WP/18/171

IMF Working Paper

Heterogeneity and Persistence in Returns to Wealth

By Andreas Fagereng, Luigi Guiso, Davide Malacrino and Luigi Pistaferri

INTERNATIONAL MONETARY FUND

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Research Department

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Authorized for distribution by Romain Duval

July 2018

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Abstract

We provide a systematic analysis of the properties of individual returns to wealth using twelve years of population data from Norway's administrative tax records. We document a number of novel results. First, during our sample period individuals earn markedly different average returns on their financial assets (a standard deviation of 14%) and on their net worth (a standard deviation of 8%). Second, heterogeneity in returns does not arise merely from differences in the allocation of wealth between safe and risky assets: returns are heterogeneous even within asset classes. Third, returns are positively correlated with wealth: moving from the 10th to the 90th percentile of the financial wealth distribution increases the return by 3 percentage points - and by 17 percentage points when the same exercise is performed for the return to net worth. Fourth, wealth returns exhibit substantial persistence over time. We argue that while this persistence partly reflects stable differences in risk exposure and assets scale, it also reflects persistent heterogeneity in sophistication and financial information, as well as entrepreneurial talent. Finally, wealth returns are (mildly) correlated across generations. We discuss the implications of these findings for several strands of the wealth inequality debate.

JEL Classification Numbers: D31, D91, E21, E24, G11

Keywords: Wealth inequality, returns to wealth, net worth, heterogeneity, intergenerational mobility.

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Note: Fagereng is with Statistics Norway, Guiso with EIEF and CEPR, Malacrino with IMF, and Pistaferri with Stanford University, NBER and CEPR. We thank four anonymous referees, Alberto Bisin, Romain Duval, Fatih Guvenen, Tullio Jappelli, Benjamin Moll, Gueorgui Kambourov, Daniele Massacci, Giovanni Mastrobuoni, Andrea Pozzi, Ali Shourideh, Kjetil Storesletten, Anton Tsoy and Gianluca Violante for very fruitful discussions. We are grateful for useful comments from seminar participants at various seminars and conferences in the US and Europe and to Sarah Eichmeier and Mike Shi for research assistance and Martin Holm and Kjersti Torstensen for help with the housing data. Funding from the Research Council of Norway and the Washington Center for Equitable Growth is gratefully acknowledged. The views expressed in this article are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management. All errors are ours. The Online Appendix can be found here.

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1 Introduction

Over time and across countries, the wealth distribution appears to be extremely skewed and with a long right tail: a small fraction of the population owns a large share of the economy's wealth. In the US, for example, the top 0.1% hold about 20% of the economy's net worth. Moreover, tail inequality seems to have more than doubled in the last three decades (Saez and Zucman, 2016).

What produces the long tail of the wealth distribution and its extreme skewness is the subject of intense research (see De Nardi and Fella, 2017 for an exhaustive critical appraisal of the literature). A traditional strand of literature started by Aiyagari (1994) has focused on the role played by idiosyncratic and uninsurable labor income (i.e., human capital) risk (see Castaneda et al., 1998; Huggett, 1996), or, more generally, heterogeneity in human capital (e.g., Castaneda et al., 2003), but with mixed success.[1] A different route, followed by Krusell and Smith (1998), has been to complement Bewley-Aiyagari models of earnings heterogeneity with heterogeneity in thriftiness, allowing individuals to differ in time discounting.[2] Differences in thriftiness, together with heterogeneity in earnings, can considerably improve the match between the wealth distribution generated by the model and that in the data. Discount rate heterogeneity has a certain appeal because of its intuitive realism. However, discount rates are hard to observe and their heterogeneity is thus difficult to assess. Furthermore, discount rate heterogeneity seems to miss one important feature of the data: the high incidence of entrepreneurs at the top of the wealth distribution. Entrepreneurship is usually associated with higher risk tolerance and idiosyncratic risk (entrepreneurs tend to hold very high stakes in their own company - see e.g., Heaton and Lucas, 2000; Moskowitz and Vissing-Jorgensen, 2002), rather than with higher than average discount factors. An alternative route followed in an attempt to match the thick tail in the distribution of wealth has been to explicitly allow for entrepreneurship and idiosyncratic returns to investment, as in Quadrini (2000) and Cagetti and De Nardi (2009; 2006).

While heterogeneity in returns to wealth can be plausibly linked to differences in entrepreneurs' ability (as in the seminal Lucas, 1978), it may arise from a variety of other

[1] For instance, while the calibrated model of Kindermann and Krueger (2014) comes close to matching the distribution of wealth in the US, it requires the top 0.25% of income earners to earn 400 to 600 times more than the median earner - a value that appears in contrast with what is observed in the data, where the ratio of the income of the top 0.25% percent to the median is 34 at most (Benhabib and Bisin, 2018).

[2] Other authors emphasize the role of non-homothetic preferences, inducing the rich to save at higher rates than the poor (see e.g., De Nardi, 2004 and Carroll, 2002), or of changes in tax and transfer policies (Kaymak and Poschke, 2016).

sources.[3] Remaining agnostic about its causes, a recent wave of papers (Benhabib et al., 2011, Benhabib et al., 2017, and Gabaix et al., 2016) has shown that models in which individuals are endowed with idiosyncratic returns to wealth that persist over time and (to some extent) across generations can generate a steady state distribution of wealth with a thick right tail that reproduces very closely what is observed in reality. In one key contribution, Benhabib et al. (2011) consider an overlapping generation model where households differ both in returns to human capital and in returns to wealth. Each household is endowed at birth with a rate of return to wealth and a return to human capital, drawn from independent distributions. Hence, there is persistence in returns to wealth (and human capital) within a generation. In addition, returns persist across generations and are independent of wealth. They show that it is the heterogeneity in returns and their intergenerational persistence that drive the thickness in the right tail of the wealth distribution, rather than the heterogeneity in returns to human capital. In another important contribution, Gabaix et al. (2016) show that, while the Benhabib et al. (2011) model can explain the long thick tail of the wealth distribution, it cannot explain the speed of changes in tail inequality observed in the data. They suggest that one way to capture the latter is to allow for some "s*cale dependence*" - a positive correlation of returns with wealth - in addition to *"type dependence"* (persistent heterogeneity in returns).

Despite their theoretical appeal, explanations of the level and the dynamics of wealth inequality and concentration based on a more sophisticated process for the returns to wealth suffer from some of the same problems as models that rely on heterogeneity in discount rates. How reasonable are the findings of heterogeneity and persistence in Benhabib et al. (2011)? Is there a correlation between wealth and returns to wealth that is compatible with the speed of tail inequality observed in the data? Unlike individual discount rates, however, individual returns on wealth have the advantage that they can be observed. What needs to be documented is that returns to wealth have an individual component; that this component persists over time; that it correlates with wealth; and that it shows some intergenerational persistence. Documenting these properties requires much more than just observability; it requires availability of long, well-measured panel data on capital income and assets covering several generations. The goal of our paper is to provide a systematic characterization of these properties.

To achieve this goal we use twelve years of administrative tax records of capital income

[3]For example, from restricted access to the stock market as in Guvenen (2009). In the literature, differences in financial literacy or sophistication, access to information, or scale effects have been offered as alternative explanations for the existing differences in returns to wealth across individual investors (see Arrow, 1987, Peress, 2004, Kacperczyk et al., 2014, Jappelli and Padula, 2017, and Deuflhard et al., 2018).

and wealth stocks for all taxpayers in Norway (2004-2015, with data for 2004 used as initial conditions). Several properties of these data make them well suited to addressing the above questions. First, measurement error and underreporting of wealth information are minimal, since wealth data are generally collected through third parties (i.e., information provided by financial intermediaries). Second, the data have universal coverage, implying that there is exhaustive information about the assets owned and incomes earned by *all* individuals, including those at the very top of the wealth distribution. Furthermore, besides information on financial assets, housing and debt, we have data on wealth held in private businesses. These two features are critical for a study of our sort, because leaving out the wealthy or the wealth in private businesses (which happens to be highly concentrated among the wealthy) could seriously understate the extent of heterogeneity in returns to wealth, particularly if returns and the extent of heterogeneity are correlated with wealth. Most importantly, the data have a long panel dimension, allowing us to study within-person persistence in returns. Finally, since we can identify parents and children, we can also study intergenerational persistence in returns to wealth.

We consider two broad measures of returns: the return to financial assets and the return to net worth. One reason for looking at these two measures separately is that financial wealth reflects more closely portfolio composition choices and risk/return considerations, while net worth is dominated by a component, housing, that individuals acquire more for consumption than for investment purposes. We find that both measures of returns exhibit substantial heterogeneity. For example, during our sample period (2005-15), the (value-weighted) average real return on financial wealth is 4.2%, but it varies considerably across households (standard deviation 14.4%). For net worth returns, the average is similar (4.1%), but with a smaller standard deviation of 8.3%.[4] We also find that the two return measures exhibit distinctive correlation with the relevant wealth concept. The return to financial wealth increases steadily with the position in the financial wealth distribution (the return difference between the 90th and the 10th percentile is roughly 260 basis points), and it accelerates substantially in the last decile. The average return to net worth is initially negative for households with negative net worth reflecting the cost of debt. For individuals with positive net worth, average returns rise with the position in the net worth distribution at a slower pace than seen for financial wealth (due to the counteracting effect of the cost of debt). The difference between the average return at the 90th and 10th percentiles of net worth is substantial (roughly 17 percentage points).

[4]For completeness, Figure OA.1 in the Online Appendix plots the cross-sectional standard deviation of value-weighted returns for each year between 2005 and 2015.

In any given year, heterogeneity in returns to wealth may arise from differences in observables (e.g., risk exposure or wealth), idiosyncratic transitory variations (good or bad luck), or from a persistent unobservable component in returns to wealth. The latter is the critical component in the new literature on wealth inequality. To separate these components, we estimate a panel data statistical model for the returns to wealth that includes an individual fixed effect. To account for heterogeneity explained by observable factors, we control for lagged wealth ("scale"), the share of wealth held in various types of assets and the extent of diversification in the stock portfolio ("risk exposure"), as well as time effects and demographics. The individual fixed effect measures the component of unobserved heterogeneity that persists over time *controlling for* scale and risk-taking. We find that observable characteristics alone explain roughly one-third of the variability in returns to financial or net worth. Adding individual fixed effects increases explained variability in returns to financial wealth (net worth) by 23% (49%). The distribution of these fixed effects is itself quite dispersed, with a standard deviation of 3.6% (for financial wealth; 5.4% for net worth). While risk tolerance may be only imperfectly captured by the shares invested in risky assets and the stock portfolio's β (and hence indirectly explain the importance of fixed effects), we show that persistent heterogeneity continues to play a statistically significant and quantitatively large role even in a setting in which risk considerations should not matter, namely deposit accounts with universal deposit insurance. Our results suggest that persistent traits of individual investors (such as financial sophistication, the ability to process and use financial information, and - for entrepreneurs - the talent to manage and organize their businesses), are capable of generating persistent differences in returns to wealth that may be as relevant as those conventionally attributed in household finance to differences in risk exposure or scale.

Besides its high level of concentration, another stylized fact of the wealth distribution is that it tends to be strongly positively correlated across generations (Charles and Hurst, 2003). One potential explanation is that returns to wealth are, at least in part, intergenerationally transmitted (Benhabib et al., 2011). To examine this possibility, we extend our analysis and focus on the intergenerational persistence in returns. We find that returns to wealth are correlated intergenerationally, although there is evidence of mean reversion at the top. While some of the correlation is explained by scale dependence in wealth, it remains positive and significant even controlling for wealth (or education).

As far as we know, this is the first paper to provide systematic evidence on individual returns to wealth over the entire wealth distribution and to characterize their properties. Bach et al. (2015) perform an exercise close to ours in spirit, but our paper differs from theirs in several respects. First, their focus is on expected returns, which they compute using standard finance models; since we want to understand what explains growth in wealth, we focus instead on actual, realized returns to wealth. Second, their main focus is the extent and nature of the correlation between returns and wealth at the top (60%) of the wealth distribution; we study the properties of the returns to wealth over the whole range of the wealth distribution. This is important for understanding wealth mobility, as some people with negative net worth are (as we document) investors short of cash but with highly productive ideas. Third, we use our longitudinal data set to study persistence in returns, the key feature emphasized by the literature cited above, while their study emphasizes more the cross-sectional features of the returns. Finally, we can study heterogeneity and persistence in returns to wealth over and above the intra-generational dimension. Indeed, our paper is the first to provide systematic evidence of persistence in returns within and across generations.[5] These two features are critical for explaining the long thick tail in the wealth distribution. We also provide evidence that the persistent component of returns is correlated with wealth and so is the degree of heterogeneity - two features of the data that reasonably calibrated models of wealth inequality should be able to accommodate.

The rest of the paper proceeds as follows. In Section 2, we present our data and discuss how we measure returns to wealth. Section 3 documents stylized facts about returns to wealth. In Section 4, we discuss our empirical model of individual returns, show how we identify persistent heterogeneity and present results about its extent. In Section 5, we discuss the relative importance of the drivers of persistent return heterogeneity. Section 6 documents intergenerational persistence. Section 7 concludes discussing several implications of our findings. For reasons of space, we have moved additional material (data description details and extra Figures and Tables) to an Online Appendix (OA henceforth), to which the interested reader is referred.

2 Data sources and variable definitions

Our analysis is based on several administrative registries maintained by Statistics Norway, which we link through unique identifiers for individuals and households. In this section, we discuss the broad features of these data; more details are provided in the OA. We start by using a rich longitudinal database that covers every Norwegian resident from 1967 to 2015. For each year, it provides relevant demographic information (gender, age, marital status,

[5]In a companion paper (Fagereng et al., 2016a), we also study how persistence in wealth across households can arise from assortative mating in wealth *and* returns to wealth.

educational attainment) and geographical identifiers. For the period 2004-2015 - the period we focus on here - we can link this database with several additional administrative registries: (a) tax records containing detailed information about the individual's sources of income (from labor and capital) as well as asset holdings and liabilities; (b) a shareholder registry with detailed information on listed and unlisted shares owned; (c) balance sheet data for the private businesses owned by the individual; (d) a housing transaction registry; and (e) deposit and loan account data, containing, for each deposit (loan) account, information on the bank identifier, the amount deposited (loan balance), and the interests received (interest paid) during the year. The value of asset holdings and liabilities is measured as of December 31. While tax records typically include information about income, they rarely (if ever) contain exhaustive information about wealth. In Norway, this happens because of a wealth tax that requires taxpayers to report their asset holdings in their tax filings.

The data we assemble have several, noteworthy advantages over those available for most other countries, particularly for the purpose of our study. First, our income and wealth data cover all individuals in the population who are subject to income and wealth tax, including people at the very top of the wealth distribution. Given the extreme concentration of wealth at the top, this is a key feature of the data.[6] In particular, steady-state wealth inequality and the speed of transition to a new steady state are likely to be sensitive to even a small correlation between returns and wealth; and the degree of correlation may be higher (as we document in Section 3) at high levels of wealth. These features can only be captured if the data include people at the very top of the wealth distribution. Second, in our data set, most components of income and wealth are reported by a third party (e.g., employers, banks, and financial intermediaries) and recorded without any top- or bottom-coding. Thus, the data do not suffer from the standard measurement errors that plague household surveys, where individuals self-report income and asset components (as for instance in the US Survey of Consumer Finances) and confidentiality considerations lead to censorship of asset holdings.[7]

[6] Wealth is highly concentrated in Norway and the degree of concentration has been trending up. In 1979 (before US wealth concentration started to drift upwards after a long period of decline, Saez and Zucman, 2016), the top 0.1% share was similar to the US (6.4% vs. 7.9%). After that, concentration in Norway has been increasing, albeit at a lower rate than in the US. See Figure OA.2 in the OA.

[7] Clearly, if some assets are held abroad and not reported to the tax authority there will be an understatement of wealth concentration since it is plausible that these assets are disproportionately held by the wealthy (Zucman, 2014). Using information on Norwegian taxpayers who disclosed assets held offshore following an amnesty in the early 2000's, Alstadsæter et al. (2017) show that the beneficiaries of the amnesty are indeed the very wealthy. Of the 1419 individuals who disclosed assets offshore, essentially none is below the 99th percentile and 50% are among the wealthiest 400. The chances of having assets offshore increases sharply with wealth but is never larger than 12% (Zucman, 2016), suggesting that many wealthy may have no wealth offshore. Alstadsæter et al. (2017) show that accounting for hidden wealth can increase the top 0.1% wealth

Third, the Norwegian data have a long panel dimension, which is crucial to identify persistent heterogeneity in returns. Because the data cover the whole relevant population, they are free from attrition, except the (unavoidable) one arising from mortality and emigration. Fourth, unique identifiers allow us to match parents with their children. This allows us to study intergenerational persistence in returns to wealth. Finally, our data include information not only on listed stocks but also on private business holdings. Because private business holders have large stakes in their firm, this feature is important for pinning down the extent of heterogeneity in returns. And because, as we will document, stakes in private businesses strongly increase with wealth, this feature is also important for understanding the correlation between wealth and returns. Besides these unambiguous merits, our data also have some shortcomings: (a) assets and liabilities are valued at an annual frequency; (b) the market value of private businesses may be mismeasured; and (c) private pension wealth data is absent. Below we discuss these issues more in detail and propose solutions. Next, we describe the administrative tax records for wealth and income and how we construct our measure of wealth returns. Details of the mapping between the capital income tax component and the specific asset category are provided in the OA.

2.1 Administrative wealth and capital income records

Norwegian households are subject to both an income tax and a wealth tax.[8] Each year, people are required to report their incomes and to provide complete information about wealth holdings to the tax authorities. Tax record data are available on an annual basis since 1993.[9] We do not use data before 2004 as the shareholder registry, and some of the other registries are only available since 2004 (in most of our analyses we use wealth data for 2004 as initial condition, and the period 2005-2015 as our sample period). The collection of tax information is mostly done through third parties. In particular, employers must send information on earned labor income both to their employees and to the tax authority; financial intermediaries where individuals hold financial accounts (such as banks, stock brokers, insurance companies,

share by roughly 1 percentage point on average.

[8]Net wealth in excess of an exemption threshold is taxed at a flat rate of around 1% during our sample period. The exemption threshold has been increasing over time and was in the later years around NOK 1.5 million for a married couple (and half that for a single person). Importantly, household assets are reported and recorded even if they fall short of this threshold. Certain assets are valued at a discount in certain years when calculating taxable wealth. For instance, stocks were valued at 85% of market value in 2007. We adjust these discounted values back to market values before constructing household wealth.

[9]The individuals in a household are taxed jointly (i.e., married couples) for the purpose of wealth taxation, and separately for income tax purposes.

etc.) do the same for the value of the assets owned by the individual as well as for the income earned on these assets. For traded assets, the value reported is the market value. The fact that financial institutions supply information about their customer's financial assets directly to the tax authority greatly reduces the scope for tax evasion.

We impose some minor sample selection designed to reduce errors in the computation of returns. First, we drop people with less than USD 500 in financial wealth (about NOK 3000). These are typically observations with highly volatile beginning- and end-of-period reported stocks that tend to introduce large errors in computed returns. Second, we trim the distribution of returns in each year at the top and bottom 0.5% and drop observations with trimmed returns. These are conservative corrections that, if anything, reduce the extent of heterogeneity in returns. Finally, we focus on the Norwegian population aged between 20 and 75 (although none of our conclusions are affected if we consider a younger or older sample). We focus on this age range to make sure that the financial decision maker is the holder of the assets and, thus, that we correctly identify his/her return fixed effect.

2.2 Wealth aggregates

Our administrative data contain information on the ownership of several asset classes and on total debt.[10] To facilitate the discussion we group assets into three broad categories: safe assets, risky assets, and housing (w^s, w^m, and w^h, respectively).

The stock of safe assets w^s is the sum of: (a) cash/bank deposits (in domestic or foreign accounts), and (b) money market funds, bond mutual funds, and bonds (government and corporate). The stock of risky assets w^m is the sum of: (a) the market value of listed stocks, $w^{m,l}$ (held directly, $w^{m,l,d}$, or indirectly through mutual funds, $w^{m,l,i}$), (b) the value of shares in private businesses and other unlisted shares, $w^{m,u}$, and (c) the value of risky assets held abroad and that of outstanding claims and receivables (debt owed to the household and payments not yet cashed in), $w^{m,x}$.[11] While listed stocks are reported at market value,[12] the value of unlisted stocks held by the individual taxpayer is obtained as the product of the equity

[10] We exclude assets that are reported in tax records but have returns that are hard to measure: vehicles, boats, cabins, and real estate abroad. These assets represent roughly 5% of the total assets owned by households. In the OA (Figure OA.3, Panel A) we show how the composition of net worth changes when we include these extra components.

[11] We treat this as a composite asset since its return is slightly more challenging to compute.

[12] More precisely, the market value of directly held stocks $w_t^{m,l,d}$ is defined as $w_t^{m,l,d} = \sum_k p^k_{12/31,t} s^k_{it}$, where s^k_{it} are the shares of security k held as of 12/31 of year t (available from the Shareholder Registry) and $p^k_{12/31,t}$ the price at the same date (which is publicly observed). The market value of mutual funds $w^{m,l,i}$ is directly available from the tax records.

share held in the firm and the "assessed value" of the firm. The latter is a value reported by the private business to the tax authority to comply with the wealth tax requirements. This value does not necessarily correspond to the "market value" of the company, i.e., what the company would realize if it were to be sold in the market. In general, the firm may have an incentive to report an assessed value below the true market value. On the other hand, the tax authority has the opposite incentive and uses control routines designed to identify firms that under-report their value. Consistent with this, the (log) assessed value is strongly correlated with the firm (log) book value (correlation 0.88, Figure OA.4 in the OA) and, in more than 50% of cases, the assessed value exceeds the book value (which may be inconsistent with the goal of minimizing the tax bill). Medium- to large-sized firms (with a turnover above NOK 5 million, or USD 500k) are required to have their balance sheet reports audited by a professional auditing firm, reducing the scope for accounting misstatements.

The stock of housing w^h includes both the value of the principal residence and of secondary homes. To obtain an estimate of these values, we merge official transaction data from the Norwegian Mapping Authority (Kartverket), the land registration, and the population Census, which allows us to identify ownership of each single dwelling and its precise location. Following tax authority methodology (described in Fagereng et al. (2018)), we estimate a hedonic model for the price per square meter as a function of house characteristics (number of rooms, etc.), time dummies, location dummies and their interactions. The predicted values are then used to impute house values for each year between 2004 and 2015.

Finally, the outstanding level of debt from the tax records is the sum of student debt, consumer debt, and long-term debt (mortgages and personal loans). To separate these three types of debt we use an administrative registry on the universe of loan (and deposit) accounts, containing (for the sample period we are focusing on and for each account) information on the lender ID, loan balances, and interests paid. Student debt is easily identifiable since loans come from the Norwegian State Education Loan Fund with a known lender ID. To separate consumer debt from other long-term debt we rely on information on the identity of the lender matched with other account information. In particular, we estimate consumer loans as the sum of loans granted by financial intermediaries that specialize in consumer lending and in loans with interest rates persistently above 10% (an observed lower bound of interest-bearing loans in the consumer lending sector over our sample period).

We consider two measures of wealth. The first is *financial wealth*, the sum of safe and risky assets:

$$F_{it} = w_{it}^{s} + w_{it}^{m}$$

and the second is *net worth*, the sum of financial wealth and housing net of outstanding debt:

$$N_{it} = G_{it} - b_{it}$$

where $G_{it} = (F_{it} + w_{it}^{h})$ is *gross wealth* and b_{it} is outstanding debt.

Panel A of Table 1 shows the composition of individual financial wealth: the share of wealth in safe assets (divided into deposits and bonds), and the share invested in risky assets (divided into foreign and outstanding claims, mutual fund holdings, directly held listed stocks and private equity) for people in selected fractiles of the financial wealth distribution (see Figure OA.5 for the entire percentile distribution). Safe assets clearly dominate the portfolio of people below median wealth. Public equity (especially through mutual funds) gains weight among people above the median and below the top 1%. The share in private businesses strongly increases with wealth above the 95th percentile and carries very large weight, close to 90%, for the top 0.01%.

Panel B of Table 1 turns to the composition of net worth. To avoid cluttering, we categorize assets into just three categories: safe assets, housing, and risky assets. To avoid negative and infinite shares when dividing assets and liabilities by net worth, we scale components of net worth by gross wealth and report the shares for people in selected fractiles of the net worth distribution (see Figure OA.6 for the entire percentile distribution). The bottom 20% of the distribution has negative net worth on average due to debt exceeding assets. As we cross into positive net worth territory, the net worth portfolio starts resembling the financial wealth portfolio, with the exception of course of housing, which is the largest asset in most people's portfolio. In fact, it is only at the very top of the distribution of net worth that housing loses its preponderant role, replaced by risky financial assets. In the last three columns we report average leverage (debt scaled by gross assets) by selected fractiles of the net worth distribution, distinguishing between consumption debt, student debt, and long-term debt (mortgages and personal loans).[13]

2.3 Measuring returns to wealth

We consider two measures of returns to wealth. The first is the average *return to financial wealth*, defined as:

[13] For legibility, we winsorize leverage levels above the 99th percentile in each year.

$$\tilde{r}^F_{it} = \frac{y^s_{it} + y^x_{it} + y^{l,i}_{it} + (d^{l,d}_{it} + g^{l,d}_{it}) + (d^u_{it} + g^u_{it})}{F_{it}} = \frac{y^F_{it}}{F_{it}} \tag{1}$$

The denominator is financial wealth measured at the *beginning* of year t. The numerator is the sum of income from safe and risky assets accrued in year t: income earned on all safe assets y^s_{it} (the sum of interest income on domestic and foreign bank deposits and bond yields), yields from risky assets held abroad and outstanding claims and receivables, y^x_{it}, yields from mutual funds, $y^{l,i}_{it}$,[14] yields from directly held listed shares (the sum of dividends, $d^{l,d}_{it}$, available from the Shareholder Registry, and accrued capital gains and losses, $g^{l,d}_{it}$),[15] and yields from all private equity holdings (the sum of distributed dividends, d^u_{it}, available from the Shareholder Registry, and the individual share of the private business' retained profits, g^u_{it}).[16] [17]

Our second measure of return is the *return to net worth*, defined as:

[14]We compute the yields from mutual funds as follows. From the tax records, we observe the market value of mutual funds owned as of 12/31 of year $t-1$, $w^{m,l,i}_{it-1}$. We assume that mutual investors own a composite index fund representative of the Oslo Stock Exchange (OSE) market (80%) and the MSCI World (20%), with (dividend-inclusive) price $q^{l,i}_{12/31,t-1}$ (on 12/31 of year $t-1$), which we take from the OSE price database. We can thus estimate the shares of this composite fund owned at the end of period $t-1$ as: $s^{l,i}_{it-1} = w^{m,l,i}_{it-1}/q^{l,i}_{12/31,t-1}$. A similar calculation for year t gives us an estimate of the shares owned at the end of that year, $s^{l,i}_{it}$. Finally, we measure the yield on mutual funds as: $y^{l,i}_{it} = (q^{l,i}_{12/31,t} - q^{l,i}_{12/31,t-1})s^{l,i}_{it-1} + ((q^{l,i}_{12/31,t} - \bar{q}^{l,i}_t)(s^{l,i}_{it} - s^{l,i}_{it-1}))\mathbf{1}\{s^{l,i}_{it-1} \neq s^{l,i}_{it}\}$, where $\bar{q}^{l,i}_t$ is the geometric average of the composite index fund price in year t, which we use to account for sales or purchases of mutual fund shares during the year with unknown transaction date.

[15]We compute the capital gains/losses on directly held listed shares using the Shareholder Registry. In particular, for each security k, we observe the shares held by the individual as of 12/31 of each year: s^k_{it} and s^k_{it-1}. From the OSE price database we recover the security prices for 12/31 of year $t-1$, and for each day of year t, including of course $p^k_{12/31,t}$. We measure the total capital gains/losses on listed shares as: $g^{l,d}_{it} = \sum_k (p^k_{12/31,t} - p^k_{12/31,t-1})s^k_{it-1} + ((p^k_{12/31,t} - \bar{p}^k_t)(s^k_{it} - s^k_{it-1}))\mathbf{1}\{s^k_{it-1} \neq s^k_{it}\}$, where $\bar{p}^k_t$ is the geometric average of the security price in year t, which we use to account for sales or purchases of securities during the year with unknown transaction date. When implementing this procedure we also account for possible company splits and splines.

[16]We recover the private business' retained profits from the business' balance sheets. We follow Alstadsæter et al. (2016) and allocate retained profits to each personal shareholder according to his/her total ownership share in the corporation in the year when the corporate profits are reported. Their procedure also accounts for indirect ownership.

[17]In the absence of information on private firms' market prices and assuming corporate tax neutrality (which is the case during our sample period), retained profits can be interpreted as an estimate of the private business' capital gains or losses. Equilibrium in capital markets implies (King, 1974): $\rho V = d + \Delta V$, where V is the value of the firm, ρ the return on a composite investment, d the distributed dividend, and ΔV the capital gain. For equilibrium in the capital market to hold, the yield on investing the money value of the holding at the market interest rate must equal the dividend plus the capital gain. Since $d = \pi - \pi^r$ (where π and π^r are total and retained profits, respectively), we can rewrite the equilibrium condition above as $\rho V = \pi - \pi^r + \Delta V$. We can then use the definition of the value of the firm as the PDV of current and expected future profits: $V = (\pi/\rho)$ (assuming profits are constant or follow a random walk process). This finally yields: $\Delta V = \pi^r$.

$$\tilde{r}_{it}^{N} = \frac{y_{it}^{F} + y_{it}^{h} - y_{it}^{b}}{G_{it}} \tag{2}$$

Relative to the return to financial wealth (1), the numerator of the return to net worth (2) adds the yield on housing y_{it}^h and subtracts interest payments on debt y_{it}^b. We express the dollar yield on net worth as a share of gross wealth (or total assets) G_{it}. This way the sign of the return depends only on the sign of the yield (and not on that of net worth) and this avoids assigning infinite returns for people with zero net worth, or positive returns to those with negative net worth and debt cost exceeding asset income (in the accounting literature (2) is also known as ROA, or return on assets). The yield on housing is estimated as: $y_{it}^h = d_{it}^h + g_{it}^h$, where d_{it}^h is the imputed rent net of ownership and maintenance cost and g_{it}^h the capital gain/loss on housing. Following Eika et al. (2017), we assume that the imputed rent is a constant fraction of the house value (which they estimate to be 2.88%); finally, we obtain the capital gain on housing as $g_{it}^h = \Delta w_{it}^h$.

Below we study the properties of both return measures. However, the return to financial wealth is likely to be more revealing about determinants of heterogeneity in individual returns. This is because financial investments are mostly motivated by risk/return considerations and their individual returns directly observed. In contrast, for most individuals the return to net worth is dominated by the housing component. This poses two problems. First, the return to housing is unavoidably imputed and likely to miss part of the individual specific component of the return (for example, the idiosyncratic increase in value induced by home renovations). In addition, owner-occupied housing is to some extent a "needed asset" whose purchase and timing is often dictated by factors (such as family demographics) that go beyond pure portfolio considerations.

Both measures of returns are net of inflation (using the 2011 CPI) and are gross of taxes/subsidies. Taxation can impact heterogeneity of returns and thus affect wealth inequality through this channel. In Section 3.3.1 we extend the analysis to after-tax returns.

2.3.1 Addressing some limitations Despite the richness of the data, our measures of the return to wealth have to account for three limitations. First, we only observe snapshots of people's assets at the end of each period, while observing the flow of income from capital throughout the period. Second, the tax value of private businesses may differ from their market value. Third, there are some components of wealth that we do not observe. We now discuss how we account for these three shortcomings.

Consider the first problem. If some assets are purchased during the year, the income from capital will partly reflect amounts earned after the purchase. This issue is most obvious in the case in which beginning-of-period wealth is zero but capital income is positive due to saving taking place during the period.[18] The opposite problem occurs when assets are sold during the period. To account for this issue, we define returns as the ratio of income from capital and the average stock of wealth at the beginning *and* end of year, i.e.:

$$r_{it}^{F} = \frac{y_{it}^{F}}{(F_{it} + F_{it+1})/2} \tag{3}$$

$$r_{it}^{N} = \frac{y_{it}^{F} + y_{it}^{h} - y_{it}^{b}}{(G_{it} + G_{it+1})/2} \tag{4}$$

respectively for the return to financial wealth and the return to net worth. We use this adjustment also when computing the return to sub-components (i.e., the return to safe assets, the return to listed shares, etc.). Expressions (3) and (4) are our *baseline* measures of returns. The results are very similar if we weight beginning and end-of-period wealth differently rather than equally.

Consider now the second limitation. Our measures of the returns to wealth (3) and (4) are overstated if private business owners understate the value of the firm relative to what they would get if they were to sell it. Since private equity is heavily concentrated at the top of the wealth distribution, this may also exaggerate the slope of the relationship between wealth and returns to wealth. There is no simple way to correct for this problem. To check whether our results are driven by private equity, we consider two approaches: (a) we obtain measures of returns that exclude private equity owners; (b) we apply industry-specific multipliers estimated from cases in which private equity firms become public, or publicly listed firms return private (see Section 3.3.3 for details).[19]

The third potential limitation is that some components of wealth are unobserved in our data. Start with pension wealth. The pension system in Norway is composed of three layers: state pensions, occupational pensions, and individual pensions. State pensions guarantee a minimum amount of income to all individuals who are 67 and older; an additional component is paid as a function of lifetime earnings. Occupational pensions are available for both public

[18] Our sample selection, dropping people with less than USD 500 in financial wealth, attenuates this problem.

[19] This is a variant of the idea of using market-to-book multipliers among listed firms to impute the value of non-listed firms. We prefer this approach because firms just listed (delisted) are more similar to private firms than companies that are persistently listed in the stock market (see Table OA.2 in the OA).

and private sector employees and, in 2015, represented roughly 12% of aggregate household gross wealth. Unfortunately, there is no data on occupational or individual pension plans in the tax records we have available, including the investment choices of the individual vested in the plans. It would still be possible to impute returns (for example, assuming that workers select some default funds), but since almost all workers own this asset, this would not add much to measured heterogeneity in returns. In the OA, Section OA.1, we discuss how we can use the history of social security contributions for selected cohorts to obtain an estimate of the internal rate of return to social security wealth (as in Geanakoplos et al., 1999 and Leimer, 1995). We then estimate an "extended" measure of return to wealth, namely a weighted average of the return to social security wealth and the return to (financial or net) wealth (3). The second component of wealth that is missed is assets held abroad that are not reported to the tax authority. While it is possible to obtain some rough estimates of such wealth (as done, e.g., by Alstadsæter et al. (2017)), imputing a return is difficult since there is no information on the portfolio composition of the wealth that is hidden abroad.[20] Finally, we exclude from our analysis of returns a variety of assets for which computing returns is challenging due to the difficulties involved in measuring yields and capital gains. Some of these components (such cars and vehicles) are subject to the wealth tax and thus reported to the tax authority, but others (such as "collectibles", art, wine, jewelry, etc.) are not (as long as some conditions are met, i.e., the painting is hanging on the taxpayer's wall).[21]

2.4 Some conceptual remarks

Before delving into the data analysis, we add some conceptual remarks.

[20] Alstadsæter et al. (2017) estimate that only people above the 99th percentile have assets offshore. For our purposes, the issue is whether the existence of wealth offshore tends to distort our measure of gross (of tax) returns on wealth. If wealth is held abroad mostly to profit from more rewarding investment opportunities not available at home (as argued by Zucman, 2013), then ours are conservative estimates of the heterogeneity in returns and their correlation with wealth. If we drop people in the top 0.5% or 1% of the wealth distribution - where all wealth offshore seems to be sitting according to Alstadsæter et al. (2017) - our results are unaffected.

[21] In principle another source of wealth for Norwegians is the Government Pension Fund Global (a sovereign wealth fund investing the surplus revenues of the Norwegian oil sector). As emphatically noted on the GPFG's website, the fund "is owned by the Norwegian people". The current (2017) market value of the fund is 8,400 billion NOK ($1,100 billion). At its face value, this would correspond to 1.6 million NOK per person ($203k). It should be noted, however, that in Norway no-one actually receives direct payments from the GPFG (unlike e.g., what happens with the Alaska Permanent Fund). Instead, every year the expected real return of the fund (formerly around 4% and recently revised to 3%) may be allocated to the government budget, resulting in lower taxes or more spending, and hence benefiting taxpayers only indirectly. In fact, if the return to the fund is used to reduce taxes, the beneficiaries are mainly at the top of the wealth distribution due to the high progressivity of the tax system; if the return to the fund is used primarily to fund government programs for the poor, the beneficiaries are mainly at the bottom of the wealth distribution.

First, all returns statistics we report below are at the individual, not the household level. In this way, we account for the fact that while households form and dissolve, individuals can be observed as they cycle through different marital arrangements. When individuals are single, the formulae above apply without modifications. When individuals are married, we assume that spouses share household wealth and capital income equally. This is consistent with Norwegian laws requiring family assets to be split equally between spouses in the event of divorce. In this case, we first assign the per-capita household wealth and capital income to each spouse, and then compute the return to individual wealth.

Second, we use *ex-post* realized returns to measure average returns to wealth. An alternative would be to rely on an asset pricing model, such as the CAPM, and attribute to an individual holding a given stock (say) the expected return predicted by the model using the time series of stock returns. This is the method used by Bach et al. (2015). Its main advantage is that it increases the precision of the estimated mean returns as one can rely on long time series of market returns. This may be valuable when one has short time series of realized individual returns. However, the method has its drawbacks. First, the higher precision comes at the cost of imposing a pricing model, typically a CAPM and its (not undisputed) underlying assumptions (e.g., ability to borrow at a risk free rate, absence of trading frictions, etc.). Second, (expected) returns attributed to an individual in a given year are affected by returns realized in future years. Third, because individuals holding a given asset are imputed the same average return independently of the holding period of the asset, differences in returns due to differences in ability to time the market (or other aspects of financial sophistication) are not captured by this method, which is therefore biased towards attributing systematic differences in returns across individuals to differences in exposure to systematic risk. Finally, and perhaps more importantly, what matters for wealth accumulation (and hence to explain concentration and inequality in wealth due to the return heterogeneity channel) are actual, realized returns, not expected returns. The *ex-post* realized returns approach that we use is thus model-free, reflects all sources of heterogeneity across individuals relevant for generating returns to wealth, and is more appropriate for addressing the research question of the link between wealth and returns to wealth.

The last important remark is that ownership of most assets (real or financial) may provide both pecuniary and non-pecuniary benefits. For example, stock-market investors may favor "socially responsible investments" - providing a "consumption" return besides the pecuniary return (Bollen, 2007). Similarly, the overall return from holding a safe asset such as a checking account may entail both a pecuniary component and a non-pecuniary one (given by the liquidity services provided by the account, such as access to ATM facilities or check-writing). In this paper we focus on the pecuniary component of the return. This is for two reasons. First, estimation of the non-pecuniary component of return is challenging, as it often involves subjective considerations. Second, wealth cumulates over time due to pecuniary returns. Given our goal of showing the empirical properties of the returns that are relevant for the relation between inequality and returns to wealth, we believe it is appropriate to focus on pecuniary returns. Nonetheless, conceptually it is important to acknowledge that some of the heterogeneity in pecuniary returns we document may be due to heterogeneity in preferences for the non-pecuniary components of the return. That is, some investors may accept lower pecuniary returns because they are compensated with higher non-pecuniary ones, while others only care about pecuniary returns. Even if the "total return" is equalized across individuals, we will observe heterogeneity in the pecuniary component of the return in equilibrium.

2.5 Descriptive statistics

Table 2 shows individual-level summary statistics for our data, pooling all years (approximately 33 million observations). Panel A reports some basic demographic characteristics. The sample is well balanced across genders and with respect to marital status. About 80% of the individuals in the sample have at least a high school degree. Finally, 12% of individuals have a degree (college or high school) with a major in economics or business, which may be indicative of above-average financial sophistication.

The remaining three panels of Table 2 show statistics describing wealth levels, its composition, and the amount of capital income received. We convert original NOK figures into constant 2011 USD. Panel B shows that total assets are $400,000 on average. As expected, the distribution is extremely skewed, with a median of about $294,000, while the 90th percentile is $750,000. As in most countries, housing represents the largest component of total assets. The stock of debt, $123,000 on average, implies an average individual net worth of $277,000. Panel C reports information on dollar yields from assets and the cost of debt. On average, individuals obtained an income flow of $930 from safe assets, $5,200 from risky assets, and $18,000 from housing. Interest payments on debt average roughly $5,000. The final Panel D provides information on portfolio holdings, reporting the fraction of individuals in the population owning the different type of assets, and the unconditional and conditional (on ownership) shares of wealth invested. Starting with the financial wealth portfolio, almost half of all individuals have some risky assets in their portfolio. Conditioning on having some listed shares, individuals invest on average 22% of their financial wealth in those financial instruments. Roughly one in ten people own shares in a private business. There is less diversification among private business owners. Conditioning on having private business wealth, almost half of total financial wealth is held in the private business itself. Moving to components of net worth, the table shows that 78% of Norwegian taxpayers are homeowners. Conditioning on owning a house, 87% of their total assets is in housing. Finally, most individuals have debt (89% of them). Leverage levels (shown separately for consumer debt, student debt and long-term debt) are substantially skewed upwards by people with large debt amounts backed up against few to no assets.

One interesting question is how Norway compares to the US. Using five waves of data from the triennial Survey of Consumer Finance (2004-2016), we construct portfolio composition figures comparable to Table 1 for Norway (see Table OA.1 in the OA). Starting with financial wealth, we notice that the pattern for the US is qualitatively similar to the one for Norway - safe assets dominate the portfolio of households below the median, and as we move up on the distribution, risky assets (especially in the form of private equity) take an increasingly larger role. As for net worth, the overall picture is also quite similar, with housing being the dominant asset in many households' portfolios and high levels of leverage pushing many households in negative net worth territory. We calculate that 23% of US households had negative net worth over the 2004-2016 period, very close to 21% in Norway over the 2005-2015 period (for comparison with the US, here we report household rather than individual statistics, unlike what done in Table 2). In terms of risk exposure, we find that the fraction of US households investing in public equity (excluding for comparison with Norway employer-based retirement accounts) is 28% (34% in Norway); the fraction with private business wealth is 12% (11% in Norway). Dollar values are more challenging to compute given that there is more wealth concentration in the US in Norway. Figure OA.7 in the OA plots selected percentiles for the distribution of household net worth in Norway and in the US and shows that the two distributions differ appreciably only above the 90th percentile due to the much longer tail of the US distribution.

By and large, the discussion above suggests that the two countries are comparable both in terms of broad portfolio composition and wealth levels. There is more wealth held in equity in the US than in Norway, mostly due to the differences in the size of the stock markets, and a more dominant role for housing in Norway, which partly reflects institutional features, as well as differences in the tax treatment of housing and debt. But besides these differences, the mechanisms at play for explaining heterogeneity in returns to wealth are fundamentally of economic nature (involving portfolio choice, risk-taking behavior, investment in financial information, entrepreneurial skills, etc.), and hence most of the findings we describe below are likely to be similar in the US or other advanced economies.

3 Stylized facts about returns to wealth

In this section, we establish a number of stylized facts about individual returns to wealth. In the next section, we provide a formal framework for modeling returns to wealth that will help to shed light on these stylized facts.

3.1 Returns to wealth are heterogeneous

Table 3 reports summary statistics for the returns to financial wealth and net worth and for some of their sub-components, pooling data for the 2005-15 period. All returns are in real terms. Our sample period was, of course, characterized by the financial crisis and large swings in average stock market returns.[22] During this period, the value-weighted average real return on financial wealth was 4.2%. However, the extent of heterogeneity is staggering. The return to financial wealth has a standard deviation of 14% and a 90th-10th percentile difference of 21 percentage points. The distribution has a long right tail (a Pearson skewness coefficient of 1.7) and is heavily leptokurtic (a kurtosis coefficient of 14.6). Looking at sub-components, the return on listed shares (2.7%) and on private equity (11.5%) exceed that on safe assets (0.6%), partly reflecting compensation for volatility (Figure OA.8 in the OA shows that the return to private equity is 15 to 65 times more volatile than the return to safe assets; for listed share, it is roughly one order of magnitude more volatile).[23] The average real return on net worth is similar to that on financial wealth, 4.1%, but with a smaller standard deviation of 8.3%. Given its large role on household total assets, the return on net worth is largely driven by the return on housing, which in this period was relatively high (4.6%) due to rapidly rising housing prices. In contrast, the average interest rate on debt (after inflation) was 2.3%. This masks enormous heterogeneity both between the three types of debt we can identify in the data as well as within: consumer debt is expensive and very heterogeneous across individuals (an average interest of 9.1%, standard deviation 12.2%), while student debt is cheap and

[22] The return of the OSE market was -52% in 2008 and -12% in 2011.

[23] The average equity premium over this period is 2.1%, below the average equity premium for 1900-2015 (3.1% as reported by Fagereng et al., 2017 based on figures from Dimson et al., 2016). This reflects two features: first, it is computed over a 11 years period that includes a rare financial collapse (the largest decline in the OSE index since 1929). Second, household perform worse than the market, buying at the peak and selling at the bottom of market valuations in 2008-09.

much less heterogenous (0.7%, standard deviation 2.5%); mortgages and long term debt falls in between (average real rate 2.2%, standard deviation 2.1%) .

While the extent of return heterogeneity from Table 3 is large, it is useful to develop a metric for how much return heterogeneity we should expect. As a simple benchmark, let us focus on financial wealth and consider a standard Merton-Samuelson (Merton, 1969; Samuelson, 1969) framework in which all investors have access to the same financial investment opportunities. In this model, the investor's optimal share of risky assets ω_{it} is a function of market expected excess returns, $E(r_t^m - r_t^s)$, the variance of risky assets σ_t^2, and investor risk aversion γ_i:

$$\omega_{it} = \frac{E(r_t^m - r_t^s)}{\gamma_i \sigma_t^2} \tag{5}$$

It follows that the individual realized return to financial wealth is a weighted average of the risk-free rate and the market return:

$$r_{it} = r_t^s + \omega_{it}(r_t^m - r_t^s) \tag{6}$$

Heterogeneity in returns is induced by differences in risk aversion and thus in (compensated) risk-taking measured by the risky share.[24] Equation (6) suggests that conditioning on having the *same* share of risky assets in a financial portfolio, total returns on wealth should be similar across investors. That is, the cross-sectional standard deviation of returns, given ω_{it}, should be close to zero. In Figure 1, we allocate individuals to different groups defined by the share of their financial wealth held in "risky" assets (from 0 to 1, in 0.01 increments), and within each bin, compute the cross-sectional standard deviation of the individual returns (the solid line in the figure). Not only is the standard deviation non-zero at all values of the risky share, but it also increases substantially with the share of risky assets held in the portfolio. Interestingly, even at $\omega_{it} = 0$ (where individuals own only "safe" financial assets), the cross sectional standard deviation of returns is positive. Thus, while the allocation of financial wealth (between risky and safe assets) does affect the extent of heterogeneity in the overall return to wealth, it is by no means the only driver (as we shall see more clearly in formal controlled regressions, discussed in Section 4). Note that some of the heterogeneity in Figure 1 may come from holding a private business with very idiosyncratic returns and possibly some measurement error. We hence repeat the exercise focusing only on investors

[24]Heterogeneity may also come from human capital, as in Viceira (2001). This is irrelevant for our argument, since in these models any extra "channel" affects only the share invested in risky assets, not the return earned on each asset class.

who do not own *any* shares in private businesses, i.e., individuals who only invest in safe assets and stocks of listed companies. The evidence is similar, although, as expected, the extent of heterogeneity is lower. Also as expected, this shows that there is much more risk involved in holding private business wealth (see among others, Carroll (2000), Guiso et al. (2002), Moskowitz and Vissing-Jorgensen (2002), and Kartashova (2014)).

3.2 Returns covary with the level of wealth

3.2.1 Financial Wealth The second stylized fact about returns to wealth is that they are strongly positively correlated with the level of wealth. Panel A of Figure 2 plots the average and median return to financial wealth for individuals in different percentiles of the financial wealth distribution, pooling data for all years (2005-15). The differences in returns across wealth levels are large. Moving from the 10th to the 90th percentile of the financial wealth distribution the average return changes by 260 basis points (from 0.2% to 2.8%); the median return changes by 180 basis points (from -0.8% to 1%) - suggesting that the correlation between returns and wealth holdings can potentially play an important role in driving wealth inequality.[25] [26]

The correlation between returns and wealth is not specific to a given year. Figure OA.10 in the OA plots average returns for individuals in different percentiles of the financial wealth distribution separately for each year between 2005 and 2015, and confirms the broad evidence from the pooled sample. Interestingly, while in most years the relation is monotonically increasing, in some years returns to wealth fall as wealth increases (at least over a certain range). These are years, like 2008 or 2011, of stock market crashes, when returns on safe assets (whose asset share is very high at the bottom of the distribution) exceed returns on stocks (whose share increases with wealth). This also explains the slightly decreasing relation between returns and wealth at very low levels of financial wealth in Figure 2, Panel A, obtained pooling all years.

In general, a correlation between returns and wealth may arise for several reasons. In Section 4, we discuss in detail various channels of influence. One simple explanation is that wealthier households have higher exposure to risk. To check whether risk-taking is the *only*

[25]As noticed by Piketty (2014), "It is perfectly possible that wealthier people obtain higher average returns than less wealthy people.... It is easy to see that such a mechanism can automatically lead to a radical divergence in the distribution of capital".

[26]Not only the mean, but also the standard deviation of returns covaries with wealth. To document this, we compute the cross-sectional standard deviation of returns for each percentile of the financial wealth distribution. Heterogeneity in returns rises almost monotonically with wealth, and accelerates in the top decile, where it is dominated by heterogeneity in the return to private equity (see Figure OA.9 in the OA).

force behind the correlation documented in Figure 2 we consider two exercises. First, we show that the positive correlation between returns and wealth holds *within* broad asset classes. In Panel B of Figure 2 we report average returns on safe assets and risky assets separately, and show that scale dependence is a pervasive phenomenon.[27] In Figures OA.11 and OA.12 in the OA we show that there is pervasive evidence of scale dependence even within much narrower risky asset categories (private equity and direct stockholding, respectively). This evidence rules out that the correlation between returns and wealth only arises because of participation costs in risky assets markets. The second exercise we consider is to compute a measure of the Sharpe ratio (a risk-adjusted measure of return) at the individual level. To increase precision in estimated average excess returns we use data for individuals that are present for the entire 2005-2015 period. The individual Sharpe ratio is defined as:

$$S_i = \frac{\frac{\sum_{t=1}^{T} \hat{r}_{it}}{T}}{\sqrt{\frac{\sum_{t=1}^{T} \hat{r}_{it}^2}{T} - \left(\frac{\sum_{t=1}^{T} \hat{r}_{it}}{T}\right)^2}} \tag{7}$$

where $\hat{r}_{it} = \omega_{it}^a (r_{it}^F - r_t^s)$, with $(r_{it}^F - r_t^s)$ being the deviation of the individual return to financial wealth from the return on a risk-free asset (the 3-month T-bill) and ω_{it}^a the weight of individual assets in period t relative to the entire 2005-15 period. We then plot the Sharpe ratio against the percentile of financial wealth in 2004, i.e., in the year preceding the 11-year period over which (7) is calculated (results are similar if we plot it against the percentile of financial wealth averaged over 2000-2004). This has the advantage of eliminating any concerns about reverse causality running from high returns to position in the wealth distribution. Figure 3 shows that the individual Sharpe ratio for 2005-15 rises monotonically with the individual wealth percentile in 2004, lending strong support to the idea that the correlation between wealth and returns is not merely due to compensation for risk-taking.

3.2.2 Net Worth Scale dependence is not limited to the return on financial wealth. In Panel A of Figure 4, we plot the average and median return to net worth for individuals in different percentiles of the net worth distribution, pooling again data for all years (2005-15). To ease legibility, we plot separately two regions of interest: below the 20th percentile (where the

[27] The heterogeneity in safe asset returns is partly due to the fact that the category includes assets of different liquidity and risk (i.e., cash vs. bonds). If we regress the average return on safe assets against the share of safe assets in domestic deposits, deposits abroad, and bonds, we find that over our sample period there is a 1.1% premium for bond holding over foreign deposits which in turn attract a 0.3% premium over domestic deposits. Scale dependence in safe asset returns arise in part from the fact that most checking accounts pay higher rates for larger amounts deposited, reflecting economies of scale in asset management.

return has a non-monotonic shape and net worth is negative), and above the 20th percentile (where the return grows with wealth, first at a decreasing rate then in a convex manner in the top two deciles; the solid line in Panel B shows the combined figure). To get a better understanding of the patterns displayed in the figure, rewrite the return to net worth as:

$$r_{it}^{N} = (r_{it}^{f}\alpha + r_{it}^{h}(1-\alpha)) - (r_{it}^{b,l}\theta^{l} + r_{it}^{b,c}\theta^{c} + r_{it}^{b,s}(1-\theta^{l}-\theta^{c}))L_{it} \tag{8}$$

where r^f, r^h $r^{b,j}$ are the return to financial wealth, the return to housing, and the cost of debt of type j (long-term debt l, consumer debt c, and student debt s), α is the share of financial wealth out of total assets, θ^j is the share of type-j debt out of total debt, and L the overall leverage. Hence, the return to net worth depends on the composition and relative returns of asset and debt types. These elements change quite substantially as we navigate through the different parts of the net worth distribution.

In the bottom 20% of the distribution, liabilities exceed assets. But the composition of debt type changes as we move from the bottom 1% to the bottom 20%. In particular, at the very bottom of the distribution debt is primarily composed of long-term debt: mortgages collateralized by housing and possibly personal loans that entrepreneurs use to finance their business activities (and that are presumably collateralized by the value of their company, personal housing or a third party personal guarantee). Indeed, as can be seen from Panel A of Figure 5, at the bottom of the distribution the proportion of homeowners and entrepreneurs are both quite high. Strikingly, there are as many entrepreneurs at the bottom 1% as there are at the top 3% (around 50%).[28] While the cost of long-term debt is relatively low (since it is mostly collateralized, see Table 2), the leverage here is at its highest, implying a large negative return to overall net worth (around -20% at the very bottom of the distribution).[29] This is only partly compensated by the relatively high return to financial wealth due to the presence of substantial private equity wealth (see Panel B of Figure 5, where we decompose the return to net worth into its three main sub-components: financial assets, housing, and debt). As one moves up towards less negative net worth, the return rises (becomes less negative) because leverage declines. However, at some point in this region debt becomes mostly uncollateralized consumer debt (featuring high rates), housing wealth shrinks, while liquid, low-return investments become the main financial asset in the household portfolio.

[28] These are mostly young entrepreneurs. The average age of entrepreneurs in the bottom 20% is 39; in the top 20%, it is 53.

[29] From equation (8), the return to net worth decreases with leverage (for given cost of debt) and with the average cost of debt (for given leverage). The latter, in turn, reflects debt composition given the higher rate charged on consumer loans.

These features explain the large decline in returns to net worth that we see around the 10th-15th percentile. Once net worth moves in positive territory, the return increases with wealth exactly as seen for financial wealth. The shape is initially concave and then turns convex roughly above the 80th percentile. But it is worth stressing that the evolution in returns to net worth as we move to higher wealth percentiles masks different trends: (a) housing is more equally distributed and its returns more homogenous (and mostly driven by time and location), while (b) returns to financial wealth increase (see Panel B of Figure 5). Nonetheless, it is worth stressing that the concentration of debt at the bottom of the distribution of net worth *enhances* scale dependence. Compared to people in the 10th percentile of net worth, people in the in top 90-th percentile have an average return on net worth that is 17 percentage points higher.[30]

3.3 Robustness

3.3.1 Before-tax vs. after-tax returns Thus far our return measures were before any taxes on capital or capital income. Here we discuss net of tax returns; we focus on net worth as it captures both taxation on assets returns as well as deduction of interests on debt. An after-tax measure of the return to net worth is:

$$r_{it}^{N} = \frac{y_{it}^{F} + y_{it}^{h} - y_{it}^{b} - T^{y} - T^{w}}{(G_{it} + G_{it+1})/2} \tag{9}$$

where T^y are taxes paid on capital income net of deductions on debt interest, and T^w are taxes on net worth.[31]In Panel B of Figure 4 we plot the before-tax vs. the after-tax return to net wealth against the position in the (before-tax) net worth distribution. Clearly, taxes smooth returns. At the bottom of the distribution the after-tax return exceed the before-tax due to the deductibility of interests on debt (especially mortgage debt). At the top of the distribution, the opposite occurs given the lower incidence of debt and the higher incidence of the wealth tax.

[30] The shape of the relation between the return to net worth and net worth documented for the pooled data holds also on a year-by-year basis (see Figure OA.13 in the OA).

[31] Over the 2005-08 period, the tax on wealth was progressive. People would pay a 0.9% rate on every NOK of net worth between a first cutoff (150k, 200k or 350k depending on the year) and a second cutoff (540k), and a 1.1% rate for every NOK of net worth above the second cutoff. After 2008 the tax on wealth became a flat 1.1% (reduced to 1% in 2014 and 0.85% in 2015) on every NOK of net worth above a cutoff (rising over time from 470k to 1250k). In the computation of net worth, different components were assessed at different face values (i.e., bonds at 100%, housing at 25%, etc.). Capital income was taxed at a flat rate (28% in 2006-12, reduced to 27% in 2013, and 25% in 2014).

3.3.2 Saving rates One worry is that the positive correlation between returns on wealth may be spurious because the way we measure returns may overstate the returns of the wealthy if the latter exhibit a higher propensity to save out of wealth, implying that a higher than average proportion of capital income over a year derives from savings over the year rather than initial wealth. To illustrate, suppose that there is a single asset and that returns are *independent* of wealth. Assume also that y_{it} is the sum of capital income out of initial wealth ($r_t w_{it}$) and capital income out of savings added during the year ($r_t s_{it} f_{it}$), where s_{it} are the extra savings added and f_{it} the fraction of year they remain invested. Take as a measure of return a simplified version of equation (3), i.e., $r_{it} = \frac{r_t w_{it} + r_t s_{it} f_{it}}{(w_{it} + w_{it+1})/2}$. Assume for simplicity $f_{it} \to 1$ (if there is any intra-year trading activity, it starts early in the year). One can then show that $sign(\frac{dr_{it}}{dw_{it}}) = sign(\frac{d(s_{it}/w_{it})}{dw_{it}})$. Hence, if the propensity to save out of wealth s_{it}/w_{it} increases with wealth, one can find a positive association between computed returns and wealth even when there is none. To check whether this is a serious concern, we construct a measure of savings as $s_{it} = w_{it+1} - w_{it} - y_{it}$ and study how the propensity to save out of wealth changes with wealth. We find no evidence that it rises with wealth, while finding some evidence that, in fact, it declines with it. The rank correlation between (s_{it}/w_{it}) and w_{it} is -0.19 (p-value <1%). Hence, if there is any bias in the correlation between returns and wealth it is likely to be *downward*. A similar result is also present in Bach et al. (2017).

3.3.3 Mismeasurement of private equity wealth A different worry is that the positive correlation between returns on wealth may spuriously arise from mismeasurement of private equity wealth. There are two reasons for this. First, our measure of private equity wealth may understate the true value of private businesses held by individuals (hence inflating returns upwards for this group); second, the fraction of private equity holders grows with the position in the financial wealth distribution. To assess whether our results are driven by private equity, we propose two exercises.

First, we drop private equity holders, eliminating any mismeasurement issue at its root. There are virtually no differences, if not at the very top, when we look at net worth returns; and moderate differences when we look at financial wealth - in both cases, the broad message is qualitatively unchanged (see Figure OA.14 in the OA).

Second, we adjust the value of equity using market-to-book multipliers from "similar" listed firms. To estimate multipliers from firms that are as close as possible to the private businesses in our sample, we focus on companies that during our sample period go through a listing or voluntary de-listing process - implying that in the year of the transition they are not too far between being public and being private (for robustness, we also confine the analysis to firms that go public). Indeed, companies that over our sample period were "sometimes listed" (i.e., they de-listed or went public at some point in the 2005-15 period) are closer in terms of observables (size, profitability, and growth) to private firms than firms that are continuously listed (see Panel A of Table OA.2 in the OA).

To compute market-to-book multipliers, we run quantile regressions of the market value of the firm against its book-to-value, allowing the estimate to vary by industry (see Panel B of Table OA.2 in the OA). The estimated multipliers range from 0.6 ("Utilities and Construction") to 2.9 ("Retail Trade"), with an average of 1.24, consistent with an understatement of book value relative to market value. Finally, we inflate (or deflate) the book value of equity by the estimated multipliers to obtain an adjusted measure of private equity wealth at the individual level. There is a downward correction (of about 100 basis point) in the return to financial wealth at the very top of the wealth distribution (see Figure OA.15 in the OA); the correction for the rest of the distribution is negligible. The effect of the adjustment on the return to net worth is even less pronounced. The results are virtually identical if we use multipliers estimated only using the sample of private firms that go public. Hence, the adjustments do not seem to change in any meaningful way the qualitative message that there is substantial scale dependence in wealth returns or any other feature of our study.

4 Modeling and estimating returns to wealth

In this section, we provide a formal statistical model of individual returns, estimate it and use the results to characterize the properties of the returns. In particular, we ask whether the heterogeneity that we have documented is just a reflection of observable characteristics and idiosyncratic realizations that are quickly reversed, or whether individuals differ persistently in the returns they earn on their wealth due to some unobserved factors. In other words, we investigate whether individual returns to wealth have a permanent component, controlling for risk exposure (as measured by the share of wealth invested in different type of assets), scale (as measured by the position in the wealth distribution), and a rich set of demographics. Persistence in returns, as argued by Benhabib et al. (2011, 2017), is essential for heterogeneity to be able to explain the fat tail of the wealth distribution as well as the fast transitions in wealth concentration at the top (Gabaix, Lasry, Lions, and Moll (2016)).

4.1 A statistical model of returns to wealth

We specify a linear panel data regression model for wealth returns:

$$r^x_{i(g)t} = X'_{i(g)t}\beta^x + u^x_{i(g)t} \tag{10}$$

where $r^x_{i(g)t}$ denotes the return to wealth type x (financial wealth or net worth) for individual i belonging to generation g in year t. $X_{i(g)t}$ is a vector of controls meant to capture predictable variation in returns due to individual observables. Equation (10) can be interpreted as a much richer empirical counterpart of equation (6).

We consider four broad specifications. Our first specification includes controls for key socio-demographic characteristics and for the composition of the portfolio. In particular, we include age dummies (to pick life cycle effects in returns induced for instance by learning from experience, as in Jappelli and Padula, 2017 and Lusardi et al., 2015), years of education and study concentration in economics or business (to proxy for financial knowledge or sophistication), gender, marital status, county dummies, homeownership status, employment status, time dummies, and a full set of dummies for the individual wealth percentiles (computed using lagged wealth values to avoid spurious correlations arising from the wealth accumulation equation). The role of the latter is to capture scale effects and fixed entry costs in risky assets that preclude participation by low wealth households. This is indeed consistent with extensive literature on participation costs (surveyed in Guiso and Sodini, 2013, and emphasized by Guvenen, 2009 in the context of the wealth inequality debate). Moreover, there are important economies of scale in wealth management that may result in lower fees or directly in higher returns as the size of the investment increases. In addition, recent work by Kacperczyk et al. (2014) and Best and Dogra (2017) (building on earlier work by Arrow, 1987 and Peress, 2004) suggests that wealthy investors are more "sophisticated" than retail investors, for example because they have access to or have stronger incentives to acquire information about investment opportunities or where the market is heading, and hence reap higher returns on average (for given exposure to risk). In this first specification we also control for the lagged composition of the investor's portfolio (i.e., shares of wealth invested in the different type of assets and liabilities we can distinguish in our data set) to account for differences in returns induced by compensation for riskier asset allocations and leverage (when we study returns on net worth).

Our second specification adds the average β of the individual stock portfolio to better control for risk exposure.[32]

Our third specification refines even further the controls for risk exposure. In a world where individuals have identical access to a menu of instruments differing by risk, liquidity and other features, including private businesses, as in Quadrini (2000), Cagetti and De Nardi (2009; 2006) and Aoki and Nirei (2015), the portfolio return is: $r^F_{i(g)t} = r^s_t + \sum_j \omega^j_{i(g)t}(r^j_t - r^s_t)$, where $\omega^j_{i(g)t}$ denotes the share invested in component j, r^j_t is the common return on wealth component j and r^s_t the common return on the less risky asset. Accordingly, in our third specification of regression (10), we add the interaction of time dummies and the individual risky assets share $\omega^j_{i(g)t}$. If individuals have identical access to a menu of financial instruments, such controls would absorb all the existing variation in returns. This is hence a useful benchmark.

Our final specification adds individual fixed effects. In particular, we assume that the error term $u^x_{i(g)t}$ of (10) can be written as the sum of an individual fixed effect and an idiosyncratic component, which may possibly exhibit serial correlation. Hence:

$$u^x_{i(g)t} = f^x_{i(g)} + e^x_{i(g)t} \tag{11}$$

The fixed effects $f^x_{i(g)}$ capture persistent differences across people in average returns. These may arise from differences in the ability to manage the portfolio or one's private business, or to identify and access alternative investment opportunities. They will also absorb persistent heterogeneity in risk tolerance (which affects portfolio composition), as well as persistent differences in the scale of assets owned (which may affect access to specific investments due to fixed participation costs). The error term $e^x_{i(g)t}$ measures unsystematic idiosyncratic variation in returns reflecting "good or bad luck". This representation allows as to decompose idiosyncratic heterogeneity in returns to wealth as $var(u^x_{i(g)t}) = var(f^x_{i(g)}) + var(e^x_{i(g)t})$. Later, we also consider the possibility that the individual fixed effects are correlated across generations.

4.2 Estimation results

Returns to financial wealth Table 4 shows the results of regression (10) when the dependent variable is our baseline measure of returns to financial wealth in year t (equation (3), expressed

[32] We construct the average β in the following way. First, we use the time series of stock market returns for security k to compute the k-specific α and β, i.e., we run k separate regressions: $r^k_t = \alpha^k + \beta^k r^m_t + \epsilon^k_t$, where r^m_t is the composite market return. The individual investor's β is therefore $\beta_{it} = \sum_k \omega^k_{it}\beta_k$, where ω^k_{it} is the fraction of individual *i's* stock market wealth in period t held in security k.

in percentage points). The first column shows estimates of our first specification from a pooled OLS regression, without the fixed effects but adding a number of individual characteristics, some of them time invariant, to gain some intuition on the role played by covariates. The controls for the portfolio composition include the share in foreign and outstanding claims, bonds, mutual funds, listed stocks and unlisted stocks. The excluded share is deposits/cash, the ones that in principle should carry the lowest average return. Hence, the estimated coefficient on the portfolio shares of asset j can be interpreted as average excess returns of that asset relative to cash and deposits. The main sample comprises close to 31 million observations.

Not surprisingly, portfolio shares in risky assets and in private businesses have both a positive and large effect on the return to wealth, with the effect of the share invested in private businesses (carrying an average premium of 8 percentage points over deposits and cash) being significantly larger than the effect of the share in directly held listed stocks (average premium of 2 percentage points). This is implied by calibrated portfolio models that allow for investment in private businesses (e.g., Heaton and Lucas, 2001). Increasing the share in listed stocks by 30 percentage points (about the move from the risky share of a non-participant in the stock market to that of the average participant) increases the return to wealth by roughly 63 basis points. Increasing the share in private businesses by the same amount is associated with a much larger increase in returns on wealth of 248 basis points. This finding is consistent with the idea that, because private business wealth is highly concentrated, it must yield a large premium to compensate for idiosyncratic risk. This runs contrary to Moskowitz and Vissing-Jorgensen (2002), who, using data from the US SCF, find no evidence that private businesses earn a premium relative to public equity; but it is consistent with the results of Kartashova (2014) who documents the existence of a private equity premium using the same survey, but extending the sample to the more recent waves. Estimated premium on the other assets conform with intuition: mutual funds have a lower premium (1.7%) than directly held stocks, but larger than the premium of bonds (1.3%) which in turn is larger than the return premium of foreign/outstanding claims over cash and banks deposits.

To obtain a richer control for risk exposure not captured by the portfolio share in listed stocks, in column (2) we also control for the average β of the individual stock portfolio. The average β has a positive and significant effect on returns to wealth, suggesting that some individuals earn higher returns on wealth partly because they tilt their stock portfolio towards riskier stocks. The effect however is somewhat contained (partly because the portfolio share of directly held listed stocks is small - 2% on average): one standard deviation increase in β increases returns on financial wealth by 4.5 basis points. It is worth noting that while the average β is a statistically significant determinant of the average return to financial wealth, its addition has no impact on explained variation in returns.

Column (3) modifies the specification by replacing the portfolio shares with their interaction with time dummies. This more flexible specification captures differential effects of the portfolio shares on individual returns as the aggregate component of return on each single asset type varies. Not surprisingly the fit of the model improves significantly (the adjusted R^2 increases from 0.10 to 0.32) consistent with the fact that assets returns, particularly those of risky assets, vary considerably over time; on the other hand, the size and significance of most effects are unchanged. This limited fit (or the larger role of unobservable heterogeneity) is remarkable because, as noted, the canonical two-asset portfolio model with fully diversified risky portfolios would imply that, controlling for time variation in returns, all heterogeneity in returns should be explained by differences in the risky shares.

Before moving to the fixed effect regression, it is worth commenting on the effect of the demographics. The role of gender is economically negligible and noisy (especially in the richer specifications). In contrast, returns are correlated with general education and with specific education in economics or business. The estimates from column (3), for example, suggest that an additional year of formal schooling raises returns by 1.6 basis points (i.e., completing a college degree results in a 6.4 basis points higher average return compared to holding a high school diploma), while having an economics or business education is associated with 10 basis points higher returns. Because education is a permanent characteristic, its effect cumulates over time. A systematic difference in returns of 16 basis points enjoyed by economics college graduates (the sum of the effect of completing college education and majoring in economics or business) can produce a difference in wealth at retirement of 4.3% compared to holders of high school diplomas for one dollar saved every year over a working life of 40 years - *conditioning* on similar wealth and portfolio composition. This effect comes thus in addition to any effect that education may have on returns to financial wealth by twisting the portfolio allocation towards riskier and more remunerative assets (e.g., by raising the stock of human capital and inducing a greater exposure to equity shares, as in Merton, 1971). This finding is consistent with Bianchi (2018) and von Gaudecker (2015), who find a positive effect of a measure of financial literacy on the return to investments among French and Dutch investors, respectively, but with reference to a specific asset. It also supports the results of Jappelli and Padula (2017), who study the effect of financial knowledge on returns to wealth and assets at retirement within a life cycle model.

Overall, the pooled OLS estimates of columns (1)-(3) suggest that part of the observable heterogeneity in returns reflects compensation for the risk of investing in listed stocks or for the idiosyncratic risk of owning private businesses. But part of the variation is captured by variables, such as length and type of education attainment, that are more plausibly associated with the financial sophistication of the investor. Estimated time fixed effects, though not shown, are always significant, as are age dummies and wealth percentile dummies. The direct contribution of the wealth dummies to the average returns is similar to the unconditional effect plotted in Figure 2.

The last column of Table (4) adds the individual fixed effects to the specification in column 3.[33] As usual, the effect of time-invariant characteristics (such as gender or education) is no longer identified and is absorbed by the fixed effects. The key result is that the individual fixed effects improve the fit substantially: compared to column (3), the adjusted R^2 of the regression increases to 0.394, a 23% increase, implying that returns have an important persistent individual component.

From (11), additional persistence in returns may in principle come from $e^F_{i(g)t}$. To check whether this is the case, we look at the auto-covariance structure of the residuals in first difference computed from the specification in column (4), i.e. $E(\Delta u^f_{i(g)t} \Delta u^f_{i(g)t-s})$ for $s \geq 0$ (since taking first differences of the residuals removes the fixed effect, i.e., $\Delta u^F_{i(g)t} = \Delta e^F_{i(g)t}$). We find that these moments are minuscule and economically indistinguishable from zero for $s \geq 2$, consistent with $e^F_{i(g)t}$ being serially uncorrelated (see Figure OA.16 in the OA).

Returns to net worth Table 5 reports the results of analogous specifications for the return to net worth. Asset shares are now relative to gross wealth and the specifications also include the housing/gross wealth ratio and leverage for the three types of debt we can identify in the data (long-term debt, consumer debt, and student debt). To account for scale we include dummies for the lagged net worth percentiles as controls. Columns (1)-(3) show the baseline OLS estimates (without fixed effects). The coefficients on financial asset shares show a similar pattern as in the returns to financial wealth (Column 1): investments in private equity carry a larger premium than investments in listed stocks and mutual funds, whose premium in

[33] Because the model includes age and time effects, the individual fixed effects also capture cohort effects, posing a well known identification problem arising from the linear relation between age, time and year of birth. We deal with this issue by using the Deaton and Paxson (1994) restriction and impose that time effects sum to zero once the variables have been detrended. Since our data cover several years, we are able to separate trend and cycle, and thus feel reasonably confident about the decomposition of age, time and cohort effect based on this restriction (Deaton, 1997).

turn exceeds that of bonds and outstanding claims. The share invested in housing has a strong positive effect on returns to net worth: financing with deposits the purchase of a house worth 50% of initial gross assets increases *ceteris paribus* the average return on net worth by 360 basis points ($0.5 \times 7.2\%$). As expected, leverage has as a negative and highly significant effect on returns. If the house purchase were instead fully financed with debt (i.e., leverage increased from 0 to 0.33), the average return on net worth would increase by only 82.5 basis points ($0.33 \times 7.2\% - 0.33 \times 4.7\%$). Furthermore, because for most people housing plays a dominant role in their net worth, and because imputed rents contain an important aggregate component and miss by construction relevant parts of the idiosyncratic component, time dummies have a strong explanatory power. This explains the relatively high fit of the regression (adjusted $R^2 = 0.33$). Column (2) adds the β of the stock portfolio, which has a small effect and no impact on the overall fit.

Column (3) shows results for the more flexible specification where asset shares and leverage are interacted with time dummies to capture aggregate movements in returns. The fit increases slightly (adjusted $R^2 = 0.36$) while the estimated coefficients on the other variables are only marginally affected. Turning to demographics, we find that unlike Table 4, the male dummy has now a positive, albeit small effect (a 4 basis point difference). One potential explanation is that the cost of debt (especially mortgage debt) is influenced by bargaining power (Woodward and Hall, 2012), and men have been shown to have a greater propensity to "lean-in" than women (e.g. Exley et al., 2016). Interestingly, returns to net worth are more responsive to general education than returns to financial wealth. One explanation is that, differently from education-sensitive financial assets (such as stocks or mutual funds), debt is very widely held and general education suffices in helping choosing cheaper debt, as documented by Campbell (2006). Compared to having just a high school education, an individual with college education and business/economics concentration would have at retirement 18.7% more net worth (saving one dollar every year for 40 years).

The final column (4) adds the individuals fixed effects. Notwithstanding the large weight of housing in net worth and the fact that there is little room for observing idiosyncratic returns to housing, individual fixed effects contribute an additional increase in the regression adjusted R^2 of 49%, implying that also individual returns to net worth have an important persistent component.[34] In the next subsection we focus our attention precisely on this component.[35]

[34] In fact, there is a strong a strong positive rank correlation (Spearman coefficient of 38%) between the fixed effect in the return to financial wealth and that in the return to net worth.

[35] We find qualitatively similar results if we focus on an after-tax measure of return to net worth. The

4.3 Persistent heterogeneity

Figure 6 Panel A plots the empirical distribution of the individual fixed effects in returns to financial wealth (from the estimates in column 4, Table 4). To maximize precision we use the fixed effects estimated for the balanced panel, measured in deviation from the overall mean.[36] The distribution has a long right tail (Pearson's skewness coefficient 3.66) and is quite dispersed, with a standard deviation of 3.6% and a 90th-10th percentile difference of 5.1 percentage points. It also shows considerable excess kurtosis (24.8, see Table 6, Panel A). Panel B of Figure 6 shows the distribution of the fixed effects in returns to net worth. Heterogeneity in returns is larger for this measure, with a standard deviation of 5.4% points and a 90th-10th percentile difference of 5.5 percentage points (Table 6, Panel A) - reflecting the added heterogeneity from incorporating diversity in the cost of debt and leverage across individuals. Furthermore, the shape of the distribution of the fixed effect on returns to net worth differs from that on returns to financial wealth. First, it shows more kurtosis (102, Table 6, Panel A); second, it has a longer tail to the left instead of to the right (Pearson's skewness coefficient -6.31). This reversal in the shape of the distribution reflects two facts: *a*) the effect of debt, pulling the distribution of returns to the left; *b*) the presence of housing and the fact that the imputation method does not fully capture the idiosyncratic component of its return, so that any skill in investing cannot be fully revealed by the fixed effects, contrary to investments in financial assets and private businesses.

One interesting question is whether the distribution of the persistent component of wealth returns is associated with observable characteristics that, *a priori*, can be deemed economically relevant. Panel A of Figure 7 plots the distribution of the estimated fixed effects of returns to financial assets for individuals with and without risky assets (first panel); business owners and non-owners (second panel); top vs. bottom wealth groups (third panel); and people with and without an economics or business degree (last panel). Because the first three characteristics (owning risky assets, being a business owner, being at the top of the wealth distribution) may vary over time, non-participants in risky assets, non-private equity owners and those in the bottom wealth groups are defined using indicators for "never owning risky assets", "never being a business owner ", and "never being in the top 10% of the distribution".

excess return on private equity declines since private equity owners are the ones most likely to be affected by the capital income and the wealth tax. In contrast, the excess return to housing does not change much since housing wealth is taxed at 25% of its assessed value (while debt can be subtracted in full from the wealth tax base); moreover, while the imputed rent on housing is not taxed, interests on debt are fully deductible. See Table OA.3 in the OA.

[36] For visual clarity we winsorize the frequency mass of fixed effects above the 99th and below the 1st percentile of the distribution.

In all cases, there is substantial heterogeneity in estimated fixed effects within each group. Group differences are also economically significant. Business owners exhibit a distribution of persistent returns that is much more spread out and shifted to the right (standard deviation of 6.4 compared to 1.6 for non-business owners). This is consistent with owners of private businesses facing more heterogeneous investment opportunities and higher returns on capital. Returns are heterogeneous both among the wealthy and among people at the bottom of the wealth distribution. But the distribution of the permanent component of returns is more spread out and returns are on average higher among the wealthy, with differences in the mean and spread becoming larger at the very top of the wealth distribution. This is also true among participants in risky assets markets while individuals with a degree in economics or business have a less volatile distribution of fixed effects (as measured by the coefficient of variation). Panel B of Figure 7 shows sub-group distributions for the persistent component of net worth returns. Given its relevance, we use "holding debt" instead of "holding risky assets" as a characteristic that *a priori* may generate significant differences in the distribution of fixed effects. This is indeed the case - the distribution of fixed effects for debt-holders shifts on the left and has a longer left tail. Qualitative features for the other three characteristics (owning a business, a high position in the wealth distribution, business/economics education) are similar, with all characteristics shifting the distribution of returns to net worth fixed effects to the right.

Table 6, Panel A shows summary statistics for the distribution of the return fixed effects for the total sample and for some population subgroups; we do this for both measures of gross returns as well as for the after-tax returns on net worth. Concerning the latter, taxation lowers persistent heterogeneity in returns considerably (standard deviation 3.6 vs. 5.4 percent) while leaving other aspects of the fixed effects distribution unchanged. For all three measures of returns Panel B computes correlations of the average fixed effects and its cross sectional standard deviation with the position in the wealth distribution. The persistent component of returns increases with wealth and the relation is steeper for returns on financial wealth, while it is flatter for net of tax returns on net worth. Cross sectional heterogeneity in returns to financial wealth increases with position in the wealth distribution; the reverse is true for returns on net worth, which are more heterogeneous at the bottom than at the top - reflecting high heterogeneity in cost of debt and leverage.

The final Panel C of Table 6 presents a simple variance decomposition of the unobserved components of the returns. Our error term representation allows as to decompose idiosyncratic variation in returns to wealth as $var(u^x_{i(g)t}) = var(f^x_{i(g)}) + var(e^x_{i(g)t})$. As shown by Shourideh

(2014), the relative importance of $var(f^x_{i(g)})$ and $var(e^x_{i(g)t})$ drives the optimal taxation of capital income, particularly its progressivity. In Panel C of Table 6 we report the estimated relative variances of the two components for different samples and definitions of returns. Using results from our baseline specification, we find that $var(f^x_{i(g)})/var(u^x_{i(g)t}) = 0.29$. The estimates for the other two definition of returns are similar. Hence, persistent differences in returns across individuals can account for 1/3 to 1/4 of the variance of the unobserved component of the returns.

5 Interpreting persistent heterogeneity

What do fixed effects in returns to wealth capture? We can think of three broad classes of explanations. The first is that persistent differences in risk tolerance shape the composition of one's portfolio. More risk tolerant individuals allocate (persistently) a larger share of their wealth to risky assets and are compensated with a return premium. Indeed, in the Merton-Samuelson model discussed in Section 3, the optimal share invested in risky assets, $\omega_{it} = \frac{E(r^m_t - r^s_t)}{\gamma_i \sigma^2_t}$, increases linearly with the degree of individual risk tolerance $1/\gamma_i$, a stable preference parameter. The second factor is persistent differences in wealth and a positive effect of the scale of wealth on returns (Piketty, 2014), consistent with low levels of wealth mobility (in Norway, the Shorrocks index is 0.16 for quartiles of net worth). The third broad explanation is that the fixed effects capture heterogeneity in financial sophistication, ability to process and use financial information, or heterogeneity in the cost of accessing investment opportunities and other persistent individual traits (such as intertemporal discounting) that affect the average return individuals extract from their financial investments and leverage choices *conditioning* on the risk exposure of their portfolio and the scale of the portfolio itself. In the case of private equity, it is plausible that, holding constant the share of wealth in the private business and the size of the business, part of the observed heterogeneity in the return to private equity may reflect differences across entrepreneurs in the ability to manage their businesses.[37]

Our evidence suggests that these three components coexist. Returns are indeed affected by the portfolio risk exposure as measured by the shares invested in risky assets and by the average β of the stock portfolio. They are also affected by the scale of wealth. However, this is not all that matters. First, the fact that measures of education affect returns, controlling

[37] We estimated a fixed effect model for the return to private equity (using the same specifications of Table 5, columns 3 and 4). We find that the adjusted R^2 of the regression jumps from 0.0279 (when fixed effects are excluded) to 0.1399 (when they are included), a five-fold increase in predictability.

for risk exposure and level of wealth (Tables 4 and 5, columns 1-3), already suggests that "financial sophistication" matters. Second, when we introduce the fixed effects there is a large increase in the explained variability of returns (the adjusted R^2 increases by 23% for returns to financial assets and 49% for returns to net worth). If risk exposure and wealth level were the only reasons behind type dependence in returns, this increase in explained variation would be hard to rationalize.

5.1 Additional evidence

To show from different perspectives that persistent heterogeneity in returns to wealth is only partially a reflection of compensation for risk-taking and for scale, we consider two additional exercises. First, we run regressions of the individual return Sharpe ratio, computed as in equation (7), on financial wealth measured in 2004 (at the beginning of our sample period) and other observable characteristics (results in Table 7).[38] In column 1 we focus on the whole sample, while in column 2 we exclude private equity owners. In both columns we enter the wealth percentile linearly and control for a quadratic in age, years of schooling and degree in business (proxying for financial knowledge) and the number of years the individual has owned shares of a private company (capturing business experience). Results are unchanged if we adopt a less parametric specification and add a full set of wealth percentile dummies, etc. A few results are worth of note: (1) More educated individuals display higher Sharpe ratios, as do individuals with a business or economics degree, suggesting that financial sophistication plays a role in explaining differences in risk-adjusted returns; (2) risk-adjusted returns are strongly and significantly increasing with the individual initial wealth percentile; (3) risk-adjusted returns increase with experience as a private equity owner. When we focus on a sample of individuals who have never owned private equity wealth, the results for the financial wealth percentile are unchanged, and suggest that risk-adjusted returns increase substantially as we climb the distribution of initial financial wealth (controlling for age, and the length and type of education). Correlation between wealth and the Sharpe ratio and the latter and education/experience are predicted by models where individuals differ in the cost or incentives to collect information, as in Arrow (1987), Peress (2004), Kacperczyk et al. (2014), and Best and Dogra (2017). On the other hand, models à la Merton with equally informed investors with heterogeneous risk tolerance predict heterogeneity in return levels but not in risk adjusted returns and no correlation between wealth and risk-adjusted returns.

[38]The individual Sharpe ratio is highly correlated with the individual fixed effect (a correlation coefficient of 0.52).

For our second exercise we consider data on the universe of individual bank deposit accounts for the period 2005-15. Similarly to the US, in Norway deposits up to 2 million NOK (approximately $260,000) are fully insured by the government through the Banks' Guarantee Fund and hence bear no risk. Thus individual heterogeneity in returns on deposits below this threshold cannot be attributed to compensation for differential risk across banks. In the data, most individuals have multiple accounts at different banks. We select individuals who have accounts for all years and eliminate accounts with a balance above the deposit insurance threshold or below $500. We then compute an account-specific return using information on the interests received on the account and the average of end- and beginning-of-year deposit balances (i.e., using an analog of (3)).[39] Finally, we run regressions of the return on deposit accounts against demographics, the number of yearly accounts held by the individual (overall and with a given bank to pick differences in the nature of the accounts), account "experience" (to model the potential impact of teasing rates), bank fixed effects (to capture systematic differences in rates offered across banks), time dummies (absorbing common shocks), and the log of the deposit balances (to account for scale effects). Table OA.4 in the OA shows that returns on deposits are positively correlated with years of education and with having an economics/business degree; they are also increasing with deposit size, consistent with a scale effect and decreasing in account "experience" (consistent with the presence of teasing rate followed by inertial behavior). These controls jointly explain 53% of the variation. When we add individual fixed effects the fit of the regression increases by 14%. Because returns on deposits bear no risk, the increase in fit cannot be attributed to unobserved risk tolerance. Statistics on bank and individual fixed effects give a good accounts of the extent of heterogeneity. First, returns on deposits are heterogeneous across individuals - i.e. there is "type dependence" in the return to a financial instrument that entails no risk. Heterogeneity is sizable with a standard deviation of 2.6%. Returns on deposits also differ systematically across banks (standard deviation 0.9%): this gives people opportunities to search for more remunerative accounts. To shed light on what is driving type dependence we look at the correlation between bank fixed effects and individual effects (schooling and the estimated deposit return individual fixed effects). These are shown in the two panels of Figure 8. The figure in the left panel plots the average bank fixed effect by years of schooling. The figure in the right panel shows that individual fixed effects and bank fixed effects are strongly positively correlated. High education people tend to deposit at high-return banks and so do high-fixed effects individuals. This suggests that individuals who earn persistently higher

[39] We also trim the return at the top 0.5%.

returns on deposits do so partly because they are able to spot high-return banks and deposit their liquidity there.

To sum up, we interpret our evidence as implying that besides reflecting compensation for risk and scale, persistent heterogeneity in returns reflects also differences in ability to generate returns and superior information about investment opportunities.

6 Intergenerational persistence in returns to wealth

Because the Norwegian data contain both an individual identifier and a family identifier, it is possible to link individuals across generations. Hence, we can study intergenerational persistence in returns to wealth, i.e., the link between $r^x_{i(g)t}$ and $r^x_{i(g-1)t}$. We can also study the relationship between the fixed effect component of returns by estimating:

$$f^x_{i(g)} = \rho f^x_{i(g-1)} + \eta^x_{i(g)} \tag{12}$$

where $f^x_{i(g)}$ is the fixed effect in returns to wealth for individual i in generation g, for wealth type x estimated from (10). We thus use our statistical model to isolate the type of heterogeneity in returns - persistent heterogeneity - whose properties (cross-sectional variance and intergenerational persistence) can in theory explain the thickness in the distribution of wealth as shown by Benhabib et al. (2011). The aforementioned variance decomposition into $var(f_{i(g)})$ and $var(e_{i(g)t})$, together with intergenerational persistence in $f_{i(g)}$, plays a key role in the design of optimal capital income taxation (Shourideh, 2014).

To focus on a sharper case, we look at fathers and children (sons and daughters). Our regression analysis provides us with an estimate of individual returns for over 11 million father-child pairs over our sample period. This allows us to test whether wealth returns are correlated across generations, and whether such correlation is explained by the persistent component or by observable characteristics that may be shared by both generations.

We start by ranking parents according to their wealth, the return to it, and the persistent component of their returns (fixed effect). In principle, it would be best to relate parents' variables and children's variables when they are of the same age. Unfortunately, our panel is not long enough to meet this requirement. To control for the fact that parents and children are observed at different points of their life cycles, we compute rank percentiles of the relevant distribution with respect to the birth cohort the individuals (father and children) belong to. Next, for each percentile of the parents' variable of interest (wealth, returns, or return fixed effect), we compute the average percentile occupied by their child in the distribution of the same relevant variable in the same year (again, relative to their year of birth cohort).

Panel A of Figure 9 plots the rank correlation between the financial wealth percentile of the parents and that of the child (left panel); the right panel repeats the exercise for the returns. Both measures display a positive correlation, although the intergenerational correlation in wealth is three times larger than that in the return to wealth (a regression slope of 0.3 vs. 0.11). Interestingly, there are important non-linearities: the linear model misses the higher polarization at the top of the wealth distribution and the lower polarization at the top of the returns distribution (most likely coming from the fact that children of extraordinary parents in terms of returns to wealth quickly revert to the mean).[40] Hence, for the very wealthy the pattern of intergenerational correlation in returns facilitates social mobility, while that in wealth weakens it. Panel B of Figures 9 repeats the exercise for net worth. The main difference is that the intergenerational correlation in wealth and that in returns to wealth is now similar (regression slopes of 0.16 vs. 0.15). However, the deviations from linearity at the top and bottom of the distributions are much stronger.

Figure OA.17 in the OA plots intergenerational rank correlations for the persistent component of the returns (equation 12). The correlation between fixed effect percentiles is stronger than between the returns themselves. This suggests that most of the intergenerational correlation in returns to wealth is a reflection of the individual persistent component.

Some of the intergenerational correlation in returns may come from parents and children sharing a private business (or family firm). It is also possible that children imitate the investment strategies of their parents, or that they inherit traits from their parents that matter for returns (such as preferences for risk or investment talent). Or, in the case of returns to housing (and net worth) that returns are correlated because of proximity in location. However, given the positive correlation between returns and wealth, all or part of the intergenerational correlation in returns documented in Figure 9 may simply reflect the intergenerational correlation in wealth or aggregate shocks to returns. The positive correlation between the child's and the father's return fixed effects rules out the second possibility, but not the first. To deal with this, we report controlled regressions of children's returns on fathers' returns. We show the results in Table 8 using children's and fathers' return percentiles; the results are similar if we use returns directly (see Panel A of Table

[40] While the literature on intergenerational income mobility is vast (see for instance Chetty et al., 2014), that on wealth has been limited due to wealth information being less frequently available to researchers, Charles and Hurst (2003) being an exception. More recently, a growing number of papers study intergenerational mobility of wealth using Scandinavian data, see for instance Boserup et al. (2014); Black et al. (2015); Fagereng et al. (2015); Knupfer et al. (2018). None of these papers study intergenerational correlation in returns to wealth.

OA.5 in the OA). The first four columns show results for returns on financial assets; the remaining four for net worth returns. The first specification has no controls, and hence reproduces the slope coefficients of the two panels of Figure 9 (0.11 and 0.15). Adding wealth controls, education dummies, age and year effects lowers the slope of the intergenerational relation between returns to financial wealth but leave the one for the returns to net worth unaffected (columns 2-3 and 6-7). In all cases, the estimated effect remains positive and significant. Finally, including individual fixed effects (columns 4 and 8) leaves the slope of the relation unaffected, but considerably raises the fit (as measured by the adjusted R^2), which is consistent with the intergenerational correlation being driven primarily by the permanent component of returns. The results are confirmed when private business owners are dropped from the sample and when using net of tax returns (see Table OA.5 in the OA).[41]

Overall, our data suggest substantial persistence and heterogeneity in returns within a generation but milder persistence across generations, particularly in returns to financial wealth. This result is similar to that found by Benhabib et al. (2017) (although their estimate is imprecise). In their calibration exercise, only mild intergenerational persistence in returns is required to match the wealth concentration data. In our case, with a much larger amount of statistical power, we find in the data an economically small but precisely measured degree of intergenerational persistence in returns to financial wealth and to net worth.

7 Discussion and Conclusions

The properties of the returns to wealth that we have documented in this paper have potentially far-reaching implications for several strands of the current debate on wealth inequality. Here, we discuss four and highlight some new lines of research that our findings call for.

Wealth inequality and returns heterogeneity Papers on wealth inequality in the spirit of Benhabib et al. (2011) face the problem that the key driver of wealth concentration at the top - the moments of the distribution of the persistent component of returns and the degree of intergenerational correlation - are typically unknown. Our paper provides estimates that can be used to calibrate these models. Given the distribution of returns, these models imply a positive relation between the average fixed effects and the wealth percentile. Table 6, Panel B shows the slope parameter of OLS regressions of the average fixed effects on wealth percentiles. Using these data and the estimates of intergenerational persistence in Section

[41] Intergenerational persistence is also detected if we use Sharpe ratios of fathers and children, confirming that it is risk-adjusted returns that correlate across generations.

6, a summary characterization of the distribution of the return fixed effects (focusing on after tax returns on net worth as this is what matters for wealth accumulation and ignoring moments higher than the second) is $f_{i(g)} \sim (mean = 3.7\% + 0.012(P_{iw} - 50), SD = 3.6\%)$ and $f_{i(g)} = const + 0.14 f_{i(g-1)}$, where P_{iw} is the wealth percentile of individual i and 3.7% is the average after tax return on net worth wealth over the sample period. This characterization is qualitatively consistent with the idea that those with persistently higher returns on wealth, measured by the fixed effects, will end up accumulating more wealth - the mechanism emphasized by Benhabib et al. (2011). Alternatively, one can choose the value of the parameters of the distribution of individual persistent returns (mean, standard deviation, and intergenerational correlation) to match the moments of the wealth distribution as done by Benhabib et al. (2017) for the US, which can then be confronted with our data-based findings. Benhabib et al. (2017) estimate average returns to wealth of 3.0% with a cross-sectional standard deviation of 2.7% and an intergenerational persistence of 0.17; these parameters are somewhat lower than our estimates based on the Norwegian data, particularly the returns standard deviation, but this is because Benhabib et al. (2017) impose tight borrowing constraints, inducing too little borrowing that counterfactually increases the returns at the bottom of the net worth distribution compressing heterogeneity in returns (and inflating the estimated shares of wealth at the bottom). They also find that the slope of the relation between the wealth percentile and the corresponding (average) individual permanent return to wealth is about 0.01, strikingly similar to the one we estimate. The remarkable consistency between our data-based evidence and the calibration-based evidence of Benhabib et al. (2017) suggests that future macro models will have to account for returns heterogeneity in the same way that they account for heterogeneity in returns to human capital if the goal is to replicate features of the wealth distribution.

Measurement of wealth trends Saez and Zucman (2016) have revived the debate around the dynamics of the shares of wealth at the very top of the distribution. Lacking time series of comprehensive data on wealth holdings for the US similar to those available for Norway, they use tax records of income from capital to obtain underlying wealth figures and trends in top wealth shares. Wealth is imputed by capitalizing the capital income components using the average rate of return of the corresponding component. The capitalization methods may overstate the amount of wealth concentration if returns are heterogeneous within asset classes and if returns correlate with the level of wealth - two features that our paper documents. Moreover, trends in wealth concentration and inequality may depend on whether the extent of return heterogeneity and the correlation between wealth and returns change over time (which is another feature of the data). In Fagereng et al. (2016b), we use the Norwegian data to contrast inequality measures based on actual wealth with measures obtained from imputed wealth using the capitalization method, and document that heterogeneity of returns can in principle generate significant deviations between measures of inequality based on imputed and actual wealth.

Inequality in income and inequality in wealth Some countries with low levels of income inequality display levels of wealth inequality that are similar to those of countries with much higher levels of income inequality. For example, using comparable definitions over the years 1993-2000, the top 0.1% income share in Norway is on average around 3% and the top 0.1% wealth share 12.5%; on the other hand, over the same period the top 0.1% income share in the US is 7.8% - more than twice that in Norway, while the average top 0.1% wealth share is as large as in Norway (13.6%).[42] Heterogeneity in returns to wealth may solve the puzzle of why two countries with very different levels of concentration of income at the top may nevertheless have similar levels of wealth concentration at the top. Surveying the theories of skewed wealth distributions, Benhabib and Bisin (2018) revisit and put in a novel perspective two theorems, one by Grey (1994) and another by Kesten (1973). Grey's theorem asserts that, in an economy with homogeneous returns to wealth and heterogeneous income, the wealth distribution inherits the properties of the income distribution, including the thickness of its tails. Kesten's theorem asserts that, under certain conditions, heterogeneity in returns to wealth can generate a thick-tailed and skewed wealth distribution even when the distribution of returns is neither skewed nor fat-tailed, and without requiring income heterogeneity. Models that rely on heterogeneity in returns to explain wealth inequality rely on the latter property. These two theorems imply that the tail of the wealth distribution is determined either by the tail of the earning distribution or by the stochastic properties of returns, not both. This is relevant to solving the above puzzle. If returns heterogeneity determines the tail, as implied in Benhabib et al. (2017), provided the degree of heterogeneity in returns is similar across countries (not an unreasonable requirement in light of the evidence discussed early in this Section), one can observe marked differences in income concentration and still see a similar level of concentration of wealth at the top.

[42]Top income shares for the US and Norway include capital gains and are taken from the Wealth and Income Database: http://www.wid.world/#Database, see also Aaberge et al. (2016); the US top wealth shares are taken from Saez and Zucman (2016), Figure 6B. For Norway, we compute top wealth shares from the registry data using definitions that are as close as possible to those of Saez and Zucman (2016).

Taxation of capital income and taxation of wealth Our findings also relate to the emerging literature on capital income and wealth taxation. In models with heterogeneous returns, taxing income from capital and taxing capital can have important efficiency implications, as shown by Guvenen et al. (2015). In fact, holding tax revenue constant, replacing a capital income tax with a wealth tax tends to widen the after-tax heterogeneity in returns. Intuitively, taxing capital income disproportionately reduces the after-tax return of individuals with high rates of return; hence, moving to a wealth tax system redistributes the burden of taxation from high- to low-return individuals. This may produce efficiency gains through two channels: capital is reallocated to high-return individuals, and the higher return of high-return individuals can motivate further wealth accumulation. The importance of these efficiency gains from tax reallocation critically depends on the nature of the heterogeneity: whether it is persistent and its extent. Our results inform both dimensions; the extent of measured persistent heterogeneity suggests that the efficiency concerns of capital income taxation raised by Guvenen et al. (2015) are of practical relevance. Furthermore, when returns have a transitory component in addition to the permanent one, the relative importance of the two sources of cross-sectional heterogeneity are relevant to the progressivity of capital income taxation (Shourideh, 2014). Our variance decomposition (Table 6, Panel C) provides information that can be used to empirically assess how far the actual taxation of capital income is from the optimal level.

Other amplifying mechanisms for wealth inequality In closely related work (Fagereng et al., 2016a) we document persistence in returns to wealth across marital statuses. This is both because people sort on the basis of pre-marital returns to wealth and because the pre-marriage returns of both spouses affect the return to household wealth. We are unaware of any model that accounts for assortative mating by returns to wealth and allocation of wealth management responsibility within the family. Yet, they are potentially relevant to heterogeneity in returns to wealth, and thus for wealth concentration.

More generally, the effects on wealth inequality and optimal taxation of the properties of the stochastic process of returns on wealth are mediated by people's reactions to these properties, which in turn depend on specific model parameters. The identification of the latter in a life-cycle households model that explicitly allows for returns heterogeneity in human and non-human capital, as well as in key preference parameters, can make it possible to empirically quantify the relative importance of the sources of wealth inequality. The estimation of such a model is tackled in ongoing work (Fagereng et al., 2018).

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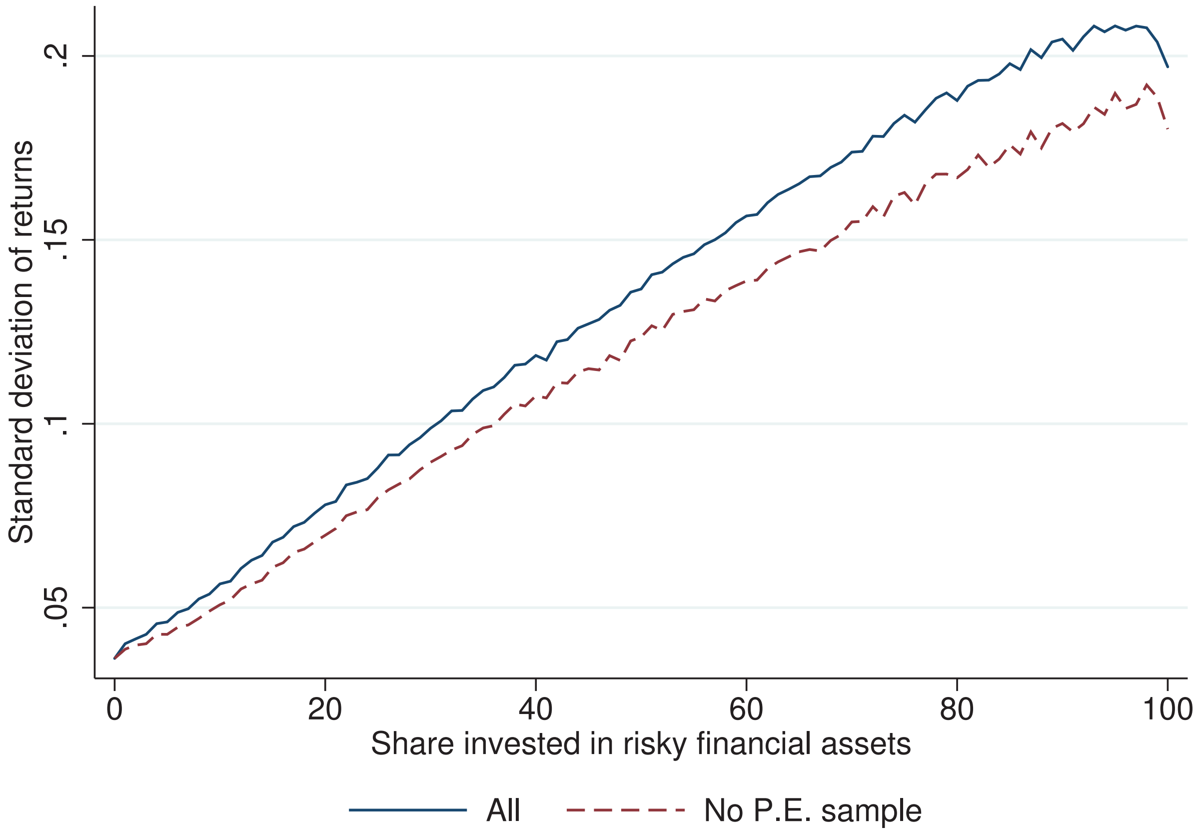
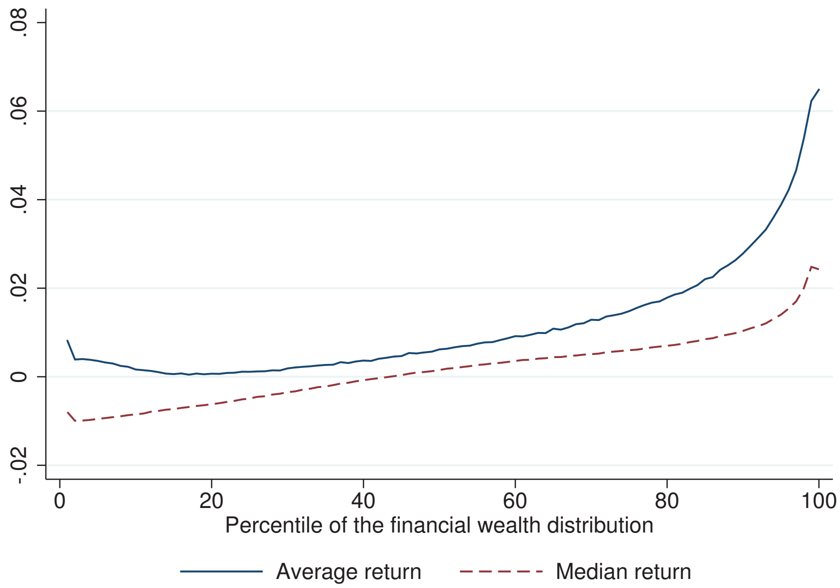
Figure 1. Heterogeneity in returns to financial wealth by share of risky assets

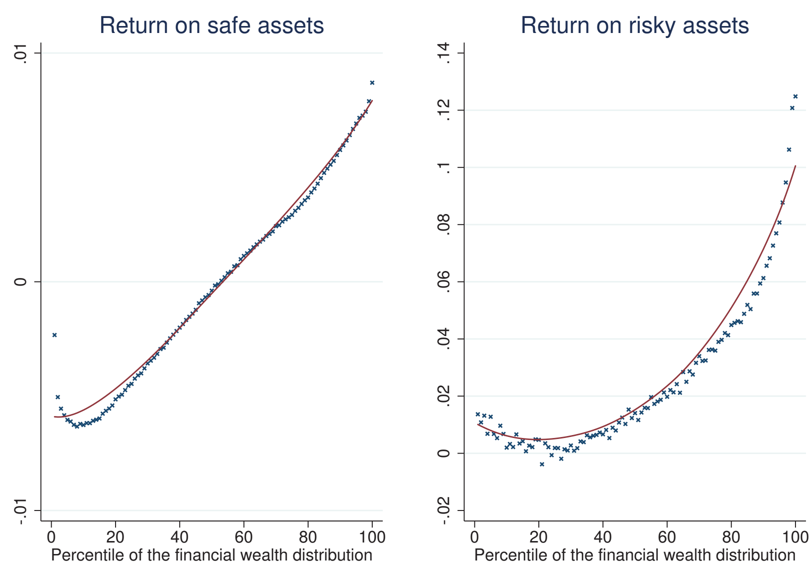


Notes: The figure plots the cross-sectional standard deviation of individual returns to wealth in the 2005-15 period by value of the share of wealth in risky assets (directly and indirectly held stocks, private equity wealth, and foreign and outstanding claims) for the full sample (solid line) and excluding private equity holders (dashed line).

Figure 2. The correlation between financial wealth and its return



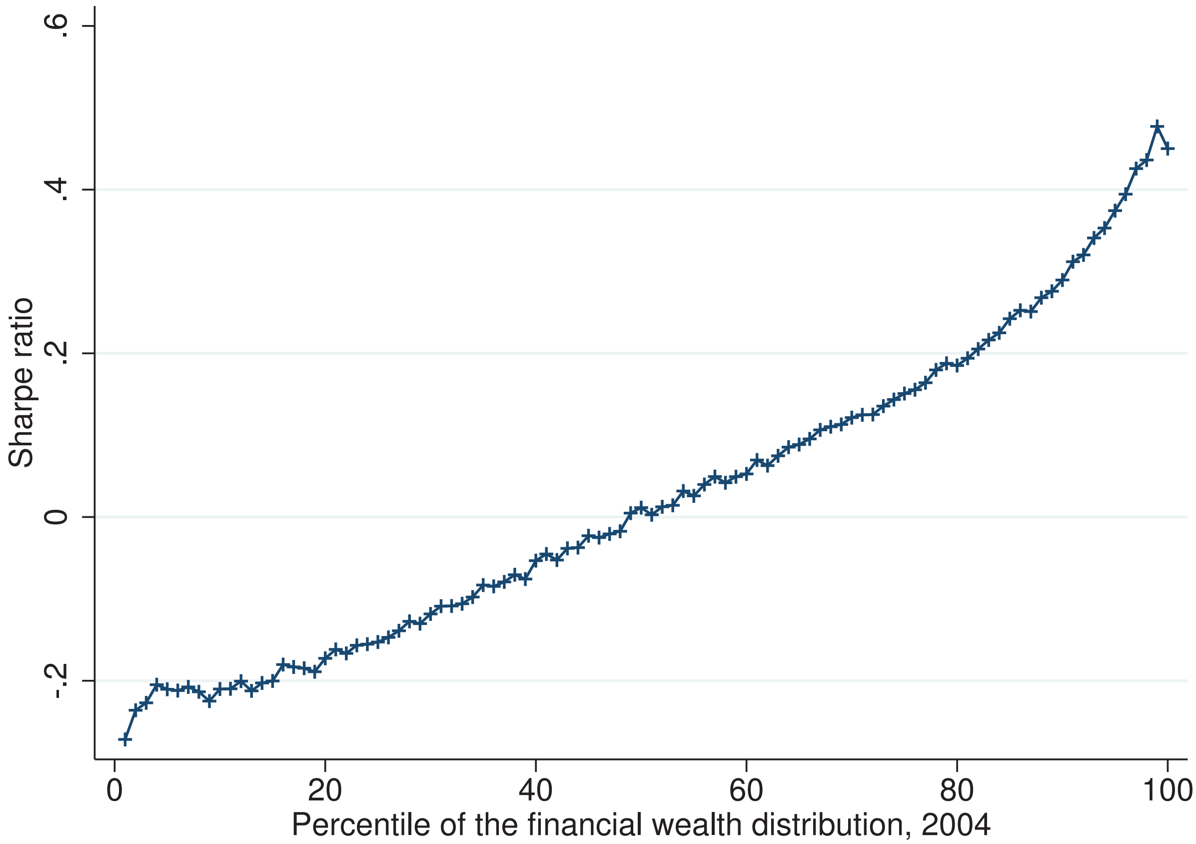
Panel A: Return to financial wealth



Panel B: Return to components of financial wealth

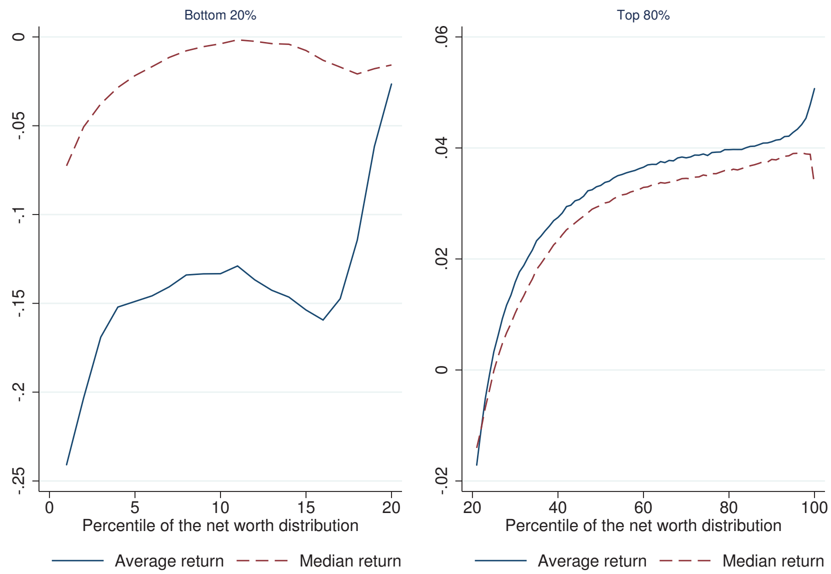
Notes: The figure shows the relation between returns to financial wealth and financial wealth percentiles pooling data for 2005-15. Panel A shows the relation for the average (solid line) and median (dashed line) return on all financial assets. Panel B shows the relation distinctly for the return to safe assets (left figure) and the return to risky assets (right figure), together with a local regression line.

Figure 3. The Sharpe ratio and initial wealth

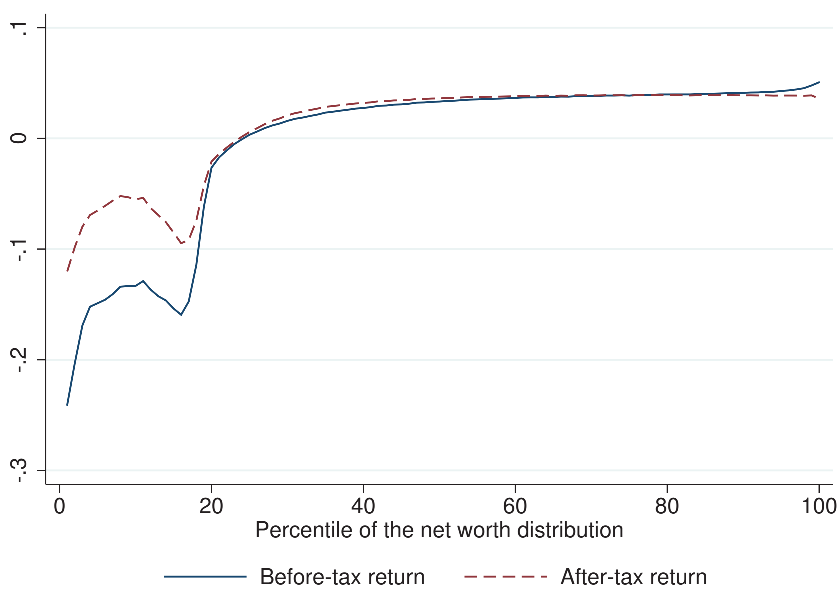


Notes: The figure shows the average Sharpe ratio of individual wealth portfolios (equation 7) by wealth percentile for the 2005-15 period. Wealth percentiles are computed using wealth figures in 2004. Only individuals with 12 consecutive observations (from 2004 to 2015) are included in the calculations.

Figure 4. The correlation between net worth and its return



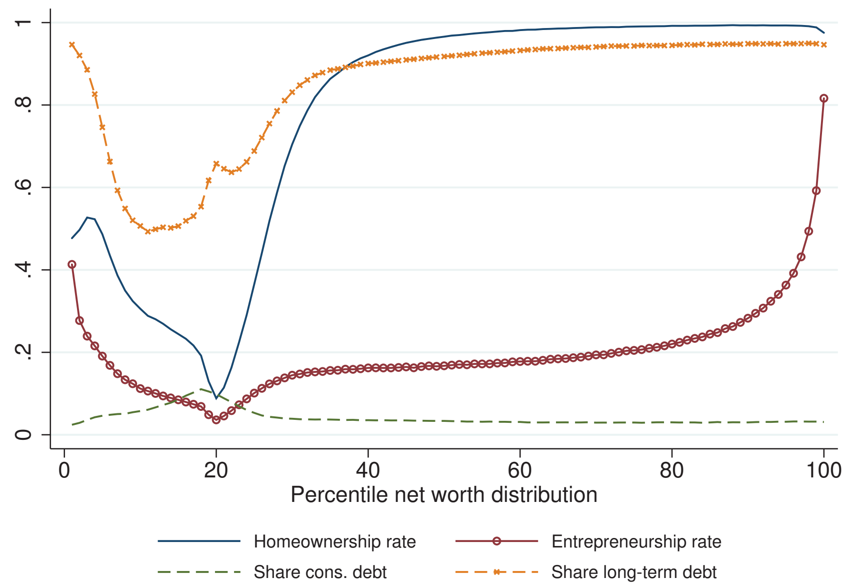
Panel A: Before-tax return to net worth, mean and median



Panel B: Before-tax vs. after-tax return to net worth

Notes: The figure shows the relation between returns to net worth and net worth percentiles pooling data for 2005-15. Panel A plots the average (solid line) and median (dashed line) return. Panel B plots before- and after-tax average return on net worth.

Figure 5. Explaining the relation between net worth and its return

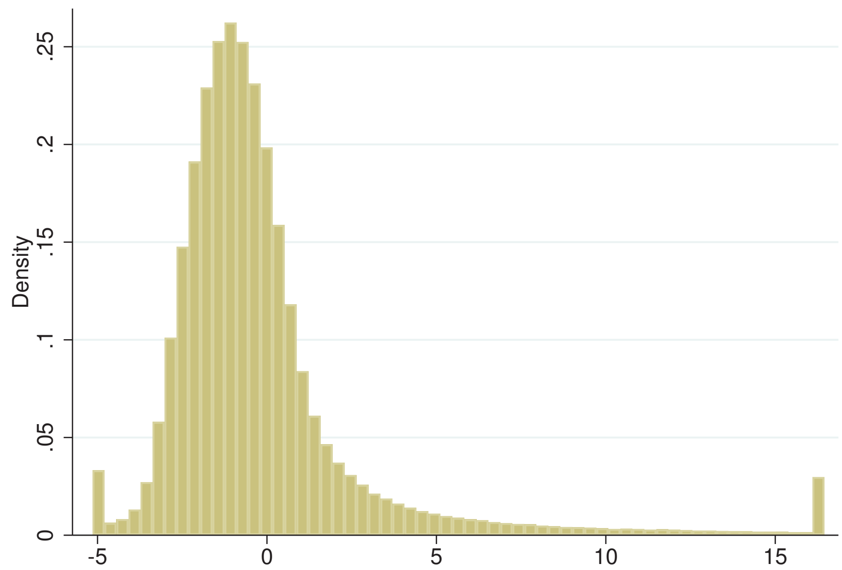


Panel A: Leverage, homeownership and entrepreneurship rates

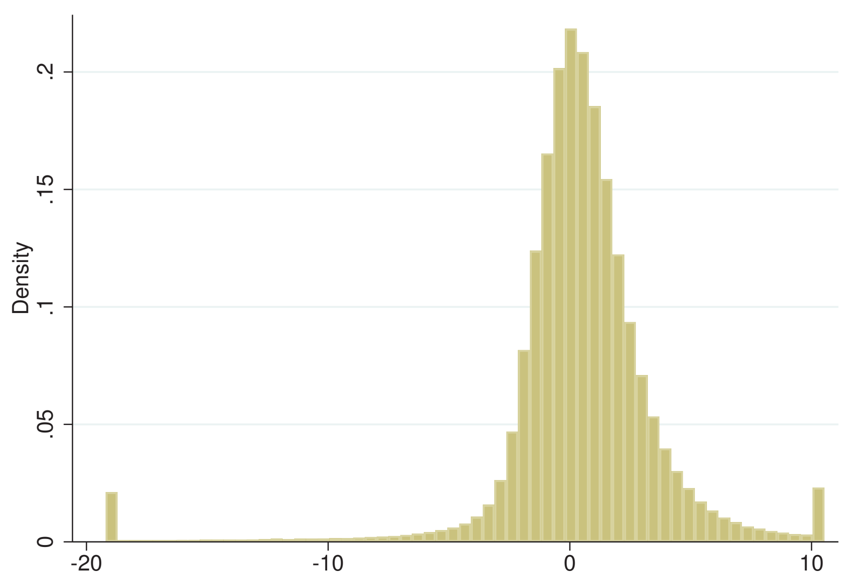
Panel B: Returns to asset components of net worth and the cost of debt

Notes: Panel A plots the fraction of individuals owning a house, the fraction of entrepreneurs, the share of consumer debt out of total debt and the share of long-term debt out of total debt for each percentile of the net worth distribution. Panel B plots the return to net worth (right axis) and the return of its sub-components, financial wealth, housing, and debt (in absolute value), against the percentile of the net worth distribution.

Figure 6. The distribution of fixed effects in the return to wealth



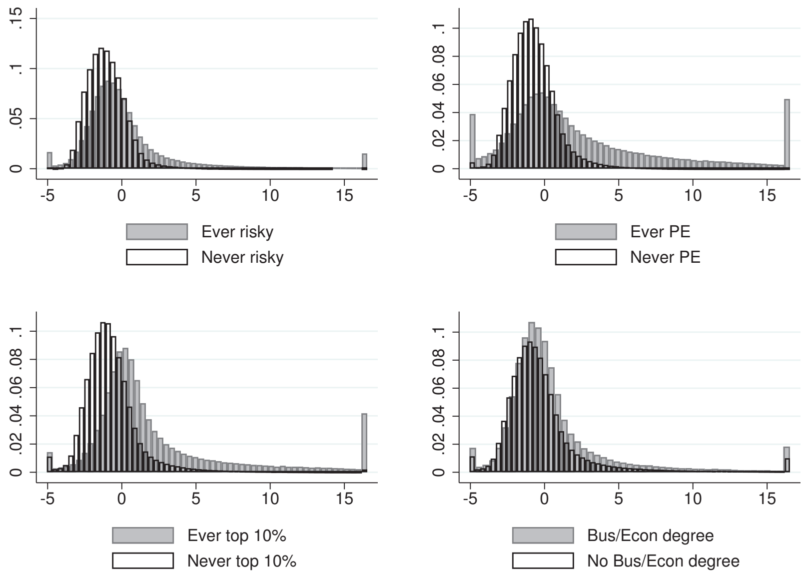
Panel A: Financial wealth



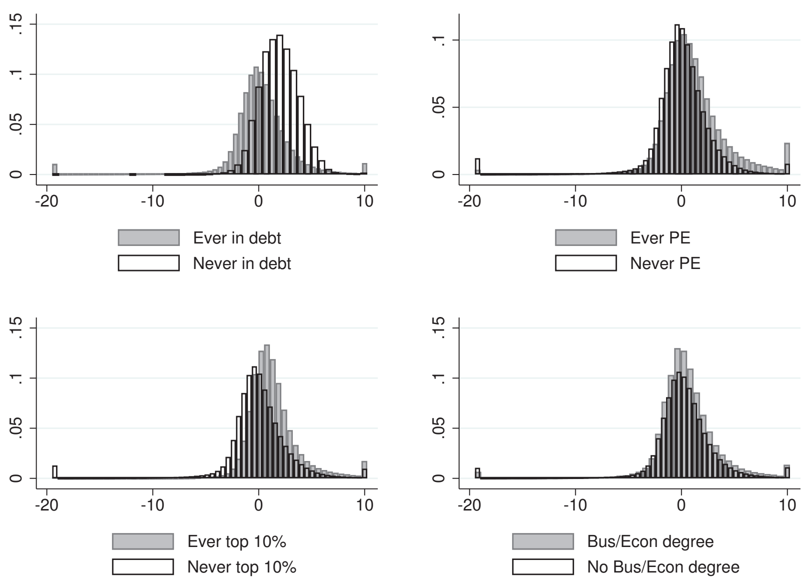
Panel B: Net worth

Notes: The figure shows the histogram of the estimated fixed effects in the wealth return regressions using estimates in Table 4, column 4 and Table 5, column 4, respectively for the return to financial wealth (Panel A) and the return to net worth (Panel B). Both distributions have been de-meaned and winsorized at the top and bottom 1%.

Figure 7. The distribution of fixed effects in the return to wealth, selected characteristics



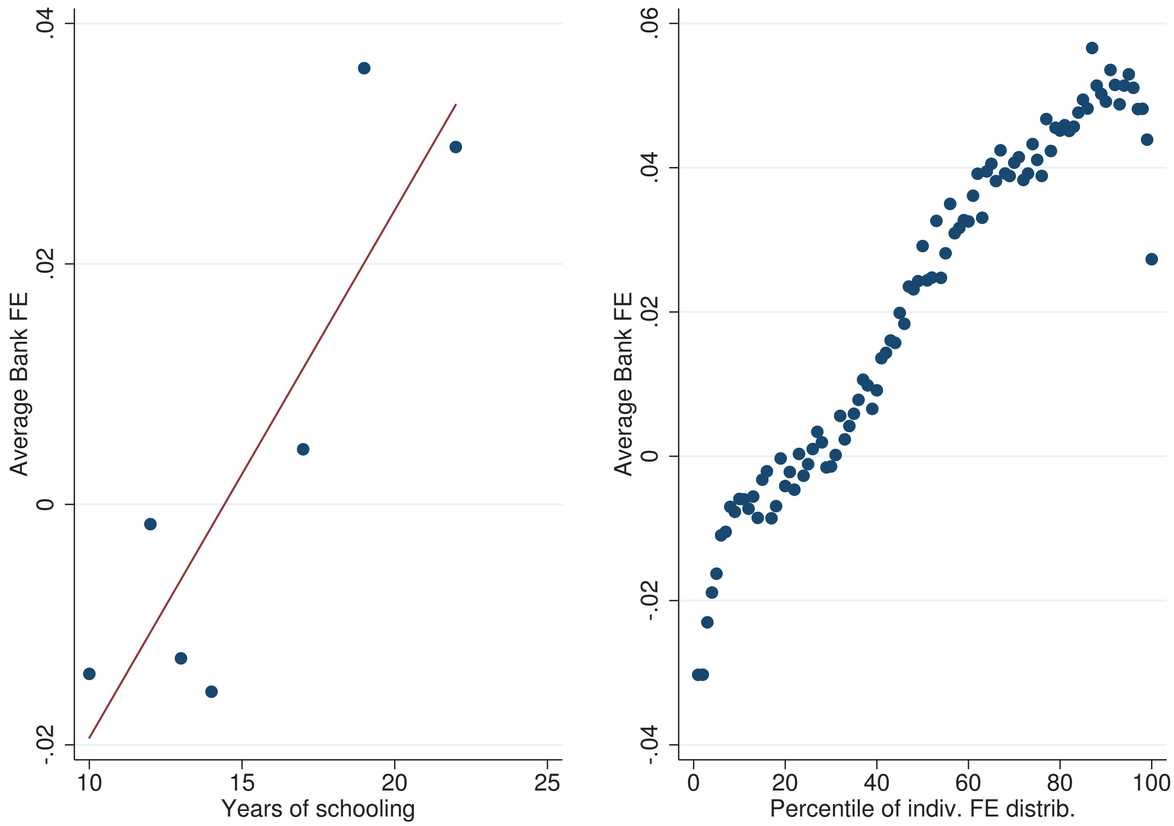
Panel A: Financial wealth



Panel B: Net worth

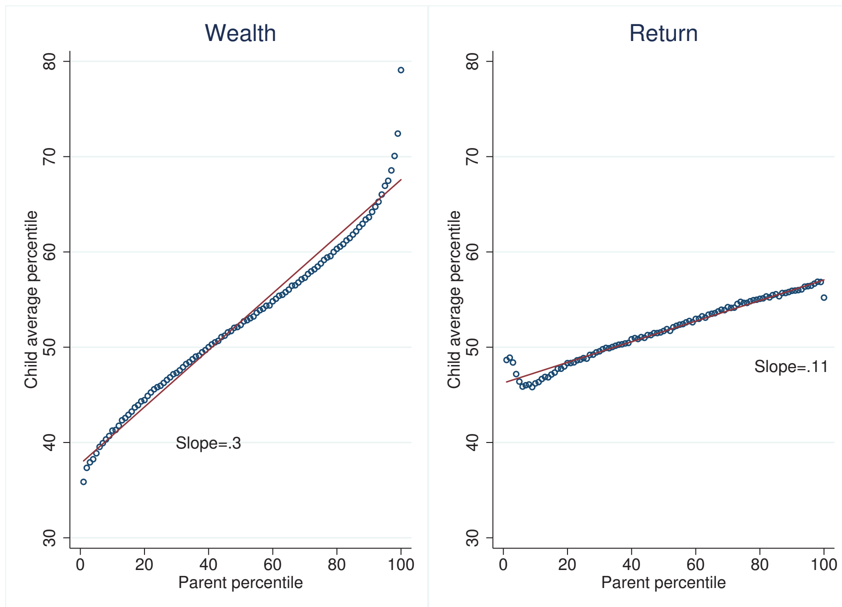
Notes: Panel B shows the histogram of the estimated fixed effects in the wealth return regression using estimates in Table 4, columns 4, for various subgroups of the population (ever risky asset holders, ever private equity owners, ever in the top 10% of the wealth distribution, individuals with a Business or Economics university degree) against the complementary sub-population. Panel B replicates the exercise for the return to net worth, using estimates from Table 5, column 4, but replace the "ever risky asset holders" category with the "ever in debt" category. All distributions are winsorized at the top and bottom 1%.

Figure 8. Deposit accounts bank and individual fixed effects

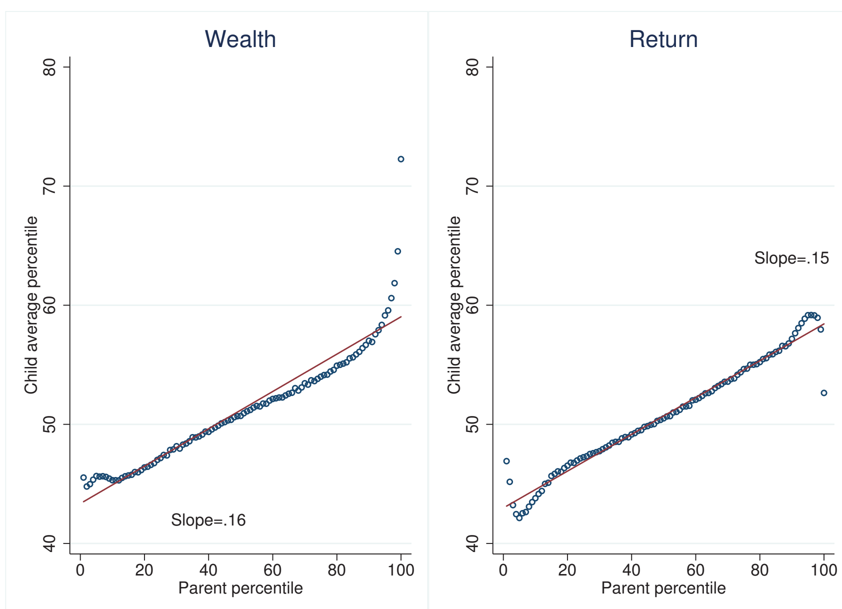


Notes: The figure on the left plots the average bank fixed effect for different levels of schooling using the deposit return regression of Table OA.4, column 2. The figure on the right repeats the exercise for different percentiles of the distribution of individual fixed effects from the same regression.

Figure 9. The intergenerational correlation in wealth and returns



Panel A: Financial wealth



Panel B: Net worth

Notes: Panel A shows the rank correlation between children (vertical axis) and fathers (horizontal axis) of wealth percentiles (left figure) and returns to financial wealth percentiles (right figure). Panel B repeats the exercise for net worth (left) and the return to net worth (right). In all graphs we also plot a simple linear regression fit and the corresponding slope regression coefficient.

Table 1. Portfolio composition, by selected fractiles

Panel A: Financial Wealth

	Deposit	Bonds	Foreign & outst. claims	Mutual funds	Listed stocks	Private equity
0-20%	0.95	0.01	0.00	0.03	0.00	0.00
20-50%	0.88	0.01	0.02	0.07	0.01	0.01
50-90%	0.77	0.02	0.04	0.08	0.03	0.06
90-95%	0.62	0.02	0.07	0.07	0.04	0.18
95-99%	0.42	0.02	0.09	0.06	0.04	0.36
99-99.9%	0.15	0.02	0.11	0.03	0.03	0.66
99.9-99.99%	0.06	0.01	0.10	0.01	0.01	0.80
Top 0.01%	0.03	0.01	0.07	0.00	0.01	0.87

Panel B: Net Worth

	Assets			Liabilities		
	Safe	Housing	Risky	Cons. debt	Stud. debt	Long-term debt
0-20%	0.64	0.30	0.06	0.44	2.74	5.90
20-50%	0.31	0.66	0.03	0.01	0.05	0.40
50-90%	0.10	0.86	0.04	0.00	0.01	0.21
90-95%	0.11	0.81	0.08	0.00	0.00	0.12
95-99%	0.11	0.73	0.16	0.00	0.00	0.10
99-99.9%	0.10	0.44	0.46	0.00	0.00	0.07
99.9-99.99%	0.06	0.11	0.83	0.00	0.00	0.04
Top 0.01%	0.03	0.03	0.94	0.00	0.00	0.02

Notes: Panel A reports the share of financial wealth in cash/deposits, bonds, foreign and outstanding claims, mutual funds, directly held listed stocks, and private business wealth for Norwegian taxpayers against selected fractiles of the financial wealth distribution. Panel B reports the share of gross wealth in safe assets (cash/deposits and bonds), risky assets (foreign and outstanding claims, mutual funds, directly held listed stocks, and private business wealth), housing, consumer debt, student debt, and long-term debt (mortgages and personal loans). Debt leverage values are winsorized at the top 1%. Data are for 2005-2015.

Table 2. Descriptive Statistics

	Mean	Std. dev	P10	Median	P90
Panel A: Demographics					
Age	45.66	15.00	25	45	67
Male	0.50	0.50	0	0	1
Married	0.50	0.50	0	0	1
Family size	2.62	1.36	1	2	4
Less than High School education	0.22	0.42	0	0	1
High School education	0.43	0.50	0	0	1
College education	0.35	0.48	0	0	1
Years of education	13.61	3.58	10	13	17
Economics/Business education	0.12	0.33	0	0	1
Panel B: Stocks					
Safe assets	38,269	132,123	1,380	13,220	90,910
Risky assets	59,555	2,305,447	0	0	43,059
Financial wealth	97,825	2,328,873	1,674	18,356	147,630
Housing	302,110	329,435	0	253,247	630,577
Gross wealth	399,936	2,374,998	6,552	294,056	757,470
Debt	122,638	217,228	0	74,366	292,475
Net worth	277,297	2,349,119	-31,190	169,849	616,581
Panel C: Flows					
Income from safe assets	928	4,084	7	180	2,163
Income from risky assets	5,185	362,439	-54	0	2,803
Housing yield	18,102	27,740	0	12,078	46,568
Interest payments on debt	4,931	8,906	0	3,023	11,961
Panel D: Asset shares and participation statistics					
Fraction with risky assets	0.47	0.50	0	0	1
Fraction with public equity	0.38	0.49	0	0	1
Public equity share	0.08	0.18	0	0	0.32
Conditional public equity share	0.22	0.23	0.01	0.13	0.59
Fraction with private equity	0.13	0.34	0	0	1
Private equity share	0.06	0.20	0	0	0.12
Conditional private equity share	0.46	0.34	0.03	0.43	0.93
Fraction with housing	0.78	0.41	0	1	1
Housing/Gross wealth ratio	0.68	0.39	0	0.89	0.99
Conditional housing/Gross wealth ratio	0.87	0.16	0.65	0.93	0.99
Fraction with debt	0.89	0.32	0	1	1
Leverage: Consumer debt	0.09	0.57	0	0	0.02
Leverage: Student debt	0.53	2.67	0	0	0.18
Leverage: Long-term debt (homeowners)	0.38	0.49	0	0.27	0.86
Leverage: Long-term debt (non-homeowners)	4.73	11.42	0	0	15.40

Notes: The table reports summary statistics for demographic characteristics of individuals in our data (Panel A), wealth amounts (Panel B), income flows (Panel C), and portfolio composition (Panel D), pooling data for 2005-15 with a total of 32,665,032 individual-year observations.

Table 3. Value-weighted returns

Wealth component	Mean	St.dev.	P10	Median	P90	Skewness	Kurtosis
Financial wealth	0.0419	0.1435	-0.0321	0.0100	0.1796	1.67	14.55
Safe assets	0.0058	0.0198	-0.0133	0.0034	0.0244	4.36	48.24
Listed shares	0.0273	0.3021	-0.3785	0.0808	0.3041	-1.47	6.76
Private equity	0.1152	0.4343	-0.0406	0.0121	0.4227	5.65	257.91
Housing	0.0459	0.0609	-0.0201	0.0428	0.1100	0.16	8.42
Gross wealth	0.0429	0.0645	-0.0200	0.0377	0.1103	0.51	9.13
Debt	-0.0226	0.0210	-0.0029	-0.0207	-0.0444	-3.20	52.91
Consumption	-0.0910	0.1221	0.0108	-0.0724	-0.1953	-43.50	9392.96
Long-term	-0.0221	0.0208	-0.0037	-0.0201	-0.0430	-11.39	2088.4
Student	-0.0074	0.0252	0.0213	-0.0071	-0.0385	-0.59	3.80
Net worth (before-tax)	0.0406	0.0825	-0.0234	0.0339	0.1094	-0.76	61.41
Net worth (before-tax, unw.)	-0.0013	0.2129	-0.0593	0.0224	0.0975	-6.82	68.91
Net worth (after-tax)	0.0366	0.0746	-0.0252	0.0314	0.1031	-0.46	35.78
Net worth (after-tax, unw.)	0.0133	0.1487	-0.0446	0.0240	0.0975	-5.49	57.71

Notes: The table reports summary statistics for various measures of real returns to wealth, pooling data for 2005-15. Except when noted, all returns are value-weighted.

Table 4. Explaining returns to wealth: Financial wealth

	(1)	(2)	(3)	(4)
Years of education	0.0129	0.0109	0.0163	
	(0.0006)	(0.0006)	(0.0006)	
Econ/Business education	0.1386	0.1255	0.1004	
	(0.0064)	(0.0064)	(0.0064)	
Male	0.0207	-0.0057	-0.0097	
	(0.0037)	(0.0037)	(0.0037)	
Outst. and foreign share	0.1918	0.1824		
	(0.0187)	(0.0187)		
Bonds share	1.2976	1.2908		
	(0.0143)	(0.0143)		
Mutual fund share	1.6937	1.6562		
	(0.0112)	(0.0112)		
Listed stocks share	2.1238	1.6050		
	(0.0398)	(0.0447)		
Private equity share	8.2705	8.2828		
	(0.0279)	(0.0279)		
β of stock market portfolio		0.1283	0.0987	0.8197
		(0.0217)	(0.0202)	(0.0482)
Observations	30,781,599	30,781,599	30,781,599	30,781,599
Adjusted R^2	0.101	0.101	0.321	0.394

Notes: The table shows regression estimates of individual returns to financial wealth (equation (3)). Columns 1-3 are OLS regressions without individual fixed effects; column 4 includes individual fixed effects. All regressions include a full set of dummies for wealth percentiles computed on one-year lagged wealth, year dummies, age dummies, and location dummies. Specifications in columns 3 and 4 include interactions between time effects and the portfolio shares. Standard errors (in parentheses) are clustered by individual.

Table 5. Explaining returns to wealth: Net worth

	(1)	(2)	(3)	(4)
Years of education	0.1261	0.1227	0.1396	
	(0.0014)	(0.0014)	(0.0014)	
Econ/Business education	0.1112	0.0920	0.1112	
	(0.0110)	(0.0111)	(0.0111)	
Male	0.0446	0.0132	0.0168	
	(0.0087)	(0.0088)	(0.0088)	
Outst. and foreign claims	3.4361	3.3979		
	(0.1169)	(0.1170)		
Bonds share	2.9926	2.9613		
	(0.1410)	(0.1410)		
Mutual fund share	3.8768	3.7882		
	(0.1152)	(0.1154)		
Listed stocks share	5.0747	3.9733		
	(0.1636)	(0.1707)		
Private equity share	10.0458	10.0421		
	(0.0479)	(0.0479)		
Housing share	7.2073	7.2209		
	(0.0185)	(0.0185)		
Leverage: Student debt	-0.1855	-0.1834		
	(0.0104)	(0.0104)		
Leverage: Long-term debt	-4.7269	-4.7250		
	(0.0119)	(0.0119)		
Leverage: Consumer debt	-6.4140	-6.4130		
	(0.0314)	(0.0314)		
β of stock market portfolio		0.0617	0.0592	0.3191
		(0.0182)	(0.0180)	(0.0338)
Observations	30,555,863	30,555,863	30,555,863	30,555,863
Adjusted R^2	0.334	0.334	0.358	0.535

Notes: The table shows regression estimates of individual returns to net worth (equation (4)). Columns 1-3 are OLS regressions without individual fixed effects; column 4 includes individual fixed effects. All regressions include a full set of dummies for wealth percentiles computed on one-year lagged wealth, year dummies, age dummies, location dummies and the interaction between location and year dummies. Specifications in columns 3 and 4 include interactions between time effects and the portfolio shares. Standard errors (in parentheses) are clustered by individual.

Table 6. Fixed effects statistics

	Panel A: Distribution statistics								
	Mean	SD	Sk.	Kur.	P10	P25	P50	P75	P90
Return to financial wealth									
Whole sample	0.00	3.59	3.66	24.78	-2.48	-1.68	-0.69	0.48	2.64
No business owners	-0.73	1.63	1.05	11.67	-2.46	-1.75	-0.88	0.06	1.06
Ever in the top 10%	2.47	5.68	2.31	10.14	-1.56	-0.46	0.70	3.13	9.59
College graduate or more	0.23	3.75	3.53	23.20	-2.30	-1.50	-0.53	0.67	3.13
Ever owned risky assets	0.46	4.14	3.14	18.78	-2.40	-1.49	-0.44	0.93	3.96
Return to net worth									
Whole sample	0.00	5.36	-6.31	101.59	-2.25	-1.07	0.13	1.54	3.29
No business owners	-0.30	5.63	-6.51	99.90	-2.37	-1.18	-0.01	1.31	2.87
Ever in the top 10%	1.37	2.87	-0.38	39.83	-0.96	-0.06	0.98	2.26	4.15
College graduate or more	0.24	4.83	-5.88	100.06	-2.16	-1.01	0.22	1.70	3.64
Ever owned risky assets	0.20	4.61	-6.49	111.23	-2.12	-0.98	0.20	1.60	3.36
After-tax return to net worth									
Whole sample	0.00	3.63	-4.79	87.47	-1.74	-0.88	0.03	1.09	2.38
No business owners	-0.20	3.80	-5.06	88.17	-1.82	-0.96	-0.07	0.92	2.10
Ever in the top 10%	0.77	2.10	0.56	27.44	-0.98	-0.26	0.52	1.43	2.75
College graduate or more	0.19	3.30	-4.12	75.47	-1.66	-0.82	0.11	1.21	2.65
Ever owned risky assets	0.13	3.12	-4.91	92.21	-1.63	-0.81	0.09	1.13	2.43

	Panel B: Additional statistics		
	Financial wealth	Net worth	After-tax net worth
$Corr(E(f_{i(g)}), P_{2004})$	0.776	0.852	0.742
$Corr(SD(f_{i(g)}), P_{2004})$	0.866	-0.795	-0.788
OLS coeff. $f_{i(g)}$ on P_{2004} (s.e.)	0.040 (0.000)	0.027 (0.000)	0.012 (0.000)
$Corr(f_{i(g)}, f_{i(g-1)})$	0.142	0.058	0.064

	Panel C: Variance decomposition		
	Financial wealth	Net worth	After-tax net worth
$Var(f_{i(g)})/Var(u_{i(g)t})$	0.29	0.28	0.26
$Var(e_{i(g)t})/Var(u_{i(g)t})$	0.71	0.72	0.74

Notes: Panel A of the table reports statistics for the distribution of fixed effects estimated from the regressions of returns in column 4 of Tables 4 (financial wealth), 5 (net worth), and OA.3 (net worth after tax). Panel B reports correlations of the fixed effects and their standard deviation with percentiles of the appropriate wealth distribution in 2004, the slope coefficient of a regression of fixed effects on wealth percentile (with its standard error) and intergenerational correlations in return fixed effects. Panel C reports variance decomposition measures.

Table 7. Explaining the Sharpe ratio

	Whole sample	No P.E. owners
Age	-0.0361	-0.0434
	(0.0003)	(0.0003)
Age^2	0.0004	0.0005
	(0.0000)	(0.0000)
Year of schooling	0.0403	0.0391
	(0.0008)	(0.0009)
Year of schooling^2	-0.0009	-0.0007
	(0.0000)	(0.0000)
Economics/Business degree	0.0401	0.0543
	(0.0013)	(0.0016)
Number of years owning priv. bus.	0.0314	
	(0.0001)	
Wealth percentile in 2004	0.0052	0.0059
	(0.0000)	(0.0000)
N	1,663,694	1,247,940
Adj. R^2	0.125	0.0869

Notes: The table shows regressions of the individual Sharpe ratio (computed using data for 2005-15) on the wealth percentile in 2004 and a set of observables. Robust standard errors in parentheses. The sample include only individuals with 12 years of data (2004-2015).

Table 8. Intergenerational return percentile regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Financial Wealth				*Net Worth*			
Father's wealth perc.	0.1082	0.0825	0.0806	0.0790	0.1546	0.1524	0.1523	0.1688
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Wealth controls	N	Y	Y	Y	N	Y	Y	Y
Year FE	N	N	Y	Y	N	N	Y	Y
Education controls	N	N	Y	N	N	N	Y	N
Demographics	N	N	Y	Y	N	N	Y	Y
Individual FE	N	N	N	Y	N	N	N	Y
Observations	11,373,294							
Adjusted R^2	0.013	0.069	0.074	0.265	0.025	0.084	0.101	0.249

Notes: The table shows regressions of the child's return percentile on the father's return percentile. Columns 1-5 have no controls. Column 2-6 add fathers and children's wealth and year fixed effects; column 3-7 also add education and age; columns 4-8 also add individual fixed effects. Columns 1-4 are for the return to financial wealth; columns 5-8 are for the return to net worth. Standard errors (in parentheses) are clustered by child.