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Heterogeneity and Persistence in Returns to Wealth*

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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, individuals earn markedly different average returns on their net worth (a standard deviation of 22.1%) and on its components. 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 narrow asset classes. Third, returns are positively correlated with wealth: moving from the 10th to the 90th percentile of the net worth distribution increases the return by 18 percentage points (and 10 percentage points if looking at net-of-tax returns). Fourth, individual wealth returns exhibit substantial persistence over time. We argue that while this persistence partly arises from stable differences in risk exposure and assets scale, it also reflects heterogeneity in sophistication and financial information, as well as entrepreneurial talent. Finally, wealth returns are correlated across generations. We discuss the implications of these findings for several strands of the wealth inequality debate.

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

JEL codes: D31, D91, E21, E24, G11.

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1 Introduction

Over time and across countries, the wealth distribution appears to be extremely right skewed: 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 has more than doubled in the last three decades (Saez and Zucman, 2016). A mirror image of this evidence is that many individuals appear to accumulate too little wealth relative to basic predictions of a life-cycle model (Skinner, 2007).[1]

What produces the inequality in wealth observed in the data and in particular its extreme right skewness are the subject of intense research (see De Nardi and Fella, 2017 for a critical appraisal of the literature). A strand of literature started by Aiyagari (1994) has focused on the role played by idiosyncratic and uninsurable labor income risk (see Castaneda et al., 1998), or, more generally, heterogeneity in human capital (e.g., Castaneda et al., 2003), but with mixed success.[2] Other papers have instead looked at crowding out from social insurance programs and behavioral biases, especially to explain low wealth accumulation at the bottom of the distribution (Hubbard et al., 1995; Gale, 1998; Bernheim et al., 2001). A different route, followed by Krusell and Smith (1998), has been to complement Bewley-Aiyagari models of earnings heterogeneity with heterogeneity in discount rates, which has a certain appeal because of its intuitive realism.[3] However, discount rates are hard to observe and their heterogeneity is thus difficult to assess. Moreover, while individuals at the bottom of the wealth distribution may be plausibly characterized by high or even hyperbolic discount rates, a large majority of individuals at the top of the wealth distribution are entrepreneurs, a group that is more often associated with higher risk tolerance and idiosyncratic risk rather than with lower than average discount rates. Indeed, 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 endogenized by appealing to differences in entrepreneurs' ability (as in the seminal Lucas, 1978), it may arise from a variety

[1]In general, Gini coefficients for wealth are much higher than those for earnings. For example, in the US the Gini coefficients for wealth and earnings are 0.85 and 0.67, respectively (Kuhn and Rios-Rull, 2015).

[2]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; in the data the income of the top 0.25% percent is at most 34 times median income (Benhabib and Bisin, 2018).

[3]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).

of other sources.[4] Remaining agnostic about its causes, a recent wave of papers (Benhabib et al., 2011, Benhabib et al., 2018, 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. Persistently low or negative returns (e.g., induced by borrowing at high rates even when cheaper alternatives exist) can also help explaining "poverty traps" at the bottom of the wealth distribution. 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 in returns to human capital) within a generation. In addition, returns persist across generations and are independent of wealth. The authors 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 US data.[5] They show that one way to capture the latter is to allow for some "*scale 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 based on a more sophisticated process for the returns to wealth suffer from 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 to wealth can be measured. What needs to be documented is that returns to wealth have an idiosyncratic component; that this component persists over time; that it correlates with wealth; and that it shows some intergenerational persistence. Documenting these properties

[4] For example, from restricted access to the stock market as in Guvenen (2009). In the literature, differences in financial 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., 2018, Jappelli and Padula, 2017, Lusardi et al., 2017 and Deuflhard et al., 2018).

[5] Kaymak and Poschke (2016) study whether changes in tax and transfer policies are responsible for the changes over time in top wealth shares in the US, while Hubmer et al. (2018) account also for the role of returns to wealth.

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 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 under-reporting of wealth information are much less severe than in survey data, 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 is 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 the level and type of wealth. Most importantly, the data have a relatively 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 measure the realized return to a given asset scaling the flow of annual income generated by the asset by the value of the asset at the beginning of each period, adjusting for intra-year asset purchases and sales (Dietz, 1968). Both flows and stocks are available from the administrative tax records. For reasons discussed below, our baseline return measure does not include non-pecuniary benefits from owning an asset (an issue mostly relevant for safe assets, such as deposit accounts offering unpriced banking services). However, we show the sensitivity of our findings from imputing these services using national accounts methodologies, which amounts to imposing that safe assets have a common return for all investors. We discuss the pros and cons of implementing these adjustments.

To reflect all sources of heterogeneity in returns we focus our analysis on the broadest notion of wealth – net worth, as typically done in the wealth inequality literature (Saez and Zucman, 2016; Castaneda et al., 2003). We find that returns exhibit substantial heterogeneity. For example, during our sample period (2005-15), the (value-weighted) average real return on net worth is 3.8%, but it varies considerably across individuals (standard deviation 8.6%). We also find that the return is positively correlated with wealth. For individuals with negative net worth, the cost of debt and the high leverage values produce negative returns on average. For those with positive net worth, the average return rises monotonically with the position in the net worth distribution and it accelerates at the very top. The difference between the average return at the 90th and 10th percentiles of net worth is substantial (about 18 percentage points); for after-tax returns, it declines to 10 percentage points (reflecting tax progressivity on wealth and capital income), but it remains substantial.

To gain insight into the sources of returns heterogeneity and given the importance that the distinction between liquid and illiquid assets has both in the finance and macroeconomics literature (see Kaplan and Violante, 2014), we also consider returns to the components of net worth: financial wealth, non-financial wealth (housing and private business), and debt. As in the case of the return to net worth, the returns of these components also exhibit a large amount of heterogeneity and positive correlation with the relevant wealth concept (negative correlation in the case of debt), as do most of their sub-components.

In any given year, heterogeneity in returns to wealth may arise from differences in time-varying observable characteristics (e.g., risk exposure or wealth), idiosyncratic transitory variations (good or bad luck), or from a persistent component (attributable to both observable factors, such as education, as well as unobserved ones, such as ability, access to information, or risk tolerance). The persistent component is the critical one in the new literature on wealth inequality. To separate these various components, we estimate a panel data statistical model for the return to wealth that includes an individual fixed effect. To account for heterogeneity explained by time-varying observable factors, we control for lagged wealth ("scale"), the share of wealth held in various types of assets as well as the covariance of their returns with market risk, or β's ("risk exposure"), along with time effects and demographics. The individual fixed effect measures the component of return heterogeneity that persists over time due to either observable or unobservable persistent factors. We find that observable characteristics alone explain roughly 1/3 of the variability in returns to net worth. Adding individual fixed effects - and thus capturing *all* sources of persistent heterogeneity - increases explained variability in returns substantially, to 1/2. The distribution of these fixed effects is itself quite dispersed, with a standard deviation of about 5 percentage points. The degree of dispersion of fixed effects varies across components of net worth: it is very large for returns to private business wealth, intermediate for housing and more contained for debt and financial wealth, where variation in returns is dominated by common components. While risk tolerance may be only imperfectly captured by the shares invested in risky assets and the various β's in the individual portfolio (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, the ability to overcome inertia, 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 when controlling for wealth (or education).

A few recent papers study heterogeneity in returns to wealth in relation to the inequality debate, but they are all restricted to a specific assets type (Fagereng et al., 2016 to financial wealth, Deuflhard et al., 2018 to bank deposits, and Campbell et al., 2019 to portfolios of single stocks). In contrast, we provide systematic evidence on individual returns to a comprehensive measure of wealth (as well as its components), and characterize return properties using population data. Bach et al. (2018) perform an exercise similar to ours. Like us, they use comprehensive measures of wealth and population data. But our paper differs from theirs in several respects. First, their main focus is on expected returns, which they compute using standard asset pricing models; since we want to understand what explains growth in wealth, we focus instead on actual, realized returns to wealth. Second, their main goal is to explain the nature of the correlation between average expected returns and wealth, which they argue reflects by and large compensation for risk. Like Bach et al. (2018), we find that differences in risk exposure are important determinants of persistent return heterogeneity. But we also find that risk compensation is not enough to fully account for it. Returns differ systematically by education, they differ systematically even when monetary returns carry no risk, and fixed effects contribute relatively more to explain variation in returns of asset types where ability is expected to play a greater role, i.e., in returns to private equity. Third, while Bach et al. (2018) confine their analysis to investors with positive net worth, we are interested in characterizing the extent and properties of persistent heterogeneity over the whole range of the net worth distribution. This is important for understanding wealth mobility, as some people with negative net worth are (as we document) entrepreneurs with higher-than-average returns on assets.[6] Fourth, we use our longitudinal data set to identify the persistent components of returns and compute second and higher order moments of this distribution. Second moments are emphasized in the theoretical literature on wealth concentration; higher order moments should be of value for calibrated studies of wealth inequality that hinge on return heterogeneity. Bach et al. (2018) mostly focus on average returns. Finally, we 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.[7] Notwithstanding these differences, our paper and Bach et al. (2018) both suggest that persistent heterogeneity, together with scale dependence, are empirically validated key factors to explain high wealth concentration at the top.

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 by discussing several implications of our findings. Due to space limitations, we place additional material in the 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.

[6] We estimate that entrepreneurs in the bottom decile of the net worth distribution in 2004 earn, during the 2005-15 period, cumulative returns on their gross wealth that exhibit two notable features: (a) they are on average much higher than those of non-entrepreneurs, and (b) they are characterized by a much longer right tail. Moreover, while the probability to move from the bottom to the top decile over the same 11-year period is 7% for non-entrepreneurs, it is 21% for private business owners.

[7] In a companion paper (Fagereng et al., 2019), we also study how persistence in wealth across households can arise from assortative mating in wealth *and* returns to wealth.

For each year, it provides relevant demographic information (gender, age, marital status, 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 deposit/lending 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.[8] 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, SCF) and confidentiality considerations lead to censorship of asset holdings.[9] Third, the Norwegian data have a long panel dimension, which is crucial to obtain

[8]Secular estimates from Alstadsæter et al. (2018), Table A.10, show that in Norway wealth is highly concentrated and has followed a U-shape pattern similar to the one documented by Saez and Zucman (2016) for the US.

[9]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. (2018) 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

reliable estimates of persistent heterogeneity in returns. Because the data cover the whole relevant population, they are free from attrition, except the (unavoidable) ones 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 shortcomings: (a) assets and liabilities are valued at an annual frequency - a feature that may affect measured returns; (b) some sources of wealth (most notably private business) may not coincide with their underlying market value; and (c) data on private pension wealth and other (more minor) wealth components are absent. Below we elaborate on these issues. In Section 2.3 we show how we deal with the first problem; in Section 2.3.1 we propose solutions for the other two. 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.[10] 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. We do not use data before 2004 as some of the key data sources for the computation of returns (such as the shareholder registry) are only available since 2004. In most of the analyses below we use wealth data for 2004 as initial condition and the period 2005-2015 as

with wealth but is never larger than 12% (Zucman, 2015), suggesting that many wealthy may have no wealth offshore. Alstadsæter et al. (2018) show that accounting for hidden wealth can increase the top 0.1% wealth share by roughly 1 percentage point on average.

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

our baseline sample period. The collection of tax information is mostly done through third parties. 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, etc.) do the same for the value of the assets owned by the individual as well as for the income earned on these assets. The fact that financial institutions supply information about their customer's financial assets directly to the tax authority greatly reduces distortions in asset value reporting.

We impose some minor sample selection designed to reduce errors in the computation of returns. First, 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 ensure that the financial decision maker is the holder of the assets and, thus, that we correctly identify his/her return fixed effect. Second, we drop individuals with financial wealth below USD 500 (about NOK 3,000), or individuals with non-zero private business wealth holdings of less than USD 500. These are typically observations with highly volatile beginning- and end-of-period reported wealth stocks that tend to introduce large errors in computed returns. This sample selection drops about 7% of the sample. Finally, 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.

2.2 Wealth aggregates

Our administrative data contain information on the ownership of several asset classes and on total debt.[11] We consider several concepts of wealth. The first is *financial wealth* w_{it}^f, the sum of safe (w_{it}^s) and risky (w_{it}^m) financial assets:

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

The second is *non-financial* (or *real*) *wealth* w_{it}^r, the sum of housing (w_{it}^h) and private business wealth (w_{it}^u):

$$w_{it}^r = w_{it}^h + w_{it}^u$$

[11]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 we show how the composition of net worth changes when we include these additional components (see Figure OA.1).

Finally, *net worth* is *gross wealth* w_{it}^g (the sum of financial and real wealth) net of outstanding debt (b_{it}):

$$w_{it} = w_{it}^g - b_{it}$$

Our data allow us to construct detailed measures of these aggregates and of various sub-aggregates as well. For example, safe financial assets can be decomposed into: (a) cash/bank deposits (in domestic or foreign accounts), (b) money market funds, bond mutual funds, and bonds (government and corporate), and (c) outstanding claims and receivables.[12] Risky financial assets can be decomposed into: (a) the market value of listed stocks held directly, (b) the market value of listed stocks held indirectly through mutual funds, and (c) the value of other (non-deposit) financial assets held abroad. All the components of financial wealth, as well as the value of liabilities, are measured at market value.

For components of non-financial wealth, there are potential discrepancies between market value and the value we use. In particular, private business wealth is obtained as the product of the equity share held in the firm (available from the shareholder registry) and the fiscally-relevant "assessed value" of the firm. The latter is the value reported by the private business to the tax authority to comply with the wealth tax requirements. Every year, private business owners are required by law to fill in a special tax form, detailing the balance sheet of the firm's asset and liability components, most of which are required to be evaluated at market value.[13] The assessed value is the net worth of the firm computed from this form and in principle it corresponds to the "market value" of the company, i.e., what the company would realize if it were to be sold in the market. There are, however, some components of the firm's net worth that are missing, such as the value of intangible capital and residual goodwill. In general, the

[12]Outstanding claims and receivables are described by the Norwegian tax authority as: "*loans to friends and family, salary and maintenance payments you are owed and/or advances you have paid for a service you had not yet received as of 31 December.*" They also include secured receivables such as mortgage bonds, debt certificates, etc. which must be valued at their market value. For private business owners, outstanding claims represent loans as well as services rendered to their own company.

[13]For example, businesses are required to report: *"Næringseiendom hvor verdi er fastsatt til markedsverdi"* (which translates to "Commercial property where value is determined at market value"). The reported market value comes from another form (RF-1098), which is effectively a calculator determining the potential sale value of the property based on location (430 municipalities), typology (industrial, workshop, warehouse, etc.), and square footage. This leaves little room for manipulation. The balance sheet reported in this form thus differs from the accounting-based balance sheet of the firm (where some assets are valued at historical cost), although in many cases there is extensive overlap between the two. Indeed, the correlation between the (log) tax-assessed value and the (log) book value is 0.88 (see OA, Figure OA.2). In more than 50% of the cases, the assessed value exceeds the book value.

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. Since private business wealth is an important component of wealth, especially at the top of the distribution, in Section 2.3.1 we discuss alternative measurements of its value.

The stock of housing 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 housing wealth for each year between 2004 and 2015. This measure may differ from its market value because of idiosyncratic components, such as the value of renovations (which we do not observe).

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). Note that to measure the return to net worth we only need a measure of *total* household debt. However, for some of the exercises described below, it is useful to separate the three types of debt. To do so, 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 loan account) information on the lender ID, loan balances, and interest 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 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).

Table 1A shows the composition of net worth, categorizing assets into four broad categories (safe financial assets, risky financial assets, housing, and private equity) and liabilities into three categories (consumer debt, student debt, and long-term debt).[14] 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

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

distribution (see OA, Figure OA.3 for the entire percentile-by-percentile distribution). The bottom 20% of the distribution has negative net worth due to debt exceeding assets. An analysis of this group reveals some interesting heterogeneity. People at the very bottom of the distribution are highly levered, mostly borrowing long-term, with borrowing backed by a large share of housing in their assets; they have also an asset share in private businesses comparable to that of people between the median and the 90-th percentile of the distribution. People in the second decile (those with mildly negative or close to zero net worth), have mostly safe assets. Furthermore, their total assets are much lower (170% less, see last column) than those of individuals at the very bottom of the distribution. We discuss this heterogeneity in greater detail in Section 3.2.2. As we cross into positive net worth territory, housing becomes the largest asset in most people's portfolio. At the very top of the distribution of net worth housing loses its preponderant role, replaced by wealth owned in private businesses. To gain further insight on the individual portfolio, Table 1B shows the composition of financial assets: the share of financial wealth held in safe instruments (divided into deposits, bonds and outstanding claims), and the share held in risky components (divided into foreign assets, mutual fund holdings, and directly held listed stocks) for people in selected fractiles of the financial wealth distribution (see OA, Figure OA.4 for the entire percentile-by-percentile distribution). Safe assets clearly dominate the financial portfolio of most people. Public equity (especially through mutual funds) gains weight among people above the median. In the top fractiles the dominant financial wealth components are deposits, outstanding claims and receivables, and assets held abroad.

2.3 Measuring returns to wealth

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

$$r_{it}^{n} = \frac{y_{it}^{f} + y_{it}^{r} - y_{it}^{b}}{w_{it}^{g} + F_{it}^{g}/2} \tag{1}$$

The numerator is the sum of income from financial assets, y_{it}^{f}, and from real assets, y_{it}^{r}, minus the cost of debt, y_{it}^{b}, all measured as flows accrued in year t. The denominator follows Dietz (1968), and is defined as the sum of beginning-of-period stock of gross wealth and net flows of gross wealth during the year (assuming they occur on average in mid-year). The second term on the denominator accounts for the fact that asset yields are generated not only by beginning-of-period wealth but also by additions/subtractions of assets during the year. Without this adjustment estimates of returns would be biased. The bias is most obvious in the case in which beginning-of-period wealth is "small" but capital income is "large" due to positive net asset flows occurring during the period. Ignoring the adjustment would clearly overstate the return. The opposite problem occurs when assets are sold during the period. We explain in the OA (Section OA.2) how to use information on asset stocks at the beginning and end of period, together with information on the income that is capitalized into wealth, to obtain an estimate of F_{it}^g.

In equation (1) we express the dollar yield on net worth as a share of *gross* wealth (or total assets). This way the sign of the return depends only on the sign of the yield (and not on that of net worth), thus avoiding assigning positive returns to individuals with negative net worth and debt cost exceeding asset income, or infinite returns to people with zero net worth. In the accounting literature (1) is known as return on assets (ROA): it measures how much net income an investor is capable of generating out of $1 worth of assets. In addition to this comprehensive measure of return to wealth, below we also provide a decomposition of the return to net worth into its main elements: the return to financial wealth, the return to housing, the return to private equity, and the cost of debt (r_{it}^f, r_{it}^h, r_{it}^u, and r_{it}^b, respectively), so that the interested reader can verify how the importance of these components vary in different parts of the net worth distribution. We define the returns on these components using analogs of equation (1), i.e., we divide yields accrued on each asset in period t by the sum of beginning-of-period assets and average net flows on that particular component during the period (see OA, Section OA.2 for details).

The yield from financial wealth is the sum of income earned on all safe assets (interest income on domestic and foreign bank deposits, bond yields and outstanding claims),[15] yields from mutual funds, from directly held listed shares (the sum of dividends, available from the Shareholder Registry, and accrued capital gains and losses), and from risky assets held abroad. 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 $g_{it}^h = \Delta w_{it}^h$. The income from private businesses is the sum of distributed dividends, available from the Shareholder Registry, and the individual share of the private business' retained profits, which we interpret as a measure of the capital gains on the value of the private business.[16] Lastly,

[15] Since households rarely report receiving interest payments on outstanding claims and receivables, we impute the return using the rate charged by banks on corporate loans.

[16] In the absence of information on private firms' market prices and assuming corporate tax neutrality (which is the case during our sample period, Alstadsæter and Fjærli, 2009), retained profits can be interpreted as an estimate of the private business' capital gains or losses. Equilibrium in capital markets implies (King,

the cost of debt y^b_{it} is the sum of interests paid on all outstanding loans.

All return measures are net of inflation (using the 2011 CPI) and 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 remaining limitations We now discuss how we address the other two shortcoming of our data mentioned in Section 2. First, the tax value of private businesses may differ from their market value. Second, there are some components of wealth that we do not observe.

Consider the first problem. Our measure of the returns to wealth is 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. For robustness, we consider alternative measures of the return to private business wealth based on market/book multipliers, following Bach et al. (2018).

Regarding the second potential limitation - some components of wealth are unobserved in our data - an important one, especially for people in the bottom half of the distribution, is private pension wealth. In the OA (Section OA.4) we discuss how we can use social security earnings data and employer information to obtain an estimate of the wealth from defined contribution occupational pensions that is consistent with national accounts. We then estimate an "extended" measure of return to wealth that accounts for this additional source of household wealth. The second component of wealth that is missed is assets held abroad 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., 2018), imputing a return is difficult since there is no information on the portfolio composition of the wealth that is hidden abroad.[17]

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: $\Delta V = \pi^r$. 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]Alstadsæter et al. (2018) 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)

Finally, we exclude from our analysis of returns a variety of assets for which computing returns is challenging. Some of these components (such as 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).[18]

2.4 Some conceptual remarks

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

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 half of household wealth and capital income to each spouse, and then compute the return to individual wealth. Standard errors of our estimates are clustered at the appropriate level (household or individual) throughout.

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 the returns of that particular stock (independently of how long the asset has been held in one's portfolio). This is the method used by Bach et al. (2018). 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

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.

[18] 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 (mid 2019) market value of the fund is 9,500 billion NOK ($1,045 billion). At its face value, this would correspond to 1.7 million NOK per person ($190k). 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 an amount up to a fixed share of the fund (around 3%, to reflect a long term real return of the fund) 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.

of realized individual returns. However, the method has its drawbacks. First, the higher precision comes at the cost of imposing a pricing model, typically the CAPM and its (not undisputed) underlying assumptions (e.g., ability to borrow at a risk free rate, absence of trading frictions, etc.). Second, 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). Housing may offer "pride of ownership", a non-pecuniary benefit. 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 services provided by the account). 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 that 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.

In the case of bank deposits there could be room for arguing that the services customers obtain on the deposits (i.e., access to ATM facilities, check-writing, etc.) are implicitly paid for with lower interest rates, implying that there is a component of the return that is hidden. To account for this, below we also show results where returns on deposits are adjusted to reflect the value of these services. Following national accounts practice, we assume that for each dollar deposited the value of unpriced banking services equals the differences between the "reference" rate (the rate at which banks borrow, which we take to be the Norwegian interbank offered rate or NIBOR) and the rate on deposits. With this adjustment, returns on deposits become identical for all depositors. Hence, the resulting measure of return to wealth offers a conservative estimate of heterogeneity - in fact, it completely eliminates any heterogeneity coming from deposits. While we perform this exercise as a robustness check, we stress that the assumption that low monetary rates on deposits reflect compensation for unpriced bank services is questionable for at least three reasons.[19] First, from a conceptual point of view it is not clear what is specific of bank services to be priced with a "barter exchange" (see Wang, 2003 for a discussion); furthermore, it is not obvious that the reference rate is the same for all banks or all consumers (given differences in the rates at which the former borrow on the interbank market and the fact that the latter have different outside options for their cash). Second, the services that are more directly linked to the deposit accounts are transaction services (as the liquidity discount of bank deposits is already reflected in the interest rate). Direct evidence we collected for this purpose shows that Norwegian banks price such transaction services explicitly, one by one.[20] If these services are already explicitly priced, the national account correction may introduce severe measurement error. Indeed, since for some individuals we measure deposit returns above the reference rate, the national accounts methodology implies that they would receive *negative* banking services. Third, if banks enjoy some monopoly power, lower rates on deposits relative to banks' borrowing rates do not reflect more services but just appropriation of consumer surplus by the bank. A large literature documents relevant mobility costs of bank customers and thus banks' monopoly power (see Ater and Landsman, 2013, and Bhutta et al., 2018). This is consistent with the fact that banks use teaser rates to attract depositors and once the latter have been captured, they lower the rates paid. As we will show, our regressions on bank deposits discussed in Section 5 lend support to this story.

[19]In the OA, Section OA.5, we discuss these issues in more detail.

[20]See for example https://www.finansportalen.no/bank/dagligbank/ for an overall view of contractual conditions at all Norwegian banks, and https://www.dnb.no/en/personal/prices/account-cards-internet-banking.html for a specific look at DNB ("Den norske Bank"), the largest bank in Norway by market share.

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. Almost 80% of the individuals in the sample have at least a high school degree, while 12% 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, amount of capital income received, and asset participation. We convert original NOK figures into constant 2011 USD. Panel B shows that total assets are about $400,000 on average. As expected, the distribution is extremely skewed, with a median of about $294,000, while the 90th percentile is $756,000. 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 $275,000. Panel C reports information on dollar yields from assets and the cost of debt. On average, individuals obtained an annual income flow of about $1,120 from safe assets, $320 from risky financial assets, $4,500 from private businesses, and $18,000 from housing (though median values are much smaller). 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 types of assets, and the unconditional and conditional (on ownership) shares of wealth invested. Almost half of all individuals have risky financial assets or private business wealth in their portfolio. Conditioning on having some listed shares, individuals invest on average 5% of their total wealth in those financial instruments. About 13% own shares in a private business. There is less diversification among private business owners. Conditioning on having private business wealth, 17% of gross wealth is held in the private business itself. Moving to other 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 upward by people with large debt amounts backed up against few to no assets (leverage ratios decline if we consider an extended measure of net worth that includes the value of cars, vehicles, cabins, and foreign real estate, see Panel B of Figure OA.1). Compared to the US, Norway is characterized by less financial wealth held in equity (mostly due to a smaller defined-contribution private pension sector), and a more dominant role for housing in net worth (partly reflecting institutional features, as well as differences in the tax treatment of housing and debt).

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 helps shedding light on these stylized facts.

3.1 Returns to wealth are heterogeneous

Table 3 reports summary statistics for the returns to net worth and for the most relevant sub-components of it, pooling data for the 2005-15 period. All returns are in real terms and value-weighted to ensure they aggregate to an economy-wide return. We also report unweighted net worth returns; in the rest of the paper, unless otherwise noted, we conduct the analyses using unweighted returns. The average, before-tax real return on net worth is 3.8% and it exhibits substantial heterogeneity (a standard deviation of 8.6%; see OA, Figure OA.5 for the time series of the standard deviation). Unweighted returns are even more heterogeneous (a standard deviation of 22.1%). The after-tax return (defined below, equation (5)) is slightly lower (3.7%) and smoother (a standard deviation of 7.8%). Next, we turn to the components of net worth. Our sample period was, of course, characterized by the financial crisis and large swings in average stock market returns.[21] During this period, the value-weighted average real return on financial wealth was 1.1%, reflecting the dominant weight of safe assets in financial wealth (82%). This notwithstanding, the extent of heterogeneity is non-negligible with a standard deviation of 6%. Looking at sub-components of financial wealth, the average return on risky financial asset (4.2%) exceed that on safe assets (0.8%), partly reflecting compensation for risk (the return to listed shares is roughly one order of magnitude more volatile than the return on safe assets, see OA, Figure OA.6).[22] The return to non-financial wealth during this period is higher (5.1%) with only a slightly larger standard deviation than the return to financial wealth (7.9%). However, this masks considerable heterogeneity between its two main sub-components. In particular, given the

[21] The return of the OSE (Oslo Stock Exchange) market was -52% in 2008 and -12% in 2011.

[22] In our sample of individuals the 2005-2015 average equity premium (the difference between the sample average real return on listed shares, which we estimate to be 6%, and the average real return on T-bills, which is 0.54%) is 5.44%, below the economy-wide equity premium for the same time period (11.2%). This reflects the fact that the household sector performs worse than the market, buying at the peak and selling at the bottom of market valuations in 2008-09.

large weight of housing in the portfolio of individual investors, the average return to non-financial wealth is mostly driven by the return on housing, which in this period was relatively high (4.9%) due to rapidly rising housing prices. The volatility is instead highly affected by that of private equity, whose average return (10.4%) reveals a much higher premium relatively to safe assets than listed stocks (as well as higher volatility, see OA, Figure OA.6), and a staggering amount of heterogeneity (standard deviation 52%). On the liabilities side, the net of inflation average interest rate on debt is 2.4%. This masks considerable differences 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 rate of 9.6%, standard deviation 10.9%), while student debt is cheap and much less heterogeneous (0.8%, standard deviation 2.6%); mortgages and long term debt fall in between (average real rate 2.3%, standard deviation 2.1%). All in all, heterogeneity in our most comprehensive measure of returns to wealth can be traced in the first place to heterogeneity in returns to private equity and the cost of debt and only partially to heterogeneity in returns to financial wealth. Returns to net worth exhibit also departures from normality, with very pronounced excess kurtosis (a coefficient of 48) and left skewness (-0.8), mostly imparted by the cost of debt.

While the extent of return heterogeneity from Table 3 is large, it is useful to develop a metric for how much return heterogeneity deviates from some theoretical benchmark. As a simple benchmark, let us focus on financial wealth and consider a standard Merton-Samuelson framework in which all investors have access to the same financial investment opportunities (Merton, 1969; Samuelson, 1969). In this model, the investor's optimal share of risky traded assets α_{it}^m is a function of the 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:

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

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

$$r_{it}^f = r_t^s + \alpha_{it}^m (r_t^m - r_t^s) \tag{3}$$

Heterogeneity in returns is induced by differences in risk aversion and thus in (compensated) risk-taking measured by the risky share.[23] Equation (3) suggests that conditioning on having

[23] 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.

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 α_{it}^m, 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). We pool all years, but identical evidence is obtained if we perform this exercise separately for each year (see OA, Figure OA.7). 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, the relationship turns concave at the top, a symptom of greater similarity in financial investment styles among the wealthy. Moreover, even at $\alpha_{it}^m = 0$ (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).

3.2 Returns covary with the level of wealth

The second stylized fact about returns to wealth is their strong positive correlation with the level of wealth (*scale dependence*). As noticed in the literature, scale dependence can potentially play an important role in driving wealth inequality.[24] The relevant question is whether scale dependence merely reflects risk-taking. For its clearer separation between safe and risky components, we start documenting scale dependence with respect to financial wealth. We then turn to net worth (and its components).

3.2.1 Financial 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 different parts of the wealth distribution are large. Moving from the 10th to the 90th percentile of the financial wealth distribution the average return increases by 160 basis points (from -0.44% to 1.15%); the median return increases by 185 basis points (from -1.03% to 0.82%).[25]

[24] As argued 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".

[25] 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 monotonically with wealth, and accelerates in the top decile (see

As explained in Section 2.4, our baseline measure of return only includes the pecuniary benefits from owning an asset. As an alternative, in Panel B of Figure 2 we plot the average return to financial wealth under two assumptions. First, to account for unpriced banking services, we impose that all deposit balances receive a common return, which we set equal to the NIBOR. Second, to produce a benchmark where *all* safe assets earn the same return, we also consider a case in which we impose both a common return on deposits and a common return on bonds, setting the latter equal to the return on the 3-month T-bill. The figure shows that scale dependence remains an important feature of the data, although the gradient is much reduced.[26] This is not surprising, of course, since the NIBOR and 3-month T-bill rates exceed the average rate on deposits and the latter carry a much larger weight at lower levels of wealth. Nevertheless, despite the fact that these adjustments eliminate by design *all* heterogeneity in the return to safe assets (even when there are genuine differences in returns induced by reasons other than compensation for unpriced banking services or non-pecuniary benefits from owning other safe assets), heterogeneity in the overall return to financial wealth (as measured by its standard deviation) is only moderately affected. Similarly, there are only small changes when looking at heterogeneity in returns to financial wealth by the share of risky assets in the financial portfolio (both exercises are reported in the OA, Figure OA.9). For reasons discussed in Section 2.4, in the rest of the paper (unless otherwise noted) we focus on our baseline measure of return to wealth, i.e. excluding non-pecuniary benefits from asset ownership.

The correlation between returns and wealth that is apparent from Figure 2 is not specific to a given year. Plots of average returns for individuals in different percentiles of the financial wealth distribution separately for each year between 2005 and 2015 confirm the broad evidence from the pooled sample (see OA, Figure OA.10). 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 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

OA, Figure OA.8).

[26] Results are qualitatively similar if we follow IMF (2014) (chapter A.3) and assign zero value to banking services when the national accounts methodology generates negative banking services.

Section 4, we discuss in detail various channels of influence.[27] One simple explanation is that wealthier households have higher exposure to risk. To check whether this is the *only* 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 Figure 3 we report average returns on safe assets and risky assets separately, and show that scale dependence is a pervasive phenomenon. In the OA, we show that there is strong evidence of scale dependence even within much narrower safe asset categories (deposits and other safe assets)[28] and risky asset categories (foreign assets, mutual funds, and direct stockholding, see Figure OA.12), and even when we look at returns on safe and risky assets (direct stockholding) on a year-by-year basis (Figures OA.13 and OA.14). This evidence rules out that the correlation between returns and wealth only arises because wealth induces greater exposure to risky assets (e.g., due to fixed participation costs). The second exercise we consider is to compute a measure of return that adjusts for the volatility of the individual portfolio (or "volatility-adjusted return" in short), and study its association with the position in the wealth distribution. To increase precision we use data for individuals that are present for the entire 2004-2015 period. The relationship between volatility-adjusted return and wealth rank is obtained by regressing the individual-specific average return for the 2005-15 time period ($\bar{r}_i^f = \frac{\sum_{t=2005}^{2015} r_{it}^f}{11}$) against the financial wealth percentile in 2004 *while* controlling for the volatility of individual returns over the same 2005-15 time period (measured by the individual standard deviation, $\sqrt{\frac{\sum_{t=2005}^{2015}(r_{it}^f)^2}{11} - (\bar{r}_i^f)^2}$). In Figure 4 we plot the estimated coefficients on the 2004 wealth percentile dummies. By conditioning the volatility-adjusted average return on financial wealth in 2004 (the year preceding the 11-year period over which the average return is calculated) we address concerns about reverse causality running from high returns to position in the wealth distribution. Figure 4 shows that the individual volatility-adjusted average return 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 reflecting compensation for risk-taking.

3.2.2 Net Worth In Panel A of Figure 5, we plot the average and median return to net worth for individuals in different percentiles of the net worth distribution, pooling again data

[27] One concern is whether the positive correlation between returns and wealth may be generated spuriously by failure to observe the exact timing of net saving flows. In the OA we show that, in expectation, this bias is absent.

[28] Scale dependence in safe asset returns arises in part from the fact that most checking accounts pay higher rates for larger amounts deposited, reflecting economies of scale in deposits management (see OA, Figure OA.11 for a specific case study).

for all years (2005-15). In Panel B we plot separately two regions of interest: below the 20th percentile (where net worth is negative and the return has a non-monotonic shape), and above the 20th percentile (where net worth is positive and the return grows with wealth, first at a decreasing rate then in a convex manner in the top two deciles). We also plot the return to gross wealth, i.e., the "positive part" of the return to net worth (1), or $r_{it}^g = \frac{y_{it}^f + y_{it}^r}{w_{it}^g + F_{it}^g/2}$. As is clear from the figure, 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 90-th percentile have an average return on net worth that is 18 percentage points higher.[29]

To get a better understanding of the patterns displayed in Figure 5, particularly the non-monotonicity at the bottom, rewrite the return to net worth as:

$$r_{it}^n = r_{it}^f \alpha_{it}^f + r_{it}^r (1 - \alpha_{it}^f) - r_{it}^b L_{it} \tag{4}$$

where r^j is the return to asset $j = \{f, r\}$ (financial wealth and non-financial wealth, respectively), r^b the cost of debt, α^f the share of financial wealth out of gross wealth, and L the overall leverage. Hence, the return to net worth depends on the composition and relative return of assets as well as the amount and cost of debt. These elements change quite substantially as we navigate through the different parts of the net worth distribution. In the left panel of Figure 6 we plot the share of financial wealth out of gross wealth and total leverage L_{it}. In the right panel we plot the returns to financial and non-financial wealth as well as the cost of debt. In both panels, variables are plotted against percentiles of the net worth distribution. Hence, Figure 6 contains all the components of equation (4). In the left panel we also report the fraction of entrepreneurs in each net worth percentile.

In the positive domain of net worth (the right panel of Figure 5B) the return grows monotonically. This is because in this region leverage is low and the cost of debt declining in the net worth position (making the influence of the second term in equation (4) negligible), while the return to financial wealth and the return to non-financial wealth both increase with wealth (as visible from the right panel of Figure 6). Interestingly, the relationship between returns and net wealth is initially concave and then turns convex roughly above the 80th percentile. This convexity is mostly driven by the return to non-financial wealth (and the return to private equity in particular). At the bottom 20% of the distribution, net worth is negative and its return has a non-monotonic pattern (left panel of Figure 5B). This

[29] 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 OA, Figure OA.15).

non-monotonicity is induced by changes in the composition of asset and debt types and by the very fast decline in leverage as we travel from the bottom 1% to the bottom 20%. As visible from the left panel of Figure 6, at the very bottom of the distribution individuals own a balanced mix of financial and non-financial assets and are extremely leveraged. Their debt is primarily composed of low-cost, 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). The entrepreneurs found at the bottom of the distribution are either individuals who were able to borrow large amounts to start new businesses, or unlucky ones whose companies have lost almost all their valuation.[30] Despite the relative low cost of their debt and the slightly better average return on their assets, the high leverage value makes the second term in (4) dominant and implies a large negative return to overall net worth (around -20% at the very bottom of the distribution). As one moves up towards less negative net worth, the return to net worth rises (i.e., it becomes less negative), mostly because leverage declines. However, at some point in this region debt becomes mostly uncollateralized consumer debt (featuring high rates - up to 7%, see the right panel of Figure 6), the non-financial wealth share declines, while liquid, low-return investments become the main financial asset in the individual portfolio (with a corresponding decline in average returns to financial wealth). This generates the non-monotonicity visible in Figure 5.[31]

[30]Figure 6 shows that there is a strikingly large fraction of entrepreneurs at the bottom of the net worth distribution (indeed, there are as many at the bottom 1% as at the top 10%). We verified that those at the bottom of the net worth distribution are mostly young entrepreneurs. The average age of entrepreneurs in the bottom two deciles is 39; in the top two deciles, it is 53. In Section 7 we show that entrepreneurs at the bottom of the distribution have higher and more positively skewed returns than non-entrepreneurs.

[31]In the OA, Figure OA.16, we dig deeper into the decomposition of equation (4). We present returns for sub-components of financial wealth (safe and risky assets) and non-financial wealth (housing and private equity), and for the cost of various types of debt (student, consumer, and long-term debt) against net worth percentiles. Returns to safe assets are U-shaped, with a minimum at zero net worth. This reflects compositional effects: People at the very bottom are extremely leveraged, but their safe assets attract higher returns, if anything because of a larger scale. People around the 20th percentile (zero net worth) are those with very limited assets (as visible from Figure OA.17), and mostly bank accounts with minimal remuneration. Evidence on scale dependence for the return to risky assets is similar to that in Figure 2, Panel B. The return to housing exhibits more modest scale dependence, and in fact returns are flat above the median. Finally, there is substantial scale dependence in the return to private equity (which also holds on a year-by-year basis, though with varying strength, see Figure OA.18). Panel B of Figure OA.16 focuses on the cost of debt. The figure on the left shows that the cost of consumer loans is high, while the cost of long term loans for homeowners (which mostly reflect mortgages) is moderate and exhibits less variation across the net worth distribution. The figure on the right shows the cost of student debt. The dip around the 20th percentile reflects the fact that low labor income individuals (which cluster around zero net worth, see Figure OA.17) and current registered students are exempt from interest payments. If we focus on individuals with income below $30,000 (approximately the threshold for the income exemption, a rough adjustment for the differences in relative cost of student debt) the dip is much reduced.

3.3 Robustness and Extensions

3.3.1 Before-tax vs. after-tax returns Thus far our measure of return was 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:

$$r_{it}^{n,at} = \frac{y_{it}^{f} + y_{it}^{r} - y_{it}^{b} - T^{y} - T^{w}}{w_{it}^{g} + F_{it}^{g}/2} \tag{5}$$

where T^y are taxes paid on capital income net of deductions on debt interest, and T^w are taxes on net worth.[32] Descriptive statistics on the after-tax return to net worth are in Table 3 (for both the value-weighted and unweighted version). In the top left panel of Figure 7 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 exceeds the before-tax return 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. Taxes also reduce the extent of scale dependence: A move from the 10th to the 90th percentile of the net worth distribution is associated with a 10 percentage point increase in the return.

3.3.2 Assuming constant returns on deposit accounts The top right panel of Figure 7 plots the average return to net worth for our baseline measure as well as a measure of average return to net worth under the assumption that safe assets receive a common return (similarly to what done in Section 3.2.1). The figure shows that the adjustment produces negligible differences in the relation between the return to net worth and the percentile of net worth, with the exception of some small differences in the bottom three deciles, where individuals gain from the common return assumption (since these individuals's wealth is mostly held in safe assets).

[32] 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).

3.3.3 Mismeasurement of private equity wealth A different concern is that the positive correlation between returns on wealth may spuriously arise from mismeasurement of private equity wealth. There could be 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 wealth distribution. To assess whether the results are driven by our measurement of private equity, we follow Bach et al. (2018) and compute an alternative measure of the return to private equity using market-to-book multipliers from all companies listed in the Oslo Stock Exchange. Comparing results from two different measures allows us to address the concern that our findings derive from incorrect measurement of this key wealth aggregate. We first estimate market-to-book multipliers using the geometric average of market-to-book values of all listed companies, separately by industry and year. The estimated multipliers have an average of 1.5 and a median of 1.4, consistent with an understatement of book values relative to market values. We then define the value of the private business $\tilde{V_{jt}}$ as the sum of financial assets and the adjusted value of non-financial assets minus debt. Assets and liabilities come from the balance sheets of the firm. Financial assets and debt are assumed to be reported at their market value. We adjust non-financial assets first by multiplying the value reported in the balance sheet by the estimated industry/year-specific market-to-book multiplier, and then applying a discount for liquidity (which we take to be 25% to be consistent with Bach et al. 2018). The estimated market price of the firm, p_{jt}, is the value so obtained ($\tilde{V_{jt}}$) divided by total shares outstanding. The return to private equity is finally defined as the sum of dividends per share paid and capital gains/losses (Δp_{jt}) divided by the firm's estimated market price.

The bottom left panel of Figure 7 shows that this alternative measure of return to private equity produces the same relation between the return to net worth and net worth percentiles as our baseline measure, except perhaps at the very top, where the return to net worth with the alternative measure is smaller. Hence, the qualitative message that there is substantial scale dependence in wealth returns remains intact.

3.3.4 Defined contribution pension wealth Finally, we discuss results obtained when we impute defined contribution pension wealth (with more details in the OA, Section OA.4). Defined contribution occupational pensions were made mandatory for all private sector employers in 2006. Employers can contribute a fraction of their employees' earnings, but no less than 2%. We assume that the average contribution rate is consistent with national accounts.

In a given year, we observe the total wage bill in the private sector from administrative social security records, Y_t. We also observe, from national accounts, the aggregate earned premiums collected by the DC funds, P_t. We assume that the average contribution rate is $c_t = P_t/Y_t$. In the data, the average contribution rate over our sample period (2006-15) is 2.5%, close to the minimum contribution rate. Finally, we use individual social security earnings records (y_{it}) to measure the annual amount contributed to the individual's fund as: $c_t y_{it}$.[33]

Since we do not observe investment choices in DC plans, we assume that individual contributions cumulate in the fund at a common rate, r_t^{DC}. We choose r_t^{DC} to be consistent with national accounts, i.e., we use aggregate data on pension liabilities (DC_t) and premiums earned (P_t) and define: $r_t^{DC} = \frac{DC_t}{DC_{t-1}+P_t} - 1$. The individual adjusted return to net worth (including DC pension wealth) is then:

$$r_{it}^{n,adj} = r_{it}^{n}(1 - \omega_{it}^{DC}) + r_t^{DC}\omega_{it}^{DC}$$

where $\omega_{it}^{DC} = \frac{DC_{it}}{w_{it}^{g}+DC_{it}}$ is the share of total assets in defined-contribution pension plans. The bottom right panel of Figure 7 plots the returns to net worth (the adjusted measure and the baseline measure) against the percentile of net worth (using data from 2006 onward given that no DC pension wealth is available before that date). As expected, the adjustment reduces inequality in returns (and wealth) by increasing the return at the bottom of the distribution (where pension wealth is a quantitatively important wealth component), but it has virtually no effect above median wealth.

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 idiosyncratic realizations that are quickly reversed, or whether individuals differ persistently in the returns they earn on their wealth due to both observable characteristics and unobserved factors. We investigate whether individual returns to wealth have a permanent component after controlling for risk exposure (as measured by the share of wealth invested in different type of assets and the covariance with market returns), scale (as measured by the position in the wealth distribution), and a rich set

[33] In doing so, we also account for the fact that contributions apply only to workers earning at least the minimum amount needed for social security contributions (an amount known as G, "Grunnbeløpet", adjusted over time with wage and price inflation - 1G equaled about \$10,000 in 2011), and that contributions are capped at a multiple of G ($12G$).

of demographics. Persistence in individual returns, as argued by Benhabib et al. (2011, 2018), is essential for heterogeneity to be able to explain the fat tail of the wealth distribution as well as, together with scale dependence, 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 the return to net worth:

$$r^n_{i(g)t} = X'_{i(g)t}\beta + u_{i(g)t} \tag{6}$$

where $r^n_{i(g)t}$ denotes the return to net worth for individual i of generation g in year t. $X_{i(g)t}$ is a vector of controls meant to capture predictable variation in returns due to observables. Equation (6) can be interpreted as a much richer empirical counterpart of equation (4).

We consider three 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 capture life cycle effects in returns induced for instance by learning from experience), years of education and study concentration in economics or business (to proxy for financial knowledge or sophistication, as in Jappelli and Padula, 2017 and Lusardi et al., 2017), gender, marital status, county dummies, 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 in a flexible non-parametric way scale effects due to fixed entry costs in risky assets that preclude participation by low wealth households. This is indeed consistent with an 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. (2018) 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 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. Finally, to better control for risk exposure beyond wealth shares, we also add the average β's for the individual stock portfolio, housing, and private equity (details about the construction of these variables are in the OA).

Our second specification refines even further the controls for risk exposure. In a world where individuals have identical access to a menu of instruments (including debt, private equity and housing) differing by risk, liquidity and other features, as in Quadrini (2000), Cagetti and De Nardi (2009; 2006) and Aoki and Nirei (2017), the return to net worth is: $r^n_{i(g)t} = r^s_t + \sum_j \alpha^j_{i(g)t}(r^j_t - r^s_t) - \sum_k r^k_t L^k_{it}$, where $\alpha^j_{i(g)t}$ denotes the share of gross wealth invested in asset j, r^j_t, r^s_t and r^k_t are the *common* return on asset component j, on a risk-free asset, and on cost of debt of type k, respectively, and L^k_{it} is the leverage of debt of type k. Accordingly, in our second specification of regression (6), we add the interaction of time dummies with the individual assets share $\alpha^j_{i(g)t}$, the β's, and the leverage of consumer, long-term, and student debt. If individuals have identical access to a menu of instruments, such controls would absorb all the existing variation in returns to net worth. Hence, this is a useful benchmark.

Our final specification adds individual fixed effects. In particular, we assume that the error term $u_{i(g)t}$ of (6) can be written as the sum of an individual fixed effect and an idiosyncratic component, which may possibly exhibit serial correlation:

$$u_{i(g)t} = f_{i(g)} + e_{i(g)t} \tag{7}$$

The fixed effects $f_{i(g)}$ 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 return-relevant persistent differences in the scale of assets owned. The error term $e_{i(g)t}$ measures non-systematic idiosyncratic variation in returns reflecting "good or bad luck". To evaluate how much the different controls (in particular individual fixed effects) contribute to explain heterogeneity in returns, we use as a metric the adjusted R^2 of the regressions. If the controls for risk exposure, scale and other observables absorb all the relevant persistent heterogeneity in returns, the third specification should signal no increase in the adjusted R^2 compared to the second. This provides a useful yardstick for evaluating the quantitative importance of persistent heterogeneity *not* arising from exposure to risk and scale.

Besides estimating model (6) for our baseline measure (the return to net worth), we also run similar regressions for the returns of the components of net worth, namely financial wealth, private equity, housing, and debt, to inform us about the sources of persistent heterogeneity in returns. We also show how the results vary when we experiment with alternative measures of net worth returns (accounting for taxes, unpriced banking services, alternative private equity wealth measurement, and private pension wealth).

4.2 Estimation results

4.2.1 Returns to net worth Table 4 shows the results of regression (6) when the dependent variable is our baseline measure of returns to net worth in year t (expressed 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, relative to gross wealth, in mutual funds, listed stocks, bonds, foreign assets, outstanding claims, unlisted stocks as well as the housing/gross wealth ratio and leverage for the three types of debt we can identify in the data. 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 the (conditional) average excess returns of that asset relative to cash and deposits. The main sample comprises close to 31 million observations.

Not surprisingly, especially in light of the differences in average returns reported in Table 3, having larger shares of wealth invested in a private business or housing display positive and large excess returns ("conditional" on covariates). In particular, the effect of the share invested in private businesses (carrying an average premium of 8.3 percentage points over deposits and cash) is larger than the effect of the share in directly held listed stocks (average premium of 6.5 percentage points), holding constant a rich set of observables. A larger private equity premium 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 194 basis points. Increasing the share in private businesses by the same amount is associated with a significantly larger increase in returns on wealth of 249 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 US data from the Survey of Consumer Finances, 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 premia on the other assets conform with intuition: mutual funds have a lower premium (4%) than directly held stocks. During this period, characterized by high stock market volatility, bonds performed only slightly worse than mutual funds and better than foreign assets (which are a mixture of safe and risky components). 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 79.2 basis points ($0.33 \times 7.2\% - 0.33 \times 4.8\%$). The specification in column (1) also includes the average β's of the individual listed stock portfolio, private equity wealth, and housing, which in principle represent richer controls for risk exposure not captured by the wealth shares. However, these variables have small (and, in the case of stocks, statistically insignificant) effects. In the case of housing, owning a property in more volatile markets provides homeowners with a slightly larger return, but the effect is moderate. Overall, the covariates in this specification explain about one-third of overall variation in returns (R^2 and adjusted R^2 are both 0.3).

Column (2) modifies the specification by replacing the portfolio shares and the average $\beta's$ 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 and liability type varies. The size and significance of the controls are unchanged and the fit of the model improves only slightly. This limited fit (or the larger role of unobservable heterogeneity) is remarkable because, as noted, canonical models 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 portfolio shares.

Before moving to the fixed effect regression, it is worth commenting on the effect of the demographics. The role of gender, though statistically significant, is economically negligible (men earn on average 5 basis point higher returns than women). In contrast, general education and specific education in economics or business induce non-negligible increase in returns. The estimates from column (2), for example, suggest that an additional year of formal schooling raises returns to net worth by 15 basis points (i.e., completing a college degree results in a 60 basis points higher average return compared to holding a high school diploma), while having an economics or business education is associated with 13 basis points higher returns.

Since education is a permanent characteristic, its effect cumulates over time. A systematic difference in returns of 73 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 about 25%, 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 remarkable effect comes 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), von Gaudecker (2015) and Deuflhard et al. (2018), who find a positive correlation between measures of financial literacy and the return to investments among French and Dutch investors, 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)-(2) suggest that part of the observable heterogeneity in returns to net worth 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. In Section 4.3.3 we discuss synthetic measures of scale dependence that may be useful summary statistics for economists dealing with calibration exercises.

The last column of Table 4 adds the individual fixed effects.[34] As usual, the effect of time-invariant characteristics (such as gender or education) is no longer identified and is absorbed by the fixed effects. Since the macro literature is interested in an evaluation of the overall persistent component (and not on its decomposition between observable and unobservable components), this is all that is needed. The key result is that the individual fixed effects, which are jointly statistically significant (p-value <0.0001), improve the fit substantially: compared to column (2), the adjusted R^2 of the regression increases from 0.33 to 0.5, a 50% increase, implying that returns have an important persistent individual

[34]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).

component. From (7), additional persistence in returns may in principle come from $e_{i(g)t}$. 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 (3), i.e. $E(\Delta u_{i(g)t}\Delta u_{i(g)t-s})$ for $s \geq 0$ (since taking first differences of the residuals removes the fixed effect, i.e., $\Delta u_{i(g)t} = \Delta e_{i(g)t}$). We find that these moments are minuscule and economically indistinguishable from zero for $s \geq 2$, consistent with $e_{i(g)t}$ being serially uncorrelated (see OA, Figure OA.19).

Extensions and robustness The results described for the before-tax measure carry over with few modifications if we use the net-of-tax return to net worth (see OA, Table OA.1). Interestingly, the effect of education on returns in the OLS specification is somewhat lower than on before-tax returns, mostly because taxes on capital increase with the stock of wealth, which is higher for high education individuals.[35] But the role of individual fixed effects is equally important: compared to the specification without fixed effects, the adjusted R^2 in the specification with fixed effects regression increases by 17 points (from 0.3 to 0.47), as much as in Table 4.

Table 5 compares results obtained with our baseline measure of net worth return against those obtained using a number of alternatives. For comparison, columns (1)-(2) of Table 5 reproduce estimates for the baseline measure (corresponding to the last two columns of Table 4). In columns (3)-(4) we impose that individuals earn a common return on deposit accounts, in keeping with the idea that heterogeneity in bank deposit interests reflects unpriced banking services (results are similar if we also impose a common return on bonds). In columns (5)-(6) we compute the return to net worth using the alternative measure of return to private equity based on market/book multipliers discussed in Section 3.3.3. Finally, in columns (7)-(8) we use a measure that includes an estimate of defined contribution private pension wealth, as described in Section 3.3.4. These alternative measures generate some small changes in the estimated effect of the observables, but remarkably little differences in the change in predictability of returns that can be attributed to persistent fixed heterogeneity. Fixed effects are in all cases jointly statistically significant with p-values <0.0001. These regressions with alternative measures of net worth returns hardly change the qualitative message that a significant amount of return heterogeneity can be explained by individual fixed effects.

[35]Using the after-tax measure of return to net worth, the excess return on private equity is lower than with the before-tax measure. This is because private equity owners are more directly affected by taxes on capital income and wealth. 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). See OA, Table OA.1.

4.2.2 Returns to the components of net worth To deepen our understanding of the sources of persistent heterogeneity in returns to wealth, we report regressions of returns on the components of net worth: return to financial wealth, private business wealth, housing, as well as for the cost of debt. By focusing on the single components we can study persistent heterogeneity in returns on a given asset *among* participants in that asset market. This is an important remark, since persistent heterogeneity in returns to net worth reflects also, as we have pointed out, systematic differences across individuals in intensity of participation to various asset markets as well as differences in average returns across assets. For each component we report two specifications of model (6): the first corresponds to column 2 of Table 4, i.e. a pooled OLS regression with all controls, including interactions between the time dummies and the shares invested in the assets included in the specific aggregate; the second specification adds the individual fixed effects. Results are shown in Table 6. Two interesting patterns emerge. First, the pooled OLS regressions reveal that years of education significantly predict returns to financial wealth and the cost of debt but have limited or no impact on private equity returns and housing. Returns are all positively correlated with having a degree in economics and finance, although the magnitude differs. The effect is larger for returns to private equity and debt and more contained for the return to financial wealth and housing. The pattern by field of education portrayed in Table 6 is intuitive. Education contributes most to asset returns for the wealth components - such as private businesses and debt or, as we will document in Section 5, bank deposits - that have an important idiosyncratic element. Consistent with this interpretation, education has a strong negative effect on the cost of debt: one extra year of schooling reduces the cost of debt by 9 basis point, while an economics/business degree is associated to a 14 basis points lower cost of debt - in other words, individuals with a university degree in economics or finance borrow on average at a full 1/2 percentage point lower rate relative to high school graduates.[36] Since interest rates on both mortgages and consumer loans differ substantially across intermediaries, this finding is consistent with the idea that more educated individuals are better informed about available borrowing opportunities and can choose cheaper debt, as documented by Campbell (2006) and Woodward and Hall (2010) among others (Section 5.2 shows evidence of this mechanism in the market for bank deposits).

The second finding from Table 6 is about the relative importance of fixed effects in explaining returns. The importance of persistent heterogeneity differs across assets with the pattern similar to the one just described with respect to the effect of education. Persistent

[36] Since we control for shares of total debt in consumer, student, and long-term loans, this effect is not a mechanical by-product of more educated individuals having a larger share of total liabilities in student loans.

individual heterogeneity in returns adds some, but not large explanatory power to the returns to financial wealth (since variation therein is largely explained by economy-wide movements in returns and observables). The adjusted R^2 of the OLS regression increases from 0.19 (unreported) to 0.74 when we add time effects interacted with financial portfolio shares (column (1) of Table 6). Individual heterogeneity is instead of great importance for explaining returns to private equity: the adjusted R^2 of the regression increases from 0.01 (column (3)) to 0.08 when adding the fixed effects (column (4)). Persistent individual heterogeneity also plays a remarkable role for fitting the variation in the cost of debt (the adjusted R^2 increases to 0.52 when adding the fixed effects from 0.19 in the pooled OLS specification that also controls for interactions between leverage in the three types of debt and time effects; columns (7) and (8)). In contrast, and predictably, fixed effects do not explain much of the variation in returns to housing, since these are imputed from characteristics (such as location, size and year) that are already controlled for, leaving little room for an individual unobserved component in the return. Indeed, this is the only case in which we fail to reject the null of jointly statistically insignificant fixed effects.

The evidence from the components of net worth implies that persistent heterogeneity in overall returns to wealth can be partly traced to enduring, systematic differences in individual returns on private equity and on interest on debt, and only slightly on returns on financial wealth. Part of the remaining persistent heterogeneity comes from enduring differences in intensity of participation in specific asset markets. In the next subsection we focus our attention on the properties of persistent heterogeneity in overall returns to net worth.

4.3 Persistent heterogeneity

4.3.1 Key distributional statistics Figure 8 plots the empirical distribution of the individual fixed effects in returns to net worth (from the estimates in column 3 of Table 4).[37] Table 7 reports some key statistics about the distribution of fixed effects. To maximize precision we use the fixed effects estimated for the balanced panel.

Panel A of Table 7 shows that the distribution of individual fixed effects on returns to net worth has a long left tail (Pearson's skewness coefficient -5.3) and considerable excess kurtosis (78.4). There is also large dispersion, as witnessed by a standard deviation of 6% and a 90th-10th percentile difference of 7.7 percentage points. These qualitative features remain unchanged if we look at net-of-tax returns to net worth, although they exhibit lower skewness,

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

kurtosis and cross sectional dispersion (a standard deviation of 4%, 1/3 smaller than for gross returns). The rest of Panel A, Table 7, reports statistics for the fixed effects computed for the returns on components of net worth: financial wealth, housing, private equity, and debt (these fixed effects come from the regressions in Table 6 and are also expressed in deviation from the mean). In the OA we show plots of the empirical distribution of the fixed effects of these various return measures (Figure OA.20). Among the components of net worth, there is moderate heterogeneity in the permanent component of returns to financial wealth (standard deviation of 1.3 percentage points and a 90th-10th percentile difference of 3.1 percentage points), intermediate for the cost of debt and the return to housing (standard deviations of 2% and 5.2%, respectively), and extremely large dispersion for private equity (where fixed effects have a standard deviation of 50.3%). There is large lepto-kurtosis and right skewness for return fixed effects to private equity and the cost of debt, implying that for some net worth components normality is a poor characterization of the distribution of persistent return heterogeneity.

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 B of Table 7 shows statistics for the fixed effects on the return to net worth (un-demeaned to appreciate differences) for selected group characteristics.[38] Figure 9 plots the empirical distribution of fixed effects in the return to net worth for some of these groups. In particular, we plot the distribution of the estimated fixed effects of net worth returns for individuals with and without risky assets (top left panel); business owners and non-owners (top right panel); top vs. bottom wealth groups (bottom left panel); and for people with parents who were in the top decile of their cohort's average net worth distribution in 2000-2004 (bottom right 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, private equity owners and those in the bottom wealth groups are defined using indicators for "never owning risky assets", "persistent business owner", and "never being in the top 10% of the distribution". In all cases, there is substantial heterogeneity in estimated fixed effects within each group - the distribution shifts on the left for groups with greater risk exposure and/or greater scale. Group mean differences are also economically significant (Panel B of Table 7). Persistent business owners exhibit a distribution of return fixed effects that is much more spread out and shifted to the right (an interquartile range of

[38] It is well know that under the assumption that $E(e_{i(g)t}|X_{i(g)t}, f_{i(g)}) = 0$ fixed effect estimates are unbiased. However, they are consistent only when $T \to \infty$. Mean fixed effects (including group mean differences, which we discuss here) are *always* consistent, even in short panels (see Wooldridge, 2010a, p. 308-309).

7.4 percentage points compared to 4 percentage points in the whole sample). 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 less spread out and returns are on average higher among the wealthy. The distribution of the fixed effects is shifted to the right for individuals with wealthy parents (a finding paving the way for the more formal analysis of Section 6). This is also true for 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).

One concern with the estimates of higher moments of fixed effects is a potential small-T bias. In the OA, Section OA.7, we shows how estimates of the standard deviation, skewness and kurtosis of the fixed effects can be corrected for this bias. Table OA.2 reports corrected and uncorrected estimates of the moments of interest. Overall, the bias appears moderate for the second moment and negligible for higher moments. For example, the standard deviation of the fixed effect for the return to before-tax net worth changes from 6.02 to 5.21 (a 13% decrease) once the correction is implemented. For after-tax return, the estimate of the standard deviation changes from 4.25 to 3.58. The bias is even smaller for skewness (3%) and kurtosis (1%).

4.3.2 Additional key statistics Table 8 presents additional key statistics for fixed effects in net worth returns (both before- and after-tax). In Panel A we use the results from Tables 4 and OA.1 to present a simple variance decomposition of the unobserved components of the returns. Our error term representation allows as to decompose unobserved idiosyncratic variation in returns to wealth as $var(u_{i(g)t}) = var(f_{i(g)}) + var(e_{i(g)t})$. As shown by Shourideh (2014), the relative importance of $var(f_{i(g)})$ and $var(e_{i(g)t})$ drives the optimal taxation of capital income, particularly its progressivity. Starting with before-tax returns, we find that $var(f_{i(g)})/var(u_{i(g)t}) = 0.26$. Hence, persistent differences in returns across individuals can account for approximately 1/4 of the variance of the unobserved component of the return to net worth. In Panel B of Table 8 we report statistics often discussed in the macro literature. The first is the association between fixed effects in returns to wealth and wealth itself. To obtain this parameter, we regress the estimated fixed effect on the net worth percentile in 2004 (a year belonging to a period of stable wealth inequality and that we do not use in estimation, minimizing the potential for spurious correlation). The estimate is positive and statistically significant. A shift from the 10th to the 90th percentile is associated with a roughly 3.5

percentage points higher individual's fixed effect. Finally, the table reports the correlation between the return fixed effect of parents and that of children, an important statistics in models such as that of Benhabib et al. (2018) that we discuss in Section 6. Statistics for the after-tax measure are similar, although the association between the fixed effect and the net worth percentile is lower than with the before-tax measure.

4.3.3 A parametric statistical characterization of scale dependence In model (6) the correlation between returns and wealth is captured through a variety of controls (directly by the dummies for the position in the wealth distribution, indirectly by controls for age and portfolio composition which tend to be correlated with wealth). To provide a summary statistic of scale dependence useful to calibrate macroeconomic models of wealth inequality that leverage on the properties of returns to wealth, we follow Gabaix et al. (2016) representation and estimate the model:

$$r^n_{i(g)t} = \theta P(w^n_{i(g)t}) + f_{i(g)} + f_t + \varepsilon_{i(g)t} \tag{8}$$

where $r^n_{i(g)t}$ is the return to net worth, $P(w^n_{i(g)t})$ the percentile of beginning-of-period net worth percentile (capturing scale), $f_{i(g)}$ is the individual fixed effect (capturing persistent heterogeneity), f_t are time fixed effects (capturing common movements in returns and wealth), and $\varepsilon_{i(g)t}$ is an error term. Scale dependence is measured by the parameter θ, while type dependence is captured by the individual fixed effect. Thus, the scale-dependence parameter θ is identified from individual-specific time variation in net worth. Since no other controls (besides the fixed effects) are included, this parameter measures all possible sources of scale dependence, direct and indirect.

Within-group estimates of θ can be biased if past shocks to return feed into current or future wealth. For this reason, we also report first-difference estimates:

$$\Delta r^n_{i(g)t} = \theta \Delta P(w^n_{i(g)t}) + \Delta f_{t(g)} + \Delta \varepsilon_{i(g)t}$$

and instrument $\Delta P(w^n_{i(g)t})$ with $\Delta P(w^n_{i(g)t-2})$. This is a valid instrument (Anderson and Hsiao, 1981) if shocks to return are not serially correlated (which, as discussed above, appears a reasonable assumption).

Estimates of θ are reported in Table 9, again separately for the before-tax and after-measure of the net worth return. There is virtually no difference between simple within-group and first difference IV estimates, suggesting that the bias mentioned above is negligible. The estimate of θ is sizable. A move from the 10th to the 90th percentile of net worth would increase average before-tax return to net worth by 11 percentage points. Notice that this is much less than the "unconditional" 18 percentage points increase visible from Figure 5, a clear indication that a non-negligible amount of scale dependence is attributable to persistent heterogeneity in returns, which, besides time effects is the only additional control in equation (8). For after-tax returns there is evidence of lower, but still sizable scale dependence: A move from the 10th to the 90th percentile of net worth would increase average after-tax return to net worth by 8 percentage points (again, this is less than the 10 percentage point unconditional increase mentioned above).

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, $\alpha_{it}^m = \frac{E(r_t^m - r_t^s)}{\gamma_i \sigma_t^2}$, 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). 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). These features affect the average return that individuals extract from their financial and non-financial investments and leverage choices *conditioning* on the risk exposure and the scale of their portfolio. 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 unobserved heterogeneity in the return to private equity may reflect differences across entrepreneurs in the ability to successfully manage their businesses.[39] This is consistent with the large increase in the adjusted R^2 of the regression of the return to private equity when in Table 6 (columns (3)-(4)) we include fixed effects.

[39] Fixed effects may also proxy for the advantages from being born and raised in an affluent family. For example, banks might provide more favorable mortgage rates to children of their long-term customers, especially if parents act as guarantors. Similarly, entrepreneurs raised in affluent families might have easier access to business loans or inherit their parents' network. This broader interpretation is consistent with the evidence on intergenerational correlation in returns to net worth (and its fixed effect component) we provide below, Section 6.

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 $\beta's$ of the stock market portfolio, private equity, and housing). 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 for risk exposure and level of wealth (as visible from Tables 4 and 6), 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 to 0.50 from 0.33 for the baseline specification). 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 a different perspective that persistent heterogeneity in returns to wealth is not merely a reflection of compensation for risk-taking and for differences in scale, we consider a case in which risk-taking should not matter and differences in scale can be directly controlled for: deposit accounts. In particular, we secured access to the universe of individual bank deposit accounts for the period 2005-16. 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 as well as end- and beginning-of-year deposit balances (i.e., using an analog of equation (1)).[40] Finally, we run regressions for 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 or banking services offered across banks), time dummies (absorbing common shocks), and the log of the deposit balances (to account for scale effects).

Table 10 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 (semi-

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

elasticity 0.37), consistent with a scale effect and decreasing in account "experience" (consistent with the presence of teasing rates followed by inertial behavior). These controls produce an adjusted R^2 of 0.52. When we add individual fixed effects the fit of the regression increases by about 1/6 (to 0.6). 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 account 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 percentage points. Returns on deposits also differ systematically across banks (standard deviation 0.9 percentage points): 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 10. 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 returns on deposits do so partly because they are able to spot high-return banks and deposit their liquidity there.[41]

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

[41] It is possible that, within each bank, higher interest rates are offered (conditioning on the scale of deposits) to clients who carry a large mortgage and can easily service it, or to clients that save large amounts in the investment products offered by the bank. In this case, higher interest rates do not reflect individual ability or superior information, but just how "profitable" a given customer is to the bank. To account for this, we re-estimated the two specifications in Table 10 adding a dummy for whether the individual has a large loan with the bank (above 25,000 NOK) as well as the overall net worth percentile, which should identify more "valuable" customers for the bank (as well as being correlated with the ability to service large loans). If this story is what explains the increase in predictability that we observe when adding fixed effects, controlling for these variables should produce no increase in explained variation in returns once we introduce individual fixed effects. The sample we use for these regressions is smaller due to some missing values on loan accounts and the fact that we do not yet have access to tax records for 2016 (while we do have access to the deposits data set for that year). We have approximately 21 million instead of 25 million observations. However, we still find that the adjusted R^2 of the regression increases from 0.408 to 0.509 when adding fixed effects - i.e., by *more* than if we omit these controls.

6 Intergenerational persistence in returns to wealth

The Norwegian data allow to link individuals across generations. Hence, we can study intergenerational persistence in returns to wealth, i.e., the relation between $r^x_{i(g)t}$ and $r^x_{i(g-1)t}$ for wealth aggregate x. We can also study the relationship between the fixed effect component of returns by estimating:

$$f^x_{i(g)} = \rho f^x_{i(g-1)} + \eta^x_{i(g)} \tag{9}$$

where $f^x_{i(g)}$ is the fixed effect in returns to wealth for individual i of generation g, for wealth type x. 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' 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 11 plots the rank correlation between the net worth percentile of the parents and that of the child (left panel); the right panel repeats the exercise for the returns. For our broadest measure of wealth, intergenerational correlation in wealth and in returns to wealth is similar (regression slopes of 0.16). However, this masks important non-linearities: the linear model misses the higher intergenerational correlation at the top of the wealth distribution and the lower intergenerational correlation at the top of the returns distribution (most likely coming from the fact that children of parents who did extraordinarily well in terms of returns quickly revert to the mean).[42] Hence, for the very wealthy the pattern of intergenerational correlation in returns facilitates social mobility, while that in wealth weakens it. Panel B of Figure 11 repeats the exercise for financial wealth. Both financial wealth and its return display a positive intergenerational 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. 0.12). Once more, we see deviations from linearity at the top and bottom of the distributions, albeit less strong than for net worth.

The correlation between fixed effect percentiles is similar to the one between the returns themselves, suggesting that a substantial share of the intergenerational correlation in returns to wealth is a reflection of the individual persistent component (see OA, Figure OA.21).

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 11 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 11 using children's and fathers' return percentiles; the results are similar if we use the returns directly (see OA, Table OA.3). We report regressions for the return to financial wealth, before-tax net worth, and after-tax net worth. In each case, we present three specification. The first has no controls, and hence reproduces the slope coefficients of Figure 11. The second specification adds wealth controls, education dummies, age, and year effects. The final specification adds individual fixed effects. The slope of the intergenerational relation between returns to financial wealth declines substantially when adding fixed effects, while the ones for the returns to net worth remain unchanged (and if,

[42] 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.

anything, increases). Including fixed effects also has a large effect on explained fit, which is consistent with the intergenerational correlation being driven primarily by the permanent component of returns.

Overall, our data suggest substantial persistence and heterogeneity in returns within a generation but milder persistence across generations, particularly in returns to financial wealth.[43] This result is similar to that found by Benhabib et al. (2018) (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 considerable more statistical power, we find 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 five and highlight some new lines of research that our findings call for.

Wealth inequality and returns heterogeneity: Steady state Papers on wealth inequality in the spirit of Benhabib et al. (2011) imply that the stationary distribution of wealth should be characterized by a higher density of high return types at higher wealth percentiles. Hence we should observe a positive relation between the average fixed effects and the wealth percentile. Table 8, Panel B shows the slope parameter of OLS regressions of the average fixed effects on the wealth percentiles of the distribution of wealth in 2004 (a year where wealth concentration is relatively stable, better proxying the stationary distribution). Using our return fixed effect estimates and their intergenerational persistence in Section 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 $f_{i(g)} \sim (mean = 3.7\% + 0.03(P_{iw} - 50), SD = 3.6\%)$ and $f_{i(g)} = const + 0.14 f_{i(g-1)}$, where P_{iw} is the net worth percentile of individual i and 3.7% is the average after tax return on net worth over the sample period. This characterization is *qualitatively* consistent with the idea that persistent heterogeneity in returns to wealth causes wealth concentration - the mechanism emphasized by Benhabib et al. (2011). To test whether measured heterogeneity is able to *quantitatively* account for wealth inequality, one can choose the values of the parameters of the distribution of individual persistent returns (mean, standard deviation, and intergenerational

[43] Our evidence lends support to Gabaix et al. (2016)'s assumption of type dynamics.

correlation) to match the moments of the wealth distribution as done by Benhabib et al. (2018) for the US, which can then be confronted with our data-based findings. Benhabib et al. (2018) estimate average returns to wealth of 3.0% with a cross-sectional standard deviation of 2.7% and an intergenerational persistence of 0.17. Average returns and intergenerational correlation are of comparable size as in our Norwegian data; the returns standard deviation is instead slightly lower. But this is because Benhabib et al. (2018) 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). For the same reason they find a slope of the relation between the average individual permanent return to wealth and the corresponding wealth percentile that is smaller than ours (0.01 vs. 0.03), albeit in a similar ballpark. The remarkable consistency between our data-based evidence and the calibration-based evidence of Benhabib et al. (2018) 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.

Wealth inequality and returns heterogeneity: Transitional dynamics A more direct way to connect persistent heterogeneity in returns with the extent of wealth concentration is to look at the relationship between past cumulative returns and future individual position in the wealth distribution, especially at the top. If returns matter, past cumulative returns should predict future position in the wealth distribution. Figure 12 reports the results of this exercise. We take the sample present throughout the 12 years for which we have data (2004-15). We first compute the cumulative net worth return for each individual, $R_i = \prod_{t=2005}^{2015}(1 + r_{it}^n)$. We then plot this against the position in the net worth distribution in the final year, 2015. Figure 12 shows that individuals at the top of the net worth distribution realize on average much higher cumulative returns than people in lower percentiles over the same time period.[44] At the 75th percentile, \$1 invested in 2004 would have yielded \$1.5 by the end of 2015; for those in the top 0.1% the same investment would have yielded \$2.4 (and close to \$3 if we do not trim returns at the top 0.5%, which obviously eliminates individuals who have genuinely done extraordinarily well).

To evaluate the effect that return heterogeneity may have on wealth inequality and wealth mobility, we run simple regressions involving changes in the relative position in the net worth distribution between 2004 (our initial year) and 2015 (our final year). First, we consider the

[44]This plot is obtained controlling for the net worth percentile in the initial year 2004.

probability of moving to the top 1% in 2015 (conditioning on being in the bottom 99% in 2004), as a function of the cumulative return R_i as well as other potential determinants of wealth mobility. Second, we construct the absolute value of the difference between percentile in 2015 and percentile in 2004 and regress it against the same variables for people who moved away from the top 1% in 2004. This allows us to address the question: How large was the "fall from the top 1%" as a function of cumulative returns? Results are reported in the OA (Table OA.4). In one specification we control only for the cumulative return. In a second specification we add controls for age in 2004 (to account for life cycle effects), years and type of education, average earnings (to account for savings potential), and parent's wealth rank in 2004 (to account for potential bequests). In all cases, cumulative returns appear to play an important role. A move from the 10-th to the 90-th percentile of the distribution of R_i increases the probability of making it to the top 1% by 1.2 percentage points. To keep things in perspective, the fraction of those who are in the bottom 99% in 2004 and make it to the top 1% in 2015 is only 0.57%. People who are at the top 1% in 2004 and experience a decline in R_i from the 90th to the 10th percentile of the distribution would, on average, fall somewhere between the 97th and 98th percentile of the distribution of net worth in 2015. As Table 1A suggests, this would correspond to a significant decline in total assets.

To further highlight the link between returns heterogeneity and wealth mobility for individuals with access to potentially high return investment opportunities, we perform an additional exercise. We focus on individuals who are in the bottom decile of the net worth distribution in 2004. As mentioned above, this group is characterized by the presence of a large fraction of entrepreneurs and individuals with negative net worth but with both high levels of assets and debt. We first compute the individual cumulative return on *gross* wealth for the 2005-15 period, distinguishing between entrepreneurs and non-entrepreneurs. The empirical distribution of these cumulative returns displays a distinctively longer right tail for the business owner group (see OA, Figure OA.22), documenting better investment opportunities for the cash they borrow. Next, we study mobility from the bottom decile in 2004 to the top 10%, 5% and 1% of the net worth distribution in 2015, contrasting entrepreneurs and non-entrepreneurs. We find that entrepreneurs, thanks to the longer tail distribution of cumulative returns on gross wealth, have a 3 to 5 times higher probability of moving to top fractiles (conditioning on being in the bottom decile in 2004) relative to non-entrepreneurs (see OA, Table OA.5).

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%).[45] 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. (2018), 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.

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

[45]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).

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 8, Panel A) 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., 2019) 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.

Additionally, 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 household 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).

The empirical importance of returns heterogeneity that we have uncovered should motivate future work on the measurement of returns to wealth. We see three broad areas of improvement. First, the measurement of housing returns to better capture the individual specific component which current imputations techniques tend to miss. This is an important issue, especially considering the weight that housing has in the total assets of a very large fraction of households. Machine learning techniques can greatly improve the imputation of owner-occupied housing values and rents. Second, the measurement of private equity returns, extending to other contexts the methodology used by Statistics Norway (ask private firms to fill in balance sheets with detailed items each valued at market prices, pre-filling values of commercial properties using central statistics information on local market prices, etc.). Third, the measurement of returns in household surveys encouraging the growing practice of merging survey data with administrative records from financial institutions.

More generally, the properties of returns on wealth that we have established have implications for the future generation of theoretical and calibrated models of wealth inequality that hinge on returns heterogeneity. First, our results imply that models of wealth inequality would gain in realism and ability to match both ends of the wealth distribution by explicitly allowing for the presence of (heterogeneously costly) debt. Second, they suggest that future calibrated models should incorporate distributions of heterogeneous returns that depart from normality, allowing for skewness and kurtosis. Third, because, as we document, the extent and properties of returns heterogeneity differ remarkably across asset types, models of wealth accumulation with multiple assets and limited heterogeneous participation should be able to provide important insights into the causes of wealth inequality, balancing the relevance of heterogeneity in returns within asset classes and heterogeneity in access to those assets.

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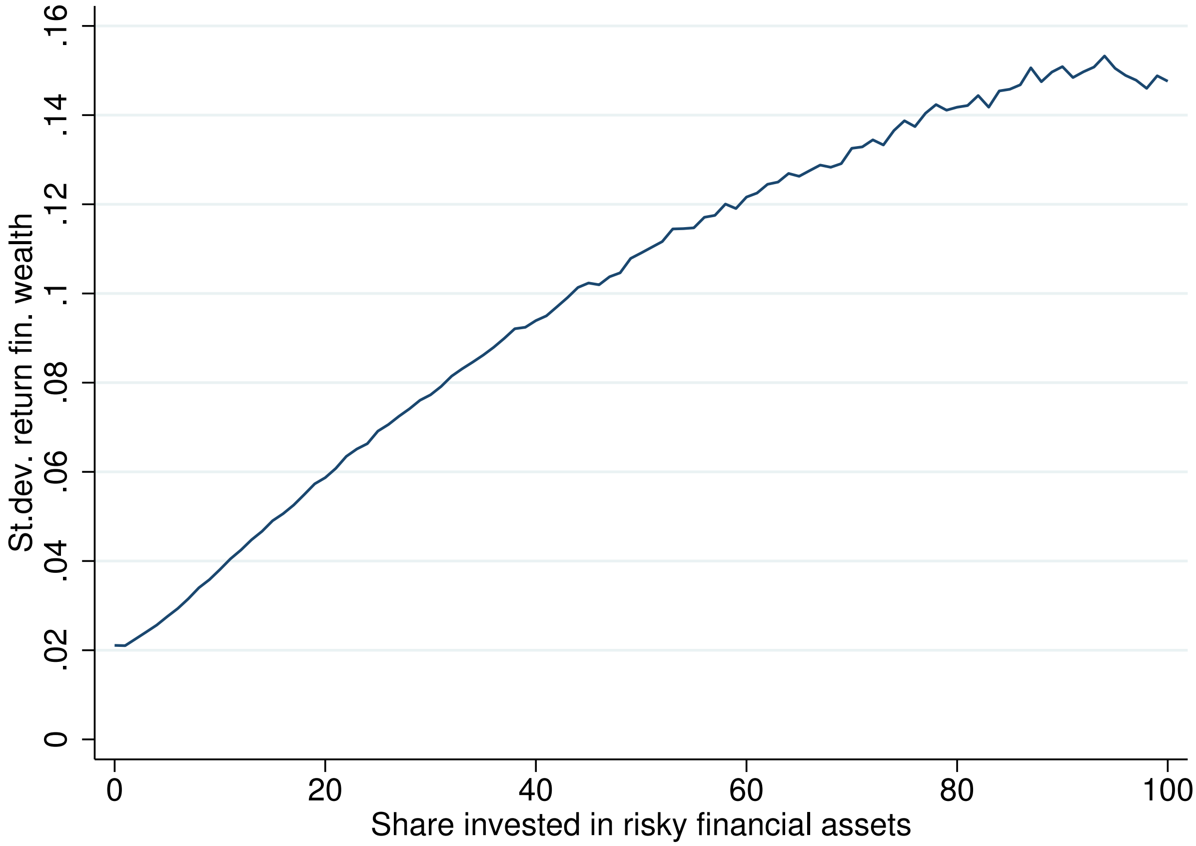
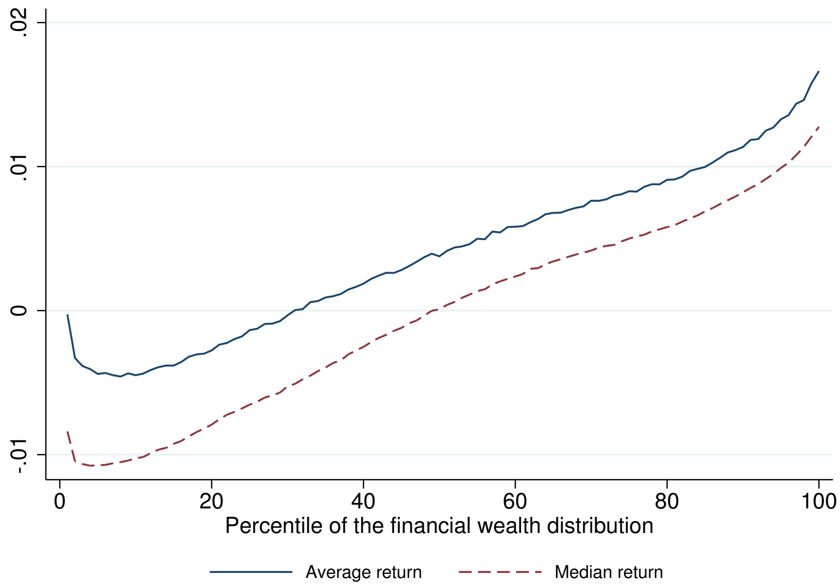
Figure 1. Heterogeneity in returns to financial wealth by share of risky assets

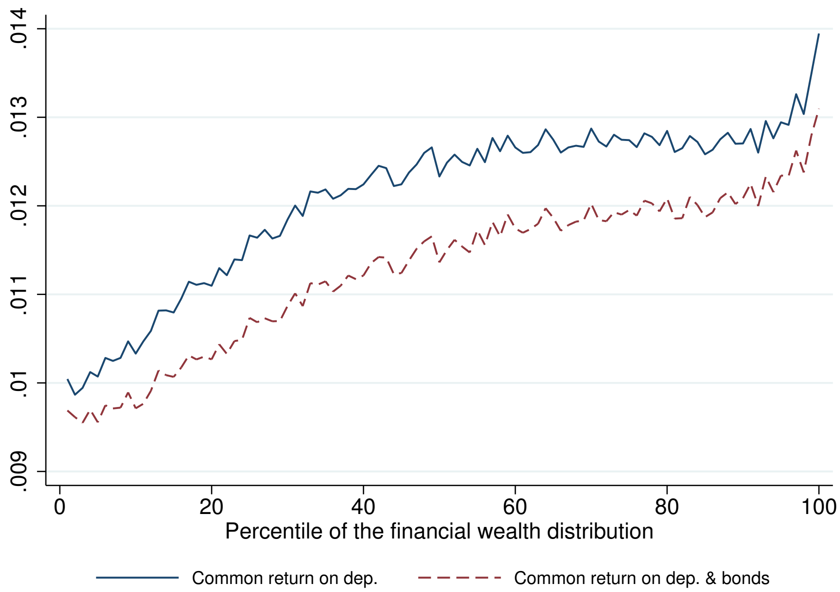


Notes: The figure plots the cross-sectional standard deviation of individual returns to wealth in the 2005-15 period against the share of financial wealth in risky assets (directly and indirectly held stocks, and foreign assets). The shares are in percentage terms.

Figure 2. The correlation between financial wealth and its return



Panel A: Return to financial wealth



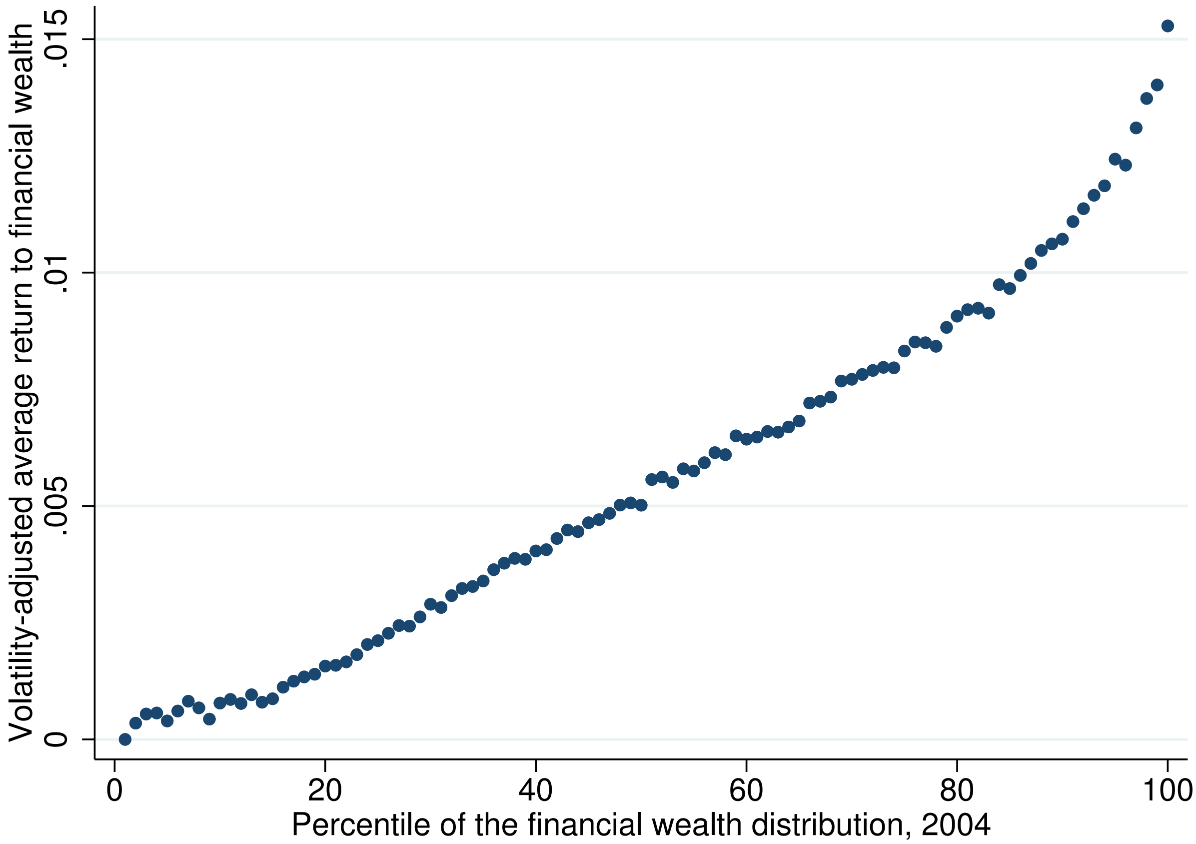
Panel B: Return to financial wealth, assuming common return on safe assets

Notes: Panel A shows the relation between average (solid line) and median (dashed line) return to financial wealth and financial wealth percentiles pooling data for 2005-15. Panel B shows the relation between average return and financial wealth percentile using a measure in which the return to deposits and bonds are assumed common across individuals.

Figure 3. The correlation between financial wealth and the return to its components

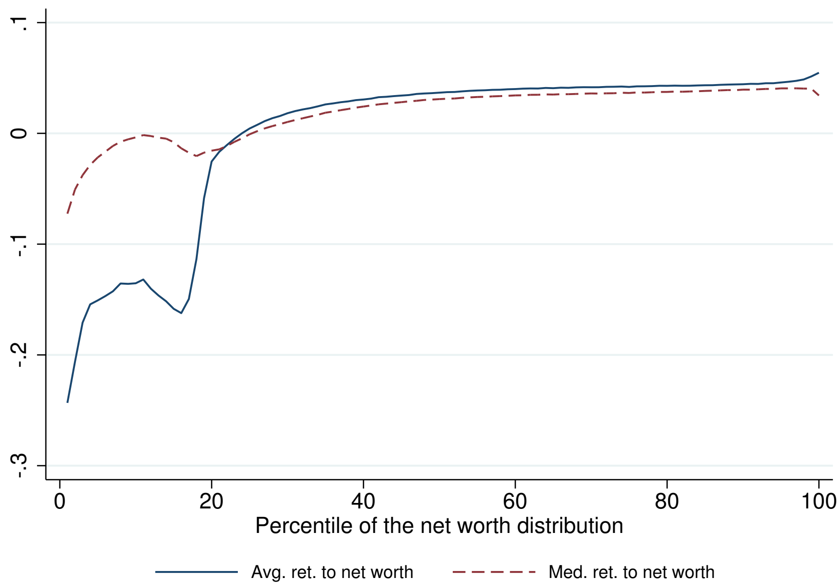
Notes: The figure shows the relation between the return to safe financial assets (left figure) and the return to risky financial assets (right figure) against financial wealth percentiles, pooling data for 2005-15. The solid lines are local regression lines.

Figure 4. The average volatility-adjusted return against initial wealth

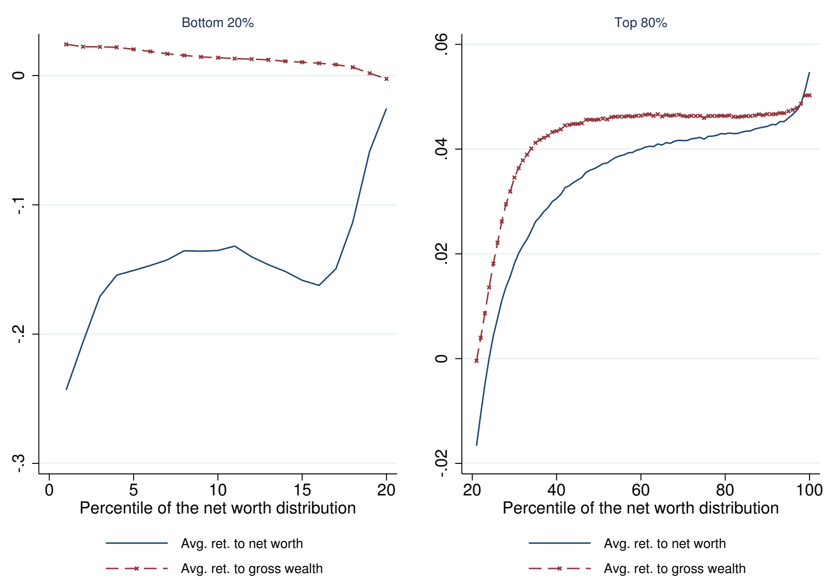


Notes: The figure shows the average return of the individual financial wealth portfolios for the 2005-15 period against the financial wealth percentile in 2004, controlling for individual return volatility. The picture is obtained regressing the individual average return for the 2005-15 period against the standard deviation of individual returns over the same period and a full set of dummies for the 2004 financial wealth percentile (whose estimated coefficients are used to produce the plot). Only individuals with 12 consecutive observations (from 2004 to 2015) are included in the calculations.

Figure 5. The correlation between net worth and its return



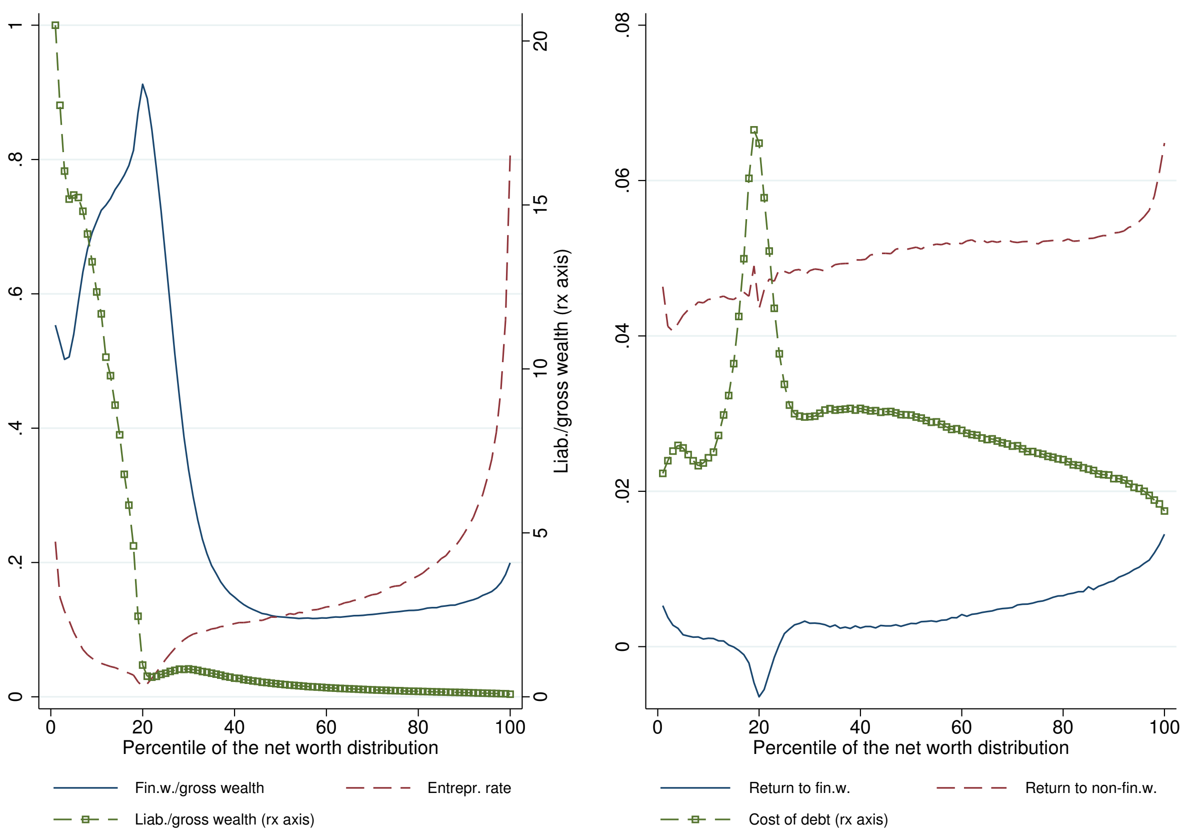
Panel A: Average and median return to net worth



Panel B: Bottom 20% vs. Top 80%

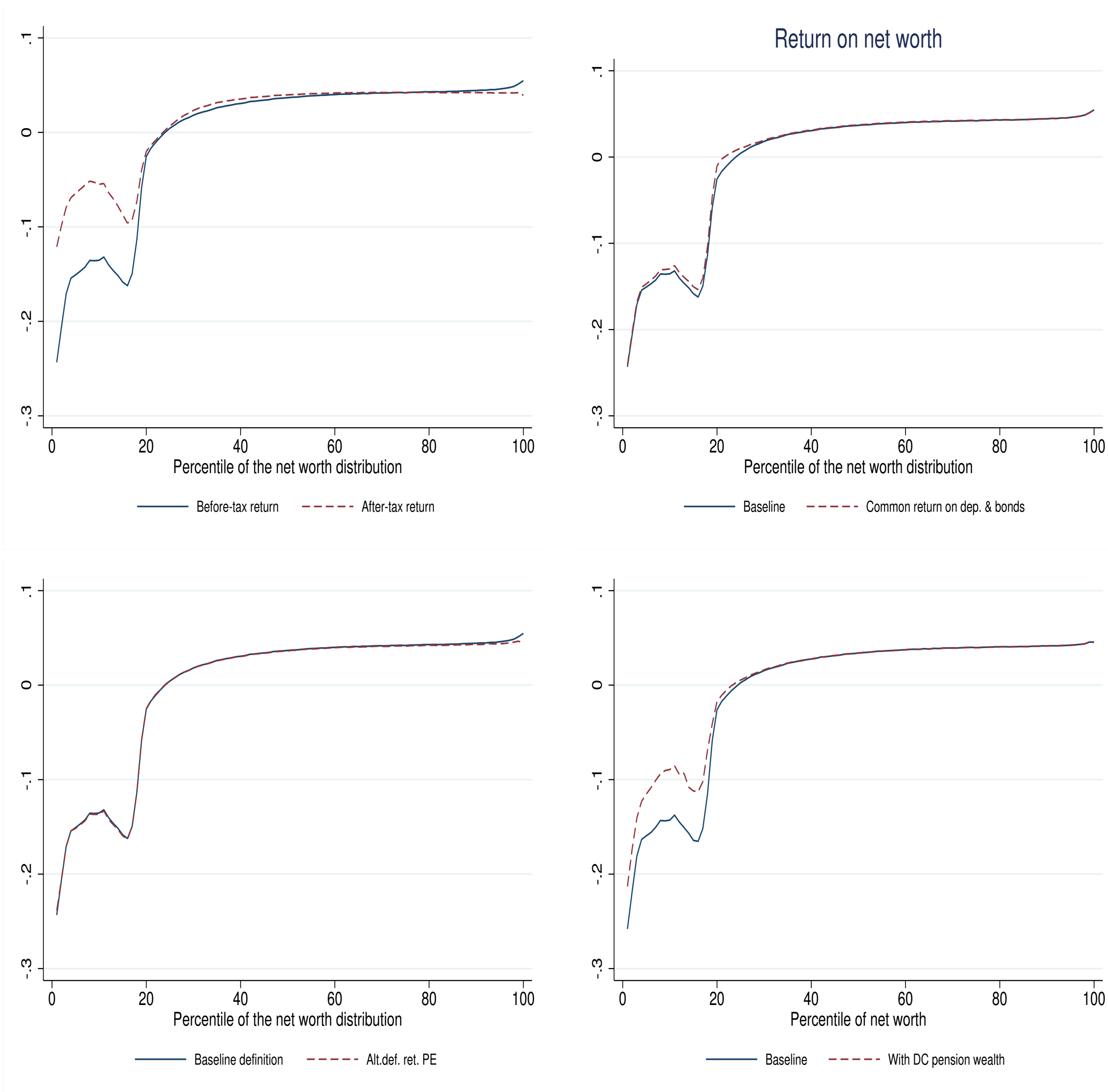
Notes: The figure shows the relation between returns to net worth and net worth percentiles pooling data for 2005-15. Panel A plots the average (solid line) and median (dashed line) return over the whole distribution. Panel B zooms on the bottom 20% (left graph) and top 80% (right graph), and adds also the return to gross wealth (i.e., the return to the positive component of net worth).

Figure 6. Explaining the relation between net worth and its return



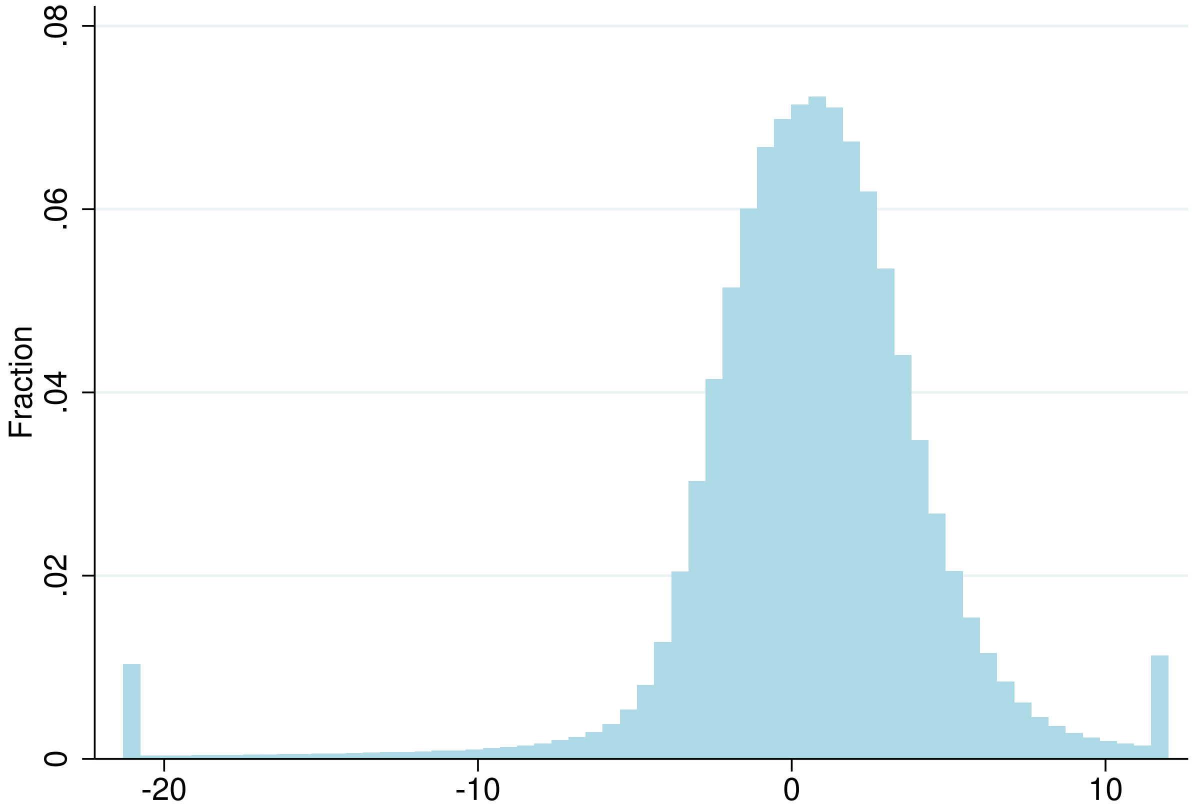
Notes: The left panel plots the share of gross wealth held in financial wealth and the fraction of entrepreneurs (left axis) and the leverage (right axis) against net worth percentiles. The right panel plots the returns on financial and non-financial wealth and the cost of debt, again against net worth percentiles.

Figure 7. Robustness: The correlation between net worth and its return



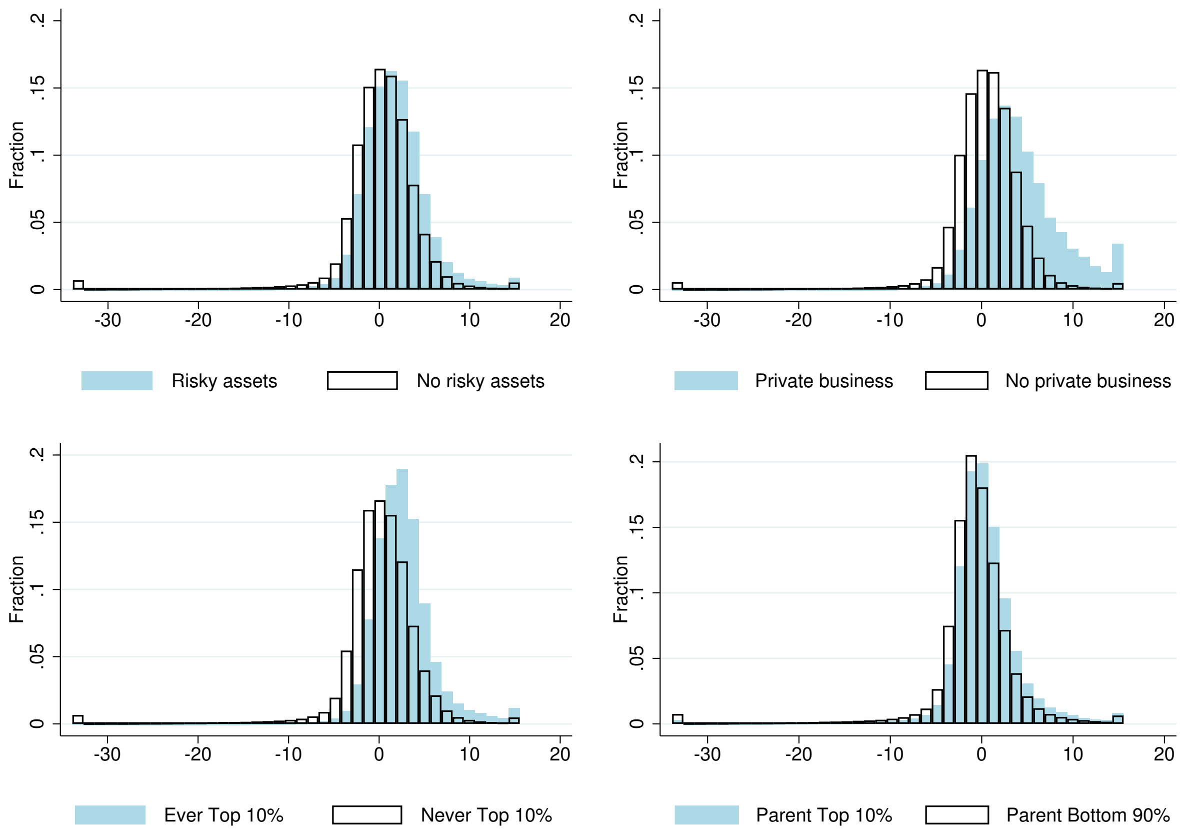
Notes: The figures shows the relation between returns to net worth and net worth percentiles pooling data for 2005-15. The top left panel compares the baseline before-tax return to net worth with the after-tax return. The top right panel compares the baseline with a measure in which the return to deposits and bonds are assumed common across individuals. The bottom left panel compares the baseline with a measure that uses the alternative definition of return to private business wealth described in Section 3.3.3. Finally, the bottom right-panel compares the baseline with a measure that includes the return to defined contribution private pension wealth.

Figure 8. The distribution of fixed effects in the return to net worth



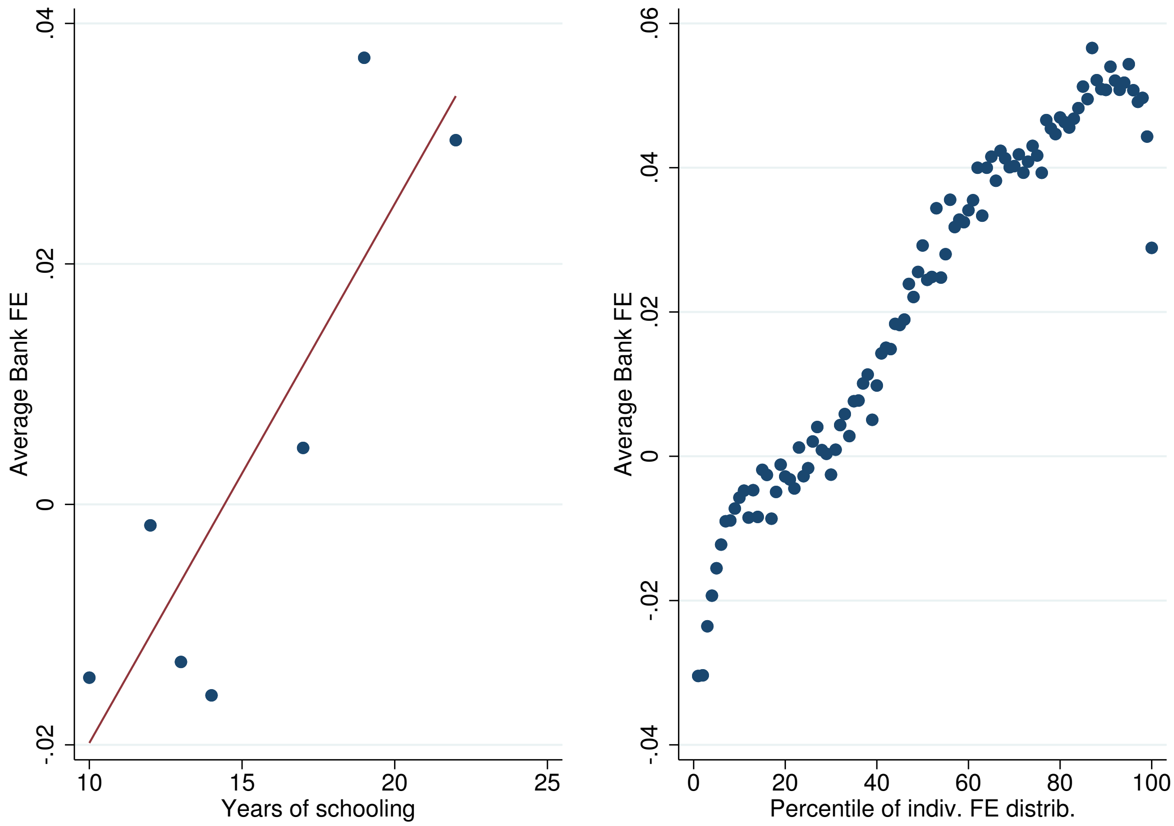
Notes: The figure shows the histogram of the estimated fixed effects in the net worth return regressions using estimates in Table 4, column 3. The distribution has been de-meaned and winsorized at the top and bottom 1%.

Figure 9. The distribution of fixed effects in the return to net worth for selected sub-groups



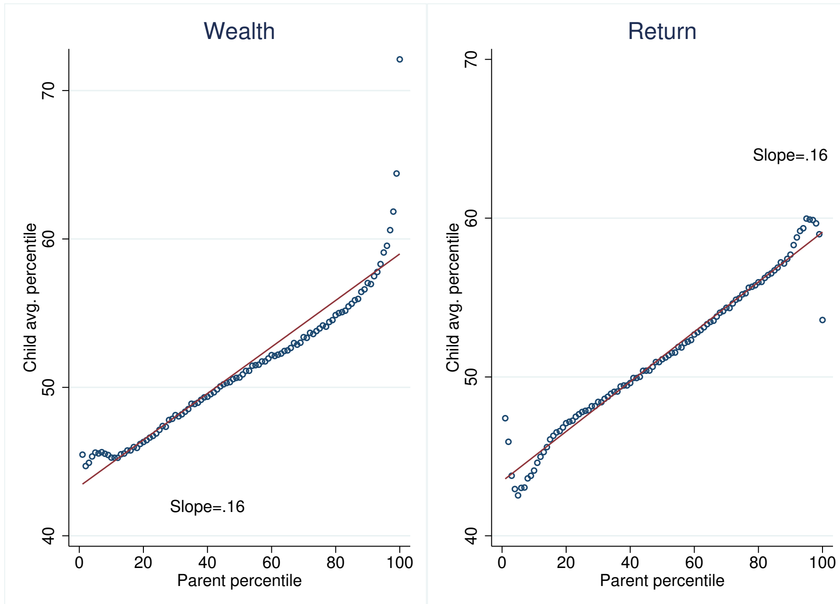
Notes: The figures shows the histogram of the estimated fixed effects in the wealth return regressions using estimates in Table 4, column 3, for selected sub-groups. All distributions have been winsorized at the top and bottom 1%. In the top left panel, we compare the distribution of fixed effects for individuals who hold risky assets at least once over the sample period (2005-15) against those who do not. The top right panel compares those who own a private business throughout the period with those who do not. The bottom left panel compares those who have been at least once in the top 10% of the net worth distribution and those who have always been below it. Finally, the right bottom panel compares those with wealthy parents (top 10%) in 2004 with those with parents in the bottom 90%.

Figure 10. Bank and individual fixed effects in returns to deposit accounts

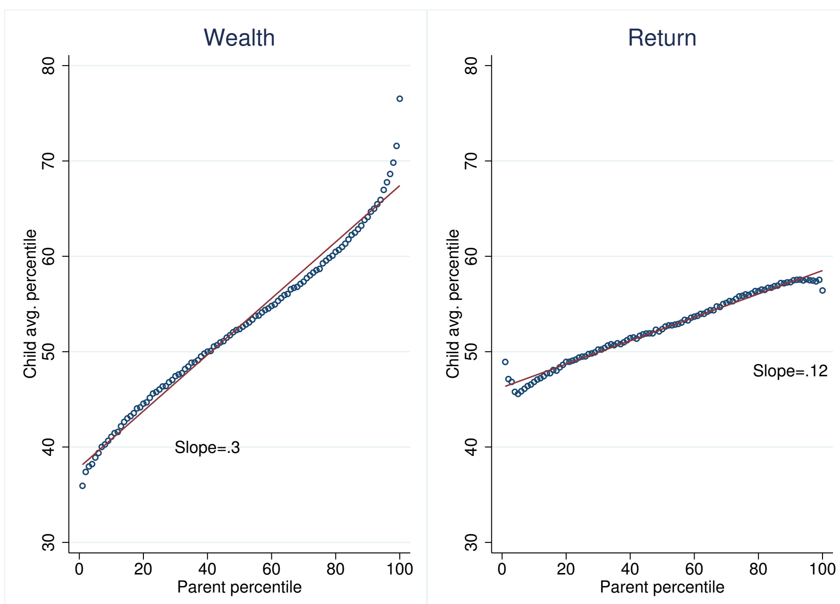


Notes: The figure on the left plots the average bank fixed effect for different levels of schooling using the deposit return regression of Table 10, column 2. The figure on the right repeats the exercise for different percentiles of the distribution of individual fixed effects from the same regression.

Figure 11. The intergenerational correlation in wealth and returns



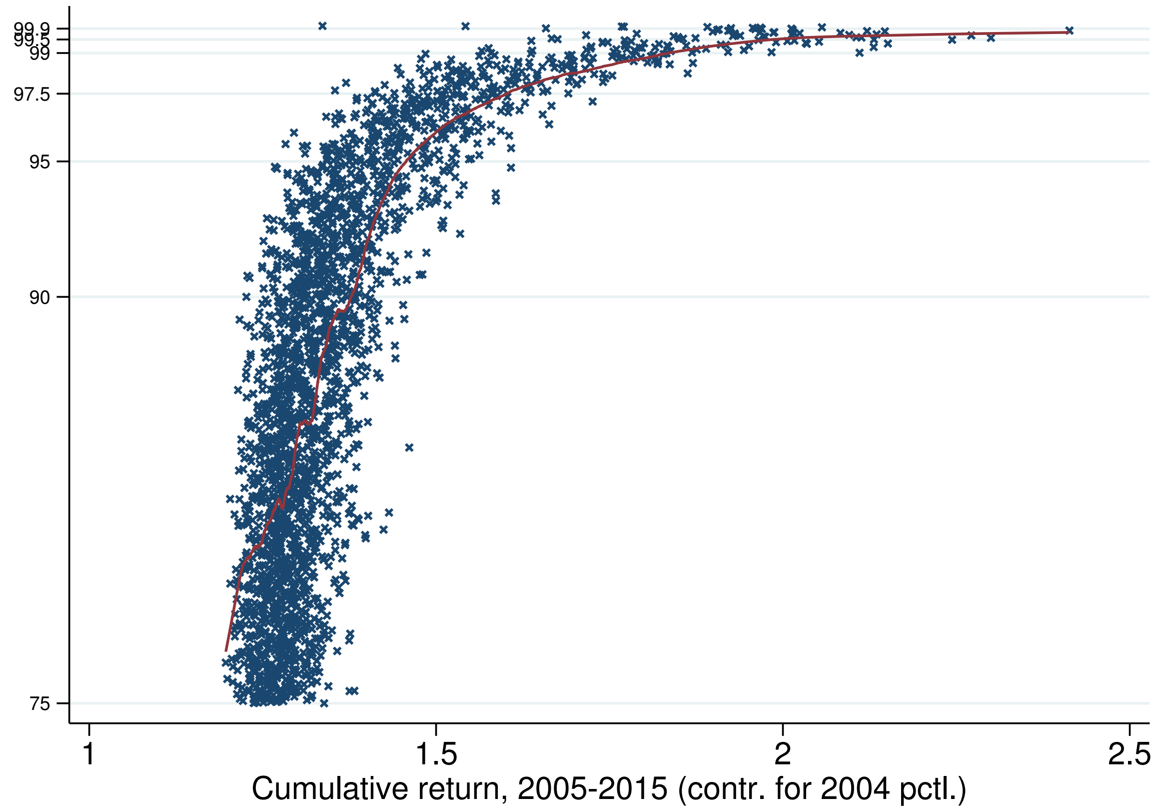
Panel A: Net worth



Panel B: Financial wealth

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.

Figure 12. Net worth percentile and cumulative net worth return



Notes: The figure shows the relation between net worth fractile in 2015 (for the top 25% only), in 0.01% increments, and average cumulative return to net worth over the 2005-15 period.

Table 1A. Portfolio composition of net worth, by selected fractiles

	Gross wealth shares				Leverage ratios			Gross
	Safe	Risky	Housing	Private equity	Consumer debt	Student debt	Long-term debt	wealth (logs)
Bottom 10%	0.51	0.03	0.43	0.02	0.50	2.47	9.08	10.73
10-20%	0.78	0.03	0.18	0.01	0.42	3.08	3.39	9.06
20-50%	0.31	0.02	0.66	0.01	0.01	0.05	0.40	11.89
50-90%	0.11	0.02	0.86	0.02	0.00	0.01	0.21	13.42
90-95%	0.12	0.02	0.81	0.05	0.00	0.00	0.12	14.12
95-99%	0.13	0.03	0.73	0.11	0.00	0.00	0.10	14.55
99-99.9%	0.15	0.04	0.44	0.36	0.00	0.00	0.07	15.41
99.9-99.99%	0.14	0.04	0.11	0.71	0.00	0.00	0.04	16.94
Top 0.01%	0.08	0.04	0.03	0.85	0.00	0.00	0.02	18.78

Notes: The table reports the share of gross wealth in safe assets (cash/deposits, bonds, outstanding claims and receivables), risky assets (foreign assets, mutual funds, directly held listed stocks), housing, private business wealth, consumer debt, student debt, and long-term debt (mortgages and personal loans) for Norwegian taxpayers against selected fractiles of the net worth distribution. Debt leverage values are winsorized at the top 1%. In the last column we report the logarithm of real gross wealth. Data are for 2005-2015.

Table 1B. Portfolio composition of financial wealth, by selected fractiles

	Financial wealth shares						Financial
	Deposits	Bonds	Outst. claims	Foreign assets	Mutual funds	Listed shares	wealth (logs)
Bottom 10%	0.95	0.01	0.03	0.00	0.00	0.00	6.58
10-20%	0.94	0.01	0.05	0.01	0.01	0.00	8.11
20-50%	0.89	0.01	0.07	0.01	0.01	0.00	9.38
50-90%	0.82	0.02	0.08	0.03	0.04	0.01	11.04
90-95%	0.76	0.03	0.08	0.05	0.07	0.02	12.39
95-99%	0.70	0.03	0.08	0.06	0.11	0.02	13.04
99-99.9%	0.54	0.04	0.09	0.08	0.21	0.04	14.05
99.9-99.99%	0.34	0.06	0.08	0.09	0.36	0.08	15.41
Top 0.01%	0.25	0.07	0.05	0.08	0.38	0.17	16.98

Notes: The table reports the portfolio composition of financial wealth into cash/deposits, bonds, outstanding claims and receivables, foreign assets, mutual funds, and directly held listed stocks for Norwegian taxpayers against selected fractiles of the financial wealth distribution. In the last column we report the logarithm of real financial wealth. Data are for 2005-2015.

Table 2. Descriptive Statistics

	Mean	Std. dev	P10	Median	P90	P99
			Panel A: Demographics			
Age	45.64	14.98	25.00	45.00	67.00	74.00
Male	0.50	0.50	0.00	0.00	1.00	1.00
Married	0.50	0.50	0.00	0.00	1.00	1.00
Family size	2.62	1.36	1.00	2.00	4.00	6.00
Less than High School education	0.22	0.42	0.00	0.00	1.00	1.00
High School education	0.43	0.50	0.00	0.00	1.00	1.00
College education	0.35	0.48	0.00	0.00	1.00	1.00
Years of education	13.61	3.58	10.00	13.00	17.00	19.00
Econ/Business education	0.12	0.33	0.00	0.00	1.00	1.00
			Panel B: Asset values			
Financial wealth (1)=(1a)+(1b)	52,032	307,505	1,571	16,430	115,462	502,705
Safe assets (1a)	43,642	203,857	1,368	13,909	98,977	420,751
Risky fin. assets (1b)	8,390	202,201	0	0	13,262	129,964
Non-financial wealth (2)=(2a)+(2b)	346,714	2,232,511	0	258,827	670,807	1,793,544
Private equity (2a)	44,783	2,189,519	0	0	5,389	634,872
Housing (2b)	301,930	329,377	0	253,094	630,082	1,388,690
Gross wealth (3)=(1)+(2)	398,746	2,319,537	6,518	293,714	756,215	2,078,912
Debt (4)	123,263	218,529	0	75,044	293,225	665,434
Net worth (5)=(3)-(4)	275,483	2,294,126	-31,709	169,030	614,672	1,813,770
			Panel C: Capital income			
Income from safe assets	1,126	6,785	7	210	2,468	12,986
Income from risky fin. assets	322	22,791	0	0	1,023	13,668
Income from priv. bus.	4,533	348,792	0	0	328	89,338
Housing yield	18,137	27,762	0	12,125	46,607	114,689
Interest payments on debt	4,960	9,092	0	3,050	12,015	27,862
			Panel D: Participation and share statistics			
Fraction with safe fin. assets	1.00	0.03	1.00	1.00	1.00	1.00
Fraction with risky fin. assets	0.39	0.49	0.00	0.00	1.00	1.00
Fraction with any risky assets	0.44	0.50	0.00	0.00	1.00	1.00
Fraction with public equity	0.38	0.49	0.00	0.00	1.00	1.00
Fraction with private equity	0.13	0.34	0.00	0.00	1.00	1.00
Fraction with housing	0.78	0.41	0.00	1.00	1.00	1.00
Fraction with some debt	0.89	0.32	0.00	1.00	1.00	1.00
Safe assets/Gross wealth	0.28	0.37	0.01	0.08	1.00	1.00
Cond. safe assets share	0.28	0.37	0.01	0.08	1.00	1.00
Public equity/Gross wealth	0.02	0.08	0.00	0.00	0.04	0.39
Cond. public equity share	0.05	0.11	0.00	0.01	0.12	0.66
Private equity/Gross wealth	0.02	0.10	0.00	0.00	0.01	0.60
Cond. private equity share	0.17	0.23	0.00	0.07	0.52	0.93
Housing/Gross wealth	0.68	0.39	0.00	0.89	0.99	1.00
Cond. housing share	0.87	0.16	0.65	0.93	0.99	1.00
Leverage, Long-term debt	1.37	5.85	0.00	0.25	1.18	37.78
Leverage, Consumpt. debt	0.09	0.60	0.00	0.00	0.02	3.97
Leverage, Stud. debt	0.55	2.72	0.00	0.00	0.18	20.49
Observations				32,787,068		

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 asset participation data (Panel D), pooling data for 2005-15.

Table 3. Returns to wealth: Summary statistics

Wealth component	Mean	St.dev.	Skewness	Kurtosis	P10	Median	P90
Net worth (before tax)	0.0379	0.0859	-0.79	47.75	-0.0308	0.0321	0.1109
Net worth (after tax)	0.0365	0.0781	-0.71	36.88	-0.0283	0.0316	0.1067
Net worth (before tax, unweighted)	0.0004	0.2205	-6.73	68.46	-0.0600	0.0230	0.1037
Net worth (after tax, unweighted)	0.0155	0.1546	-5.28	56.42	-0.0449	0.0247	0.1040
Financial wealth	0.0105	0.0596	-1.78	22.17	-0.0171	0.0084	0.0530
Safe fin. assets	0.0078	0.0188	4.38	53.52	-0.0106	0.0059	0.0268
Risky fin. assets	0.0425	0.2473	-0.08	6.22	-0.2443	0.0418	0.3037
Non-financial wealth	0.0511	0.0786	1.80	15.47	-0.0215	0.0429	0.1275
Housing	0.0485	0.0653	0.73	9.95	-0.0209	0.0441	0.1165
Private equity	0.1040	0.5169	18.01	836.79	-0.0531	0.0052	0.3616
Debt	0.0236	0.0216	2.51	29.50	0.0030	0.0215	0.0461
Long-term debt	0.0230	0.0209	3.54	56.92	0.0038	0.0209	0.0446
Consumer debt	0.0961	0.1086	4.60	82.60	-0.0124	0.0741	0.2119
Student debt	0.0078	0.0260	0.68	4.14	-0.0213	0.0074	0.0399

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: Net worth

	(1)	(2)	(3)
Years of education	0.1098	0.1492	
	(0.0015)	(0.0015)	
Econ/Business education	0.1068	0.1296	
	(0.0118)	(0.0117)	
Male	-0.0228	0.0495	
	(0.0078)	(0.0076)	
Mutual fund share	3.9939		
	(0.1543)		
Direct stockh. share	6.4783		
	(0.2308)		
Bonds share	3.8432		
	(0.1594)		
Foreign w. share	1.7160		
	(0.2637)		
Outst.cl. share	5.7039		
	(0.1632)		
Private equity share	8.3067		
	(0.0709)		
Housing share	7.2332		
	(0.0222)		
Leverage, long-t. debt	-4.7928		
	(0.0138)		
Leverage, cons. debt	-6.5772		
	(0.0362)		
Leverage, stud. debt	-0.1422		
	(0.0116)		
Average β stock m.	-0.0085		
	(0.0202)		
Average β PE	0.0083		
	(0.0008)		
Average β Housing	0.4162		
	(0.0318)		
Demographics	Y	Y	Y
Year effects	Y	Y	Y
Shares*Year effects	N	Y	Y
Individual FE	N	N	Y
Observations	30,786,984	30,786,984	30,786,984
Adjusted R^2	0.301	0.327	0.500
P-value all $f_i = 0$			<0.0001

Notes: The table shows regression estimates of individual returns to net worth (equation (6)). All regressions include a full set of dummies for wealth percentiles computed on one-year lagged wealth, year dummies, age dummies, county dummies, a dummy for employment, and marital status dummies. Specifications in columns 2 and 3 include interactions between time effects and the portfolio shares, and between time effects and the β's. Standard errors (in parentheses) are clustered by household.

Table 5. Explaining returns to wealth: Robustness

	Baseline		Common return on deposits		Alternative PE measure		With DC pension wealth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years of education	0.1492		0.1348		0.1393		0.0898	
	(0.0015)		(0.0015)		(0.0016)		(0.0014)	
Econ/Business education	0.1296		0.0877		0.1127		0.1664	
	(0.0117)		(0.0117)		(0.0121)		(0.0102)	
Male	0.0495		-0.0082		-0.0008		0.2062	
	(0.0076)		(0.0078)		(0.0079)		(0.0070)	
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
Year effects	Y	Y	Y	Y	Y	Y	Y	Y
Shares*Year effects	Y	Y	Y	Y	Y	Y	Y	Y
β's*Year effects	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	N	Y	N	Y	N	Y	N	Y
Observations	30,786,984	30,786,984	30,786,543	30,786,543	30,781,213	30,781,213	21,925,425	21,925,425
Adjusted R^2	0.327	0.500	0.322	0.497	0.317	0.484	0.296	0.489
P-value all $f_i = 0$		<0.0001		<0.0001		<0.0001		<0.0001

Notes: The table shows regression estimates of individual returns to net worth (equation (6)). All regressions include a full set of dummies for wealth percentiles computed on one-year lagged wealth, year dummies, age dummies, county dummies, a dummy for employment, marital status dummies, asset shares, $\beta's$, and interactions between time effects and the portfolio shares, and between time effects and the β's. For specifications in columns 7 and 8 we re-define net worth to include defined contribution private pension wealth and re-compute net worth percentiles. Standard errors (in parentheses) are clustered by household.

Table 6. Return to components of net worth

	Fin. wealth		Priv. eq.		Housing		Debt	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years of education	0.0192		-0.0406		-0.0037		-0.0946	
	(0.0002)		(0.0271)		(0.0003)		(0.0005)	
Econ/Business education	0.0552		0.7092		0.0373		-0.1359	
	(0.0020)		(0.1917)		(0.0025)		(0.0035)	
Male	-0.0594		0.6145		0.1654		0.0074	
	(0.0008)		(0.0551)		(0.0012)		(0.0020)	
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
PE experience controls	N	N	Y	Y	N	N	N	N
Year effects	Y	Y	Y	Y	Y	Y	Y	Y
Shares*Year effects	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	N	Y	N	Y	N	Y	N	Y
Observations	31,039,355	31,039,355	4,581,990	4,581,990	25,220,371	25,220,371	26,954,082	26,954,082
Adjusted R^2	0.739	0.762	0.006	0.076	0.235	0.192	0.187	0.524
P-value all $f_i = 0$		<0.0001		<0.0001		1.0000		<0.0001

Notes: The table shows regression estimates of individual returns to components of net worth: financial wealth, private equity, housing, and debt. All regressions include a full set of dummies for wealth percentiles computed on one-year lagged wealth, year dummies, age dummies, county dummies, a dummy for employment, marital status dummies and (when appropriate) asset shares, $\beta's$, and interactions between time effects and the portfolio shares, and between time effects and the β's. For specifications in columns 3 and 4 we replace dummies for age with dummies for PE experience. Standard errors (in parentheses) are clustered by household.

Table 7. Fixed effects statistics

	Mean	SD	Sk.	Kurt.	P10	P25	P50	P75	P90
Panel A: FE statistics for various return measures, Whole sample									
Return to net worth	0.00	6.02	-5.26	78.42	-3.43	-1.70	0.28	2.29	4.28
Return to after-tax net worth	0.00	4.25	-3.43	56.68	-3.03	-1.58	0.11	1.86	3.50
Return to financial wealth	0.00	1.29	0.77	4.92	-1.47	-0.89	-0.16	0.77	1.66
Return to housing	0.00	5.22	0.08	2.14	-6.86	-4.21	-0.15	4.21	7.05
Return to private equity	0.00	50.25	1.92	16.84	-49.95	-30.38	-4.05	23.97	50.68
Cost of debt	0.00	1.95	2.46	20.10	-1.76	-0.76	-0.10	0.56	1.57
Panel B: FE statistics, return to net worth in selected sub-samples									
Business owners	4.08	4.76	0.30	14.24	-0.77	1.11	3.41	6.28	10.09
Ever in top 10 percent NW	2.60	3.68	-0.16	24.55	-0.86	0.59	2.31	4.07	6.23
Parents in top 10 percent NW	0.27	5.02	-4.08	69.76	-2.84	-1.47	0.05	1.93	4.34
Ever owned risky assets	0.71	5.22	-4.92	77.60	-2.82	-1.18	0.79	2.87	4.93
College graduate or more	0.44	5.44	-4.88	75.90	-2.98	-1.39	0.52	2.62	4.70
Econ/business degree	0.78	5.27	-4.98	86.48	-2.67	-1.05	0.86	2.87	4.89

Notes: Panel A of the table reports statistics for the distribution of fixed effects estimated from the regressions of returns in column 3 of Tables 4 (net worth) and OA.1 (net worth after tax), and for columns 2, 4, 6, 8 of Table 6, respectively for financial wealth, private equity, housing, and debt. All statistics are expressed in deviation from the mean. Panel B uses the regressions of returns in column 3 of Table 4 and reports fixed effect statistics for selected sub-groups.

Table 8. Fixed effects: Additional statistics

Panel A: Variance decomposition		
	Before-tax return	After-tax return
$Var(f_{i,g})/Var(u_{i,g,t})$	0.2657	0.2363
$Var(e_{i,g,t})/Var(u_{i,g,t})$	0.7343	0.7637
Panel B: Other moments of interest		
	Before-tax return	After-tax return
OLS coeff. $f_{i,g}$ on $P_{NW,2004}$	0.0512	0.0341
(s.e.)	(0.0002)	(0.0001)
$Corr(f_{i,g}, f_{i,g-1})$	0.0761	0.0858
OLS coeff. $f_{i,g}$ on $f_{i,g-1}$	0.1268	0.1356
(s.e.)	(0.0026)	(0.0025)

Notes: Panel A reports variance decomposition measures using the fixed effects estimated from the regression reported in column 3 of Tables 4 and OA.1. Panel B uses the same estimates to report the correlation with the net worth percentile in 2004 (P_{NW}), the intergenerational correlation, and the slope of the intergenerational relation for fixed effects.

Table 9. Scale dependence regressions

	Before-tax return		*After-tax return*	
	(1)	(2)	(3)	(4)
θ	0.1383	0.1386	0.0899	0.1004
	(0.0004)	(0.0014)	(0.0003)	(0.0011)
Time FE	Y	Y	Y	Y
Observations	31,012,291	22,352,589	31,014,688	22,360,612

Notes: The table shows regressions of the return to net worth (before- and after-tax) on the net worth percentile, controlling for time dummies. Columns (1) and (3) are individual fixed effect (within-group) regression. Columns (2) and (4) are specifications in first differences where the change in net worth percentile is instrumented with its second lag. Clustered (by household) standard errors are reported in parentheses.

Table 10. Regressions for the return on deposit accounts

	(1)	(2)
Age	-0.0991	-0.2251
	(0.0003)	(0.0005)
Age^2	0.0009	0.0001
	(0.0000)	(0.0000)
Male	-0.1374	
	(0.0009)	
Econ/Business education	0.0431	
	(0.0013)	
Years of schooling	0.0121	
	(0.0002)	
# of accounts	0.0097	-0.0210
	(0.0005)	(0.0006)
# of accounts w/ same bank	-0.0225	-0.0273
	(0.0002)	(0.0002)
Account experience	0.0325	0.0243
	(0.0006)	(0.0007)
log(Deposit balance)	0.3719	0.3741
	(0.0003)	(0.0004)
N	25,397,491	25,397,491
adj. R^2	0.520	0.597

Notes: The table shows regressions of the return on deposit accounts on the log of the deposit balance and various demographic and account characteristics. Column 1 is an OLS regression pooling data for all years and including bank fixed effects. Column 2 includes also individual fixed effects. Clustered (by household) standard errors are reported in parentheses.

Table 11. Intergenerational return percentile regressions

	Financial wealth			Before-tax net worth			After-tax net worth		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Father's wealth perc.	0.1226	0.0808	0.0793	0.1569	0.1550	0.1717	0.1595	0.1621	0.1797
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Wealth controls	N	Y	Y	N	Y	Y	N	Y	Y
Year FE	N	Y	Y	N	Y	Y	N	Y	Y
Demographics	N	Y	Y	N	Y	Y	N	Y	Y
Individual FE	N	N	Y	N	N	Y	N	N	Y
Adjusted R^2	0.016	0.115	0.305	0.025	0.104	0.251	0.026	0.084	0.223

Notes: The table shows regressions of the child's return percentile on the father's return percentile. Columns 1, 4 and 7 have no controls. Column 2, 5 and 8 add fathers and children's wealth and year fixed effects, age, and other demographics. Columns 3,6, and 9 add individual fixed effects. Columns 1-3 are for the return to financial wealth; columns 4-6 are for the before-tax return to net worth; columns 7-9 are for the after-tax return to net worth. Standard errors (in parentheses) are clustered by child.