Heterogeneity in Returns to Wealth*

Evidence from Swiss Administrative Data

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Abstract

In this paper we address how returns on financial assets vary across the population. Exploiting rich administrative data, we are able to neatly describe the heterogeneity across all parts of the distribution of wealth. We find compelling evidence that the rich benefit from higher returns. Likely, this is due to two different effects that have been called *scale dependence* and *type dependence*. The former is due to an observed positive correlation between net worth and returns. The latter describes a high persistence of returns for each individual, most possibly due to better information and market access advantages. We find evidence that both channels play an important role. Further, with respect to inequality, our results suggest that there is a wide heterogeneity across different socio-demographic dimensions in Switzerland which has been growing over time. Conceptually, this paper contributes by modelling the full distribution of returns. This allows to address the scale effect of net worth on the returns throughout the distribution of the latter. We find that net worth crucially determines the top of the return's distribution highlighting another channel through which wealth inequality reinforces itself.

JEL class: C21, D31, E21, G11, G51

Keywords: Wealth Inequality, Returns to Wealth, Financial Wealth, Net Worth, Heterogeneity, Portfolio Choice

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1 Introduction

At odds with predictions from classic economic theory, wealth inequality has strongly increased over the last few decades. In the US, tail inequality has more than doubled in the last thirty years (Saez and Zucman, 2016), while many individuals save far less than predicted by a basic life-cycle model (Skinner, 2007). This phenomena is not limited to the US as Zucman (2019) shows. He discusses the recent advances in measuring worldwide wealth inequality and finds that the fraction of the wealth belonging to the one percent richest has increased from 28% in 1980 to 33% in 2016. Different theories were put forward to explain the existence of wealth inequality and its persistence. A first stream of the literature is based on Bewley (1977) model. This model was first brought to the data by Aiyagari (1994) who considers the infinitely-lived cases and studies the implication of uninsurable idiosyncratic labor income risk. However, this approach shows little success in explaining the extreme wealth inequality observed at the very top of the distribution. By accounting for the possibility of death, Huggett (1996) is able to decrease the gap between the observed data and the model. Nevertheless, even the life-cycle version is not able to match all relevant moments of the wealth distribution. In the following, many different extensions have been proposed in order to improve the match between theoretical and empirical moments. For example Krusell and Smith (1998) look at the effect of heterogeneous discount rates. However, while they are able to explain some of the extreme inequality, discount rates are generally hard to observe which makes it difficult to study their role in an empirical setting. Further, it seems implausible that the wealth concentration at very top of the distribution is simply due to a higher patience. A large fraction of the individuals holding a big portion of the wealth are often entrepreneurs, usually associated with a lower risk aversion rather then lower discount rates. Indeed, Quadrini (2000) and Cagetti and De Nardi (2006, 2009) explicitly study the role of entrepreneurs allowing for idiosyncratic returns on investment. Atkeson and Irie (2020) consider the role of entrepreneur in a broader sense, namely by modelling the evolution of family firms, i.e. firms founded by one member which where then inherited to the next generation. While these approaches can replicate some of the wealth inequality at the top, there may be other reasons for heterogeneity in returns than entrepreneurial decisions. Finally, De Nardi, French, and Jones (2010) introduce medical expenses, which makes it possible to match the saving behavior of the retired and therefore also contribute to the wealth inequality.[1] In his influential work Piketty (2014) identifies the positive difference between the return on capital and the growth rate of an economy as the main driver of the continuously growing unequal distribution of wealth. This result follows because the upper tail generates higher returns on wealth than the bottom tail is able to earn from labor. This explanation is challenged by Acemoglu and Robinson (2015), which argue that the political and economical institutions are of greater importance than the difference between return on capital and the economical growth rate. Nevertheless, Benhabib, Bisin, and Zhu (2011) show analytically, that, if agents are exposed to labor and capital income risk, only the later is able to explain the right skewed wealth distribution. Proposing two extensions to standard theories, namely *scale* and *type dependence*, Gabaix et al. (2016) contribute to the existing literature by not only matching the empirical distribution, but also the fast rise in top inequality, i.e. the inequality within the

[1] Apart from the previously mentioned potential drivers, many other exists. See De Nardi and Fella (2017) for an extensive summary of the existing literature with regards to Bewley (1977) models.

highest wealth percentiles. The authors use the term *scale dependence* to describe a dependence that arises from changes in skills that affect agents differently based on their wealth level. An example of *scale dependence* are the different investment opportunities that a high wealth investor has in comparison to an investor with only little wealth. The richer investor may have the opportunities to invest in private equity or hedge funds, both investments which are known to require high initial investments. Likewise, they may be able to afford a family office in which investment professional manage their wealth portfolio. These factors lead to higher returns for people with a higher level of wealth, therefore, leading to a self-reinforcing increase in wealth inequality. In comparison, *type dependence* describes individual specific skills that lead to higher returns throughout the wealth distribution and is therefore able to explain the persistence of the wealth inequality. Serial entrepreneurs such as Elon Musk, Richard Branson or successful mutual fund managers are classical examples of *type dependence*. Recently, Fagereng et al. (2020) and Bach, Calvet, and Sodini (2020) provide empirical support for the theory by Gabaix et al. (2016). Using administrative data from Norway, Fagereng et al. (2020) start by documenting that gross wealth shares as well as asset shares within financial wealth differ remarkably across the distribution of net worth. Their analysis then shows that the return on net worth is positively correlated with the level of net worth. In a final step, the authors propose a simple OLS approach to model the average return on net worth. According to the regression results especially the portfolio shares, the leverage as well as individual fixed effects play a large role in determining the returns. Similarly, Bach, Calvet, and Sodini (2020) use administrative data from Sweden to show that the expected return on wealth is persistent and increasing in wealth.

The goal of this paper is to provide additional empirical evidence for the heterogeneity in returns on wealth by modelling their full distribution. For doing so, we use a large administrative tax data set from the canton of Bern, Switzerland. There are several factors that make our data set suitable for addressing our goal. First, the data set covers the entire population above 18 from 2002 – 2017. The large panel structure is a necessary component to measure the effect of *type dependence* on the returns on wealth. Additionally, because we cover the entire population, we have reliable data for the full distribution of wealth, including the top, who are generally underrepresented in survey data. Second, Switzerland knows a wealth tax, which makes it mandatory for the households to give a detailed description of their wealth composition, a feature that is often missing in other large panel structured data sets. Last, because we are using administrative data measurement error and underreporting of wealth information are much less severe, as tax authorities have a strong incentive to control for such effects. We measure the returns on wealth using the realized income divided by an average level of wealth from the current and previous period to take into consideration the effect of intra year purchases. We do not consider non-pecuniary returns such as shareholder voting rights or other benefits of owning an asset for two reasons. First, non-pecuniary returns are hard to measure and depend on the individuals preferences that are unobservable. Second, we are interested in measuring the heterogeneity in returns and how they can explain wealth inequality. Non-pecuniary returns have by definition no effect on wealth inequality which makes them irrelevant for the purpose of our paper. Additionally, we do not consider capital gains but focus on pecuniary income such as dividends and interest payments. We do so because capital gains are subject to high risk and may never be realised if the household decides not to sell the asset at hand. While there are ways to estimate capital gains, we could only do so for an average financial portfolio, which would disregard a households portfolio choice. In addition, not including capital gains does not jeopardize our results but yields a conservative measurement of heterogeneity, since existing literature by Fagereng et al. (2019) shows that capital gains are relatively more important for the top of the wealth distribution.

A simple descriptive analysis of our data shows that, (*i*) financial and real estate wealth are the most important wealth classes, (*ii*) the return on financial wealth increases across the distribution of net worth and this observations also holds for specific asset classes such as equity or bonds, and (*iii*) socio-demographic characteristics have an effect on the heterogeneity in returns on financial wealth. As in Fagereng et al. (2020), we then estimate the average effects of asset shares, leverage ratio, and socio-demographic variables on the return to financial wealth. In line with the existing literature, we find evidence for *scale dependence*, i.e. a statistically significant positive correlation between net worth and returns. Individuals with a higher share of financial wealth are also able to generate a higher return on average, whereas a higher share of real estate or business wealth is associated with a lower return on average. Further, we find that *type dependence* plays an important role to explain the heterogeneity. Exploiting one unique feature for a subgroup of our data set, namely the information about the amount of financial wealth invested in equity, bonds, and bank deposits, we show that *scale dependence* and *type dependence* play a more important role in explaining returns on equity and bonds compared to returns from bank deposits. However, OLS techniques only allow us to model the average effect on the return. This is a large drawback, if one is interested in heterogeneity of the returns. In order to mitigate this issue, we use distributional regression techniques developed by Chernozhukov, Fernández-Val, and Melly (2013) to model the conditional distribution of return on financial wealth. This method allows us to obtain the full distribution of returns for different quantiles of net worth conditional on all other observables. In a further step we compute the unconditional distribution of returns to isolate the pure effect of net worth. In line with our expectations, we find considerable heterogeneity in the distributions across net worth. We show that the 10th percentile of the return distribution is almost constant across all levels of net worth whereas *scale dependence* is mainly driven by the 10 percent highest returns. From the full distribution of returns for different quantiles we are able to investigate the influence of net worth on the higher moments of the return distribution. The variance of the returns increases with net worth, at the 20th percentile, the interquartile range is 50 percentage points whereas at the 80th percentile it is twice as large. Using within percentile Sharpe Ratios, i.e. the average return divided by the respective variance for each percentile, shows that individuals with more wealth take more risk, however, the increase in risk does not fully offset the higher average returns which they yield. Therefore, also the Sharpe Ratio increases across the net worth distribution raising from 0.4 at the 10th percentile to almost 1 at the very top. With regards to existing literature, our paper is closest related to Fagereng et al. (2020) and Bach, Calvet, and Sodini (2020). However, we are different in several aspects. First, we show that *scale dependence* does not only exist for returns on total net worth but is observable for more narrow asset classes such as equity or bonds. Second, we model the full distribution of returns to show that *scale* *dependence* is significantly different across the distribution. Third, we provide evidence of *scale* and *type dependence* for a new region.

Apart from being related to the literature that investigates the link between returns and wealth, our paper is also linked to the growing empirical evidence about wealth inequality in Switzerland. Comparing data on income and wealth between countries in Continental Europe and English-speaking countries, Dell, Piketty, and Saez (2007) show that, in contrast with many other industrialized countries, Switzerland used to have a relatively low concentration of wealth and income at the beginning of the last century. This changed dramatically until the 1970s when Switzerland was one of the countries with the highest level of inequality. Using similar data to ours, Foellmi and Martínez (2017) document that the income inequality has risen from 1981 to 2010 and that, at the same time, also the fraction of labor income relative to capital income has increased for the top of the income distribution. Their results are in line with previous findings by Schaltegger and Gorgas (2011) and Frey, Gorgas, and Schaltegger (2016). Kuhn (2020) finds that accounting for pension wealth has a significant negative effect on the wealth inequality in Switzerland. Focusing on the joint distribution of income and wealth, Martínez (2020) shows that the correlation between wealth and income is especially pronounced at the top using detailed tax data from eight cantons. Exploiting the socio-demographic information in her data set, she additionally provides evidence on a strong positive correlation between age and gender with net worth.

Our paper contributes to the existing literature in the following ways: (*i*) we provide detailed information on wealth and portfolio allocation across the full distribution, (*ii*) using our detailed data, we neatly describe the heterogeneity of returns across the full population and demographic factors, (*iii*) conceptually, by modelling the entire distribution of returns and evaluating the importance of scale dependence for both the conditional and unconditional distribution.

The rest of this paper proceeds as follows. In section 2, we describe the data set that we are using, and present an overview of the individuals we observe report some descriptive statistics as well as a simple portfolio composition for the distribution of net worth. In section 3 we present empirical regularities on the correlation between net worth and returns conditional and unconditional on socio-demographics. We continue with section 4 by modelling the average effect of socio-demographic variables on the return on financial wealth and assessing the importance of *scale* and *type dependence* in our data. Finally, in section 5 we discuss the influence of net worth on returns across the full distribution of returns and section 6 concludes.

2 Data

We use a large data set with administrative tax records of individual households as our main data source. The data covers all taxpayers in the canton of Bern, Switzerland, from 2002 to 2017. Starting at the age of 16, residents have to hand in a detailed tax return which includes all sources of income as well as all components of their wealth and debt. These returns are processed by the tax authorities and build the basis of our analysis. A list of factors renders this data attractive for our purposes. First, individuals can be tracked over time which allows us to tackle our analysis from a panel perspective. Second, we observe the entire population. This is crucial as it enables the precise analysis of wealth and its returns at the very tails of the distribution. Third, the data covers a long time period giving us the opportunity to estimate precise individual effects. Finally, measurement error and unreliable observations are a rare exception, since the data is checked by the tax authorities to determine the tax payments of each individual. The tax data is available at the household level, i.e. married individuals hand in only one tax record. In order to facilitate an individual specific analysis that allows us to track individuals even if their marital status changes, we follow the method by Fagereng et al. (2020) and duplicate all observations where two individuals are married and split up the income and wealth equally between the two partners. As our data covers the whole population, the results are not jeopardized by any selection biases. The only changes of the sample composition are due to migration and mortality. It is highly unlikely these causes induce a selection bias. With respect to external validity, the canton of Bern is roughly representative for Switzerland which is confirmed by the similar portfolio compositions reported in Martínez (2020), which covers roughly half of Switzerland's population. Subsequently, we start describing our data by characterizing our main variables. Later, we describe the preparation of our data. Last, we briefly discuss the individual's summary statistics and present the portfolio composition across the net worth distribution.

2.1 Variable Description

2.1.1 Wealth and Its Components

Our data set consists of five different wealth components: Financial wealth (w_{it}^f), real estate (w_{it}^r), business wealth, wealth from self-employment and additional wealth (w_{it}^a). The latter is a category that consists of wealth which is not well categorized by the remaining components such as vehicles, art, and also cash holdings, which is reported separately from financial wealth.[2] In the following discussion we will aggregate business wealth and wealth from self-employment to one category, named business wealth (w_{it}^b), as the distinction between the two components is mainly based on the legal construction of the enterprise. For a subsample of our population, we can decompose financial wealth into three subcomponents: Bank deposits (w_{it}^d), equity (w_{it}^e) and bonds (w_{it}^o).[3] For most individuals, financial assets make up for the largest share of their fortune, followed by real estate and additional wealth. Finally, a small number of taxpayers own shares of private companies. On one hand, this includes shares at limited partnerships, construction companies and business buildings. On the other hand, business wealth incorporates equity capital invested in self-owned businesses. For tax purposes, real estate is priced at a hypothetical value which underestimates the market price. We adjust for the undervaluation using a study from the tax authorities of the canton of Bern (Steuerverwaltung des Kantons Bern, 2020). The study estimates the average difference between market value and tax value for each of the 346 municipalities of the canton, looking at all housing transactions in the canton of Bern between 2013 and 2016. This allows us to adjust the real estate value on a municipality level to find a proxy for the market

[2] The full list consists of cash, gold, vehicles, boats, horses, art and shares at heritage trust funds.

[3] From 2015 onwards, this decomposition is possible for individuals filling in their tax reports online. Roughly 45% of the residents use these online tools.

value of each individual's real estate wealth. We observe financial wealth on a gross level, and a separate category for debt (d_{it}), which is negative if the individual has outstanding debt. Apart from mortgages, debt captures credits, loans and consumption debt. In the following we will refer to an individual's *gross wealth* (w_{it}^g) as the sum of all wealth components

$$w_{it}^g = w_{it}^f + w_{it}^r + w_{it}^b + w_{it}^a$$

and *net worth* to be the total gross wealth net of outstanding debt

$$w_{it}^n = w_{it}^g + d_{it}.$$

2.1.2 Income and transfers

The focus of the present paper lies on returns on wealth, defined as income from period t divided by the average wealth between period $t-1$ and t.

$$r_{it}^x = \frac{y_{it}^x}{\frac{1}{2}(w_{it}^x + w_{it-1}^x)}, \quad x \in \{f, d, e, o\}.$$

We use the average wealth level as the denominator to account for the fact that an asset receives an income flow during the year, while we only observe end of period levels of wealth. As a result, we underestimate the return if an asset was bought in period t after dividend and interest payments on the underlying asset and overestimate returns if the asset was sold in period t but after the cash flows of the same period are realised. The numerator y_{it}^x is the pecuniary income stream of asset x in period t. In terms of taxes, this sort of income constitute a part of the taxable income. Note that income from financial wealth is either subject to withholding taxes or not. For our analysis, we will aggregate the gross values, i.e. the income plus the withholding taxes since this represents the effective income from wealth.[4] At its core, financial income captures interest to deposits, bonds as well as dividends. Note that in Switzerland capital gains are not part of the taxable income and therefore not available in our data. Since we do only observe the total wealth at the end of each tax period and have no information about purchases and/or sales within the period, we are unable to compute the precise capital gains and hence do no include them in our definition of income. While there are ways to estimate capital gains based on asset market performance, we withstand from doing so for this paper. The reason being that capital gains are subject to high risk until the underlying asset is sold. Additionally, estimating the portfolio performance would be determined greatly by the overall asset market performance, thus there would surely be a mean reversion within our data set and individual performance would not be captured adequately. Finally, Fagereng et al. (2019) show that capital gains are relatively more important for the top of the wealth distribution. Therefore, our measure of returns will yield conservative results with respect to heterogeneity. Beyond these forms of income from wealth, our data covers a large range of other income sources such as labor income, income from self-employment and pension income.

[4] Assets excluded from withholding taxes include foreign equity or bonds and interest on private loans. This makes up for roughly one third of all returns on financial wealth.

2.1.3 Socio-demographics

Our data set is anonymised, nevertheless, we observe the year of birth, the marital status (single, married, separated, divorced, widowed), the number of children, and the place of residence for each individual. Since some of those variables are potentially correlated with net worth, it is important to control for them in the empirical analysis.[5]

2.2 Data construction

To ensure reliability of our estimates, we take six steps to homogenize the data. First, we exclude roughly 7.3% of our observations because they are fundamentally different than normal taxpayers. These include (*i*) individuals going abroad or returning from abroad (1.9%), (*ii*) individuals which forgot to hand in a record[6] (2.8%) and (*iii*) individuals younger than 18 or older than 100 (2.6%). Second, we exclude individual-year duplicates, which make up 0.3% of the observations. These duplicates mainly exists for an individual right after marriage or after seperation/divorce. Third, we drop individuals with impossible changes in their marital status, e.g. from widowed to single. This cleaning step affects 0.3% of our sample. Forth, we exclude cases where individuals mistype their records. In about 0.7% of all observations, we observe that income from wealth exactly equals the level of wealth.[7] These records can not be trusted, however, we do not have to exclude all observations of such an individual as these mistakes seem to be uncorrelated over time. Fifth, there may be substantial changes in financial or aggregate wealth, e.g. caused by marriage or heritage.[8] In such years, it would be delicate to calculate any returns to wealth. Thus, we keep these observations but do not calculate returns in such years. Overall, about 0.3% of all observations fall into that criterion. Finally, we label implausibly high returns as such.[9] Besides interests and dividends, payments from liquidations and gifted assets count as financial returns. These special incomes can not be compared to standard returns on wealth, however, we can not separate them in the data. As these forms of incomes are causing implausibility, our main results in sections 3, 4, and 5 are derived without these observations. In total, roughly 0.8% of our data are unreliable due to immense returns.

2.3 Summary Statistics

In table 1 we report the summary statistics of our data set, pooling the observations from all years. We report the mean, standard deviation and a few selected percentiles of the variable of interest. The data set consists of around 12 million observations over the period from 2002 until 2017 and includes data from 1,070,884 distinct individuals. The observations are almost equally distributed across years, with a small positive time trend. Panel A shows basic socio-demographic characteristics. The sample is well balanced across gender and marital status. Panel B gives an

[5] For example, Martínez (2020) finds that age is positively correlated with wealth in Switzerland.

[6] If an individual forgets to hand in their tax report they are taxed with a substantial mark-up based on their previous year's tax report.

[7] The tax authorities in Bern have confirmed that these are individual mistakes made by the taxpayer.

[8] We define a substantial change to be higher than 500'000 CHF in absolute terms and to be either a relative change of -66% or +200% compared to the previous year.

[9] We label returns higher than +/- 30% as implausibly high. Note that it practically infeasible to get return above that level by only holding deposits, bonds and equity. For returns to business wealth, we set the bar at +/- 100% as business wealth is evidently more volatile.

Table 1: Summary Statistics on Individual Level

	Mean	**SD**	**P10**	**Median**	**P90**	**P99**	**Obs.**
			Panel A: Socio-Demographics				
Age	49.89	18.59	25.00	49.00	76.00	90.00	11,962,563
Female (%)	52.38	49.94	0.00	100.00	100.00	100.00	11,962,563
Married (%)	53.71	49.86	0.00	100.00	100.00	100.00	11,962,563
Number of Children	0.48	0.92	0.00	0.00	2.00	3.00	11,962,563
			Panel B: Income				
Total Income	47,461	96,322	14,152	43,420	80,624	165,212	11,962,563
Total Labor Income	36,835	41,523	0	34,961	77,970	149,662	11,962,563
Additional Income	-1,697	42,175	-5,905	0	40	22,000	11,962,563
Pension Income	3,814	10,625	0	0	15,614	49,372	11,962,563
Social Security Income	6,603	10,117	0	0	21,468	29,064	11,962,563
Total Financial Income	2,043	76,802	0	101	2,498	25,837	11,962,563
Bank Deposits	362	7,540	0	24	356	5,786	1,115,278
Bonds	37	840	0	0	0	813	1,115,278
Equity	1,009	129,063	0	0	370	10,859	1,115,278
Real Estate Income	-494	14,966	-3,750	0	2,452	20,481	11,962,563
Business Income	358	11,677	0	0	0	1,136	11,962,563
			Panel C: Wealth				
Total Wealth	355,902	5,468,635	2	88,124	746,600	3,155,332	11,962,563
Total Financial Wealth	138,796	4,629,607	0	25,756	243,111	1,383,371	11,962,563
Bank Deposits	85,713	337,118	2,127	30,073	192,925	803,642	1,115,278
Bonds	1,671	21,397	0	0	0	42,528	1,115,278
Equity	29,543	998,596	0	0	30,135	444,931	1,115,278
Real Estate	199,753	1,094,191	0	0	522,748	1,837,412	11,962,563
Additional Wealth	10,005	265,316	0	0	9,100	164,030	11,962,563
Business Wealth	9,482	143,540	0	0	0	239,414	11,962,563
Debt	-90,841	419,768	-269,500	0	0	0	11,962,563
			Panel D: Returns on Wealth				
Financial Wealth (%)	0.91	17.37	0.04	0.55	1.76	5.18	8,959,646
Bank Deposits (%)	0.33	29.81	0.00	0.07	0.48	2.18	648,732
Bonds (%)	2.15	7.39	0.39	1.47	3.83	11.43	15,213
Equity (%)	2.81	13.66	0.00	1.50	4.55	26.17	175,152
Business Wealth (%)	6.10	37.80	0.00	0.03	1.84	160.37	679,218

Note: The summary statistics cover the entire population in the canton of Bern, Switzerland, above the age 18 pooling data from 2002 – 2017. We exclude specially taxed people, i.e. individuals going abroad or returning from abroad, people who forgot to hand in their tax report, and people with obvious mistakes in their tax report.

overview of the individual's income. Total income captures all taxable income after deductions. The main source is labor income with an average of around 33,942 CHF. This is followed by social security payments and pension income. Our main focus lies on financial income and its subcomponents which are used to compute the returns on the individual assets. Around 80% of the observations report a positive level of financial income. Financial income is not the most important source of income, nevertheless, it accounts on average for almost 5% of the total income.

In panel C, we report the statistics for all components of wealth. On average the most important assets held by an individual are financial wealth and real estate. More than half of the observations report no wealth in real estate. This is typical for a Swiss data set as the majority of the population does not own real estate but is renting instead.[10] We find business wealth to be the least important asset on average and less than 10% of the observations report a positive entry for that asset class. For the individuals of whom we have more detailed information about their financial wealth for the period 2015 – 2017, we find that the median tax payer holds no financial assets apart from bank deposits.[11] Finally, panel D displays the return on different assets. Within our sample, the average return to financial wealth is 0.91% across the entire sample period. There is a large heterogeneity within the sample, as the percentile range between the 10th and the 90th percentile with 5.14 percentage points shows. As one would expect, this is mainly driven by the large differences in returns to business wealth and equity. Interestingly, we find in unreported results that the large variation in total financial wealth is almost equally shared between and within individuals, whereas for business wealth the main driver of the variation is the between variation. Overall, we note that our summary statistics are similar to the one previously found for Switzerland (Martínez, 2020).

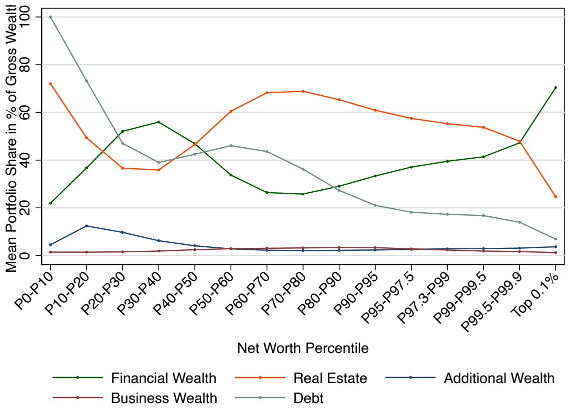
2.4 Portfolio Composition

Figure 1 show the portfolio composition of the average individual across different percentiles of net worth including the very top of the distribution. The figure shows the average asset position as a share of the average gross wealth held by an individual at a specific percentile of net worth. Individuals at the 10th percentile hold, on average, around zero net worth. A median person of our data set has on average a net worth of approximately 60k CHF and a gross wealth of around 110k CHF. Approximately 40% of its gross wealth is invested in financial asset. For the bottom half of the distribution the majority of its wealth is held in financial assets. However, even at the bottom half of the distribution we find a relatively large share of the portfolio is invested in real estate but accompanied with a large outstanding term debt. For individuals around the median net worth, real estate is on average the most important asset of their portfolio and they hold smaller mortgages on their house compared to the bottom half of the distribution. Financial wealth on the other hand becomes less important. This observation remains true until we reach the very top of the distribution. For individuals at the top of the net worth distribution, financial assets make up the largest share of their portfolio and debt plays only a minor role. Interestingly, in our data set business wealth is irrelevant for the average person at each percentile of the distribution, although for an individual observation it may be a large share of its portfolio. Note that we cannot differentiate between public equity and private equity, i.e. financial wealth is a mix of both which implies that the share of business wealth may be underestimated for the richest individuals who hold shares of larger more complicated legal enterprises in their financial portfolio. In addition to the overall portfolio composition we can decompose the financial portfolio into three broad categories (equity, bonds and bank deposits) for a subsample of our data. We report the allocation of financial assets in section A of the appendix.

[10] see Martínez (2020) for similar results.

[11] In total we have 1,115,278 observations with detailed data from 436,022 distinct individuals. As in the main data set, the observations are almost equally distributed across years.

Figure 1: Portfolio Composition across the Net Worth Distribution



In the following we turn our attention to some empirical regularities observed in the data. We first focus on the unconditional correlation between total net worth and returns. Later we discuss the implications of risk taking and socio-demographic variables.

3 Empirical Regularities and the Influence of Socio Demographics

In this section, we present some empirical regularities within our data set that motivate the modelling approach in the following section. First, we discuss the heterogeneity in returns on financial wealth across different percentiles of net worth. We then show that even within narrow asset classes there is a strong correlation between net worth and financial returns. Later, we discuss the connection between socio-demographic variables and financial returns and argue why it is important to control for these variables when modelling the returns on financial wealth.

3.1 Average Returns Increase with Total Financial Wealth

In table 2 we report the average return on specific asset classes of financial wealth for selected percentiles of net worth, using the entire data set from 2002 − 2017 or 2015–2017, respectively. For each asset class returns are computed for all individuals who hold at least 500 CHF in the corresponding asset at $t-1$ and t. Individuals are ranked in every year based on their net worth, conditional that they surpassed the minimum level of wealth for the asset of interest. We report the average return across individuals and year within the given percentile. Note that while this procedure yields more meaningful results because we only look at individuals invested in the asset, it makes it difficult to compare the returns between different asset classes. This follows from the fact that individuals may change their relative rank in the net worth distribution because the overall sample of individuals differs across asset classes. This is true in particular when comparing the returns between bonds and the remaining assets as only a small share of individuals are invested in bonds, with high net worth individuals being overrepresented for that asset class.

Table 2: Average Return for Selected Percentiles of Net Worth

	Total Financial Wealth (%)	Equity (%)	Bonds (%)	Bank Deposits (%)
$P(w_{it}^n) = 5$	0.4	1.6	1.4	0.2
$P(w_{it}^n) = 25$	0.6	1.9	1.5	0.2
$P(w_{it}^n) = 50$	0.8	2.0	2.1	0.2
$P(w_{it}^n) = 75$	0.9	2.4	2.0	0.2
$P(w_{it}^n) = 90$	1.1	2.8	2.5	0.3
$P(w_{it}^n) = 95$	1.3	3.3	2.2	0.3
Top 1%	1.8	3.3	3.5	0.6

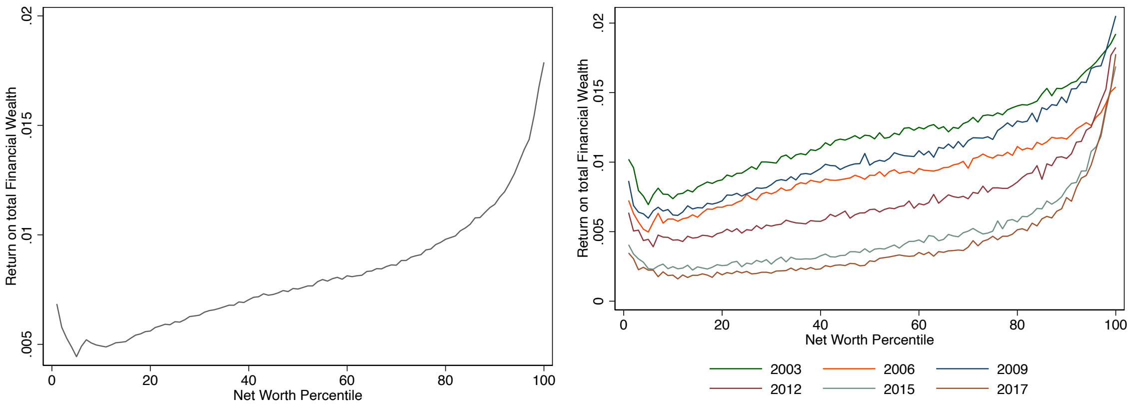
Note: Percentiles are computed for each asset seperately, conditional on an invidual holding an average level of wealth above 500 CHF. The reported returns are the average within each group.

In the previous section we document in table 1 that the average before-tax return on financial wealth is 0.91%, with substantial heterogeneity. We observe a standard deviation of 17.37 and the median return is given by 0.55% compared to a return of 5.18% for the 99th percentile of the distribution. Considering the net worth of an individual, column 1 of table 2 shows a first empirical regularity, namely a strong positive correlation between net worth and financial returns. A similar finding has previously been documented by Fagereng et al. (2020) and Bach, Calvet, and Sodini (2020) using a similar data set with Norwegian and Swedish tax payers respectively. The top 1% in our data set make a return on financial wealth that is more than two times the size of the median household, and almost five times larger than the bottom 5%. These differences are substantial, and imply that if an average household in the top 1% of the distribution invests 1 CHF in financial assets at the age of 25, her investment will have a level that is more than 50% higher at her retirement age of 65 compared to the median household.

Part (a) of figure 2 is the graphical counterpart to table 2 and shows the average return on financial wealth across all quantiles of total net worth. We find the typical shape of returns on financial wealth previously documented by Fagereng et al. (2020) and Bach, Calvet, and Sodini (2020). In part (b) of figure 2 we show the evolution of returns within the observed period from 2003 – 2017. The most predominant observation that we make, is that the average return on financial wealth steadily decreased over the past few years, this is in line with the LIBOR rate going to zero and the subsequent fall of the nominal interest on long term investments. This led to a more important role of public and private equity, an asset that is mostly held by the wealthier household (see figure 11 in appendix A), while, at the same time, increasing the prices of equity due to lower discount rates. We find that the heterogeneity in returns has decreased between 2003 and 2017 for the households up to the 80th percentile of total net worth. However, in the same time period, the difference in returns at the top of the distribution has increased heavily, leading to a situation where the top 5% of the distribution earn a return that is about four times higher than the return earned by the 80th percentile of the distribution. As we mentioned in section 2 all returns are computed by realized returns, without capital gains. Considering that the SPI (a Swiss Stock Index, covering the most important listed companies in Switzerland) had an average yearly return of around 7.5% during the same time period, our results can serve as a lower bound for the true heterogeneity. This is based on the fact that the average share of equity and bond holdings strictly increase as we move further to top of the net worth distribution, implying that the richest would be more affected by the inclusion of capital than the bottom of the distribution.

Figure 2: Average Return on Financial Wealth across the Financial Wealth Distribution

(a) Over the entire sample   (b) For specific years



3.2 Systematic Risk Taking Plays an important Role

Focusing on a more detailed description of the returns on financial wealth, we turn our attention to the most important subcomponents of financial wealth holdings. Given the data set at hand we can divide the total financial assets into three broad categories: Equity, Bonds and Bank Deposit. We use this information to shed more light on the source of heterogeneity in returns to financial wealth we reported in section 3.1.

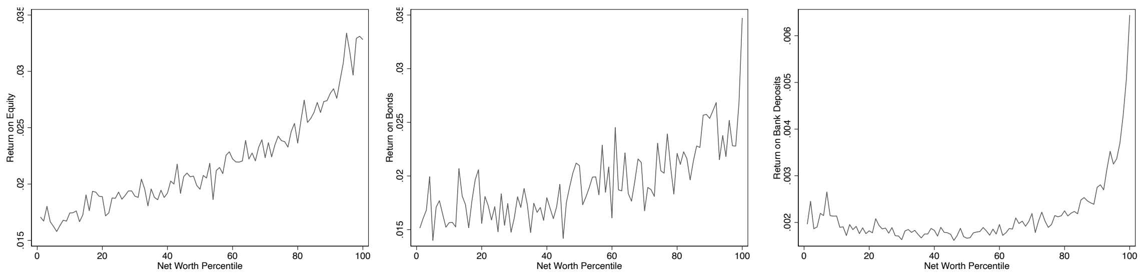
Columns 2 − 4 of table 2 report the returns for the three subgroups of financial wealth for a few selected percentiles of net worth. Overall, equity yields the highest return, compared to bonds and bank deposits although the top 1% of the net worth distribution have similar returns for both equity and bonds.[12] While some of the heterogeneity in financial returns can be explained through the different portfolio compositions we have displayed in figure 1 there is still a strong correlation between net worth and returns on individual asset classes. The two effects combined yield the strong heterogeneity in returns that we report in column one of table 2. The median individual holds on average less than 20% of its financial wealth in equity compared to the top 1% who hold more than half in either public or private equity. In addition, wealthier households make a significantly larger return on their risky asset. This is an indication that, while some of the differences may be explained based on different risk attitudes, a non-negligible contribution may be due to the better performance of high net worth individuals across all investment opportunities. Figure 3 gives a more detailed insight to the heterogeneity in returns on the different components of financial wealth. The figure looks very similar compared to the returns on total financial wealth, though the levels of return vary across the different groups. We find that even for the safest asset of the three, bank deposits, wealthy individuals are able to generate a higher return. A possible

[12] Note that only a small portion of the individuals hold bonds with the majority in the top end of the net worth distribution. As we compute the percentiles conditional on an individual holding on to at least 500 CHF of the specific asset the different groups are not perfectly comparable.

explanation may be that wealthy households have a smaller liquidity constraint, enabling them to invest into saving accounts rather than checking accounts.

Figure 3: Average Return on specific assets across the Financial Wealth Distribution

(a) Equity (b) Bonds (c) Bank Deposits



Note: On the x-axis we show all quantiles of the financial wealth distribution, conditional that the household holds the specific asset.

3.3 Differences across Marital Status

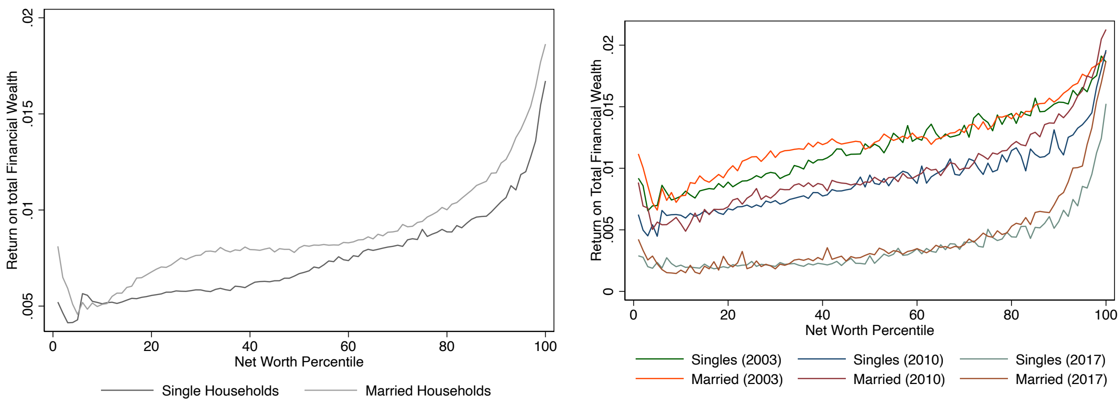
In figure 4 we report the differences in returns on total financial wealth for single and married individuals. We find that married individuals are able to achieve a higher return on average for all percentiles of the net worth distribution. However, looking at separate years individually we notice that the difference in returns has shifted over the years. While married individuals in the lower part of the distribution were able to generate a higher return in the years before 2010, this difference has perished over time. For the most recent year, we find that both single and married individuals generated the same level of return with an average return of around 0.25%. The opposite is true for the top of the distribution. It seems that married individuals generated a higher return in 2010 and 2017. A possible reason for the observed difference is the long term horizon for married individuals. Singles are exposed to more risk as they are unable to share income shocks between each other. This makes them vulnerable for sudden changes in income which may restrict their investment horizon on different assets. Put differently, single individuals with low financial wealth are unable to take the same risk as their married counterparts which might lead to the observed difference in returns.

3.4 Differences across Age Groups

We divide the population into four distinct groups conditional on their age. For that purpose, we chose three thresholds by which we separate our sample population: All individuals below the age 35 (*young*), between 35 and 49 (*middle aged*), between 50 and 64 (*senior workers*), and individuals from 65 and older (*retired*). In figure 5 we plot the four groups together. We find almost no difference in returns across all age cohorts which suggests that age is not a suitable indicator for financial experience. The biggest difference, we find is between the top net worth individuals who are middle aged and retired. The explaining factor may the different investment horizons of the separate groups. While middle aged workers are saving for their retirement they may choose to invest in volatile assets as they are less exposed to short term price changes. On the other hand

Figure 4: Average Return on Financial Wealth for Single and Married Households across the Financial Wealth Distribution

(a) Over the entire sample (b) For specific years



retired individuals have generally little to no labor income which makes them rely more heavily on their financial portfolio to finance consumption. This makes them more exposed to sudden changes in asset prices which may lead to a more conservative portfolio allocation. This factor is less prominent for individuals at the lower part of the net worth distribution due to their financial restrictions. In particular for middle aged and young individuals at the lower part of the distribution the liquidity constraint may be a more important driver for their portfolio allocation. Given their age they may be saving for costly durable goods such as real estate or vehicles which restricts them from investing into long term investments. Overall, we document only small differences in financial returns across the four different age groups.

Figure 5: Average Return on Financial Wealth for Different Age Groups

Note: We divide the population into four groups: individuals below the age of 35, from 35 to 49, from 50 to 64 and above the age of 64. We control for separate years, when constructing the net worth percentiles and show the average return for each percentile.

In a next step we use different econometric modelling tools to estimate the effect of net worth, portfolio allocations and socio-demographics on returns to wealth.

4 Modelling Average Effects on Returns to Wealth

In this section, we aim at modelling individual returns on wealth for financial assets. In contrast to the previous section where we computed average returns for specific quantiles, we now introduce formal models to analyze how returns depend on observables. In a first step, we use classical OLS techniques to identify average effects on returns.

In the spirit of Fagereng et al. (2020), we regress returns on different assets r_{it} of individual i in year t on a set of covariates denoted by X_{it}. The latter includes information on marital status, gender, age, number of children, the logarithm of total net worth, portfolio composition and yearly indicator variables.[13] Based on the results of the previous section, we suspect that the level of net worth is a strong predictor for high returns. This would correspond to *scale dependence*, that is, higher wealth correlates with higher returns. However, it is a priori unclear whether this relation holds once we control for the socio-demographic variables. Formally, the linear regression model is represented in the following equation.

$$r_{it} = X'_{it}\beta + \epsilon_{it} \tag{1}$$

Beyond *scale dependence*, Gabaix et al. (2016) suggest that *type dependence*, the presence of high growth types, is a determining factor of returns. We tackle this issue by including individual fixed effects into the regression model from equation (1). In essence, individual fixed effects account for the persistence of returns. Comparing the two type of models, with and without individual fixed effects, we are able to deduce which type of dependence exist in the data. Note, that all time invariant variables are omitted once we control for individual fixed effects. However, we keep net worth as predictor because potential changes in wealth may drive returns. For our baseline exercise we choose r_{it} to be the return on financial wealth (r^f_{it}). In addition we run the same exercise for the three broad categories of financial wealth that we can identify. Namely for the return on bank deposits (r^d_{it}), equity (r^e_{it}) and bonds (r^o_{it}). Accordingly, Table 3 presents the estimates of the baseline model with and without fixed effects and table 4 for the subgroups of financial wealth.

As one might expect, we show in column (1) that only 5.2% in the variation of the return on financial wealth can be explained by year fixed effects. Moving to column (2) we see that net worth not only has the expected positive impact, but is also of large economic relevance. A 1% increase in net worth would predict an increase in financial returns by more than ten basis points on average. In addition to net worth the most relevant predictors for financial returns are the individual portfolio compositions. A larger share in financial wealth predicts an increase in returns, the same is true for a higher leverage ratio, computed as the ratio of total debt to gross wealth. The opposite findings are made with real estate and business wealth, while the latter

[13] We use the logarithm as net worth is highly skewed to the right as described in the previous sections. This has the drawback that we can only use individuals with positive net worth. As a robustness check we do the same exercise using the net worth percentile ranks, which allows us to use the full data set. The results are qualitatively unchanged and reported in table 7 of the appendix.

Table 3: Average Effects: Scale and Type Dependence

	Without Individual FE		Including Individual FE	
	(1)	**(2)**	**(3)**	**(4)**
ln(Net Worth (CHF))		0.00176***		0.00093***
		(0.000)		(0.000)
Share in w_{it}^{f}		0.00264***		0.00122***
		(0.000)		(0.000)
Share in w_{it}^{r}		-0.00249***		-0.00094***
		(0.000)		(0.000)
Share in w_{it}^{b}		-0.00024***		-0.00001
		(0.000)		(0.000)
Leverage Ratio		0.00324***		0.00133***
		(0.000)		(0.000)
Socio-Demographics	no	yes	no	yes
Year FE	yes	yes	yes	yes
Ind. FE	no	no	yes	yes
R^2	0.052	0.105	0.398	0.412
adj. R^2	0.052	0.105	0.335	0.349
N	8,875,289	8,462,780	8,816,922	8,401,047

Note: The outcome variable is individual returns on financial wealth r_{it}^{f} in all columns. All models additionally include a constant. Standard errors clustered at the individual level in parentheses, *** $p < 0.001$ ** $p < 0.01$, * $p < 0.05$. The data set is cleaned as described in section 2.

has only a small economic relevance. There are different possible reasons for this finding. First, individuals may have more sophisticated portfolios if a large share of their net worth is invested in financial assets, this may allow for better diversification which leads to higher returns on average. Second, individuals with high financial shares might choose to seek riskier investment opportunities because they have a smaller demand for liquidity as they are less exposed to risk that occurs from unexpected damage to the house or their own business. Last, it may be that some effect that is due to *scale dependence* may be captured by the share in financial assets, which is positively correlated with net worth. Similar explanations may cause the negative effect of real estate shares. Individuals with high exposure in real estate may choose to hold less risky financial assets to satisfy the demand for liquid assets.[14] Regarding the leverage ratio, we reason that households with more long term debt are able to exploit the low nominal interest rates to invest in riskier financial assets. This allows them to earn higher returns on their financial wealth while financing it with relatively cheap borrowings. In addition high leverage ratios are negatively correlated with high net worth, and may capture some of the effect due to *scale dependence.*

Before, we turn to the regression with fixed effects we briefly discuss the role played by the socio-demographic variables. Based on the findings in section 3 we have seen that socio-demographics may play an important role to predict the returns on financial wealth. While all socio-demographic variables except age are statistically significant, only marital status has an economically relevant. Married individuals have, ceteris paribus, an average return that is 10 basis points higher compared to their single counterparts. Similar to the argument we have stated previously, we consider the demand for liquidity to be the most important factor to drive these results. Single households are

[14]We can control for the risk exposure of the financial portfolio using only a subsample of the data set. The coefficients for the share in both financial assets and real estate are significantly smaller in absolute terms. This is an indication that the demand for liquid financial assets such as bank deposit is inversely related to the share in financial wealth.

more exposed to income shocks and have higher fixed costs (such as rent and insurance payments) compared to married households. This is likely causing them to hold less risky assets and invest a higher share of their financial wealth in bank deposits. Shifting our attention to column (3) and (4) we first need to discuss what individual fixed effects are capturing. We follow the arguments of Fagereng et al. (2020). They present three different categories that may be captured by the fixed effect: the fixed effects (*i*) capture the persistent difference in risk tolerance, (*ii*) the persistent differences in net worth and the positive effect of wealth on returns (Piketty, 2014)) and (*iii*) the persistent difference in financial sophistication, ability to access information on financial markets and other persistent individual characteristics (such as intertemporal discounting). Further, as we have a mixture of public and private equity as part of the financial assets we may also capture persistent differences in entrepreneurial skills. All of the aforementioned persistent differences may affect the return of an individual portfolio conditioning on the size of their net worth.[15] Given the large increase in the explained variation of the returns (measured by the adjusted R^2) our data suggests that all of the three effects coexist. Indeed, we find that even after controlling for the persistent difference in net worth the scale of the portfolio positively correlates with high returns. Further, we show with a subsample of our data set in section B that conditional on risk exposure and the level of net worth there is a large difference in the explained variation of returns. We take this as evidence that financial sophistication and access to private equity have a positive effect on the individual returns as it would otherwise be hard to justify the large difference in the adjusted R^2.

Table 4: Average Effects: Scale and Type Dependence for Returns on Different Asset Classes

	r^d_{it}		r^e_{it}		r^o_{it}	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ln(Net Worth (CHF))	0.00039***	0.00011*	0.00323***	0.00135**	0.00361***	0.00350**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Share in w^f_{it}	0.00025**	0.00032	0.00097	-0.00030	0.00495*	0.02754
	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.014)
Share in w^r_{it}	-0.00101***	0.00015	-0.00561***	-0.00174	0.00024	0.01900
	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.014)
Share in w^b_{it}	-0.00054**	-0.00020	0.00721***	0.00084	0.01381**	0.00905
	(0.000)	(0.001)	(0.002)	(0.005)	(0.005)	(0.027)
Leverage Ratio	0.00102***	0.00050*	0.00580***	0.00061	0.00924***	0.00748
	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.006)
Socio-Demographics	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Ind. FE	no	yes	no	yes	no	yes
R^2	0.006	0.691	0.020	0.807	0.034	0.842
adj. R^2	0.006	0.381	0.020	0.613	0.033	0.683
N	609,738	547,880	168,620	148,826	15,060	12,240

Note: Standard errors clustered at the individual level in parentheses, *** $p < 0.001$ ** $p < 0.01$, * $p < 0.05$.

[15] For a subsample of our data set we can also condition on the risk exposure of their portfolio by taking into account the different shares invested into bank deposits, equity and bonds. In section B we show that the effects are qualitatively the same and the following conclusions go through.

Using a subsample of our data set, namely observations from 2015 – 2017 for whom we have a detailed composition of their portfolio, we redo our previous regression analysis using the return on deposits, on bonds, and on equity as dependent variables. Note that in this case the fixed effect models are equal to a cross-sectional first difference. The results of this analysis are displayed in table 4[16]. For all three types of returns we find similar result to the overall portfolio. This is another indication that even after controlling for the riskiness of an asset, the size of net worth plays an important role to predict an individuals return. The coefficient of net worth is weakest for the return on bank deposits. There are two reasons for that. First, bank deposits yield on average the lowest return and second, there is little that the investor can do to impact the return on bank deposits. This is reflected in the smaller increase in the explained variation after including fixed effects. Indeed, the only options an investor has is to choose the bank whom they want to work with and how much of the wealth to invest in a saving account rather than a checking account. After controlling for the individual fixed effect the only covariate that is a significant predictor for high returns is the individual's level of net worth, a strong indication that *scale dependence* is an important factor that drives the return on financial assets. Compared to the benchmark case in table 3, we find a stronger increase in the adjusted R^2 for the different asset classes. This suggests that conditional on the level of net worth and the risk exposure of the individual, financial sophistication plays an important role on returns.[17]

Overall the simple regression analysis shows that both *scale* and *type dependence* co-exist and are crucial factors to determine the return of different investment vehicles. These results are consistent with the previous findings of Bach, Calvet, and Sodini (2020) and Fagereng et al. (2020) who do a similar exercise with a Swedish and Norwegian data set, respectively. Considering that this simple model can only capture average effects and that we have seen the returns to be very heterogeneous across the distribution, we continue our analysis looking not only at the marginal effect at the average but rather model the entire distribution of returns. In the following subsection we discuss the different effects across the distribution with a focus on the impact of *scale dependence*.

5 Modelling Distributional Effects on Returns to Wealth

In principle, the effects presented in the section 4 may vary across different levels of the returns. If so, we would neglect this heterogeneity by only running ordinary regressions. Thus, we introduce a more flexible and comprehensive approach in the following. In essence, we are isolating the effect of net worth on the returns on financial wealth throughout the distribution of the latter. Thereby, we will control for the same set of regressors as in the previous section. Note that it would be possible to isolate any effect of an observable, yet, we are most interested in the pure effect of net worth. This will enable us to estimate the importance of *scale dependence* across the distribution of returns. We will model the conditional distribution of returns using Distribution Regression (DR) techniques developed by Chernozhukov, Fernández-Val, and Melly (2013). Formally, equation (2)

[16] We do not report the full table including all socio-demographics as they do not yield any additional information. In table **??** in the appendix we report the result after controlling for detailed portfolio allocation. However, note that the interpretation of the different shares is no longer clear as the dependent variable is already the return of a specific asset.

[17] Note that when the dependent variable is the return of a specific asset, we implicitly control for the riskiness of the asset.

introduces this approach.

$$F_{r_{it}|X_{it}}(y) = \Lambda(X_{it}'\beta(y)), \tag{2}$$

where $F_{r|X}(y)$ denotes the cumulative distribution function (CDF) of r_{it} conditional on a matrix of regressors X_{it} at a threshold y, Λ is a parametric link function (e.g. logit or probit) and $\beta(y)$ is a coefficient vector. The estimated coefficients in (2) provide information on how a covariate shifts the CDF of returns at a certain threshold. Note that this is a semi-parametric approach in the sense that $\beta(y)$ varies with the thresholds. This is, we allow the effects of the regressors to vary across the distribution of r_{it} which generates a high degree of flexibility. Compared to other methods that aim at distributional effects, DR does not require the outcome to be continuous. For a more profound documentation of DR, the reader may consider the influential work by Chernozhukov, Fernández-Val, and Melly (2013).

Conceptually, our goal is to draw conclusions on the effect of net worth only. Therefore, we need to translate effects at the conditional distribution of r_{it} into unconditional effects. Equation (3) derives the unconditional CDF from the conditional one in equation (2).

$$F_{\langle r|w_{it}^n=\cdot\rangle}(y) = \int_{\mathcal{X}} F_{r_{it}|X_{it}}(y)dF(\mathcal{X}). \tag{3}$$

In a nutshell, we integrate over the covariates to eliminate the effects of all regressors in X_{it} apart from net worth, w_{it}^n. With respect to the latter, we artificially set w_{it}^n to specific values to get the distribution of returns which then only depends on w_{it}^n. We denote this modified covariate distribution by $\mathcal{X}$. For instance, $F_{\langle r|w_{it}^n=10,000\rangle}(y)$ denotes the CDF of returns on financial wealth provided that all individuals would hold 10'000 CHF of net worth. Setting net worth to its values at the unconditional quantiles $q \in (.01, .99)$ we obtain a distribution of returns at every quantile of net worth. As these distributions are hypothetical, we will refer to them as counterfactuals hereafter. In essence, we model the distribution of returns for each quantile of net worth. In the following, we will present two sets of results. In subsection 5.1, we elaborate on how the distribution of returns to financial wealth depends on net worth. In a second step, we will discuss in subsection 5.2 how different sets of covariates alter the effect of net worth on the returns.

5.1 Distribution of Returns by Net Worth

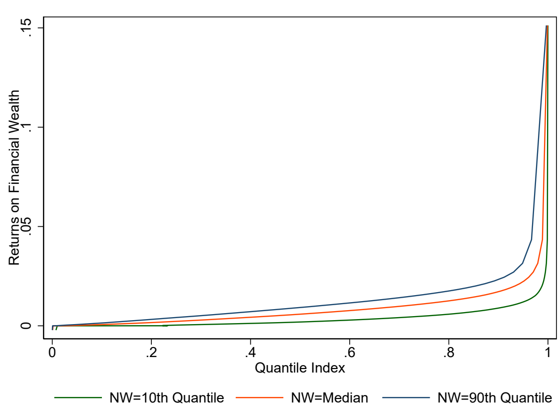
The analysis in this subsection rely on the full sample and a benchmark model including the same covariates as the OLS regression models above. In a first step, figure 6 describes the distribution of returns for three different levels of net worth: The 10th (2,646 CHF), 50th (105,325 CHF) and 90th (685,381 CHF) quantile of net worth.[18] Both panels of figure 6 present functionals of the counterfactual distributions in equation (3). We obtain the quantile function by taking the left inverse of the distribution function. To get the probability mass function (PDF) we do have to differentiate the CDF with respect to the support.[19] In the left panel, we observe that the quantile function of returns is shifted upwards for higher levels of net worth. Further, the shift seems largest

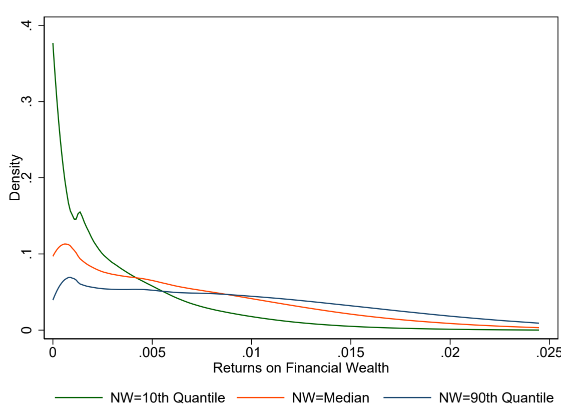
[18]For the counterfactual distributions, we use the percentile values of 2017.

[19]Note that the PDF is consistently estimated but at a lower rate of convergence. For more details on this issue, see Rothe and Wied (2020).

for the top quantiles of returns. This is a first indication that net worth drives all returns, but has a relatively stronger impact on the highest returns. On the other hand, the PDF illustrates that for high levels of net worth, we only observe few low returns. Instead, net worth increases the number of average and top returns by a substantial amount.

Figure 6: Distribution of Returns for Specific Values of Net Worth



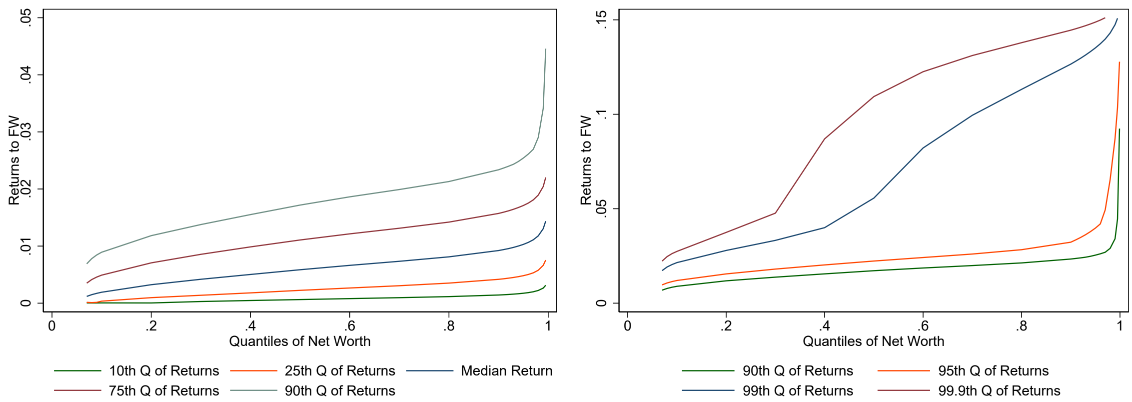


In the following, we consider the full distribution of returns at all quantiles of net worth. The left panel of figure 7 visualizes how specific quantile values of the returns change depending on net worth. This figure implies two patterns. For higher levels of net worth, the distribution of returns is (i) more wide spread and (ii) more skewed. Both suggest that net worth changes the distribution of returns. The higher variance of returns towards the top levels of net worth can be interpreted in several ways. For instance, wealthier individuals may be able to take higher risks that lead to more volatile returns. Alternatively, the wealthy are likely to hold more diversified portfolios that include higher shares of equity. As equity is generally more volatile than bank deposits, this would imply a higher variance on returns. Largely, these arguments support to the ones in the previous sections. In any case, we observe that the heterogeneity of the returns due to net worth is more pronounced for high levels of net worth. The right panel of figure 7 illustrates the relationship between returns and net worth at the top quantiles of the returns. In particular, the very top quantiles of returns experience a major increase once we move along the distribution of net worth. The values of the 99.9 quantile of returns demonstrate that distribution of returns is highly skewed and largely driven by net worth. This relates to the literature on wealth inequality by showing that the very rich have higher average returns, but more importantly, they potentially gain extensively high returns. On the other hand, for moderate levels of wealth the possible gains are limited.

Finally, we would like to highlight how modelling the distribution of returns may generate novel insights. For this purpose, we compute the well-known Sharpe Ratio (SR) for all counterfactual distributions indexed by values of net worth. The SR is seen as a simplified measure of risk adjusted returns. Formally, the SR is defined as the quotient of the average return and the standard deviation. As we have estimated the full distribution our method allows us to compute the SR for all quantiles of net worth. According to figure 7 net worth increases the average and

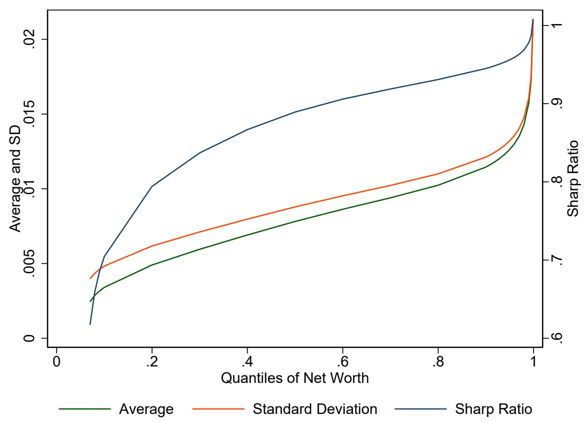
Figure 7: Distribution of Returns by Quantile of Net Worth

(a) Full Distribution (b) Top Quantiles



variance of returns. Thus, it is a priori unclear whether net worth drives the SR. In principle, the variance may account for the substantial risk that is taken by the wealthy and thus yield a lower SR. Figure 8 describes the average, standard deviation, and SR of returns by quantile of net worth. We find that the standard deviation and the average co-move tightly and the variance does not disproportionately increase for top levels of net worth. As a result, adjusted for the higher risk that they take, the wealthy still gain a higher return.

Figure 8: Sharpe Ratio



Taken together, our findings provide two novel insights. (i) A larger stock of net worth increases all quantiles of the returns. Similarly, the variance is substantially higher at the top values of net worth. This is in line with what we have found in the previous section. (ii) The increase in returns is largest at the top quantiles. We offer two potential explanations for this pattern. First, risk taking could be a key element. Very low returns may not be increased by any amount of wealth as these portfolios consist of deposits only. For wealthy individuals, additional wealth may be of substantial gain as more can be invested into risky assets, keeping the buffer fixed. An alternative explanation could be that individuals may not share the same information. Likely, at the bottom of the distribution, individuals have no experience with equity. Hence, additional wealth would not be invested in equity or bonds and would therefore not yield a higher return. Similar to the argument involving risk, the marginal gain of additional wealth may be highest at the top quantiles as these individuals are likely to be best informed.

5.2 Towards the Immediate Effect of Net Worth

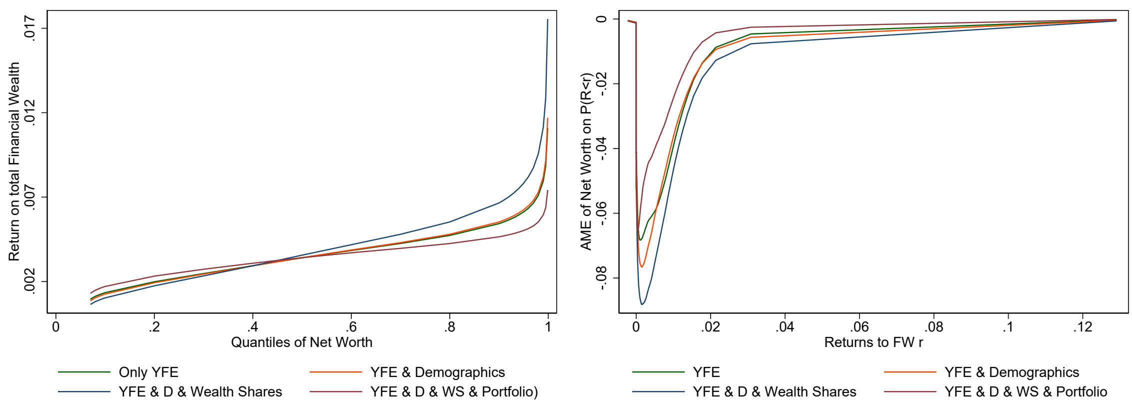
This subsection relies on information about the composition of the financial portfolio. Thus, we only use the sample period from 2015 to 2017 which incorporates these characteristics.[20] The primary goal of this exercise is to discuss the channels through which net worth affects returns. More precisely, we focus on how the heterogeneity in returns due to net worth changes for different sets of covariates.

We start the discussion of the results by comparing the average return across different levels of net worth. Figure 9 shows how different model specifications alter this relationship. We consider three set of control variables: (*i*) Demographic variables, (*ii*) shares of wealth classes of gross wealth, and (*iii*) shares of bonds and equity of total financial wealth. The demographic variables include age, gender, number of children and marital status. Further, we include the following shares of total wealth: business wealth, real estate wealth, financial wealth, and leverage ratio. Note that in this setting including covariates serves the purpose to approach the immediate effects of net worth. By equation (3), we compute the distribution of returns that only depends on net worth. Thus, the presented results do no longer explicitly depend on the included control variables. Instead, a large difference between the models would imply that the included covariates correlate with net worth and thus alter the unconditional effect of the latter.

Figure 9: 4 Models for the Unconditional Effect of Net Worth

(a) Average Return by Quantile of NW

(b) Average Marginal Effect



The left panel of figure 9 shows that net worth increases the average return to financial wealth irrespective of the model specifications. Thus, we observe a scale effect of net worth even when we account for other channels driving the returns. Yet, the heterogeneity in returns depends on the included covariates. While the demographic variables do not significantly alter the effect of net worth, the contrary is true for the wealth shares and portfolio composition. First, we consider

[20] Qualitatively, we get the same results using the full sample period for the models not involving portfolio shares. This set of results can be found in Appendix C.

the inclusion of the wealth shares. The results of the previous sections implied that (*i*) a larger share of real estate wealth decreases returns and (*ii*) a larger share of financial wealth increases returns. Further, (*iii*) figure 1 suggests that wealthier individuals are more invested in real estate and hold fewer assets in financial wealth. Due to (*i*) and (*ii*), these individuals tend to gain lower returns. Thus, not including the wealth shares underestimates the immediate effect of net worth. The converse is true once we control for the shares of equity, bonds and bank deposits. Wealthier individuals hold larger shares in equity and bonds which boosts returns. The direct effect of net worth is thus lower as part of the higher returns stems from a beneficial portfolio composition and higher risk taking by the wealthy and is not due to a scale effect.

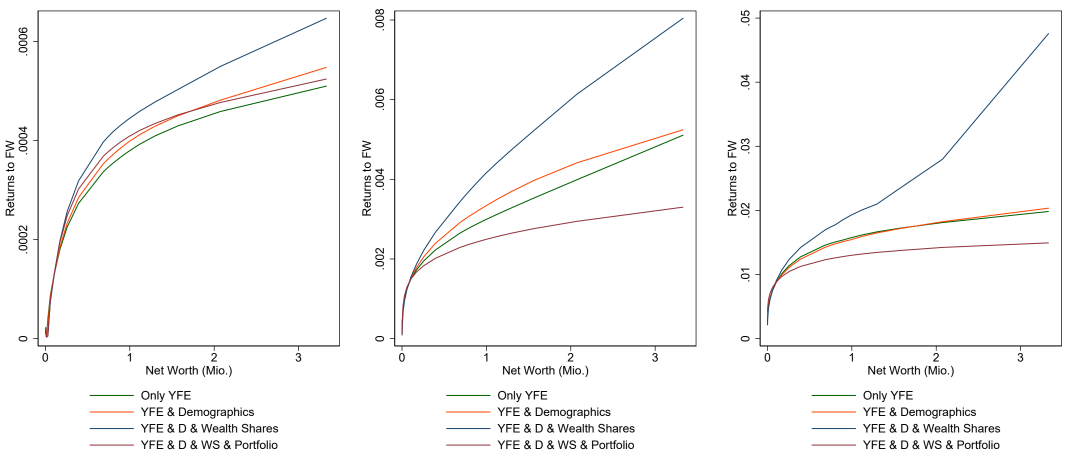
Next, we turn to the marginal effect of net worth. Compared to standard regression models this parameter represents the analogue to a OLS slope coefficient. The right panel of figure 9 illustrates how net worth affects the probability to gain a return lower than r, the value on the x-axis. Intuitively, a higher value of net worth leads to a lower probability for low returns. Thus, individuals with high net worth are less likely to end up with a low return. Being in line with the implications from the left panel of figure 9, the negative effect of net worth is strongest once we control for the wealth shares. Accounting for the effects of the financial portfolio shares weakens the immediate effect of net worth. Based on figure 9, we observe that several covariates alter the channels through which net worth drives returns. In the following, we investigate whether these patterns vary across the distribution of returns.

In the previous figure 9, we discussed the average return by quantile of net worth. In contrast, we will now model the 10th, 50th and 90th quantile of returns. In addition, we present the returns computed by values in CHF to ease the interpretation of figure 10. The results in figure 10 suggest two conclusions. First, the discussed relations across the included sets of covariates are qualititatively independente of the levels of returns. Second, the model specification matters most at top values of net worth. To see this, consider the returns predicted by the model with all but the financial portfolio composition (blue line) and the full model (red line). An individual holding 100'000 CHF (median) gains roughly the same return throughout all model specifications. Yet, an individual holding three million CHF gains up to 2.6 times higher returns according to the model that abstracts from the risk attitude of the portfolio (i.e. does not consider the financial portfolio composition). Thus, for high levels of net worth, adequately controlling for all channels is crucial. Surprisingly, the model specification has roughly the same relative effect at the 10th, 50th and 90th quantile of the returns. For this purpose, consider the return predicted by the model including all variables but the financial portfolio composition relative to the return predicted by the full model. The relative value is almost identical for individuals holding 100,000 CHF: .99 at the 10th quantile, 1.02 at the median, and 1.01 at the 90th quantile. Even for wealthier individuals holding one million CHF, this fraction is remarkably close (1.10, 1.33, 1.32). The predicted values differ substantially only at the very top of the distribution of net worth.

In subsection 5.2, we draw two main conclusions. (*i*) The heterogeneous effect of net worth on the returns is intensified by the fact that the wealthy hold lower shares in real estate. In contrast, part of the heterogeneity is due to risk attitude of the investor and not due to net worth. (*ii*) We find that these relations hold throughout the distribution of returns with only minor changes.

Figure 10: Distributional Effect of Net Worth for Different Quantiles of the Returns

(a) 10th Quantile of Returns (b) Median Return (c) 90th Quantile of Returns



6 Conclusion

Piketty (2014) identifies the difference between the return on capital and the growth rate of an economy as the main driver of the continuously growing unequal distribution of wealth. However, there is not one single return on capital within a population and existing studies show that there is a reasonable amount of heterogeneity in those returns (see for example Fagereng et al. (2020) and Bach, Calvet, and Sodini (2020)). From a theoretical perspective, this heterogeneity is able to replicate the skewed wealth distribution as shown by Benhabib, Bisin, and Zhu (2011), Gabaix et al. (2016) and Benhabib, Bisin, and Luo (2019). A wide range of research identifies, based on theoretical models, potential drivers of this difference in returns, such as diverse discount rates (Krusell and Smith (1998)) or return on investment from entrepreneurs (Cagetti and De Nardi (2006, 2009)). However, due to a limited availability of high quality and sufficiently detailed data, it proved to be difficult to provide empirical evidence for this heterogeneity. Two notable expectations are the work by Fagereng et al. (2020) and Bach, Calvet, and Sodini (2020). The former is based on Norwegian tax data and is able to show that (i) there is a significant amount of heterogeneity across the population which is positively correlated with wealth and that (ii) this heterogeneity is not driven by the asset allocation since the difference remains even when looking at narrow asset classes. The latter sets its main focus on expected returns and finds similar results. They differ somewhat in their finding in that Bach, Calvet, and Sodini (2020) argue that the compensation of risk is the main driver in the correlation between net worth and average expected returns. Using tax data from the canton of Bern, Switzerland, we are able to provide additional empirical evidence for this stream of the literature. Our data set, which covers the entire taxable population in the canton from 2002 until 2017, allows us to calculate actual, realized returns on wealth, while also including a vast range of socio-demographic characteristics and portfolio compositions. This allows us to investigate the heterogeneity in returns for different subgroups of our sample. For the last three years of our sample and for almost 50% of the population, we have detailed data on how the wealth is allocated to the asset classes bank deposits, bonds, and equity.

Using this, we are able to explore the financial asset allocation across the wealth distribution as well as provide information about the heterogeneity for different asset classes.

Our results reveal, that, while the average return on financial wealth for the median net worth individual is around 0.8%, the wealthiest 1% generate a return that is twice as large on average whereas the poorest 5% earn only half of that. With respect to the asset allocation we find that financial wealth is the predominant source of wealth for the bottom half of the distribution, before real estate becomes predominant as a larger share of households are able to afford a private real estate. This only changes for the top 1% for whom financial wealth is the most important wealth class. We find that for the average individual at each percentile of the net worth distribution, business wealth plays only a minor role. This is due to the small number of entrepreneurs in our data. The allocation of financial wealth follows the expected path across the wealth distribution. Bank deposits remain the predominant asset class until the top of the distribution where equity becomes the most important investment class. Bonds only play an insignificant roll for all percentiles. Further, we find that the positive correlation between net worth and returns on the different financial assets (bank depostis, bonds and equity) is clearly visible in the data. Overall, the ranking of returns on wealth across the different asset classes is in line with their respective risk. Equity generates the highest returns throughout the wealth distribution followed by bonds and deposits. The inequality with respect to returns is increasing over time, which is mainly driven by the fact that only the top 20% percent were able to keep their return constant over time whereas the rest of the wealth distribution is suffering from lower returns, in particular once nominal interest rates dropped to zero. Dividing individuals into subgroups based on their socio-demographic characteristics, we find that married individuals are able to generate higher returns compared to singles. Further we show that there is no clear difference in the performance of different age cohorts.

After a descriptive analysis of the heterogeneity in returns, we take a step further and present an econometric model to show what the best predictors for high individual returns are. In contrast to the existing literature we use two different models to explain both the average effect on returns as well as the effect of covariates across the entire distribution of returns. For the latter, we apply novel Distribution Regression techniques as proposed by Chernozhukov, Fernández-Val, and Melly (2013). In line with the stylized facts from the descriptive analysis we find that net worth is the strongest predictor for high returns on wealth followed by the portfolio choice. Further, we show that this finding is still true when we control for the portfolios risk exposure as suggested by Bach, Calvet, and Sodini (2020). With respect to *scale* and *type dependence* our results clearly suggest that both effects co-exist and explain the majority of the variation in returns. This is in line with the previous finding by Fagereng et al. (2020).

Methodologically, we contribute in two ways. First, modelling the distribution of returns provides valuable information on higher order moments such as the top quantiles and the variance. Second, aiming at the immediate effect of net worth, we derive the unconditional distribution of returns where the latter only depends on net worth. This allows us to qualify how different sets of covariates affect the direct relation between net worth and returns. Taken together, our Distribution Regression results are threefold: (i) we find that the *scale* effect of net worth is prevalent and is strongest at the top of the distribution of returns. In particular, net worth substantially boosts the top quantiles of the returns. Moving from the 20th to the 80th quantile of net worth, the median of returns increases by a factor of 2.5 (from .3% to .8%). Yet, the 99th percentile is more than four times higher (from 2.8% to 11.3%). This demonstrates that while on average individuals may have comparable opportunities, only the rich have the chance to realize extensive returns. Potentially, the wealthy are better informed and able to take higher risks which could explain this pattern. (*ii*) Taking the sharp ratio as an example, we show that modelling the distribution of returns provides further insights. Our findings suggest that, as a function of net worth, the average return increases faster than the variance of returns. Thus, richer individuals earn higher returns even when we account for the higher risk they take. To some extent, this can explain the extreme wealth inequality in the data. (*iii*) Finally, we address how the asset allocation (financial, real estate and business wealth) and the financial portfolio composition (deposits, bonds and equity) alter the immediate effect of net worth on the returns. The wealthy hold lower shares in real estate and higher shares in financial wealth. Both lead to higher returns which intensifies the effect of net worth on returns. In essence, not accounting for the asset allocation underestimates the returns of the rich. The financial portfolio composition has the opposite effect. Part of the high returns at the top of the distribution of net worth can be explained by higher shares of bonds and equity. Thus, not accounting for the portfolio composition overestimates the direct effect of net worth on the returns. Exploiting our rich data, we are able to neatly address the different channels through which net worth drives the returns on financial wealth. We hope that future work may focus more strongly on a households financial portfolio composition to study the importance of risk attitude and give more insights to the source of heterogeneous returns.

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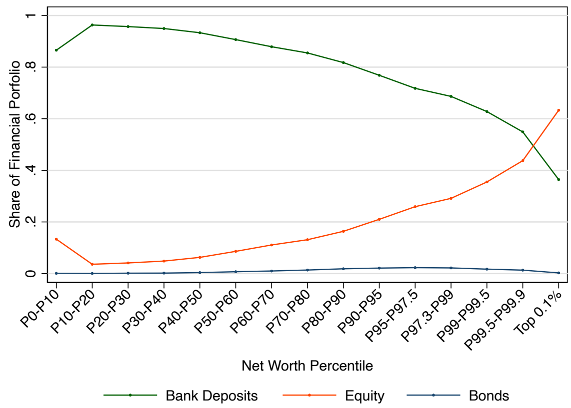
A Data

Using around half of the individuals from 2015 – 2017 we can deconstruct the overall financial wealth into three asset classes: Equity, bonds and bank deposits. Figure 11 reports the asset allocation of the financial portfolio for a few selected cohorts of the net worth distribution with a focus on the wealthiest individuals. The figure reports the average investment allocation for each group of interest, where we ranked individuals according to their net worth position in a given year. Throughout most of the distribution the majority of financial assets are invested in bank deposits, differing only for the top 0.1% of the net worth distribution. This is a striking observation and shows the high risk aversion of the individuals, given that the median household possesses on average financial wealth around 24k CHF and invests only 10% in risky assets. Throughout the full distribution bond holdings are close to irrelevant for the average individual. However, given that we are, to the best of our knowledge, the first to show a detailed financial portfolio composition for a Swiss data set we are cautions to what extent our results are representative for the entire population of Switzerland.

Figure 11: Financial Portfolio Composition across the Net Worth Distribution



B Modelling Average Effects on Returns to Wealth

In this section we provide additional information to section 4 and present some robustness checks to the previously discussed results.

Table 5 is an extension to table 3 discussed in section 4 including the coefficients for socio-demographic variables. Note that while all except marital status are significant for predicting individual returns, they contain only little economic relevance. The exception to the former can be found for married individuals. On average the model predicts an increase in returns of around ten basis points (both in the model with and without fixed effects).

As we mentioned in the main part of the paper, the data contains additional information on the financial asset allocation for a subsample of our observations. For roughly half of the population we have a detailed description of the financial portfolio, allowing us to divide total financial wealth into three broad asset categories. Using this information table 6 reports the results

Table 5: Average Effects: Scale and Type Dependence

	Without Individual FE		Including Individual FE	
	(1)	**(2)**	**(3)**	**(4)**
ln(Net Worth (CHF))		0.00176***		0.00093***
		(0.000)		(0.000)
Share in w_{it}^f		0.00264***		0.00122***
		(0.000)		(0.000)
Share in w_{it}^r		-0.00249***		-0.00094***
		(0.000)		(0.000)
Share in w_{it}^b		-0.00024***		-0.00001
		(0.000)		(0.000)
Leverage Ratio		0.00324***		0.00133***
		(0.000)		(0.000)
Female		0.00003*		0.00000
		(0.000)		(.)
Married		0.00111***		0.00124***
		(0.000)		(0.000)
Widowed		-0.00030***		-0.00092***
		(0.000)		(0.000)
Divorced		-0.00014***		0.00078***
		(0.000)		(0.000)
Separated		0.00001		0.00060***
		(0.000)		(0.000)
Children		0.00009***		0.00006***
		(0.000)		(0.000)
Age		-0.00000		-0.00057***
		(0.000)		(0.000)
Year FE	yes	yes	yes	yes
Ind. FE	no	no	yes	yes
R^2	0.052	0.105	0.398	0.412
adj. R^2	0.052	0.105	0.335	0.349
N	8,875,289	8,462,780	8,816,922	8,401,047

Note: The outcome variable is individual returns on financial wealth r_{it}^f in all columns. All models additionally include a constant. Standard errors clustered at the individual level in parentheses, *** $p < 0.001$ ** $p < 0.01$, * $p < 0.05$. The data set is cleaned as described in section 2.

of the regression discussed in section 4 but controlling for the risk attitude of the individual. More precisely we include both equity and bond shares into the list of control variables captured by X_{it}. For comparison we included the results from the benchmark model in column (1) and (3). As expected both equity and bond shares are significant predictors for high returns and yield the largest explanatory power. Overall the qualitative results are similar to the one we obtain without conditioning on the portfolios risk exposure. However, there are a few noteworthy differences. First, as was shown by Bach, Calvet, and Sodini (2020) some part of the variation in return is clearly due to the riskiness of the portfolio. Comparing the magnitude of *scale dependence* (i.e. the coefficient for the logarithm of net worth) we show that the size of the coefficient is significantly lower when we condition on the shares in financial asset classes. Nevertheless, we find a clear indication that *scale dependence* is a significant and economically relevant factor for the variation in returns even after controlling for the level of net worth by including individual fixed effects. Second, after controlling for individual fixed effects we find that the overall portfolio composition is no longer significant and only the allocation of financial assets and the changes in net worth are significant predictors of the individual's return. One interpretation might be that the positive correlation between shares in financial wealth and shares invested in equity was previously captured by the former where the true channel driving the increasing returns was through the latter. Last, we find that controlling for the financial asset allocation yields a significant increase in the predictive power of the full model. Including, equity and bond shares into the regression increases the adjusted R^2 by almost 50% in both model specifications, indicating that the financial investment decision is a strong channel for predicting returns and should not be neglected whenever possible.

Table 6: *Robustness:* Average Effects: Scale and Type Dependence

	Without Individual FE		Including Individual FE	
	(1)	**(2)**	**(3)**	**(4)**
ln(Net Worth (CHF))	0.00176***	0.00057***	0.00093***	0.00013***
	(0.000)	(0.000)	(0.000)	(0.000)
Share in w_{it}^{f}	0.00264***	0.00033***	0.00122***	0.00019
	(0.000)	(0.000)	(0.000)	(0.000)
Share in w_{it}^{r}	-0.00249***	-0.00135***	-0.00094***	0.00011
	(0.000)	(0.000)	(0.000)	(0.000)
Share in w_{it}^{b}	-0.00024***	-0.00040*	-0.00001	-0.00042
	(0.000)	(0.000)	(0.000)	(0.001)
Leverage Ratio	0.00324***	0.00112***	0.00133***	0.00028
	(0.000)	(0.000)	(0.000)	(0.000)
Equity Share		0.01629***		0.00639***
		(0.000)		(0.000)
Bonds Share		0.01055***		0.00527***
		(0.000)		(0.000)
Socio-Demographics	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Ind. FE	no	no	yes	yes
R^2	0.105	0.142	0.412	0.685
adj. R^2	0.105	0.142	0.349	0.512
N	8,462,780	950,626	8,401,047	885,441

Note: The outcome variable is individual returns on financial wealth r_{it}^{f} in all columns. All models additionally include a constant. Standard errors clustered at the individual level in parentheses, *** $p < 0.001$ ** $p < 0.01$, * $p < 0.05$. The data set is cleaned as described in section 2.

In addition to the benchmark model of section 4 we provide the results for a slightly differnt specification. Table 7 shows the result of the model we previously discussed but replacing the logarithm of net worth the individual's percentile rank of net worth denoted by $P(w_{it}^{n})$. This specification brings the advantage that we can use the full number of observations including the individuals with negative or zero net worth. However, the drawback of this approach is that there is no clear interpretation what it means to jump one percentile rank in the distribution and the difference in CHF between percentile ranks at the top of the distribution is much larger compared to the bottom. For these reasons we consider the results in tabel 3 to be economically more meaningful. We find that there is no qualititative difference between the two models and that both models give clear evidence for the existence of *scale* and *type dependence*.

Table 7: *Robustness:* Average Effects: Scale and Type Dependence

	Without Individual FE		Including Individual FE	
	(1)	**(2)**	**(3)**	**(4)**
$P(w_{it}^n)$		0.00014***		0.00008***
		(0.000)		(0.000)
Share in w_{it}^f		0.00266***		0.00115***
		(0.000)		(0.000)
Share in w_{it}^r		-0.00309***		-0.00136***
		(0.000)		(0.000)
Share in w_{it}^b		-0.00032***		-0.00023*
		(0.000)		(0.000)
Leverage Ratio		0.00411***		0.00179***
		(0.000)		(0.000)
Socio-Demographics	no	yes	no	yes
Year FE	yes	yes	yes	yes
Ind. FE	no	no	yes	yes
R^2	0.052	0.104	0.398	0.401
adj. R^2	0.052	0.104	0.335	0.338
N	8,875,289	8,875,289	8,816,922	8,816,922

Note: The outcome variable is individual returns on financial wealth r_{it}^f in all columns. All models additionally include a constant. Standard errors clustered at the individual level in parentheses, *** $p < 0.001$ ** $p < 0.01$, * $p < 0.05$. The data set is cleaned as described in section 2.

C Modelling Distributional Effects on Returns to Wealth

Figure 12: 4 Models for the Unconditional Effect of Net Worth: Data 2002-2017

(a) Average Return by Quantile of NW

(b) Average Marginal Effect

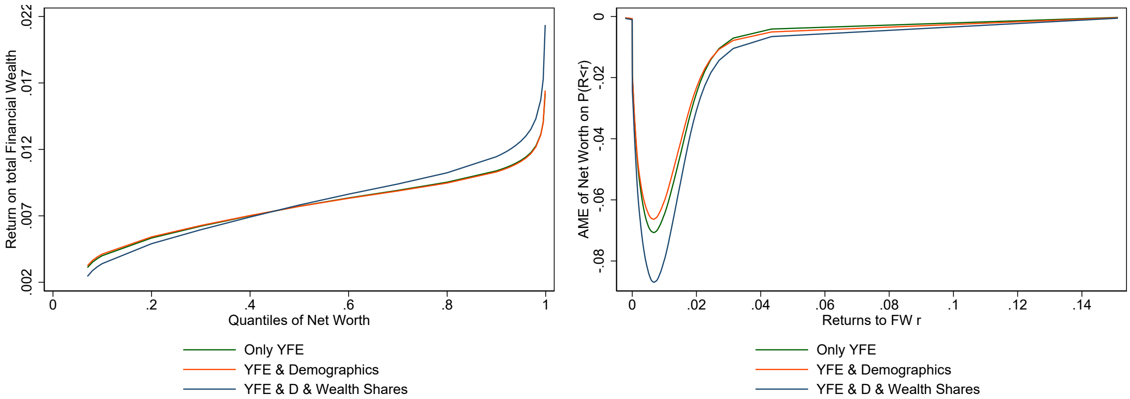


Figure 13: Distributional Effect of Net Worth for Different Quantiles of the Returns: Data 2002-2017

(a) 10th Quantile of Returns (b) Median Return (c) 90th Quantile of Returns