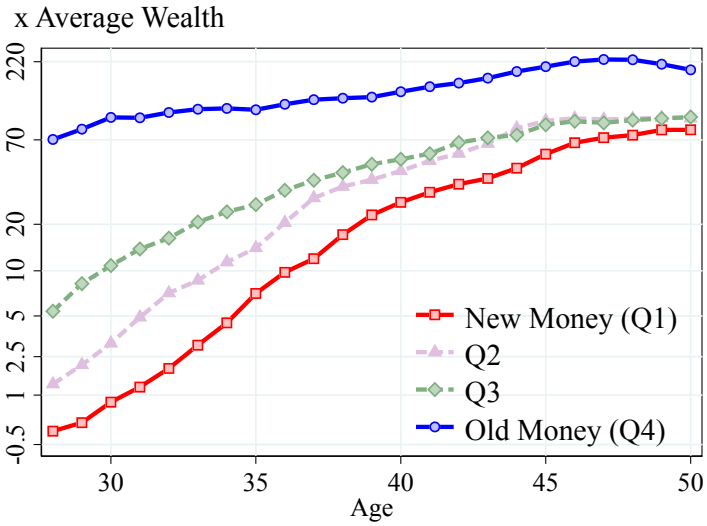
A potential concern is that the positive correlation between wealth and saving rates is mechanical, as higher saving rates move households up the wealth distribution. However, Figure 7b confirms that lifetime saving rates across the wealth distribution are also strongly increasing in wealth when ordering households by initial wealth instead (FW_h^j). Although the relationship is quantitatively weaker—the mechanical effect discussed above is present—it is still strong: While households starting below P75 save around 25% of their lifetime income, those in the top 0.1% save between 40% and 55%.

4 New Money versus Old Money

While, *on average,* the wealthiest households start their working lives very rich, at least a quarter of them start with very little wealth (Section 3.2). In this section, we study within-group heterogeneity among the wealthiest. For this purpose, we rank the households in the top 0.1% group aged 50–54 $\left(BW^{50-54}_{\geq P99.9}\right)$ into four quartiles according to the sum of their initial average wealth ($\overline{W}_{i,1994}$) and net present value of all future inheritances.[20] We call the bottom quartile households the "New Money," who start

[20] We discount future inheritances using the average return on net wealth of 3.3%. In an earlier version (Ozkan *et al.* (2023)), we rank only according to their wealth in 1993, with very similar results.

Figure 8 – Average Wealth Profile: Old Money and New Money



Notes: Figure 8 shows the average wealth profile for households in the $BW^{50-54}_{\geq P99.9}$ wealth-age group, which are ranked in quartiles according to the sum of their initial average wealth $(\overline{W}_{i,1994})$ and the present value of all future inheritances net of taxes.

their working lives with little wealth and receive little intergenerational transfers but reach the top of the wealth distribution eventually. The top quartile is then called the "Old Money," who start at the top of the wealth distribution within their cohort and remain in the top wealth group. We further confirm that the New Money actually come from modest backgrounds with little resources, whereas the Old Money are much more likely to have rich parents. For instance, 6.2% and 26.5% of the Old Money have parents in the top 0.1% and top 1% of their cohorts' wealth distribution, respectively (see Figure OA.6). In contrast, only 1.1% and 6.8% of the New Money have parents in the top 0.1% and top 1% of the wealth distribution, with 75% of their parents being in the bottom 90%.

4.1 Average Wealth Profiles

The Old Money have, on average, a net worth of around 70 × AW in the economy in 1993 versus a negative −0.1 × AW for New Money (Figure 8). The New Money then experience steep wealth growth especially in the first 10 years of their working lives, after which the growth rate slows down, generating a concave lifecycle wealth profile. As for the Old Money, their wealth more than doubles over the next two decades. As a result, even though the gap between the Old Money and New Money shrinks significantly, it remains quite large even after 22 years. Figure 8 also shows that 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.[21]

Where does initial wealth (of the Old Money) come from? Although we do not have data on inter vivos transfers and inheritances prior to 1994, we use data on post-tax and transfer labor earnings since 1967 to argue that the vast majority of initial Old Money wealth should be thought of as intergenerational transfers. First, the sum of earnings prior to 1993 after age 18—the age individuals enter the tax records—amounts to only 5.4 × AW, or 7.1% of initial Old Money wealth. Second, instead of simply summing up all labor income, we capitalize it after age 18 until 1993 using the average saving rate and return on wealth observed between 1993 and 2015 for this group. They would have accumulated 5.7 × AW from their labor income prior to 1993, which again accounts for only 7.5% of their initial wealth.[22] Finally, in Section 5 we extend the S-O decomposition back to age 18 by finding younger "twins" of the Old Money to show that the fundamental source of their wealth in their late 20s is intergenerational transfers.

4.2 Portfolio Composition

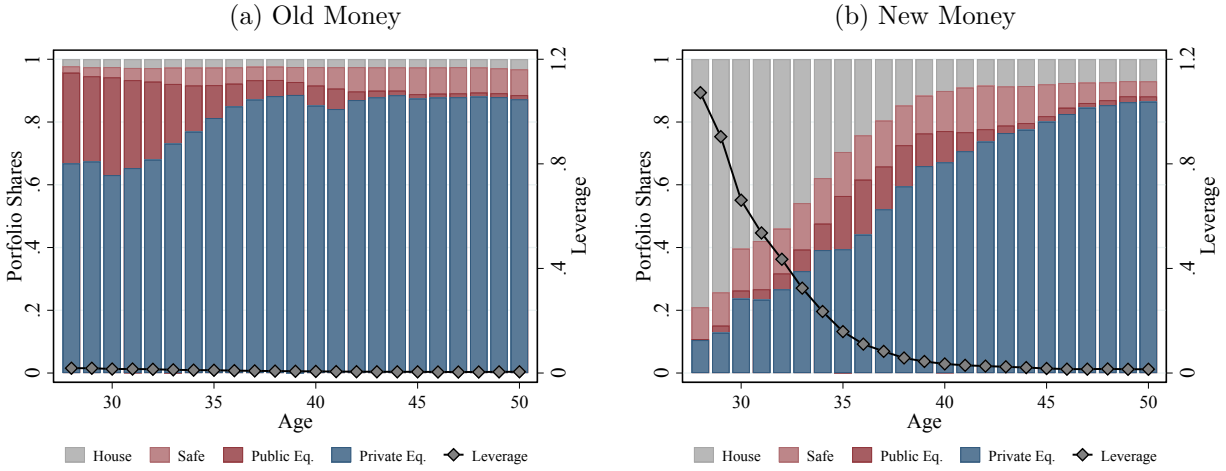
In Section 3.3 we showed that the wealthiest on average have invested a substantially higher share of their portfolio in equity starting from very young ages. However, the (weighted) average portfolio shares mask interesting heterogeneity among top wealth owners. The New Money start their working lives with 10.8% of their portfolios invested in equity (Figure 9). As they grow their wealth, its composition shifts from housing to private equity, whose share reaches 88.1% by their 50s, similar to the private equity share of the Old Money. Interestingly, the New Money start highly indebted—with a 1.1 debt-to-asset ratio (thereby starting with negative average net wealth)—but quickly reduce their leverage over the first 10 years. As we revisit in Section 6, these facts are consistent with standard entrepreneurship models with borrowing constraints (as in Cagetti and De Nardi (2006); Quadrini (2000)), in which highly productive but poor entrepreneurs leverage to invest in their firms.[23] Similar to our results for top wealth

[21] 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.

[22] Wealth accumulation from labor income varies between 3.3% of the initial wealth for the 40- to 44-year-old households to 9.2% of the initial wealth of those aged 55–59.

[23] Do the New Money typically own single-establishment firms in professional services (e.g., lawyers, consultants) or health services (e.g., medical doctors, dentists)? First, only 10% of the New Money and

Figure 9 – Portfolio Shares: Old Money and New Money



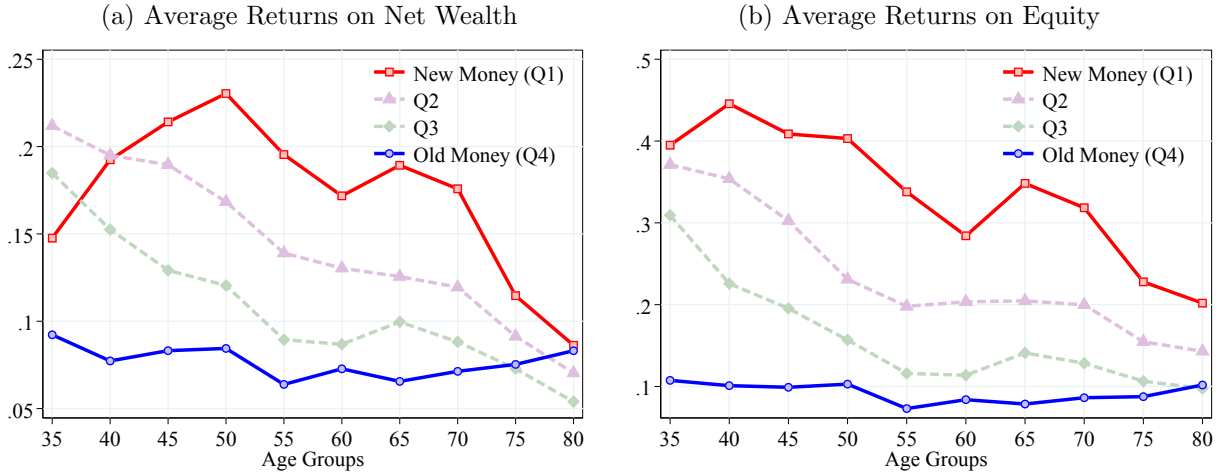
Notes: Figure 9 shows the portfolio composition and leverage for households in the $BW^{50-54}_{\geq P99.9}$ wealth-age group. Old Money in Panel a (New Money in Panel b) are households in the fourth quartile (first quartile) according to the sum of their initial average wealth $(\overline{W}_{i,1994})$ and the present value of all future inheritances net of taxes.

owners, we find that the Old Money have always been heavily invested in equity and, in particular, in private business. And they further skew the composition of their risky assets toward private businesses as they get older but keep the total share of risky assets more or less constant over their lifetime. They are not levered at all; their debt-to-asset ratio is broadly less than 1%. We find similar patterns for other age groups and the top 1% of households, $BW^{h}_{\geq P99}$ (see OSM).

Rates of Return on Investment. Having shown the differences in portfolio allocation between the New Money and Old Money, we now turn to rates of return on their investment. Starting with the return on net wealth, we find that the New Money have earned substantially higher returns across all age groups, though the differences are more pronounced for younger cohorts (Figure 10a). For example, for those between 35 and 39 years of age, the average return on net wealth is around 15% for the New Money versus around 10% for the Old Money. This is surprising because, as we discussed above, the New Money initially have less equity in their portfolios, which earns much higher returns

Old Money have law or medical degrees, whereas a significant fraction have a high school education or less (38% of New Money and 48% of Old Money; see OSM for details). Second, wealth accumulation dynamics for both groups are similar among medical doctors and lawyers. Therefore, highly educated entrepreneurs neither drive the differences between the New Money and Old Money nor are heavily represented in the top wealth groups (unlike Smith *et al.* (2019) have shown for the US). This is, in part, because unlike the US health care is provided by the public sector in Norway. And, Norway is a civil law country, whereas the US follows the common law legal system (where lawyers play a more significant role).

Figure 10 – Long-Term Average Returns: Old Money and New Money



Notes: Figure 10 shows the 11-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 $(\overline{W}_{i,1994})$ and the present value of all future inheritances net of taxes.

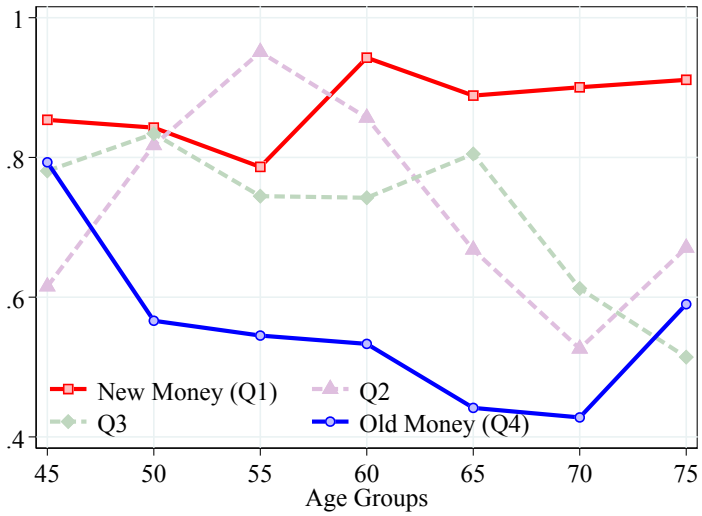
compared with other types of assets. Hence, we also investigate average returns for each asset class individually.

Earlier in life, the New Money are mostly invested in housing, from which they do not earn higher returns compared with the Old Money. Moreover, we do not find significant differences for returns from safe assets between these groups either (see OSM for returns on housing and safe assets). Instead, the differences in net wealth returns are mainly accounted for by the higher equity returns for the New Money relative to the Old Money (Figure 10b). For example, again for the youngest cohort, the New Money have earned a staggering 40% annual average return on their equity investment versus around 10% for the Old Money. Thus, even though the New Money have a smaller share of their wealth invested in equity, the much higher returns from these investments allow them to earn higher long-term returns on net wealth relative to the Old Money.

Interestingly, differences in returns between the Old and New Money are more pronounced among younger cohorts. Furthermore, the decline in returns as we move from Old to New Money is mostly monotonic in that the returns for the middle two quartiles are in between those of the Old and New Money. These patterns suggest a decreasing returns-to-scale production function which we further investigate in Section 6.

The higher returns on equity for the New Money, however, are associated with higher

Figure 11 – Saving Rate: Old Money and New Money



Notes: Figure 11 shows the lifetime saving rate for four quartiles in the $BW^{h}_{\geq P99.9}$ group according to the sum of their initial average wealth $(\overline{W}_{i,1994})$ and the present value of all future inheritances net of taxes. For the definition of the lifetime saving rate, see Section 3.5.

risk. For instance, among 35- to 39-year-olds, the P90-P10 gap of the returns on net wealth is around 60% for the New Money versus slightly below 40% for the Old Money. Again, these differences are more pronounced for the youngest age groups. Furthermore, they are mainly driven by riskier equity investment for the New Money relative to the Old Money. However, the higher dispersion of equity returns for the New Money is also accompanied by a more positive skewness, indicating higher upside risk.

4.3 Lifetime Saving Rate

The large differences in rates of return, and the corresponding increase in the portfolio share of private equity among the New Money, explain some of the convergence of wealth accumulation displayed in Figure 8. However, we find that the New Money also save at higher rates than the Old Money. Figure 11 shows that within the top 0.1% of wealth owners, the saving rate—defined in Section 3.5—is generally declining from the first quartile of initial wealth $(\overline{W}_{i,1994})$ to the top quartile, ranging from around 87% for the New Money to around 55% for the Old Money. That is, the New Money's saving rate is 30 p.p. higher than that of the Old Money. In the next section, we quantify the importance of these channels (e.g., saving rate, rate of returns, 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 rich households differ from the rest of the population in their initial wealth, portfolio composition, rates of return, 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 four main sources of heterogeneity: rates of return, saving rates, labor income, and inheritances (including inter vivos transfers). The starting point of this decomposition is the budget constraint of household i in year t:

$$W_{i,t} = W_{i,t-1} + \left(\tilde{L}_{i,t} + \tilde{H}_{i,t} + \tilde{R}_{i,t} W_{i,t-1}\right) \times S_{i,t}, \tag{2}$$

where $\tilde{L}_{i,t}$ denotes labor earnings (including self-employment income) after taxes and government transfers (such as unemployment and disability benefits), whereas $\tilde{H}_{i,t}$ is the after-tax value of inheritances.[24] The after-tax return on net wealth is given by,

$$\tilde{R}_{i,t} = \left(R^E_{i,t} + R^S_{i,t} + R^H_{i,t} - I^L_{i,t} - T^W_{i,t}\right) / W_{i,t-1},$$

where $R^E_{i,t}$, $R^S_{i,t}$, and $R^H_{i,t}$ denote household income (including unrealized capital gains) from public and private equity, safe assets, and real estate, respectively. Here, $I^L_{i,t}$ and $T^W_{i,t}$ denote the total interest payments and total taxes paid for wealth and capital income, respectively. Finally, we define the gross saving rate as

$$S_{i,t} = \left(W_{i,t} - W_{i,t-1}\right) / \left(\tilde{L}_{i,t} + \tilde{H}_{i,t} + \tilde{R}_{i,t} W_{i,t-1}\right),$$

which is the per-period equivalent of the gross saving rate discussed in Section 3.5.[25] Using the budget constraint defined in Equation (2), we define the path of net worth between 1994 and τ as a function of five sets of contributing factors (initial wealth, labor income, inheritance, rates of return, and saving rate):

$$\{W_{i,t}\}_{t=1994}^{\tau} = f\left(W_{i,1993}, \left\{\tilde{L}_{i,t}, \tilde{H}_{i,t}, \tilde{R}_{i,t} S_{i,t}\right\}_{t=1994}^{\tau}\right).$$

[24] In equation (1), the variable, T_{it}, denotes all taxes and transfers. Instead, here we split the total taxes into taxes paid for labor income, inheritances, wealth, and capital income.

[25] One can write the above budget constraint using alternative saving rate definitions. For example, we have considered the budget constraint with a saving rate out of cash-on-hand (i.e., $\tilde{S}_{it} = W_{i,t} / \left(W_{i,t-1} + \tilde{L}_{i,t} + \tilde{H}_{i,t} + \tilde{R}_{i,t} W_{i,t-1}\right)$) and we have come to similar conclusions (seeOSM).

We then use this function to reconstruct the evolution of wealth when counterfactually replacing these factors by the values of a reference group.[26] We use the middle 50% of the population (households between the 25th and 75th percentiles of wealth) in the same age group, $BW^h_{[P25,P75)}$, as the reference group. So, for a group BW^h_j, we start from the budget constraint in the initial year and simulate the counterfactual evolution of wealth consecutively for the following years by simply setting some or all factors to their value for the $BW^h_{[P25,P75)}$ group. For example, to investigate how the wealth profile would look for the top 0.1% of wealth owners if they had earned the same rates of return as the middle 50% of the population, we construct the counterfactual average wealth profile for $BW^{50-54}_{\geq P99.9}$ by assigning them the after-tax return of $BW^{50-54}_{\geq[P25,P75)}$ while keeping all other factors fixed at their actual values—that is, $f\left(W_{i,1993}, \left\{\tilde{L}_{i,t}, \tilde{H}_{i,t}, \tilde{R}_{BW^{50-54}_{[P25,P75)}}, S_{i,t}\right\}^{\tau}_{t=1994}\right)$.[27]

Because our data cover a 23-year period, our baseline analysis for households aged 50–54 can only go back to when they were 28 years old in 1993. However, the wealthiest households, especially the Old Money, already have a very large amount of wealth in their late 20s. Therefore, it is important that we start our decomposition exercise from age 18—the age individuals enter the tax records—to shed light on the determinants of the large wealth gap before age 28. To this end, we find younger "twins" of the wealthiest households in our baseline sample that (i) have similar wealth profiles and (ii) are 18 years old or younger in 1993. We use the Mahalanobis (1936) multivariate distance metric to measure the distance between a potential twin's wealth profile between ages 28 and 37 and the distribution of those from the original wealthiest households aged 50–54. We then pick as many twins as the number of original wealthiest that have the minimum Mahalanobis (1936) distance between them. The average wealth profiles of twins and originals between ages 28 and 37 match well (Figure OA.1). Additional details of the implementation of this method can be found in Appendix OA.2. Finally, since we start our decomposition at age 18, we interpret the initial wealth of 18-year-olds

[26] To be precise, we implement this exercise at the age-wealth group level by aggregating the budget constraint in equation 2 within each BW^h_j: $\bar{W}^{h,j}_t = \bar{W}^{h,j}_{t-1} + \left(\bar{L}^{h,j}_t + \bar{H}^{h,j}_t + \bar{R}^{h,j}_t \bar{W}^{h,j}_{t-1}\right) \times \bar{S}^{h,j}_t$, where $\overline{W}^{h,j}_t$, $\overline{L}^{h,j}_t$, and $\overline{H}^{h,j}_t$ are the average wealth, after-tax labor income, and after-tax inheritances of BW^h_j in year t, respectively. We then take a weighted average of after tax returns (weighted by $W_{i,t-1}$) to construct $\bar{R}^{h,j}_t$ and of $S_{i,t}$ (weighted by total income $(\tilde{L}_{i,t} + \tilde{H}_{i,t} + \tilde{R}_{i,t} W_{i,t-1})$) to construct $\bar{S}^{h,j}_t$.

[27] As in the rest of our analysis, we repeat our analysis for each base year $\tau \in \{2010, 2011, ..., 2015\}$ and take the average over τ. See Appendix OA.2 for details including the average values of each component for each wealth group among 50- to-54-year olds, BW^{50-54}_j.

as intergenerational transfers. For brevity, in Figure 1a we combine initial wealth and inheritances (including inter-vivos transfers) in one category. However, in our analysis below we show inheritances before age 18 (initial wealth) and after age 18 separately to illustrate their individual roles in wealth accumulation.

To start with, we construct wealth profiles, changing only one factor at a time. This simple exercise uncovers the importance of one particular factor in isolation from changes in other contributing factors. In our main exercise, in order to provide a cumulative decomposition of the wealth gap relative to the reference group, we employ a Shapley-Owen decomposition. In this exercise, we account for the entire wealth gap between the reference group by setting all factors to their counterfactual values in all possible different sequences (i.e., $5! = 120$ combinations for five sets of variables). The effect of each contributing factor is then measured as the average of its marginal contribution across all possible permutations (Shorrocks *et al.* (2013)).

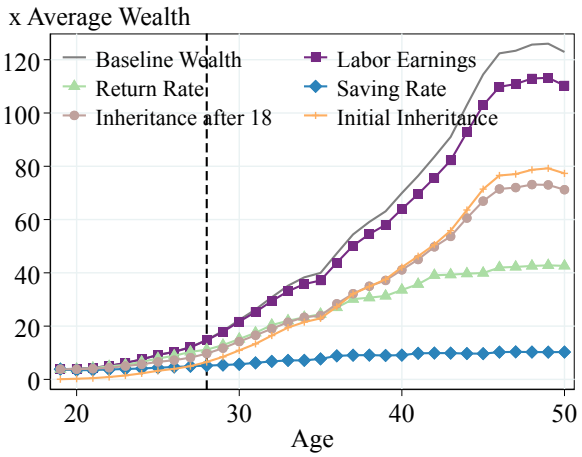
These exercises, however, do not take into account behavioral responses. Thus, they have to be understood as capturing the first-order effects of each dimension of heterogeneity. Replacing, for instance, the labor income of a group with average labor income could also change their saving rate, portfolio composition, rates of return, and so on. While we agree that these interactions could affect the overall quantitative importance of each component, we see our approach as a simple and transparent empirical decomposition to inform structural models on the importance of different economic forces for wealth inequality. Therefore, in Section 6 we also use this new set of dynamic moments to evaluate and estimate structural models of wealth inequality.

5.1 Decomposing Top Wealth Inequality

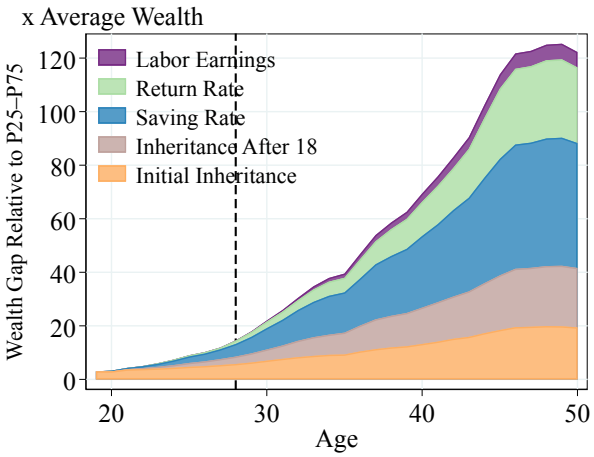
We start with the first counterfactual exercise, changing only one factor at a time while keeping the others unchanged. Figure 12a displays our results for the top 0.1% group among households aged 50–54, $BW^{50-54}_{\geq P99.9}$. To fix ideas, the gray line shows the (retrospective) average wealth profile for this group, as in Section 3.2. Replacing the labor income of this group by the average labor income of mid-wealth households does not have a significant impact on the wealth profile of the rich. This result is not surprising considering the small fraction of lifetime income that the top 0.1% obtain from labor (Figure 6). In contrast, replacing their higher-than-average return on wealth with the one of the median-wealth households reduces their end-of-period wealth from $124.7 \times$ AW

Figure 12 – Determinants of the Top 0.1% Wealth Accumulation

(a) Counterfactual Average Wealth Profiles



(b) Shapley-Owen Decomposition



Notes: Figure 12a shows the counterfactual wealth profiles for households in the $BW^{[50-54]}_{\geq P99.9}$ age-wealth group. Counterfactuals are calculated by replacing the value of a particular variable with the average value of the same variable observed for the reference group ($BW^{[50-54]}_{[P25-P75)}$). Figure 12b shows the average marginal contribution from a S-O decomposition.

to $42 \times$ AW. Next, we find that in the counterfactual with inheritances received after age 18 wealth at age 50 declines to $71 \times$ AW. Initial inheritances—before age 18—also have a large impact, reducing wealth at age 50 to around $77 \times$AW in the counterfactual wealth profile. Given that inheritances and initial wealth only account for a small share of lifetime resources from a static perspective (Figure 6), these results show the importance of the compounding effects of high saving rates and returns.

Finally, we find that the high saving rate of rich households—which combines savings from different sources of income including capital gains—plays a major role in the lifecycle wealth dynamics of the wealthiest. In particular, we find that if rich households had the saving rate of mid-wealth households, their end-of-period wealth would drop to about $10 \times$ AW. Thus, for the wealthiest households, their higher saving rate is the single most important factor that accounts for almost all of their fortunes.

Shapley-Owen Decomposition.

The previous results quantify the importance of each factor when holding all other components 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 the rate of return of mid-wealth households while keeping their actual high

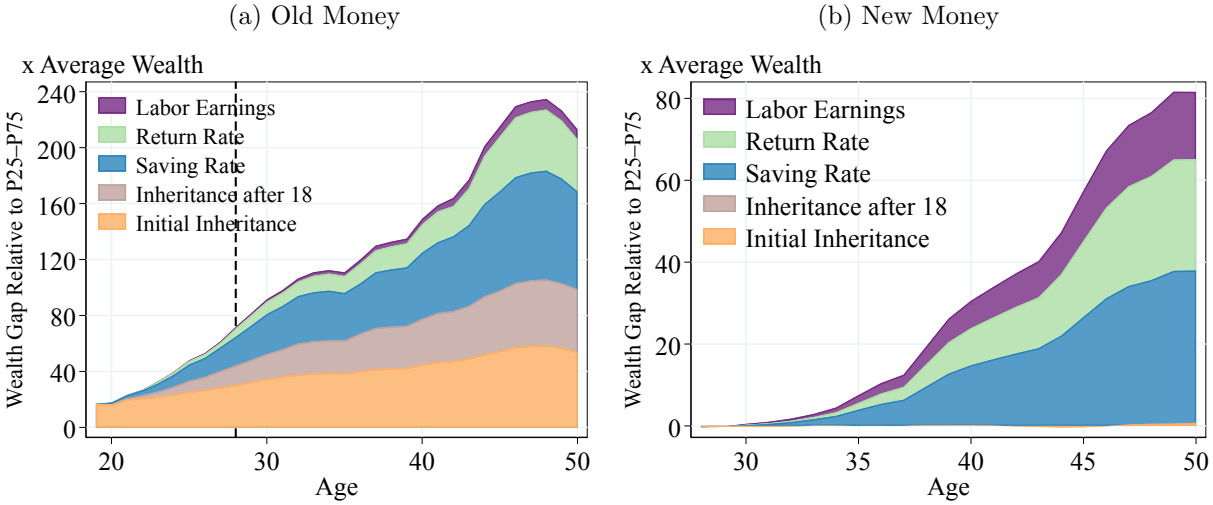
inheritances. The importance of a high return on wealth, however, would be diminished if the wealthiest received the (lower) inheritances of mid-wealth households. More generally, because the budget constraint is jointly non-linear in the respective components, summing the marginal effects in the previous section does not add up to explain 100% of the wealth gap between top and mid-wealth households. Relatedly, the order in which the respective components of the budget constraint are replaced matters. To address these concerns, we perform a Shapley-Owen decomposition, which cycles through all possible permutations of the order in which different components of the budget constraint are replaced (see Appendix OA.2 for details). Furthermore, the resulting average marginal effects exactly add up to explain the gap between the wealth of any given group and the reference group of mid-wealth households.

Figure 12b shows that inheritances (both at age 18 and afterward) account for a significant fraction of the wealth gap, declining from 100% of the gap in the beginning by construction to 34.0% of the gap by age 50. As individuals age, the relevance of inheritances declines—even though individuals receive inheritances later in life as well—and higher saving rates and rates of return rise in importance to 38.2% and 23.1% of the gap, respectively. Taken together, for households in their early 50s, these three components account for over 95% of the total wealth accumulation gap. The small remainder (4.7%) 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, are jointly responsible for less than one third of the wealth gap. Second, differences in saving rates are at least as important a factor, and—as demonstrated in Section 6—they are difficult to attribute to precautionary saving motives or higher expected returns, and instead necessitate non-homothetic preferences. Lastly, while previous research has found a minor role for intergenerational wealth transfers in perpetuating wealth inequality, we show that inheritances account for at least one-third of the top wealth gap.[28] This also reflects that wealthier households re-

[28]Most recently, similar to us, Black *et al.* (2022) have used Norwegian data to show that inheritances constitute a small fraction of lifetime resources. Similarly, Boserup *et al.* (2016) demonstrate that the flow of bequests following death of a parent reduces the top 1% wealth share of among children age 45–50 in Danish data. Furthermore, Wolff (2002) show that inheritances and other wealth transfers tend to equalize the distribution of household wealth in the SCF data. Charles and Hurst (2003) use PSID data to show that inter vivos transfers and bequests explain little of the intergenerational wealth persistence. An exception is Nekoei and Seim (2023) who illustrate that in Sweden wealth inequality increases a decade after inheritances are received because the average heir depletes her inheritance, while

Figure 13 – Shapley-Owen Decomposition: New Money versus Old Money



Notes: Figure 13 decomposes the excess wealth of the New Money and Old Money relative to the $BW^{[50-54]}_{[P25-P75)}$ group using a S-O decomposition. See definitions of Old Money and New Money in the text. In Figure 13a, the vertical line marks the age in which the Old Money are matched with their younger "twins."

ceive intergenerational transfers earlier in life and compound them at significantly higher rates compared with the rest of the population.

5.2 Decomposing the New Money–Old Money Wealth Gap

The importance of each variable in the budget constraint for wealth accumulation is quite different for the Old Money, with vast initial wealth, compared with the New Money, who start with very little wealth. To quantify these differences, we apply the S-O decomposition to each subgroup of the top 0.1%. Figure 13a breaks down the lifetime wealth gap of the Old Money (relative to the P25-P75 group) into the contribution of each component. For this group, inheritances represent the majority of their wealth over their entire lifetime, seconded by an increasing importance of their relatively higher saving rate. By age 50, 46.5% and 32.7% of the wealth gap of the Old Money is explained by higher inheritances and higher saving rates, respectively. A higher return on wealth represents 17.5%, whereas only 3.3% is accounted for by relatively higher labor income.

The results are very different for the New Money, as depicted in Figure 13b. For this group, the three most important components are (i) a high saving rate that accounts

the inheritances of wealthy heirs remain intact. Boserup *et al.* (2018) also find that initial wealth at age 18 is important for wealth inequality later in life in Denmark. We further show that the wealthiest grow their inheritances by enjoying higher rates of return and saving at higher rates.

for 45.6% of their excess wealth relative to mid-wealth households, (ii) a high return on wealth (33.3%), and (iii) higher labor income (20.1%). In contrast, above-average inheritances account for only 1.0% of the wealth gap. These differences in importance of various components between Old Money and New Money reveal the distinct economic forces driving their wealth accumulation dynamics. In the next section, we exploit these insights to distinguish between different theories of top wealth inequality.

6 Testing Theories of Wealth Inequality

We now use our empirical findings to evaluate standard theories of wealth inequality. We show how our novel empirical dynamic wealth decomposition can be used to distinguish between competing drivers of wealth inequality, even when each of these drivers by itself can fully rationalize cross-sectional inequality moments. Specifically, we examine whether commonly used structural models of wealth inequality accurately reflect the quantitative importance of inheritances, saving rates, returns, and labor earnings as measured by the empirical S-O decomposition. Additionally, we investigate whether these models can account for a significant proportion of New Money households.

Basic model. For comparison, we start from a baseline heterogeneous-agents lifecycle model à la Aiyagari-Bewely-Huggett-Imrohoroglu with log consumption utility, $u(c) = \ln c$. In this model, agents live for a finite number of periods, divided into working and retirement years, and die stochastically with an age-specific conditional probability of ψ_{h+1}. During their working years, they are subject to a labor income process which is estimated to match the lifecycle profile and non-Gaussian features of the labor income process in Norway (Halvorsen *et al.* (2022)), whereas during retirement households receive income that follows the Norwegian pension system. The labor income process contains a fixed type ($\bar{e}$), a first-order Markov persistent component (η) whose innovations are drawn from 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

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

where a, τ^a, and τ^k denote household assets, the progressive wealth tax, and the flat capital income tax, respectively. Furthermore, $w \cdot e_h(\Theta)$ represents post-tax-and-transfer earnings. All taxes and transfers are calibrated to the Norwegian data (see Appendix OA.5 for the externally calibrated parameter values). Finally, the baseline model features accidental bequests.

We calibrate only one parameter, the discount factor $\beta = 0.973$, to match an aggregate wealth-to-labor income ratio of 6.4. The baseline model is known to not generate enough top wealth inequality (Aiyagari (1994)) even under a sophisticated non-Gaussian labor income process (Guvenen *et al.* (2024)). Similarly, in our baseline model calibration, the top 0.1% wealth share at age 50 is only 0.8%, which is much lower than 9.7% as observed in the data (see Column (1) of Table III).

Building on this basic model, we consider four augmented versions in columns (2) to (5) in Table III. Each of these models corresponds to a prominent theory of wealth inequality with an empirical counterpart in our dynamic decomposition. We calibrate all of them to match cross-sectional wealth inequality in the spirit of seminal papers in this literature.

Superstars. In column (2), we add to the basic model an additional state in the labor income process—a *superstar* income shock *à la* Castañeda *et al.* (2003). Similarly to their calibration strategy, we pick the value (85.1 × average labor income) and persistence (0.938) of this shock to match two key cross-sectional inequality statistics at age 50: the top 0.1% wealth share (9.7%) as well as the top 0.1% total income share (5.8%).

Heterogeneous returns. In column (3), we augment 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 by $(1 - \tau^k) \cdot z \cdot r \cdot a$, where z is an AR(1) process with Gaussian innovations. We calibrate the persistence (0.715) and the cross-sectional standard deviation (0.172) of this process to again match the top 0.1% wealth and income shares.[29]

Stochastic-β. Column (4) adds fundamental heterogeneity in the saving rate via heterogeneity in the discount factor as in 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

[29] Alternatively, we have disciplined the return process by directly matching the cross-sectional return standard deviation (10.2 pp). The results, available on request, are almost identical.

generations. We fix the persistence of this process to the one of permanent labor ability (0.24) and calibrate the dispersion (0.119) to match again the top 0.1% wealth share.

Non-homothetic bequests. Finally, in Column (5) we augment the basic model with a non-homothetic bequest motive (e.g., De Nardi (2004)). We add to preferences a warm-glow bequest utility function $\nu(b) = \chi \ln(b + \bar{b})$, scaled by the death rate $1 - \psi_{h+1}$. We estimate the non-homotheticity parameter $\bar{b} = 10.1 \times$ AW and the scalar $\chi = 41.8$ to match the top wealth inequality and the average amount of wealth at death (0.8 AW).

Evaluation of augmented models matched to cross-section. Each of these four augmented models in (2) to (5) replicates the extent of wealth inequality at age 50, as well as other relevant cross-sectional moments. Thus, without data on the dynamics of wealth accumulation, these models are all valid candidate theories of wealth inequality. To evaluate the fit of these models to the dynamics of wealth accumulation, we treat the simulated data in the same way as we do in our empirical section and compute the S-O decomposition for a group of households aged 50–54 in the stationary equilibrium of the model. The results are shown in the middle panel of Table III.

Comparing the shares obtained from our data (column Data) shows that these models, to varying degrees, put too much weight on inheritances to generate the large wealth concentration observed in the data, and too little weight on return and saving rate heterogeneity. Since large inheritances are the defining feature of Old Money households, we conclude that these models generate too few New Money households and do not generate, on average, the fast wealth transitions we observe in the data. This is also reflected in the bottom panel of Table III: Defining the New and Old Money as in the data, the initial wealth of the Old Money ranges between 84 and 144 $\times$ AW in these models, compared with 39.7 $\times$ AW in the data.[30] By implication, these models generally do not generate enough wealth growth for the Old Money as seen in the data. In this sense, in these models the Old Money can be described as rentiers with higher initial wealth that are otherwise closer to median households' behavior, whereas our empirical work shows that they exhibit above-average returns and saving rates. The Superstar model comes closest to explaining the New Money; however, it does not feature enough saving rate variation and no return heterogeneity.[31] In summary, neither of these models

[30] We compute initial wealth as of age 24 in model and data, since that is the first model period. We start the model at age 24 and not earlier because we abstract from modeling the education stage.

[31] Superstar income can be thought of as entrepreneurial income from both labor and capital. Yet,

accounts accurately for the dynamics of wealth accumulation, despite the fact that each of them is consistent with cross-sectional inequality statistics.

Full model. Based on the previous findings, we conclude that two elements are crucial to match the new salient features of the data. The first is heterogeneous returns, decreasing in wealth, that allow households to experience large wealth gains early in life—so as to generate New Money households who start out without any wealth. The second is some mechanism that encourages high-wealth households to save at higher rates already *early in life*, and to pass wealth to their offsprings, so as to generate Old Money households—while at the same time not overstating the importance of inheritances as the aforementioned models do. We incorporate these elements in the full model (column (6) of Table III), which augments the basic model in two ways. First, households access a decreasing-returns-to-scale production technology with heterogeneous returns to a fixed factor. Second, we allow for non-homothetic preferences via wealth in the utility function. We discipline the importance of these mechanisms by targeting our dynamic S-O decomposition facts.

First, the production technology uses capital (subject to a collateral constraint) and is subject to idiosyncratic productivity shocks. Decreasing returns are important to match the high returns to equity early in life and the corresponding fast-wealth transitions while preventing the wealth distribution from diverging too much later in life.[32] We pick the dispersion of (i) the fixed type (0.357) and (ii) the i.i.d. shock (0.350), jointly with the other parameters discussed below, to match the cross-sectional top 0.1% income and wealth shares at age 50. Households pay (iii) a fixed cost to operate this technology, which we select to replicate the 7.2% population fraction of entrepreneurs.

Second, period utility is modified to $\ln c + \chi \ln(a + \bar{a})$, where the latter can be interpreted as "capitalist spirit" motive (e.g., Carroll (1998); Straub (2019)). This preference for wealth is identical to 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 actually features a negative saving rate contribution (since wealthy heirs initially deplete their

the superstar model still loads too much on the joint labor and capital returns contributions (48.1% vs. 27.8% in the data).

[32] Entrepreneurs receive profits given by $\pi(a, z, \zeta) = \max\{0, \max_{k \leq \lambda a}\{P \cdot (e^{z+\zeta} \cdot k)^{\mu} - (\delta + r) \cdot k - c_f\}\}$ where c_f is a fixed production cost, z is a fixed type and ζ is an i.i.d. shock.

Table III – Quantitative Models and Dynamics Moments

		(1)	(2)	(3)	(4)	(5)	(6)
	Data	Basic	Superstar	Returns	β	Bequest	Full model
Target cross-section			✓	✓	✓	✓	✓
Target dynamics							✓
Cross-Sectional Moments							
Wealth/Lab.Inc. ratio	6.4	**6.4**	**6.3**	**6.4**	**6.4**	**6.2**	**6.2**
Top 0.1% wealth (%)	9.7	0.8	**9.3**	**9.7**	**9.7**	**9.5**	**9.5**
Top 0.1% income (%)	5.8	0.8	**6.0**	**5.8**	1.9	2.1	**5.9**
Wealth Decomposition for 50-year-old top 0.1% group (%)							
Inheritance	34.0	31.9	28.3	60.6	69.0	106.9	33.5
Labor income	4.7	50.0	48.3	0.2	0.2	-0.1	6.0
Returns	23.1	-0.1	-0.2	18.4	-0.4	0.0	25.1
Saving rate	38.2	18.3	23.6	20.9	31.2	-6.8	35.4
Initial Wealth of New and Old Money (in AW)							
New Money	-0.1	0.1	0.1	3.8	20.5	109.5	0.1
Old Money	39.7	9.9	83.8	143.5	93.9	137.1	39.7

Notes: Table III compares different moments of the wealth and income distribution across different model economies. In each column, targeted moments are in **bold**.

wealth).[33] We pick (iv) the scalar $\chi = 0.85$ and (v) the non-homotheticity parameter $\bar{a} = 10.3 \times$ AW to replicate the importance of inheritances and the saving rate in the S-O decomposition. Finally, as in all model versions, we pick (vi) $\beta = 0.924$ to match the wealth-labor income ratio.[34]

The results are shown in column (6) of Table III. This model is successful in matching both the cross-sectional and the dynamic moments as summarized by the S-O decomposition. In particular, the importance of inheritances, labor income, and returns, and as a consequence the saving rate, are quite close to the empirical estimates. Furthermore, the model is able to generate rapid wealth growth among the New Money: Similar to the data, the New Money start with near zero wealth ($0.1 \times$ AW) and reach $79.7 \times$ AW around age 50. At the same time, the Old Money start with initial wealth (fully inherited) of $39.7 \times$ AW, which is close to what we observe in the data (Figure 13a).

[33] 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.

[34] We remove accidental bequests as these overstate the importance of inheritances, even when $\chi = 0$. We relegate non-essential calibration details to Appendix OA.5.

As in the data, the New Money in this model have even higher returns than the Old Money, who already enjoy above-average returns. This is because of decreasing returns to scale technology, implying that returns decline in wealth conditional on productivity. Therefore, the New Money own very productive but constrained start-ups that grow very fast due to much higher returns, whereas the Old Money own relatively mature productive firms with healthy returns that allow them to grow their wealth further. Finally, both the average return and differences across the wealth distribution are also higher early in the life cycle—as in the data. These findings are highly relevant for the optimal design of capital income and wealth tax policies. The equity-efficiency trade-off, at the heart of these questions, depends on the nature of wealth dynamics of the wealthiest, on which our findings shed light.

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 2015 to quantify the importance of each of these channels for the wealth accumulation of the richest households. We find that, at age 50, the excess wealth of the top 0.1% relative to mid-wealth households is accounted for by higher saving rates (38%), higher inheritances (34%), and higher returns (23%), 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 but experience rapid wealth growth early in life. Their fast ascent to the top is accounted for by a higher saving rate (46%) and by higher returns on net wealth (33%), with higher labor income (20%) also contributing significantly. In contrast, the Old Money are mainly characterized by higher inheritances (46.5%) and to a lesser extent by higher saving rates (32.7%) and higher returns (17.5%).

Our empirical findings shed light on the underlying mechanisms behind wealth accumulation, especially for the richest. Compared with the new empirical evidence we

provide, standard models of wealth inequality put too much emphasis on inheritances and too little on return and saving rate heterogeneity in accounting for top wealth concentration. Therefore, they do not feature the New Money seen in the data. A model with heterogeneous returns that tend to decrease on average when households reach high wealth levels, in combination with non-homothetic consumption-saving preferences, replicates both cross-sectional inequality as well as our novel evidence on the dynamics of wealth accumulation.

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

OA.1 Data Appendix

OA.1.1 Data sources

Tax returns (TAX). The main data source is tax returns for all persons in Norway 1993-2015. The tax system is residence based, so Norwegians living abroad are not included. The basic income tax unit is an individual, but wealth is jointly taxed for married couples. Cohabitant couples (with or without children) are taxed separately even though they may own assets jointly. The division of assets jointly owned follows the formal ownership shares in the case of housing but can be chosen freely for mortgages. For most households, the division of assets on the tax returns has little consequence, as only a small fraction of households actually pay wealth taxes (due to an exception level). All values are measured on December 31st of each year. Some items in the tax records are reported with discounted values used to calculate a household's wealth tax. We revert these items to their initial value.

Most of the information in personal tax records is third-party reported by employers or financial intermediaries such as banks, brokers, insurance companies, or the Norwegian Central Securities Depository (VPS). Components of income and wealth not provided by third parties (e.g., foreign income or dividends not registered in the VPS) are added by the individual and checked by the tax authority. In addition, tax authorities have control routines that flag tax returns with extreme movements in either income or wealth, and these are checked in more detail.

Shareholder register (SHR). All private limited companies in Norway must submit information about shareholders and the number of shares each person owns to the Norwegian Tax Administration's Shareholder Register. The register is complete from 2004 and is searchable online from 2014 (https://www.aksjeeiere.no/). The shareholder registry contains information on individuals' and firms' ownership of stocks in all companies in Norway. By combining the number of shares owned individually with the total number

of shares, we get the ownership fraction of a particular individual. Some companies are held directly. In this case, the ownership share is the fraction of total shares owned by the individual. However, many companies are owned by other firms, which we trace back to the owner. In particular, if an individual owns shares in company A and company A owns shares in company B, the individual's ownership share in company B is equal to that individual's ownership share in company A multiplied with A's ownership share in company B. We compute indirect ownership up to 7 layers. We can also sum up and obtain the number of companies in which an individual owns shares in through direct and indirect ownership.

Firm balance sheet and tax return. For the equity value in unlisted firms, we must rely on the assessed value that private businesses report to tax authorities. This assessed value is derived from firm balance sheets and book values. Balance sheets contain information about total equity (total assets minus total debt), accumulated retained earnings, total revenue, and profits before and after tax. Tax authorities have routines to identify underreporting of assessed values of private businesses. In addition, medium- and lager-sized firms (with turnover above about USD 500,000) are required to have their balance sheet audited by an approved auditing entity.

Housing wealth database. Housing wealth is imputed using an ensemble machine-learning method on housing transaction data for the period 1993-2015. The imputation includes owner-occupied housing, secondary housing, and cabins (holiday homes). Housing wealth is allocated to individuals according to ownership shares, i.e., the fraction of the house owned by an individual. Construction of housing wealth is described in detail in Fagereng, Holm and Torstensen (2020b).

Central population registry and Norwegian educational database. Annual national register since 1964. Contains individual identification numbers, residence, marital status, and highest completed education.

Inheritance tax records. Information about inheritances and inter-vivos gifts as derived from Inheritance tax records 1995-2013. The inheritance tax in Norway was abolished in 2014.

OA.1.2 Variable Definitions

Personal and household id, marital status and head of household. Source: *The Central Population Registry [annual, 1964-].* Every individual has a unique personal ID number. The marital status is either single, married/cohabitant, widow/widower, divorced or separated. Based on a combination of spousal ID and marital status, a household ID number is created. A change in marital status (marriage/divorce) will generate a new household ID. The household ID is used to aggregate up from individual-level data to household-level data. The head of household is defined as the eldest person.

Year of death. Source: *The Central Population Registry [annual, 1964-].* A living person will have year of death equal to missing. A household's year of death is defined as the maximum year of death by household ID. If the remaining spouse is still alive, the maximum value will be equal to missing.

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

Labor income: Measures of labor income are comprehensive and include wages and salaries, bonuses and other irregular payments. The information is third-party reported by employers. Corresponding code in the tax return is TAX 2.1.

Labor income from self-employment: Norway has a dual-income tax system where tax on capital is proportional and tax on labor is progressive. To avoid income shifting and achieve neutrality in the tax treatment of wage earners and entrepreneurs, the Norwegian dual-income tax splits the income from self-employment and from small companies into an imputed return to capital, taxable as capital income, and a residual income subject to labor income tax. Corresponding codes in the tax return for the labor part are TAX 1.6, TAX 1.7 and TAX 2.7.

Transfers: Transfers include unemployment benefits, sickness benefits, paid parental leave, remuneration for participation in various government activity programs, disability benefits, public pensions, and other social welfare payments. Corresponding codes in the tax return are TAX 2.1.7, TAX 2.2 and *sykepenger, foreldrepenger, dagpenger, arbeidsavklaringspenger, tidbegrenset uførestønad, bostøtte* og *sosialhjelp* from the Social Security Administration (NAV).

Interest. Source: *Tax records [annual, 1993-].* 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), interest income on bank deposits abroad (TAX 3.1.11). In addition, we do as in Fagereng *et al.* (2020a) and 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 home and abroad (TAX 3.3.1 + TAX 3.3.2).

Dividends. Source: *Tax records [annual, 1993-] , Shareholder registry [annual, 2004-], Firm balance sheet and tax return [annual, 1995-].* Tax records contain taxable dividends received from stocks and shares registered in the Norwegian Central Securities Depository VPS (TAX 3.1.5), from mutual funds (TAX 3.1.6), and from private equity/Norwegian and foreign shares or unit trusts not registered with the VPS (TAX 3.1.7). From 2004, an alternative value for 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 Shareholder registry, 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 $\sum_k s_{it}^k D_t^k$.

Since we have two sources of information about dividends after 2004 - tax returns (TAX), and the combination of shareholder registry (SHR) and firm accounts - there may be conflicting information. 92% of observations are equal in the two datasets, 7% have a positive value in tax records (TAX) and zero in the shareholder registry (SHR) - we assign these dividends to public equity; i.e. we use tax values (TAX) up to and including 2003, and shareholder registry (SHR) from 2004.

Dividends were not a part of the capital income tax base until 2006, when a tax on dividends was introduced as part of a major tax reform. There were two major consequences of this reform. First, large dividends were taken out prior to the reform. Second, a large number of holding companies were created so that dividends could be paid to the holding company from its subsidiaries, and the ultimate owner could thereby avoid paying dividend tax on the personal income side. In sum, there was an overall shift from dividends to retained earnings after the tax reform on 2006.

Capital gains from housing. Capital gains from housing are calculated as the annual change in imputed house value in years with no transactions. In years with market transactions, capital gains from housing are set to zero. This is because 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 it would not add up if we tried to decompose the two parts. Capital gains from housing is also set to zero if housing value is zero in year $t-1$ and non-zero in t, and vice versa if housing value is zero in year t and non-zero in $t-1$. For comparison, Fagereng *et al.* (2020a) used an hedonic price imputation of housing values, while we use the new machine learning method from Fagereng, Holm and Torstensen (2020b). Imputed income from housing is defined as imputed rent from housing using the rental equivalence approach and calculated as the aggregate value of owner-occupied housing services from the National Accounts relative to the aggregate value of housing wealth in our sample, which implies a rent-to-value ratio of 2.23 percent (over the period of observation). Total income from housing is thus imputed income plus income from ownership of real assets as measured in the tax returns; taxable income from renting out holiday home (TAX 2.8.3) or property abroad (TAX 2.8.5).

Capital gains and dividends from private equity. Capital gains on equity is obtained by linking individual and firm data using the shareholder registry (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 is obtained by assuming as Fagereng *et al.* (2019) 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 December 31st 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 is 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.

Inheritances. *Source: Inheritance registry [annual, 1995-2013].* Prior to 2014, both inheritances and gifts were subject to taxation and were reported to tax authorities. In 2013, the inheritance and gift tax had a zero rate for taxable amounts up to NOK 470,000 from each donor (around 52,000 USD dollars in 2022). From this level, the rates ranged from 6% to 15% depending on the status of the beneficiary and the size of the taxable amount. The Norwegian inheritance taxation was recipient based, meaning that the total gift and inheritance received by one individual from one donor constituted the tax base. More precisely, a child inheriting his or her last surviving parent would therefore usually inherit from both parents and thus face an exception level of NOK 940,000. Norway has fairly strict rules on heirship. Under Norwegian laws, the deceased's children and spouse are legally entitled to inheritance from the deceased. The law states the deceased's children are entitled to two-thirds of the deceased's total estate, split equally among them.

OA.1.3 Correcting for under measurement of inheritances

The tax records only report the value of taxable inheritances and intervivos transfers after the application of the statutory discount. Such discount might affect our measurement of the saving rate since, in subsequent periods, discounted assets will appear in the wealth of the recipient as measured by its full value. Therefore, we correct for under-measurement of bequests and intervivos transfers, using the statutory discount rates defined in the tax code for different asset classes. For example, transfers of private equity were given a 70% discount on assessed values below NOK 10 million (around $1.5 million) until 2009 and a 40% discount later. As for housing, they received a 50% discount until 2001 and then a 60%. We use these to adjust the amount of bequests and intervivos transfers we see in the data. Since we do not observe the portfolio composition of inheritances, we use recipients' portfolio shares as a proxy. In particular, for each year we compute the average statutory discount rate for a portfolio of assets weighted by the portfolio shares, which we use to inflate measured inheritances. For instance, in 2013 our inflated value of inheritances is 2.15 times larger than the observed values.

OA.1.4 Imputing Capital Gains Prior to 2005

Capital gains are calculated using a combination of firm-level balance sheet data and the share holder registry, which allows us to link capital gains to the owner of the

firm. The share holder registry, however, is only available from 2005 on, restricting the measures of capital gains from private equity between that year and 2015. To perform our analysis, and extend our data as much as possible, we append the information available on capital gains by imputing capital income from equity (private and public) prior to 2005 for all households in our sample. We proceed as follows.

For each year after 2005, we rank household within a year by their total equity holdings in year t and $t-1$ calculated as the sum of their holdings in private and public equity. We then calculate the *relative* equity holdings as the ratio of these holdings relative to the average total equity in the economy within a year. We then separately sort households in period t and in period $t-1$ by their *relative* equity holdings (two different rank) and calculate the return within pair of t and $t-1$ ranks as the ratio of capital income (sum of dividends and capital gains for public and private equity) and the average equity holdings between periods $t-1$ and t across all individuals within an age group. Finally, take an average across all years between 2005 and 2015 of these returns within a pair of ranks and age groups. These returns are saved and used for the imputation.

For each year prior to 2005, calculate the total amount of equity holdings for each household in years t and $t-1$. Then, within each year t, calculate the ratio between the individual ownership of equity over the average equity holding within that year. Then, we classify individuals within different groups according to relative equity holdings in years t and $t-1$ and merge (by age group) the information on returns calculated *after* 2005 in step 1 for each of these groups. Finally, we calculate the income from capital as the product of the imputed return times the average of the equity holdings in periods t and $t-1$. Notice that this implies that we impute data starting in 1994. We use this measure of imputed income from equity (public plus private) as our measure of capital income from equity prior to 2005.

OA.1.5 Assets and Liabilities

Inheritance tax. Norway had an inheritance tax during most of the studied period. The inheritance registry was digitalized in 1995 and the tax was abolished in 2014, which explains the limited observation period. We observe the exact amount of inheritance taxes paid by each heir.

Safe assets. Source: *Tax records [annual, 1993-].* 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 out standing claims/loans to friends and family (TAX 4.1.6).

Public equity. Source: *Tax records [annual, 1993-].* Mutual funds/stock market funds (TAX 4.1.4) and shares/stocks and shares listed in the Norwegian Central Securities Depository (VPS), (TAX 4.1.7).

Private equity. Source: *Tax records [annual, 1993-], Shareholder registry [annual, 2004-], Firm balance sheet and tax return [annual, 1995-]*

Private equity in tax returns is measured as 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 but owned by a small number of shareholders. Control of the firm is therefore limited to a few persons. 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 Shareholder registry, and including indirect ownership), s_{it}^k, and multiplying with an assessed value of an unlisted company (V_t^k), gives us an alternative measure of the overall value of unlisted shares owned as s $\sum_k s_{it}^k V_t^k$. Correlation between equity values in TAX and SHR is 0.86 for non-zero values in both registers. We use private equity from tax records as our main variable in net wealth to get a consistent measure over time, but make corrections when equity is zero in TAX and positive in SHR.

Housing. Source: *Dataset from Fagereng, Holm and Torstensen (2020b).* Tax records contain values for owner-occupied and secondary housing at tax value (TAX 4.3.2). Between 1993 and 2009 these tax values were related to construction value and adjusted

irregularly. Since 2010 this value has been imputed using hedonic price regressions. As a consequence there is no measure of housing in tax records that is consistent over time. Instead 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, i.e., 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.

Other real assets. Source: *Tax records [annual, 1993-].* Cars and other motor vehicles at tax value (TAX 4.2.5 and TAX 4.2.6), boats at tax value (TAX 4.2.4), and other real estate apart from housing and holiday homes.

Foreign wealth/offshore tax havens. Source: *Tax records [annual, 1993-].* Inclusion of foreign wealth varies from country to country, depending on tax treaties.[1] The corresponding tax codes for foreign wealth is deposits in foreign banks (TAX 4.1.9), foreign real estate (TAX 4.6.11) and debt in foreign banks (TAX 4.8.3.1). These are allocated to deposits, other real estate and liabilities, respectively.

According to Alstadsæter *et al.* (2019), the richest Scandinavians keep a substantial part of their wealth in offshore tax havens. The wealth of the top 0.01 of Norwegian households increases by about 25 percent if offshore wealth is included. On the other hand, Norwegian tax authorities offer tax amnesty for voluntary disclosure of foreign wealth.[2] Since 2007, an extra NOK 1.5 billion of taxable wealth and income has been disclosed because of this program. The number of amnesty participants picked up significantly in 2009, when G20 countries compelled tax havens to exchange bank information upon request with foreign authorities (Johannesen and Zucman, 2014), it was negligible before. According to Alstadsæter *et al.* (2019), the effect of tax amnesty has been quantitatively small; if anything, wealthier tax evaders seem to be slightly less likely to participate in an amnesty.

Pension wealth & life insurance. More than 80 percent of all pension wealth in Norway is provided through a National Insurance scheme, a pay-as-you go (PAYG)

[1] More information on tax treaties can be found here.
[2] More information of tax amnesties can be found here.

scheme, with a large degree of redistribution from rich to poor. Another 18 percent are covered by employer-provided pension plans, and 0.3% of total pension wealth is held as personal pension plans. Only this tiny fraction of 0.3 percent is reported on the tax return (TAX 4.5.1). The majority of Norwegians have life insurance through their employer. Personal life insurance is reported on tax returns with its repurchase value (TAX 4.5.2).

Liabilities. Source: *Tax records [annual, 1993-].* Total debt, i.e. the sum of mortgages, student loans and consumer debt (TAX 4.8).

OA.1.6 Taxes

Total taxes. Source: *Tax records [annual, 1993-].* Total taxes paid on labor income, capital income and wealth. It is possible to observe the wealth tax separately (see more about the wealth tax below), but it is not so straightforward to separate tax on labor income from tax on capital income.

Labor income tax. In order to calculate labor income after tax we make the simplifying assumption that tax on labor (T^l) can approximated as follows: $T_t^l = \left[1 - \tau_t^c \left(\frac{Y_t^c}{Y_t^c + Y_t^l}\right)\right] \times (T_t - T_t^w)$ 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 the flat tax rate on capital income, which was 28 percent until 2014.

Capital income tax. 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 percent until 2014. From 2014 to 2019 the tax rate on capital was gradually reduced downward to 22%.

Wealth tax. During our sample period, wealth taxation has become more lenient, both through a reduced rate and through specific valuation concessions. Table OA.1 shows the evolution of the wealth tax over our sample period.

OA.2 Shapley-Owen Decomposition

In a regression setting, the Shapley-Owen decomposition is a statistical method to measure the marginal contribution of each regressor to the goodness of fit of an econometric model, measured for instance by its R^2 (Hüttner and Sunder, 2011). We apply

Table OA.1 – The wealth tax 1993-2015

		Tax Value (%)						Tax Value (%)	
		Allowances	Primary	Public	Private			Allowances	Primary
Year	Rates		home*	stock**	equity	Year	Rates		home*
1993	1/1.3	120/235	20-25	100(75)	30	2009	1.1	470	20-25
1994-97	1.1/1.4/1.5	120/235/530	20-25	100(75)	30	2010	1.1	700	25
1998-04	0.9/1.3	120/540	20-25	100(65)	65	2011	1.1	700	25
2005	0.9/1.3	151/540	20-25	65	65	2012	1.1	750	25
2006	0.9/1.3	200/540	20-25	80	80	2013	1.1	870	25
2007	0.9/1.3	220/540	20-25	85	85	2014	1.0	1000	25
2008	0.9/1.3	350/540	20-25	100	100	2015	0.85	1200	25

Allowances in 000s of NOK. * Prior to 2010, tax values were based on construction value and adjusted irregularly, but on average kept at level corresponding to 20-25% of market value. Not shown in the table is 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 (SMB). After 2008, the tax value for Public and Private Equity was set to 100.

this idea to decompose the difference between the wealth of a particular wealth group (top 0.1% of wealth owners) relative to the wealth of a comparison group. We proceed as follows.

Step 1: obtaining the moments of the wealth and income distributions for the comparison group. We first compute the time series of the average of different components of the budget constraint (e.g., after-tax average labor earnings, interest income, inheritances, and so on) for those individuals whose average wealth calculated in τ and $\tau+1$ (denoted by BW_τ) is between the 25th and 75th percentiles of the BW_τ distribution, our *comparison group*. To be more precise, define $x_{\tau,t}^{a,p}$ as the average of a particular variable in the budget constraint given a conditioning year $\tau \in \{2009, ..., 2014\}$, in year t, for age group $a \in$, for a given quantile p of the BW_τ distribution. We obtain $x_{\tau,t}^{a,p}$ as follows.

- **Age.** For each age group $a \in \{35, ..., 50\}$ define the age in year t as $h = a-(\tau+1-t)$ for each year in $t \in [1993, 2015]$. This implies, for instance, that those households who are between 50 and 54 years old in year $\tau = 2014$ (our baseline group) are between 28 and 32 years old in 1993. Younger cohorts, however, can be traced back to when they were 18 years old—the age at which they enter our dataset.

- **Averages conditioning on τ.** For a given τ year, calculate the average of $x_{\tau,t}^{a,p}$ within an age h for the comparison group.

Table OA.2 – Average Values and Counterfactual for 50-to-54-year-old households

Wealth Rank	Labor Income, $\tilde{l}$	Inheritances $\tilde{h}$	Saving Rate,s	Capital Income,R^{INC}	Initial Wealth*
<0	407,266	9,615	-0.81	-0.15	0.00
$[0, W_{min}]$	265,827	5,460	-0.02	-0.32	0.04
$[W_{min}, P50]$	441,424	13,568	0.08	0.04	0.25
$[P50, P75]$	516,047	22,237	0.20	0.08	0.50
$[P75, P90]$	584,986	33,729	0.28	0.11	0.70
$[P90, P95]$	682,008	50,342	0.34	0.13	0.93
$[P95, P99]$	802,292	68,162	0.37	0.15	1.42
$[P99, P99.9]$	1,048,610	115,041	0.42	0.20	3.74
Top 0.1%	1,354,062	274,699	0.74	0.16	29.61
Counterfactual	471,402	17,051	0.13	0.06	0.25

Notes: Table OA.2 the average of the component of the budget constraint for households who are 50 to 54 years old. *Initial wealth is expressed relative to the average wealth in the economy. Labor and Inheritances (sum if inheritances and inter-vivos transfers) are in real NOK of 2018.

- **Average across τ.** Proceed as above for all conditioning years and then average across $\tau's$ within an age group. This generates a unique time series of average x, which is the average used as the comparison group in the S-O decomposition.

Step 2: obtaining the baseline group moments. Similarly to Step 1, we calculate the average of $x_{\tau,t}^{a,p}$ for those individuals in the top 0.1 of the BW_τ distribution. Age is calculated in the same way for each τ. We then average across all $\tau's$ to obtain one time series of $x_{\tau,t}^{a,p}$ between 1993 and 2015, which we denote as $x_h^{a,p}$. Notice that because our data span 2015 and 1993, the resulting time series only covers ages 28-32 to 50-54 years old for the baseline group, denoted by $a = 50$. In what follows, we concentrate on this group which we use for our baseline results. Table OA.2 show the average value (across all years t and τ) of each component and the corresponding value for the middle-wealth group used in the counterfactual.

Step 3: obtaining the twin group. The goal of this step is to obtain a time series of x that allows us to complete the ages 18 to 27 for those households who are in the top 0.1% of the BW_τ distribution and are $a = 50$. We proceed as follows.

- **Sorting individuals.** We start by calculating the average wealth profile for 50-to-54 years old in year τ who belong to the top 0.1% of the BW_τ distribution and within different quartiles of the FW_{93} distribution. FW_{93} is the sum of the average wealth holdings in 1993 and 1994 for each household plus the discounted value of all the bequests and intervivos transfers received by this household between 1994 and year τ.

We use a rate of return of 3%, which is equal to the unconditional weighted average return between 2005 and 2015 in our sample. Given a conditioning year τ, this provides four time series of average net wealth, which we scale by the average wealth in the economy in year t. Denote these series as $y^{a,q}_{\tau,t}$ where $q \in \{1, .., 4\}$. In the main text, we define those household in $q = 1$ as New Money and those in $q = 4$ as Old Money.

- **Finding twins.** Consider a particular series, $y^{a,q}_{\tau,t}$. Since these individuals are in the 50-to-54-years old group ($a = 50$), they are $h_{93} = a - (\tau + 1 - 1993)$ years old in 1993 (e.g., 28 years old if $\tau = 2014$). Then, the goal is to find a group of individuals who are 28 years old in the middle of our sample (e.g., 2006), which can be followed back until the year they were 18 years old. Importantly, we do this search separately for individuals to age $h \in \{50, ..., 54\}$. To find these twins, we rely on the Mahalanobis distance, which is a measure of the distance between a point and a distribution (see Section OA.2.1 for additional details).

  We calculate this distance for each household in calendar year t and at age h_{93} based on the two characteristics, i) the average wealth level of $y^{a,q}_{\tau,1993}$ and ii) the nine-year change of wealth of $y^{a,q}_{\tau,2002} - y^{a,q}_{\tau,1993}$. The nine-year change maximizes the number of years we can use in our analysis. Since different individuals could be h_{93} in different calendar years, we calculate this measure for years $\bar{\tau} = \{2002, ..., 2006\}$.

  For a given $y^{a,q}_{\tau,t}$, h, and conditioning year τ, we calculate the Mahalanobis distance for all households within a $\bar{\tau}$. We then sort all these households and select the 150 with the lowest Mahalanobis distance. We proceed in the same way for each q, generating a sample of at most 600 individuals. This is because some individuals could be selected as good twins in different q groups. Figure OA.1 shows the average wealth for the baseline set of individuals and the twins found for each group. With the exception of years 2009 and 2012, which have an uncharacteristically large average level of wealth for the Old Money in 1993, the twins match quite closely the wealth level of the Old and New Money at age 28.

- **Cross-sectional moments.** Finally, for each of these households, we calculate life-cycle moments across all years t between 1993 and 2015 for all the variables used in our analysis. We proceed in the same way for each year τ. This gives use time series of wealth, labor earnings, and other variables in the budget constraint for a set

of households who are similar to our baseline households, but who can be traded to when they were 18 years old. Denote these series $\overline{y}_{\tau,t}^{a,q}$, where a is 28 years old.

Step 4: Completing the time series. Once the *twins* have been obtained, for each variable $\overline{y}_{\tau,t}^{a,q}$ we have two time series, one that goes from a to h_{93} and a second that goes from h_{93} to 18 years old. For a $\tau = 2014$ this implies that we have a time series for between ages 28 and 50 years old, and another for 18 and 28 years old. Using these two time series, we obtain a unique time series of each y from 18 to 50 years old. Notice that the end points might still differ. To address this issue, we simply re scale the series of the twins to have the same value at 28 years old. This complete time series allows us to obtain a complete budget constraint that we use to estimate an SO decomposition.

Step 5: Calculate the SO decomposition. After completing the time series, we can proceed to calculate the S-O decomposition between ages 18 and 50. We start with the definition of the budget constraint for each group. The budget constraint of a household of type (a, g) where a is age and g is a wealth group is given by

$$c_t(a,g) + w_t(a,g) = \tilde{l}_t(a,g) + \tilde{h}_t(a,g) + \tilde{i}_t(a,g) + k_t^e(a,g) + k_t^h(a,g) + w_{t-1}(a,g),$$

where $\tilde{l}_t(a,g) \equiv \left[l_t(a,g) + e_t(a,g) + tr_t(a,g) - \tau_t^l(a,g)\right]$ is income from labor and self employment, government transfers, minus labor taxes; $\tilde{h}_t(a,g) \equiv \left[h_t(a,g) - \tau_t^h(a,g)\right]$ is post-tax inheritances and intervivos transfers; $\tilde{i}_t(a,g) \equiv d_t(a,g) + i_t^i(a,g) + i_t^h(a,g) - i_t^p(a,g) - \tau_t^e(a,g) - \tau_t^w(a,g)$ is the sum of income from dividends, risky assets and safe assets (e.g., mutual funds and bonds), minus interest payments, and minus capital income tax and taxes on wealth. Define the income from capital as $R_t^{INC} w_{t-1} \equiv \tilde{i}_t(a,g) + k_t^e(a,g) + k_t^h(a,g)$ to obtain the gross saving rate as

$$s_t(a,g) = \frac{\tilde{l}_t(a,g) + \tilde{h}_t(a,g) + R_t^{INC}(a,g)\, w_{t-1} - c_t(a,g)}{\tilde{l}_t(a,g) + \tilde{h}_t(a,g) + R_t^{INC} w_{t-1}}.$$

Given these definitions, the budget constraint can be written as

$$w_t(a,g) = \left[\tilde{l}_t(a,g) + \tilde{h}_t(a,g) + R_t^{INC}(a,g)\, w_{t-1}(a,g)\right] s_t(a,g) + w_{t-1}(a,g).$$

We consider $p = 5$ possible variables to permute, $x(a,g) = \left\{\tilde{l}_t, \tilde{h}_t, R_t^{INC}, s_t, w_{18}\right\}$, where w_{18} is the wealth that a group had at age 18. Then, if we want to measure the importance

of the saving rate *and* capital income for the wealth gap between the top 0.1% of wealth owners and the comparison group, we re-calculate the evolution of wealth as

$$\overline{w}_t\left(a,g;\overline{R^{INC}},\overline{s}\right) = \left[\tilde{l}_t\left(a,g\right)+\tilde{h}_t\left(a,g\right)+\overline{R^{INC}}w_{t-1}\left(a,g\right)\right]\overline{s}+\overline{w}_{t-1}\left(a,g;\overline{R^{INC}},\overline{s}\right),$$

conditional on a starting value of wealth equal to $w_{18}\left(a,g\right)$.

In this context, the Shapley value adds the marginal contribution to the gap between the groups under analysis by replacing component x_j (e.g. the saving rate) in the budget constraint after we have already replaced a different component (e.g. income from capital) or group of components (e.g. income from capital and initial wealth), weighted by the number of permutations possible *after* adding x_j. Hence, the contribution of $x_j\left(a,g\right)$ for the wealth gap between group (a,g) and the control group can be written as

$$C_j\left(a,g\right) = \sum_{T\subseteq Z\setminus\{x_j(a,g)\}}\frac{k!\times(p-k-1)!}{p!}\left[\overline{w}_t\left(a,g;T\cup\{x_j\left(a,g\right)\}\right)-\overline{w}_t\left(a,g;T\right)\right],$$

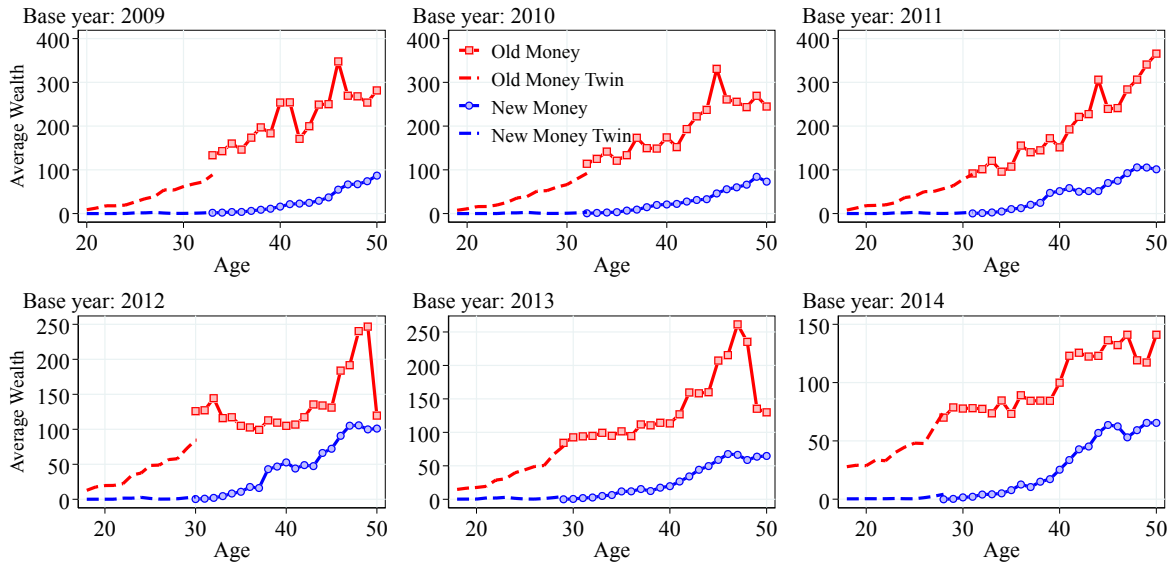
where $\overline{w}_t\left(a,g;T\right)$ is the wealth gap accounted in the case where we have replaced k of the components but without the component x_j, and $T\cup\{x_j\left(a,g\right)\}$ is the same case but with the k components plus $x_j\left(a,g\right)$. Notice that, for the case in which one replace only one of the components (e.g. only the saving rate), $\overline{w}_t$ is equal to the actual wealth of the group in a particular year (the case in which we do not replace any component). We then iterate across all potential permutations. Given this, the total difference between the wealth of a particular group and the control group, $\overline{C}(a,g)$ is equal to $\overline{C}\left(a,g\right)=\sum_j C_j\left(a,g\right)$, and the corresponding share as $C_j^S\left(a,g\right)=C_j\left(a,g\right)/\overline{C}\left(a,g\right)$.

OA.2.1 The Mahalanobis distance

Mahalanobis distance (Mahalanobi, 1936) measures the distance of a particular point with respect to a multivariate distribution.[3] Suppose for instance we want to asses how close a set of observations x are with respect to a multivariate distribution characterized by means m and covariance matrix C. Then, the Mahalanobis distance is given by $D^2=\left(x-m\right)^T\times C^{-1}\times\left(x-m\right)$, where D^2 is the square of the distance, x is a set of observations with different variables (e.g., age, wealth, and income), m is a vector of

[3]Mahalanobis, Prasanta Chandra (1936). "On the generalized distance in statistics". Proceedings of the National Institute of Sciences of India. 2 (1): 49–55.

Figure OA.1 – Wealth Profiles of Baseline and Twins



Notes: Figure OA.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 for each baseline year in our sample

mean values of independent variables (e.g., averages of age, wealth, and income of the distribution) and C^{-1} is the inverse of the covariance matrix of independent variables. The main gain from using this measure versus, for instance, the Euclidean distance, is that if the variables in the vector x are correlated, the covariance matrix will be high, hence reducing the distance between the two points. Alternatively, if the variables in x are not correlated, the distance will not be affected. In the extreme case, if the correlations are equal to 0, the C^{-1} reduces to a diagonal matrix, and D^2 is equivalent—in the one-dimensional case—to the square of the standard measure $\frac{x-m}{\sigma}$.

OA.3 Long-term Transition Matrix

For a more granular picture of the intragenerational wealth mobility, we construct backward- and forward-looking long-term transition probability matrices. To this end, Figure OA.2a shows, among the 50- to 54-year-olds in the end of the sample period, the fraction of each wealth group j, BW_j^{50-54} (rows of the matrix), that comes from the nth initial average wealth ($\overline{W}_{i,1994}$) quantile (columns of the matrix).[4] Similarly,

[4]We again take the average of transition probabilities over six base years $\tau \in \{2010, 2011, ..., 2015\}$, across which the length of the transition period varies between 23 years (between 2015 and 1993) and

Figure OA.2 – Long-term Intragenerational Transition Matrix

(a) Backward-Looking Transition

End-of-Period Wealth Rank, BW^h_j	Initial Average Wealth Rank [0,50]	(50-75]	(75-90]	(90-95]	(95-99]	(99-99.9]	Top 0.1%
[0,50]	63.2	23.2	9.4	2.3	1.6	0.2	0.0
(50-75]	41.9	29.8	19.2	5.3	3.4	0.4	0.0
(75-90]	34.6	26.1	23.1	9.0	6.2	1.0	0.0
(90-95]	30.1	22.8	22.4	11.7	10.7	2.3	0.1
(95-99]	25.7	18.7	19.4	12.2	17.0	6.6	0.3
(99-99.9]	20.5	14.5	15.6	9.0	18.9	17.5	3.9
Top 0.1%	15.4	6.0	7.4	5.9	13.0	23.2	29.2

(b) Forward-Looking Transition

Start-of-Period Wealth Rank, FW^h_j	Ending Average Wealth Rank [0,50]	(50-75]	(75-90]	(90-95]	(95-99]	(99-99.9]	Top 0.1%
[0,50]	58.4	22.1	12.2	3.8	2.8	0.6	0.1
(50-75]	49.4	27.1	15.0	4.6	3.3	0.6	0.0
(75-90]	39.1	30.2	18.6	6.4	4.7	0.9	0.1
(90-95]	29.7	30.9	22.8	8.1	6.9	1.4	0.1
(95-99]	22.2	25.2	26.1	11.7	11.5	3.1	0.3
(99-99.9]	10.7	14.6	19.0	13.9	29.7	10.9	1.1
Top 0.1%	2.8	2.3	6.3	5.1	22.0	37.6	23.9

Note: Figure OA.2a 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 OA.2b shows similar results by initial wealth, FW_j^{25-29} (rows), and the wealth distribution in $\overline{W}_{i,2015}$ (columns).

Figure OA.2b shows the transition probabilities between FW_j^{25-29} groups and 2014-2015 average wealth ($\overline{W}_{i,2015}$) quantiles for the households aged 25–29 in the beginning of the sample period. These two figures roughly correspond to the same cohorts.

For older cohorts, wealth mobility is even weaker (see Ozkan *et al.* (2023)). For example, more than 80% of the top 0.1% group among 50- to 54-year-olds in the early years of the sample (i.e., $FW_{\geq 99.9}^{50-54}$ group) are still in the top 1% of their cohort in 2015. Thus, fewer individuals enter or exit the top wealth group among older households. Furthermore, the degree of mobility at the top end of the wealth distribution is slightly weaker compared with the labor-earnings mobility in Norway, as reported by Halvorsen *et al.* (2022). Because the wealth distribution is very skewed, the top 1% and top 0.1% wealth brackets are quite wide, which can mechanically explain the persistence at the top of the wealth distribution. Therefore, we have constructed an alternative transition matrix whose logarithmic states are equally distanced. These results, developed in Ozkan *et al.* (2023), shows similar patterns.

18 years (between 2010 and 1993). The transition matrices for each base year are quantitatively very similar to each other and available upon request.

OA.4 Calculation of Returns

We follow Fagereng *et al.* (2020a) (FGMP thereafter) and calculate returns for total net worth, safe assets, equity (private and public), and housing. For consistency with the rest of our empirical results, we compute household-level returns—rather than individual-level returns as in FGMP. In particular, we aggregate all wealth variables and income flows at the household-level. In our measure we consider public equity and private equity as one category. We calculate 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 (dividend income plus capital gains from stock plus capital gains from private equity), and housing (income from housing plus capital gains from housing), respectively. The value of y^b_{it} is the sum of interest paid in all forms of debt, and w^g_{it} is the stock of wealth at the beginning of the period. Finally, F^g_{it} is net flows of gross wealth during period t (assets yields happen during year and households add/subtract from assets). We calculate similar returns for safe assets, equity, and housing.

We note a few differences between our and FGMP's methodologies. First, FGMP use hedonic house price indices to determine the value of the real estate, whereas we impute house values according to their features (e.g., number of rooms) from contemporaneous transactions data using the machine-learning approach developed by Fagereng *et al.* (2020b). Second, we calculate returns at the household level, rather than at the individual level, by aggregating all income from assets at the household level. Third, we consider individuals 25 years and older with no maximum age limit. Finally, to avoid having our results to be influenced by outliers, we drop returns observations with assets below a time-varying minimum value (about 6,000 NOK in 2015) in a given year for a given asset class (i.e., net wealth, safe assets, equity, and housing) and we winsorize the top and bottom 0.5% of the distribution of returns in a given year.

OA.4.1 Comparing returns across specifications

As described above, our measure of returns differs from FGMP in several aspects. Despite these differences, however, our estimates are relatively close to those presented by FGMP and confirm several of their findings. To see this, we start by reproducing their sample selection of FGMP in our data and calculate value-weighted cross-sectional moments pooling together all available data from 2005 to 2015. The results—reported

Table OA.3 – Wealth Returns

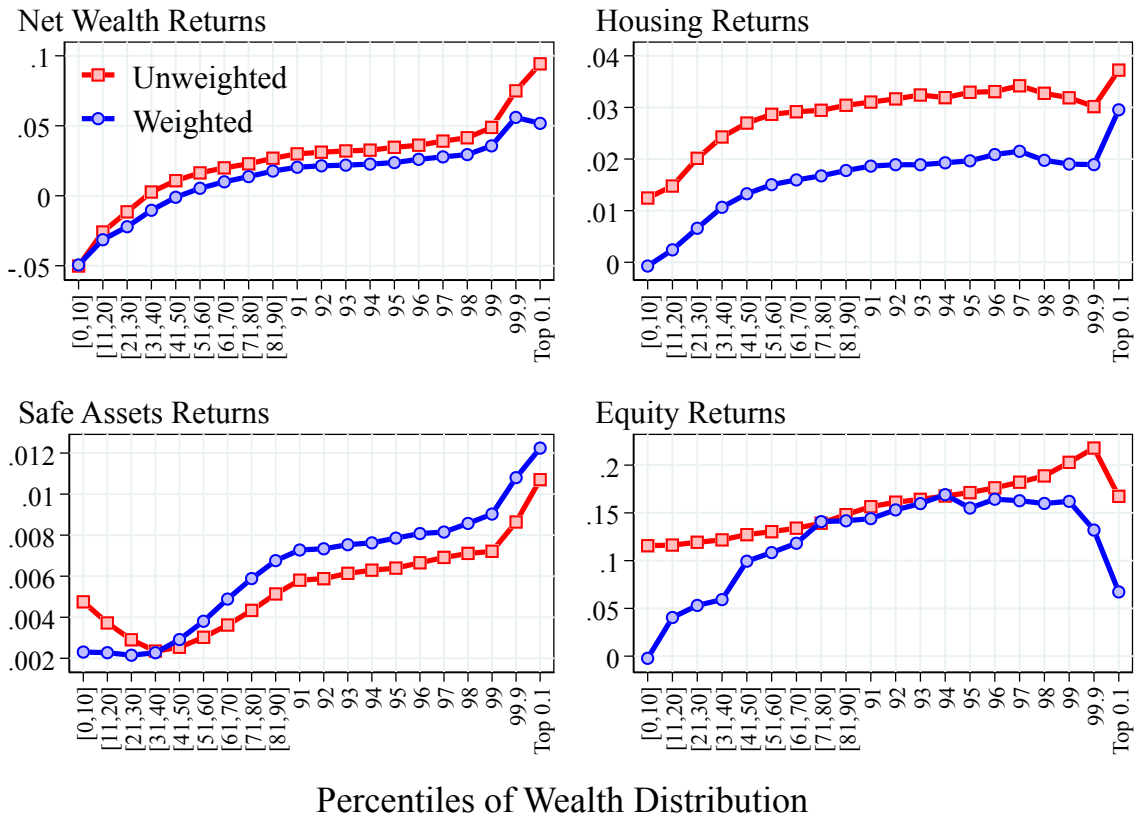
	N 000s	Mean	SD.	Skew.	Kurt.	P1	P5	P10	P50	P90	P95	P99
Panel A: Individual-level returns: FGMP (2005/2015)												
All	27,318	0.034	0.203	0.296	23.974	-0.622	-0.236	-0.103	0.022	0.185	0.292	0.735
Equity	10,072	0.083	0.363	2.463	24.412	-0.793	-0.350	-0.157	0.035	0.374	0.605	1.476
Housing	21,333	0.045	0.201	2.668	30.762	-0.534	-0.229	-0.088	0.025	0.183	0.281	0.811
Safe	27,374	-0.012	0.034	4.787	50.634	-0.061	-0.043	-0.042	-0.017	0.020	0.030	0.104
Panel B: Individual-level returns: This paper (2005/2015)												
All	29,482	0.033	0.202	0.702	19.911	-0.628	-0.241	-0.106	0.022	0.186	0.293	0.740
Equity	8,538	0.119	0.376	2.516	25.905	-0.920	-0.302	-0.119	0.069	0.414	0.643	1.545
Housing	23,558	0.045	0.201	2.619	30.030	-0.533	-0.229	-0.089	0.025	0.184	0.282	0.809
Safe	26,907	0.026	0.026	4.459	41.027	0.000	0.000	0.000	0.024	0.049	0.061	0.127
Panel C: Household-level returns: FGMP (2005/2015)												
All	19,356	0.032	0.183	0.506	16.993	-0.576	-0.228	-0.100	0.022	0.177	0.276	0.655
Equity	7,977	0.084	0.381	3.018	30.796	-0.837	-0.352	-0.157	0.034	0.374	0.608	1.537
Housing	14,550	0.044	0.187	2.246	26.583	-0.504	-0.215	-0.084	0.028	0.179	0.275	0.738
Safe	19,431	-0.013	0.030	3.387	31.369	-0.057	-0.042	-0.042	-0.017	0.020	0.029	0.083
Panel D: Household-level returns: This paper (2005/2015)												
All	20,902	0.030	0.186	0.468	16.887	-0.587	-0.234	-0.103	0.022	0.177	0.276	0.658
Equity	6,968	0.120	0.383	2.872	30.027	-0.905	-0.301	-0.117	0.068	0.413	0.643	1.569
Housing	16,070	0.044	0.187	2.207	26.019	-0.505	-0.216	-0.085	0.028	0.180	0.276	0.738
Safe	19,823	0.026	0.025	4.216	40.075	0.000	0.000	0.000	0.025	0.049	0.060	0.116

Notes: Table OA.3 shows cross-sectional statistics of the returns distribution for different asset classes based on a pooled sample of households between 2004 and 2015 (Panel A to D) We calculate returns following Fagereng *et al.* (2020a). Equity corresponds to the sum of equity on private and publicly traded firms.

in Panel A of Table OA.3—are quite similar to those presented in Table 3 of FGMP. For instance, FGMP report a mean return on assets of 3.8% and a standard deviation of 8.5%. We obtain a mean return of 3.3% and a standard deviation of 20.3%, mostly coming from the larger dispersion on the returns on housing: FGMP's mean return on housing is 4.9% with a standard deviation of 6.5%, whereas our average is 4.5% with a standard deviation of 20.1%. The rest of the estimates are in line with FGMP. We then apply our sample selection. As shown in Panel B of Table OA.3, the results do not change much, with the exception of an increase in the returns on equity. Intuitively, our sample selection is somewhat less restrictive, leaving in the sample a larger number of households with more volatile returns. The results do not change significantly if we consider household-level returns.

We now examine the returns across the wealth distribution, as shown in OA.3. Similar to FGMP, the average annual return on net wealth increases with wealth, from -5% for

Figure OA.3 – Cross-Sectional Average Returns



Notes: Figure OA.3 shows the average returns within different quantiles of the households net worth distribution. To construct this figure, we pool household observations between 2005 and 2015. Weighted averages are weighted using the value of the corresponding asset. Negative or missing asset values are assigned a weight of 0.

the first decile to 10% for the top 0.1%. Returns on safe assets also rise with net wealth but only above the 40th percentile. The return on housing shows a hump-shaped pattern, with a significant increase for the top 0.1%. The weighted and unweighted average returns for net wealth, safe assets, and housing are similar. However, returns on equity differ significantly: Unweighted returns rise from 12% for the bottom decile to over 20% for the top 1%, then drop to 16% for the top 0.1%. The weighted average returns are hump-shaped relative to wealth, peaking at 15% around the 90th 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)).

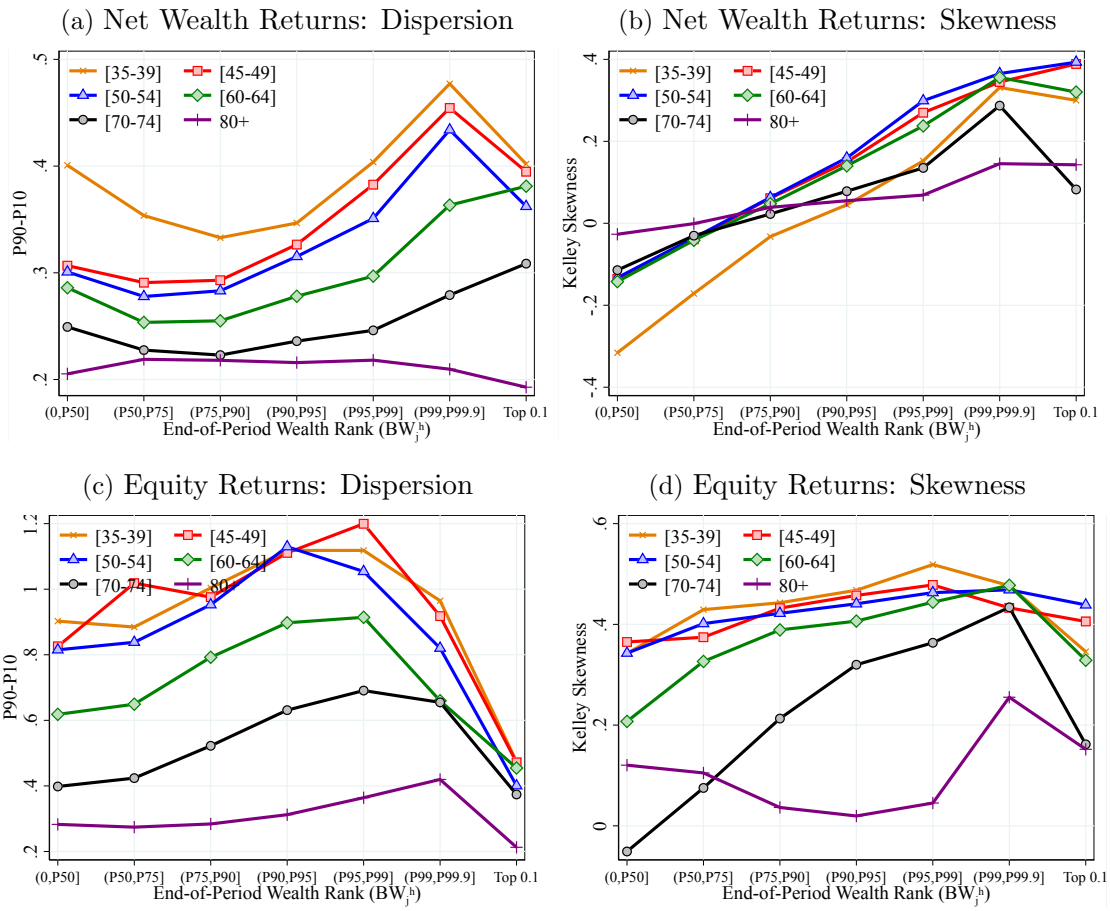
OA.4.2 Higher-Order Moments of Returns

Do the wealthier earn higher returns because their investments are riskier? To answer this question, we study differences in the higher-order moments of the distribution of returns across wealth and age groups.[5] First, wealthier households face a somewhat more-dispersed distribution of returns especially among the younger cohorts. For instance, among 45-year-olds the P90-P10 gap of the returns on assets increases from around 35% for households in the bottom 90% of the distribution to around 45% in the top 1% (Figure OA.4a). Returns become less volatile over the life cycle for all wealth groups but more so for the wealthiest, thereby leading to very small differences between wealth groups in older cohorts. The higher dispersion of returns for high-wealth households is explained by the larger share of equity in their portfolios, as returns for equity are more volatile with a standard deviation of 0.38 versus 0.025 and 0.19 for safe assets and housing, respectively (Table OA.3). Otherwise, we find equity returns to be less volatile for the top 1% of wealth groups compared with the rest of the population (Figure OA.4c).

Figure OA.4d shows that the higher dispersion of returns on assets for richer households is also accompanied by a more positive skewness, indicating higher upside risk. For example, among households aged 50–54, those below the 50th percentile of the wealth distribution ($BW^{50-54}_{\left[W_t^{\min}, P50\right)}$), the lower half of the return distribution constitutes 60% of the total dispersion of returns (i.e., $\mathcal{S}_{\mathcal{K}} = -0.2$). In contrast, those in the top 0.1% $\left(BW^{50-54}_{\geq P99.9}\right)$ have experienced positively skewed returns, with almost 70% of the total dispersion accounted for by the right tail (i.e., $\mathcal{S}_{\mathcal{K}} = 0.4$). Again, these differences between wealth groups are explained more by the differences in portfolio composition—returns on equity are more strongly positively skewed relative to safe assets and housing (Table OA.3)—than by within-asset class differences, as the skewness on returns on equity is relatively flat across the wealth distribution (Figure OA.4d). Some of these results can be explained by conditioning on an endogenous variable—that is, we select those who experienced higher and positively skewed returns, thereby becoming rich. We find similar results if we condition by initial wealth (see OSM).

[5] As in the rest of the analysis, for each base year $\tau \in \{2010, 2011, ..., 2015\}$ and for each wealth and age group j, h, we first calculate the value-weighted higher-order moments of the return distribution in each year t between 2004 and τ and then take an average across years t and base years τ.

Figure OA.4 – Dispersion and Skewness of Returns



Notes: Figure OA.4 shows value-weighted cross-sectional moments of annual returns within age and wealth groups. The Kelley skewness is defined as $\mathcal{S}_{\mathcal{K}} = \frac{P90-P50}{P90-P10} - \frac{P50-P10}{P90-P10}$.

OA.5 Details of Quantitative Exercises

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

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

where κ_h is a life-cycle component—which is common for all households—assumed to be a quadratic function of age. $\bar{e}_i$ 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 persistent 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, which includes wages, self-employed income, unemployment benefits, paid sick leave and parental leave. 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 OA.4 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. In

Table OA.4 – 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

the full model, we set the curvature of the entrepreneurial production function to $\mu = 0.9$ and $\lambda = 3$, so that at least one-third of capital has to be financed with owner equity.

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 discussed in the main text. As a consequence, except in the warm glow bequest model of column (5), initial wealth is zero for all model agents, and consequently the contribution of inheritances to the wealth gap is zero as well (middle panel of Table OA.5.) Moreover, several model versions have trouble generating enough wealth inequality by age 50 without differences in initial wealth—most strikingly, the stochastic-β model in (4), but the superstar (2) and return heterogeneity (3) models fall short to some extent as well. This is because, when respecting income concentration, it not possible for these models to generate enough wealth at the top of the distribution when starting all agents from zero wealth.

Table OA.5 – Re-estimated models without accidental bequest

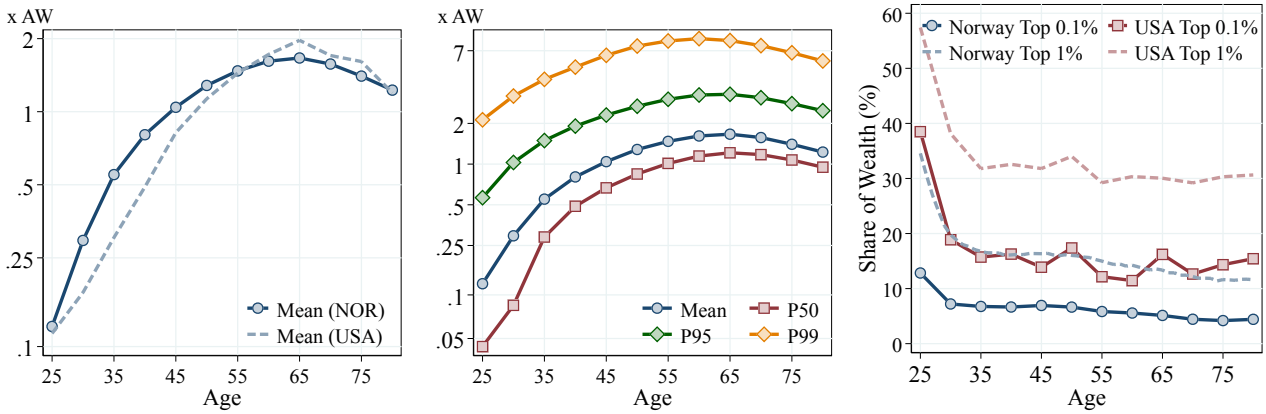
		(1)	(2)	(3)	(4)	(5)
	Data	Basic	Superstar	Returns	β	Bequest
Target cross-section			✓	✓	✓	✓
Cross-Sectional Moments						
Wealth/Lab.Inc. ratio	*6.4*	**6.4**	**6.1**	**6.1**	**3.6**	**4.5**
Top 0.1% wealth (%)	*9.7*	0.8	**8.9**	**8.7**	**5.3**	**7.9**
Top 0.1% income (%)	*5.8*	0.8	**6.3**	**6.5**	0.9	1.4
Wealth Decomposition for 50-year-old top 0.1% group (%)						
Inheritance	*34.0*	0.0	0.0	0.0	0.0	110.7
Labor income	*4.7*	75.6	70.2	6.1	30.5	0.0
Returns	*23.1*	-0.1	-0.1	41.7	-1.0	0.1
Saving rate	*38.2*	24.5	29.9	52.3	70.5	-10.7
Initial Wealth of New and Old Money (in AW)						
New Money	*-0.1*	0.0	0.0	0.0	0.0	100.6
Old Money	*39.7*	0.0	0.0	0.0	0.0	113.6

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

OA.6 Additional Figures and Tables

Figure OA.5 – 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. In Panels A and B, we plot the age fixed effects from a Deaton-Paxson regression controlling for year effects. All values are expressed relative to the average wealth in the economy (AW) and scaled using an inverse hyperbolic sine transformation. Panel C shows the within-age-group share of wealth.

Figure OA.6 – 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 OA.6 shows a intergenerational transition matrix between households wealth in 2015 and their parental household wealth for households in different age groups. Each cell represent the fraction of household 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 calculate as the rank of the average wealth adjusted for an age and year specific mean.