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Differential returns in Germany

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Abstract

This paper estimates rates of return on wealth across gross wealth groups by matching individual-level survey data with macroeconomic return data for Germany. Using machine learning for more detailed financial asset categories, we find that the average nominal rate of return on gross assets for the bottom 50% is 1%, for the upper middle 40% it amounts to about 5.4%, and for the top 10% to 6.3%. Adjusted for inflation and interest payments on loans, the average rate of return for the bottom 50% is negative. We show that an intersectional analysis of wealth returns matters, with certain socio-economic characteristics such as gender or migration background predicting the position of individuals in the wealth distribution.

1 Introduction

Wealth is highly concentrated (Schröder et al., 2020, for Germany), and so are its returns (Fagereng et al., 2020; Bach et al., 2020; Ederer et al., 2021; Bundesbank, 2022). This leads to a cumulative causation of self-perpetuating wealth concentration (Piketty, 2014; Garbinti et al., 2021). This paper investigates these so-called differential returns, that is, returns that differ according to wealth groups, for Germany at the person level.

Empirical research has consistently shown that rates of return on wealth increase with the level of wealth (see, for example, Bach et al., 2020; Bundesbank, 2022; Ederer et al., 2021; Fagereng et al., 2020). However, the analyses for Germany focus on the household level and

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use broad wealth groups as the primary differentiating factor (Bundesbank, 2022; Ederer et al., 2021). This study advances the existing literature by employing an individual-level analysis, and by incorporating a rich set of socio-demographic characteristics, which permits taking a more intersectional approach.

Concretely, this paper combines data from the German Socio-Economic Panel (SOEP) with the Household Finance and Consumption Survey (HFCS) (ECB, 2021) using machine learning to identify the composition of wealth portfolios. It applies return data from Jordà et al. (2019), the Bundesbank and FMH Finanzberatung e.K. to estimate average rate of returns for the period 1995-2020 across three gross wealth groups: the bottom 50%, the upper middle 40%, and the top 10%. We find that nominal rates of return increase with wealth that range from 1.00% to 6.3%; the difference between the bottom 50% and the upper middle 40% is primarily due to home ownership within the latter group. Accounting for interest and inflation costs reduces the rates of return that are earned by the bottom 50% to -0.3%. Furthermore, our findings show that certain demographics – such as women, young adults aged 18-30, people with a migration background, single individuals, single parents, unemployed individuals, and those in education and residents of eastern Germany – are more likely to be in the lower half of the wealth distribution. For some intersectional example groups, for instance single parents or young, single women, we find that their overrepresentation in the bottom 50% is associated with lower than average rates of return.

2 Literature

The development economics literature covers two concepts relevant to this paper, of a poverty trap (Barrett & Carter, 2013; Sachs et al., 2004) and of a poverty penalty (Prahalad, 2005). The first, a poverty trap, is defined as a "self-reinforcing mechanism, which causes poverty to persist" (Azariadis & Stachurski, 2005). Particularly relevant to this report is the work on micro-economic poverty traps. For instance, Carter and Barrett (2006) develop an asset-based approach, emphasizing locally increasing returns for different asset levels. Their analysis reveals that households with lower incomes are constrained from participating in economic activities with higher returns due to the existence of a specific asset threshold. These effects are perpetuated by structural barriers such as institutional obstacles, financial exclusion, and unequal market access. Zimmerman and Carter (2003) address the issue of differential asset returns conceptually using a stochastic dynamic programming model with endogenous asset price risk. Their findings reveal a bifurcation in optimal portfolio strategies: wealthier agents acquire higher-yielding portfolios

and smooth consumption, while poorer agents focus on asset smoothing due to subsistence constraints. Adato et al. (2006) similarly document the perpetuating disparity of types of various assets among different social strata in South Africa between 1993 and 1998, emphasizing the differential returns on these assets and the structural factors leading to their persistence. In a further analysis, Barrett et al. (2006) examine wealth dynamics empirically using household data in rural Kenya and Madagascar. Their findings underscore the significance of differential asset returns, as households with limited assets are constrained from pursuing higher-return livelihood strategies due to factors such as restricted access to credit and insurance, geographic isolation, and other exclusionary processes. Poverty traps are often depicted in multiple equilibrium growth models (Barrett et al., 2016). These models illustrate how, below a specific asset threshold, countries or individuals gain lower returns on their investments due a nonconcave growth function (Adato et al., 2006; Bloom et al., 2003). These low-level equilibria can only be exited through exogenous intervention (Sachs et al., 2004).

The second concept, the poverty penalty, underscores the higher costs that low-income individuals face for goods and services compared to their wealthier counterparts (Mendoza, 2011). Initially identified in basic necessities such as food (Caplovitz, 1967; Kunreuther, 1973), Prahalad and Hammond (2002) empirically demonstrate the magnitude of the poverty penalty across various categories of goods and services, including medicine, mobile data, and interest rates. Albeit focused on India, the paper claims external validity on a global scale. It finds that the most significant poverty penalty occurs in the credit market, where interest rates faced by individuals living in very poor areas are 53 times higher than interest rates faced by people in suburbs. Gutiérrez-Nieto et al. (2017) show similar effects in their study of effective interest rates of microcredit across 17 countries. They demonstrate that microfinance institutions tend to discriminate against the poorest borrowers, with effective interest rates on microcredits consistently higher than national lending rates in every country studied. These rates exceed national lending rates by up to 90 percentage points. Such financial burdens not only perpetuate poverty but also hinder economic progress, reinforcing the challenge of achieving sustainable improvements in livelihoods despite increased access to microcredit (Banerjee et al., 2015). For the US, Bertrand and Morse (2011) analyze the interest rates of payday loans in 2008, which are commonly utilised by low-income households and carry annual interest rates exceeding 400%. These findings, predominantly from the development economics literature, point to the possibility that there is, if not discrimination, then structural disadvantages for lower-income and lower-wealth groups in low-income countries.

This paper relates to the literature on poverty traps by applying the micro-level differential returns-approach to a high-income country, namely Germany.¹ Several empirical analyses have demonstrated the relevance of differential returns in high-income contexts. Our analysis is most comparable to that of Ederer et al. (2021), who utilise survey data at the household level and long-run returns for individual asset classes to estimate returns for eight European countries. They show that returns increase with wealth and link the empirical results to post-Keynesian theory. For Germany, the authors calculate an average real rate of return of 2.6% for asset-poor households, 3.7% for home-owning middle-class households, and 5.9% for business-owning top 5% households. Using data from the distributional wealth accounts, Bundesbank (2022) calculates average real rates of return from 2009 to 2022 for households in Germany. Due to the differing compositions of their portfolios, the average rate of return for the lower half of the net wealth distribution amount to 1%, 5.5% for the middle 40, and approximately 6% for the top 10.

Additionally, empirical analyses have been conducted for other countries. Bach et al. (2020) investigate wealth returns with an administrative panel for Sweden and demonstrate that rates of return on wealth increase with net wealth. Fagereng et al. (2020) also show an increase in rates of return with net worth in their analysis using Norwegian administrative data. For the United States, Kuhn et al. (2020) provide empirical evidence demonstrating that portfolio composition and asset prices significantly influence wealth dynamics. Using household-level data from the Survey of Consumer Finances (SCF), they show that changes in income distribution alone are insufficient to fully explain shifts in wealth distribution. Furthermore, Xavier (2021) shows heterogeneity in rates of return in the United States, with wealthier households earning on average higher returns, also using household-level SCF data for 1989 to 2019. The findings of Brunner et al. (2020) indicate with administrative data differential returns on financial assets in the canton of Bern with the return of the top 1% of the net wealth distribution being twice as high as that of the median household. Campbell et al. (2018) show that heterogeneity of rates of return is the primary contributor to increasing inequality of wealth held in equity, using an analysis of Indian stock portfolios. The majority of these empirical analyses differentiate returns primarily according to wealth groups. Petach and Tavani (2021), however, go beyond this by using household-level data from the SCF and data on rates of return from Jordà et al. (2019) to identify a persistent racial gap in rates of return on assets between 1 and 4 percentage points for the US.

¹The second part of the project that funded this research covers the potential discrimination alleged to in the poverty penalty literature.

There are two competing explanations for differences in rates of return can arise: structural and individual factors, for which Gabaix et al. (2016) coined the two mechanisms of scale and type dependence. Scale dependence in the context of returns suggests that returns are higher due to the level of wealth, that is, heterogeneity is explained through systemic or structural reasons. Type dependence, on the other hand, implies that differences in returns depend on the characteristics of the individual person or household.² Evidence in the empirical literature for these two channels is mixed: Bach et al. (2020) and Brunner et al. (2020) find evidence for both mechanisms as drivers for returns. However, while Bach et al. (2020) do not find effects on returns for investment skills or information, Fagereng et al. (2020) argue that heterogeneity in sophistication, financial information and entrepreneurial talent are reasons for differences in returns.

In practice, however, the fact that structural factors manifest at the individual level make the two aspects difficult to distinguish. Ederer et al. (2021) and Piketty (2014) discuss possible reasons for differences, including households’ balance sheets, individual ability, professional portfolio management, and networks. While some of these, like individual ability such as financial education, can be situated clearly within individuals, the composition of balance sheets may be driven either by individual or by structural factors. While not a focus of this paper, we assume that tendencies that can be observed in larger groups are indicative of unobservable structural factors at work, while individual factors are more likely to be distributed relatively evenly across population groups.

3 Data and Methods

To calculate rates of return for different wealth groups (specifically, the bottom half, the next 40% and the richest 10%), we combine microdata from the SOEP (Goebel et al., 2023) with data on rates of return on different asset classes from various data sources. The SOEP is Germany’s largest and longest-running study, surveying approximately 30,000 respondents annually. We use the data from the 36th wave of the SOEP in 2019, which is the most recent wave to include the survey’s wealth modules. Furthermore, the 2019 wave of the SOEP includes the ‘Top Shareholder Sample’, which was specifically designed to address the under-reporting of highly affluent households in Germany (Siegers et al., 2022, p. 31). Including respondents with complete answers in

²The implicit assumption here is that these aspects are within the individual’s sphere of influence. Socio-demographic characteristics that are difficult to change, such as age or gender, would therefore not fall under ‘type dependency’.

the wealth module³ and without missing information in the socio-demographic variables⁴ in our analysis leaves us with 20,819 observations.

The questionnaire’s wealth module provides detailed self-reported information on individual wealth distributed across various asset categories. We define gross wealth as the sum of all assets, including owner-occupied residential property, other real estate, business assets, vehicles, tangible assets, and financial assets, but excluding tangible assets. Net wealth is defined as gross wealth minus loans on housing and other debts.⁵

Two points merit some discussion here: First, our analysis excludes tangible assets, since they make up a small proportion of assets while at the same time being very heterogeneous: tangible assets comprise gold, coins, and valuable collections such as art, and would thus require strong assumptions as to their average rate of return. Second, there is a debate surrounding the inclusion of pension entitlements in the analysis of wealth inequality. Statutory pension entitlements are excluded as an asset category in this study, since they do not fulfill all conditions for private wealth. We focus on marketable wealth, which excludes statutory pension entitlements that are neither transferable nor usable as collateral (Bönke et al., 2019; Fessler & Schürz, 2018).⁶ This approach is in line with the OECD’s definition of wealth as outlined in the Guidelines for Micro Statistics and Household Wealth, which exclude public and occupational pensions plans (OECD, 2013).

Note that, unlike the 2012 and 2017 waves, the data of the 2019 wealth modules are not imputed by the SOEP team (see Grabka & Westermeier, 2015, for details on the preparation of the earlier SOEP wealth data). The questionnaire allows respondents to provide an absolute value for a specific asset or estimate its value using different price groups (e.g. a value higher than 10,000€ and lower than 50,000€). If a respondent indicates a range, we impute the value using the median of the absolute values given by other respondents within the corresponding price range.⁷ Using the median instead of the mean as an imputation value for the indicated values within a price group likely leads us to underestimate wealth inequality and is thus a cautious

³Observations are dropped if an individual does not disclose ownership of an asset, indicates owning a specific asset class but does not provide any information on the value of the asset, or indicates co-ownership of an asset without providing information on the share of ownership.

⁴Furthermore, we dropped one observation due to inconsistent information in the employment status and income variable after consultation with the SOEP. This observation was identified as unemployed in the SOEP, yet reported high but implausible self-employment income.

⁵In the SOEP data, debt other than mortgages are distinguished between those derived from loans from banks, other financial institutions, or private individuals and those taken to finance education, such as “BAföG”. The sum of both types of credits is used here and they are referred to as “debt” hereafter.

⁶Studies on wealth inequality for Germany indicate that the wealth inequality is lower when considering social security pension entitlements (Bönke et al., 2019; Bartels et al., 2023).

⁷If a person indicates that the asset value is above the lower boundary of the price group or ‘don’t know’ and below the upper boundary or ‘don’t know’, they are assigned the imputed median.

assumption. If a respondent indicates co-ownership of an asset, we calculate the value of their share by taking their given ownership percentage into account.

In the SOEP, financial assets are only itemized into building loan contracts, life insurance/private pension insurance, and monetary investments. The latter encompasses various asset classes such as deposits, bonds, and shares. Since these are likely to exhibit substantial differences in their rates of return, we use data from the fourth wave of the HFCS (ECB, 2021) to estimate the differentiation in these monetary investment portfolios. The HFCS data provides detailed information on real and financial asset categories for households in 19 European countries. The sample for Germany consists of 4,119 households. To impute the information on the distribution of the financial assets across different financial products from the HFCS, we employ a multivariate random forest across different socio-demographic characteristics to predict this information for the SOEP data. With the imputed information on the distribution of the financial assets, we calculate absolute values for the following financial asset classes: sight accounts, saving accounts, bonds, mutual funds, shares and other assets (including managed accounts and others assets like derivatives). We exclude the asset class 'money owed to the household' which is covered in the HFCS, since the SOEP does not take informal credits as an asset category into account. Furthermore, non-self-employment private business wealth is reported under financial assets in the HFCS; a distinction that is not made in the SOEP which contains data for total business assets. Consequently, we exclude non-self-employment private business wealth from the imputation of financial investment shares in the HFCS.

For rates of return, we use different data sources and calculate average returns between 1995 and 2020. Data for housing comes from the data set of Jordà et al. (2019), for building loan contracts, we use data from FMH Finanzberatung e.K. (2024) and for shares, bonds, funds, sight accounts, saving accounts and insurances, data is obtained from the Deutsche Bundesbank (2015, 2024a, 2024b). Rates of return on *housing* cover capital gains and imputed rents for owners and renters and are constructed in Jordà et al. (2019) based on house price series in Knoll et al. (2017) and on rent data in Knoll (2017) using the rent-price approach. The data in the house price series for Germany is based on various data sources with urban data (Knoll et al., 2017, p. 336). They are net yields adjusted for maintenance costs, management and insurance fees, and depreciation, but not for interest, taxes, or utilities (Jordà et al., 2019, p. 1252).

Data for shares, bonds, funds and insurance are from Bundesbank (2024b). The Bundesbank data are based on the macroeconomic financial accounts. The Bundesbank calculations for *shares* are based on the total return index of the CDAX until 2006 and thereafter on sub-indices of the

Prime All Share Index. For shares of foreign issuers, the calculation is based on the MSCI World. The returns are weighted according to domestic and foreign issuers. The values for *funds* are based on Bundesbank data on the price development of mutual funds subject to reporting requirements in Germany. In the case of *bonds*, the Bundesbank calculation differentiates between different issuers. For public sector issuers, the REXP total return index is used until 2006, after which the German Government Index from Merrill Lynch, the EMU Germany Index from J. P. Morgan and the WGBI Germany Index from Citigroup are applied. For domestic banks, the FTSE Pfandbrief Index is used. For insurance companies, investment funds and other financial institutions, the calculation is based on the Merrill Lynch Euro Financial Index, while the data for non-financial companies is based on Bundesbank calculations using BBB-rated corporate bonds from Merrill Lynch. Finally, the yields on bonds from foreign issuers are calculated by the Bundesbank using the WGBI World Index from Citigroup, the Global Broad Market Index and the Global Non-Sovereign Index from Merrill Lynch. Returns on shares, bonds and funds are calculated as the sum of the changes in value and the income generated by the securities (interest and dividends/earnings). This sum is divided by the value of the portfolio held in the previous period. Costs are not taken into account. The calculation of returns for *insurances* is based on data on the current interest rate of life insurance policies from Assekurata. Note that these are not returns in the sense of interest rates. The concept of the figures of Assekurata is based on the idea of a fictive interest rate before costs. However, these interest rates only reflect the interest on the invested portion of the premiums and therefore do not take into account the portion of the premium that is lost to costs such as incentives for intermediaries. These costs reduce interest rates by an average of 2.62 per cent for unit-linked products and 1.91 per cent for traditional products with a contract term of 12 years (Bundesanstalt für Finanzdienstleistungsaufsicht, 2023); however, these cannot be taken into account here due to a lack of data. For a detailed descriptions of the data basis and the calculation, see Bundesbank (2015, 17ff). The Bundesbank data are available in the form of quarterly data. In order to obtain annual rates of return, we calculate the geometric mean for each year and thus have rolling annual average returns.

We calculate rates of return on saving and sight accounts with data on rates of interest on deposits from Bundesbank (2024a). For *saving accounts* for the years 1995 to 2002, we use ‘Bundesbank-Zinsstatistik’ data. For this period, there are no volumes recorded and the data refer only to new business and not to existing business. We thus calculate rates of return for saving accounts until 2003 as the annual unweighted average of interest on new business with different maturities. From 2003 onwards, interest rate statistics come from the ‘MFI-Zinsstatistik’, which

differentiates between new and existing business and indicates volumes for different periods. We therefore calculate the rates of return as the weighted annual average of interest on existing business with different maturities for 2003 to 2020.⁸ For *sight accounts*, we employ data on higher-yielding sight deposits of individuals up until 2003, and data on overnight deposits from private households in new business from 2003 onwards.

For calculating rates of return on net assets, we also use loan interest rate data from Bundesbank (2024a). From 2003 onwards, we apply the weighted average interest rates on housing loans for *loans* and the weighted average of consumer and other loans for other *debts*. For the period before 2003, we use the simple average interest rates, since here, too, volume data is not available.

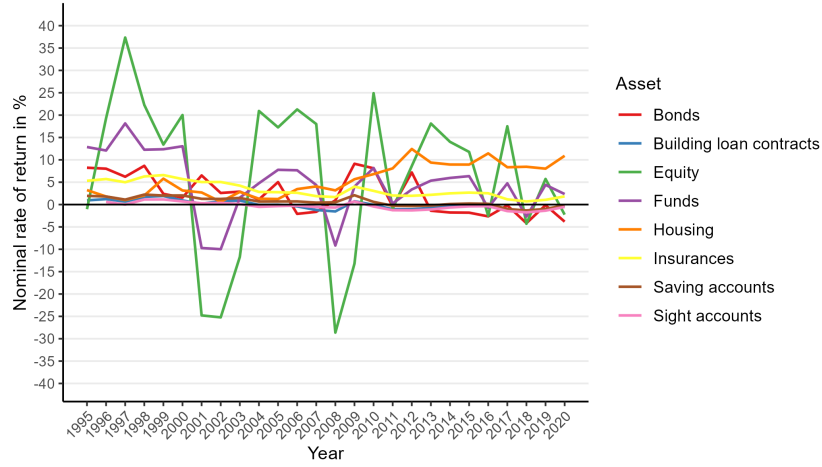
The data from the Bundesbank and FMH Finanzberatung e.K. are gross, i.e. before deduction of any potential costs and taxes. We calculate nominal (real) rates of return using Fisher's equation and the respective inflation data⁹ where only real (nominal) rates of return are available in the data.

Figure 1 shows nominal rates of return by asset category from 1995 to 2020. Overall, the period under consideration here was marked by an interest rate environment ranging from 2 to 5 percent until the financial and economic crisis, and by a low-interest environment thereafter (ECB, 2024).

⁸Note that certain new business items (e.g. deposits redeemable at notice) are included as new business in the Bundesbank data, but need to be redefined as existing business (personal correspondence with Bundesbank).

⁹Jordà et al. (2019) and the Bundesbank provide data on the consumer price index.

Figure 1: Annual nominal rates of return by assets (1995-2020)



Note: This figure shows annual nominal rates of return by assets from 1995 to 2020. Source: Bundesbank (2015), Bundesbank (2024a), Bundesbank (2024b), Jordà et al. (2019), and FMH Finanzberatung e.K. (2024).

Over the time period under consideration here, the rates of return on shares exhibited the greatest volatility, with the majority of periods indicating positive returns. Rates of return on bonds and funds were less volatile and also positive on average throughout the time period under consideration. The returns on housing were also positive, with a notable increase after 2009. It is noteworthy that rates of return on insurances, building loan contracts, saving accounts and sight accounts were also positive throughout the period, but at lower rates of return. A more detailed illustration of the asset classes with lower returns can be found in the appendix (see Figure 6).

Taking inflation into account shows that real rates of return were almost zero or negative for several asset categories. These include bonds, building loan contracts, saving and sight accounts in the low-interest phase. Figure 7 in the appendix shows real rates of return by asset category from 1995 to 2020.

Table 1 shows the SOEP asset categories, their average annual nominal and real rate of return for the different asset classes for the period 1995-2020 calculated as the geometric mean, and the various data sources utilized here for calculating their rates of return.

Table 1: Asset categories, nominal and real rates of return, and data sources

Asset	Nominal rate of return	Real rate of return	Data source	Rate of return
Home ownership	6.98	5.48	Jordà et al (2019)	Housing
Other real estate	6.98	5.48	Jordà et al (2019)	Housing
Equity	6.81	5.33	Bundesbank	Shares
Vehicles	0.00	-1.38	/	Other
Sight account	1.06	-0.32	Bundesbank	Sight account
Saving account	2.06	0.65	Bundesbank	Saving account
Bonds	3.6	2.17	Bundesbank	Bond
Mutual Funds	5.82	4.36	Bundesbank	Mutual Funds
Shares	6.81	5.33	Bundesbank	Shares
Other financial assets	6.81	5.33	Bundesbank	Shares
Insurances	4.75	3.31	Bundesbank	Insurances
Building loan contract	1.36	-0.04	FMH Finanzberatung	Building loan contract
Housing loans	4.77	3.32	Bundesbank	Loans
Other credits	6.05	4.59	Bundesbank	Debts

Note: This table shows the asset categories in the SOEP, with monetary investments imputed from HFCS data, and the corresponding nominal and real rates of return with their respective data sources. For housing loans and other credits, the rate of return is the interest rate, which enters the calculation negatively, i.e. as a cost. Source: SOEP 2019, ECB (2021), Bundesbank (2015), Bundesbank (2024a), Bundesbank (2024b), Jordà et al. (2019), and FMH Finanzberatung e.K. (2024); own elaboration.

Methods

We use machine learning to estimate the distribution of monetary investments across financial asset types in the SOEP, training a multivariate random forest algorithm on HFCS data. A random forest generates predictions using a set of decision trees (Breiman, 2001). A multivariate random forest can be used to predict joint estimations for a set of different values with potential dependencies (Segal & Xiao, 2011). These dependencies also apply to our application, as the proportions of the different asset classes always add up to 100%. In order to avoid perfect multicollinearity, the variable ‘other financial assets’ is not predicted by the multivariate random forest, but is calculated as 1 minus the sum of the shares of the other assets. We train the model using several characteristics, including ownership of different assets, the gross wealth decile, highest educational attainment ¹⁰, occupational status, marital status, the gross income decile, age group ¹¹, and region. For single households, we also use gender. For multi-person households, we use the reference person of the household. The model specifications are as follows: 101 trees are used, with four features considered for splitting in each regression tree node, and four is the

¹⁰This is defined according to the International Standard Classification of Education (ISCED) and is differentiated into four categories: no formal education, low, mid and higher education.

¹¹For multi-person households, the age of the household is calculated as the average age of all adults in the household members

minimum number of samples in the leaf node. Predicted values are generated for all individuals in the SOEP indicating the ownership of monetary investments.

Before predicting values for the SOEP data, we test our random forest model within the HFCS data set for Germany. We use 70% of the data as training data and 30% as testing data. Table 2 shows the mean absolute errors (MAE) for the predicted variables both at the observation level and aggregated by our gross wealth group using the example of one-adult households. The mean absolute error represents the mean value of the discrepancy between the actual and predicted values generated by the random forest model. The results show that at the level of the gross wealth groups (last column), which are mainly relevant for the analysis here, the mean errors are consistently in the low range with values below 0.04. This means, for example, that the predicted share of savings accounts at wealth group level deviates on average by 4 percentage points from the share in the actual HFCS test data. At the observation level, the errors are also small, with the exception of savings and demand accounts with a mean error of 0.19 each.¹².

Table 2: Mean absolute errors (MAE) of model testing with HFCS data on single households

	MAE observation level	MAE by wealth group
Sight accounts	0.19	0.02
Saving accounts	0.19	0.04
Bonds	0.01	0.01
Funds	0.08	0.01
Shares	0.06	0.02
Other financial assets	0.01	0.02

Note: The table presents the mean absolute errors associated with the testing of our multiple random forest model, which has been applied for the purpose of imputation and differentiation of monetary investments within the SOEP data set. The calculated average deviations between the actual and predicted values of the various asset classes are presented at two different levels: at the level of the individual observations (column 2) and at the level of the three asset groups lower 50%, middle 40% and top 10% (column 3). Source: ECB (2021).

4 Results

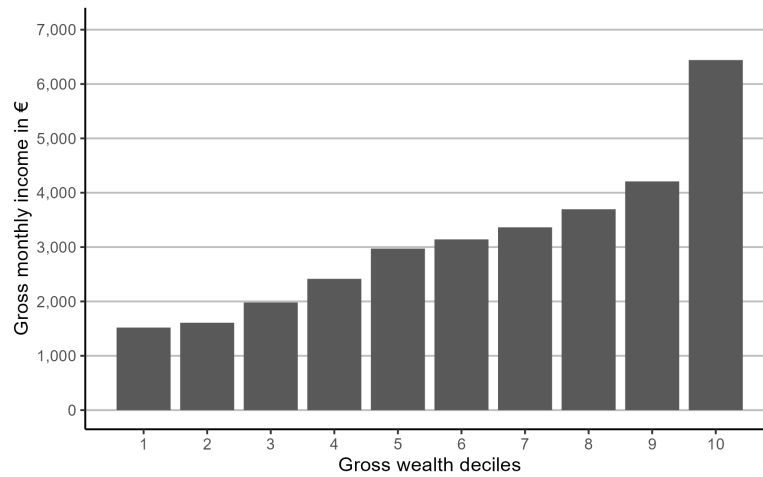
4.1 Wealth groups

We group our sample by gross wealth into the bottom 50%, the upper middle 40% and the top 10%. We group along gross wealth and not gross income, because wealth is the relevant category for returns, which is also used in previous studies on differential returns (Fagereng et al., 2020;

¹²This is possibly due to the fact that the algorithm cannot distinguish well between these two asset categories. In this case, the error would be small even at the observation level, as the returns show little difference

Bach et al., 2020; Ederer et al., 2021; Bundesbank, 2022). Note, however, that gross income and gross wealth are statistically significantly correlated, with a positive, medium-high correlation coefficient of 0.31 in our data. Figure 2 illustrates the average gross monthly income by gross wealth decile, indicating an increase in mean income with wealth. Note that this figure shows the average total income, rather than the average full-time salary and encompasses a range of income sources, including part-time earnings, pensions and unemployment benefits. Furthermore, note that the data on wages refers to 2018 and thus does not reflect wage increases for the most recent years.¹³

Figure 2: Average gross monthly income per wealth decile (in 2019)



Note: This figure shows the average gross monthly income per gross wealth decile at an individual level. Source: SOEP 2019.

For group-specific analyses of rates of return, we use various socio-demographic characteris-

¹³We calculate gross personal income as the sum of all income components at the individual level and of income components at the household level, divided by the number of adults in the household.

tics including gender, age, migration background¹⁴, family status¹⁵, occupational status¹⁶, and region. Table 3 shows summary statistics of the SOEP data, including the total number of observations and the weighted percentage shares of different socio-demographic characteristics for the whole population and three different gross wealth groups. The values displayed in the Summary Statistics table provide an initial indication of the demographic composition of different wealth groups. The data reveals that women, 18-30 years old, people with a migration background, single individuals, single parents, unemployed and non-working individuals, and those in education and from eastern Germany are over-represented in the bottom 50%. Table 4 shows the percentage of individuals with a specific socio-demographic characteristic who belong to a specific wealth group with the same results. It shows e.g. that 67% of the people with a migration background and 76% of single parents belong to the bottom 50%. It is also noteworthy that a considerable proportion of older individuals continue to be represented in the bottom 50% of wealth distribution (39.51% of people older than 71 and 42.02% of the pensioners). This is particularly relevant given that the phase of accumulation of wealth through saving out of labor income for this group has already ended.

¹⁴In the SOEP data, a distinction is made between individuals with no, direct, and indirect migration backgrounds. An individual is defined as having a direct migration background if they were born in a country other than Germany. An indirect migration background is defined as existing if at least one parent has a direct migration background. In our analysis, we summarize direct and indirect migration backgrounds.

¹⁵Family status is defined as follows: a person is considered to be in a couple relationship if there are exactly two people in the household, both with a partner-ID, and there are no children under 18. A person is considered to be a parent in a family (meaning they live in a partner relationship and have children) if there are more than two people in the household, the person has a partner-ID, and there is at least one child under the age of 18. A person is classified as single when the number of household members is exactly one. A person is classified as a single parent if there is no partner-ID in the household, there is no other adult over 25 years old, the person is the oldest member of the household, and at least one child is under the age of 18. All other individuals are classified as 'other', which may apply to individuals living in shared flats, multigenerational homes, and adult children who still reside with their parents.

¹⁶Occupational status is defined as follows: a person is considered unemployed if they are non-working and have indicated that they are unemployed. A person is considered non-working if they have not provided any further information about being non-working. Those who are considered employed include all workers, employees and officials. Self-employed individuals and freelancers are categorized as self-employed. Pensioners are individuals that are non-working and receive a pension. A person is considered to be in education if they are currently non-working and have indicated that they are in education, are in military or community service, or are a trainee or intern.

Table 3: Summary Statistics SOEP 2019 (N = 20 819) with weighted shares

Variable	Value	Total population		bottom 50%	upper middle 40%	top 10%
		N	in %	in %	in %	in %
Gender	Female	10,751	50.23	54.10	47.49	41.82
	Male	10,068	49.77	45.90	52.51	58.18
Age	18-30	3,288	16.1	28.49	4.36	1.13
	31-50	6,949	30.46	30.69	31.24	26.20
	51-70	7,706	34.92	26.21	42.12	49.73
	71+	2,876	18.51	14.60	22.29	22.94
Migration	No	16,204	77.86	70.13	85.01	87.93
	Yes	4,615	22.14	29.87	14.99	12.07
Marital status	Single	3,479	26.78	31.36	21.43	25.26
	Couple	6,944	34.44	27.72	42.45	36.01
	Family	5,519	17.72	14.7	20.65	21.10
	Single Parent	679	2.09	3.18	0.94	1.24
	Other	4,198	18.97	23.04	14.53	16.38
Occupation	Employed	10,891	52.71	50.87	56.30	47.54
	Self-employed	1,918	4.99	2.58	4.83	17.79
	Unemployed	956	4.39	7.65	1.30	0.41
	Non-working	1,088	4.61	5.41	3.86	3.60
	In education	1,273	5.43	10.09	0.79	0.62
	Pensioners	4,693	27.88	23.40	32.93	30.05
Region	East Germany	4,521	17.44	19.79	17.34	6.05
	West Germany	16,298	82.56	80.21	82.66	93.95

Note: This table shows the number of observations and the shares of different socio-demographic characteristics in the total population and in the bottom 50%, the upper middle 40%, and the top 10% of the population by gross wealth, at the individual level. Depending on the category for each variable (e.g. gender), the columns add up to 100 %; for example, 54.10 % are women and 45.90 % are men in the bottom 50 %. Source: SOEP 2019, own elaboration.

Table 4: Distribution of socio-demographic characteristics

		bottom 50%	upper middle 40%	top 10%
Gender	Female	53.85	37.84	8.31
	Male	46.11	42.22	11.66
Age	18-30	88.48	10.83	0.70
	31-50	50.38	41.04	8.58
	51-70	37.53	48.27	14.21
	71+	39.45	48.18	12.37
Migration	No	45.04	43.70	11.27
	Yes	67.46	27.10	5.44
Marital status	Single	58.56	32.03	9.41
	Couple	40.24	49.34	10.43
	Family	41.48	46.64	11.88
	Single Parent	76.11	17.95	5.94
	Other	60.74	30.65	8.62
Occupation	Employed	48.26	42.74	9.00
	Self-employed	25.84	38.61	35.55
	Unemployed	87.19	11.89	0.93
	Non-working	58.69	33.53	7.78
	In education	92.99	5.86	1.14
	Pensioners	41.98	47.27	10.75
Region	East Germany	56.74	39.80	3.46
	West Germany	48.58	40.07	11.35

Note: This table shows the distribution of each socio-demographic characteristics across the respective wealth groups in percent. The rows add up to 100% for each characteristic, for instance, 53.85% of women are located in the bottom 50%, 37.84% in the upper middle 40%, and 8.31% in the top 10%. Source: SOEP 2019.

In addition to differences in gross wealth, there is also variation between wealth groups in other dimensions, such as the composition of the asset portfolio, mean gross income, and the most common occupations. Home ownership is virtually non-existent in the bottom 50%. In the upper middle 40%, home ownership represents a significant share of the average total gross wealth, with approximately 70% of this group owning housing. However, there are also differences in financial assets, such as investments and insurance.¹⁷ The top 10% are distinguished from the other two groups by their ownership of corporate assets and other real estate. Almost half of this group owns other real estate and 14% own business assets (see Table 5).

¹⁷In the case of investments, it should be noted that the SOEP does not ask whether a person owns certain financial products, but instead asks about investments in these financial products. So if a person has a current account, but has not saved much more than enough for monthly living expenses and has no other financial investments, this person will probably have stated 'no' for financial investments. The fact that around 25% of the lower half state that they have financial investments means that they have assets in the form of financial investments and not that only 25% of the group has a current account. In addition, surveys such as the SOEP assume that financial assets and financial assets in general are underreported.

Table 5: Participation in asset classes in 2019

	bottom 50%	upper middle 40%	top 10%
Vehicles	43.56	72.78	79.41
Owner-occupied residential property	0.73	69.71	89.47
Other real estate	0.54	13.18	49.17
Business assets	0.64	3.20	14.09
Monetary investments	25.31	58.47	70.44
Insurances	16.54	40.36	49.84
Building loan contract	13.22	34.14	35.52

Note: This table displays the proportion of an asset group that is owning the respective asset in percent. Source: SOEP 2019, own elaboration.

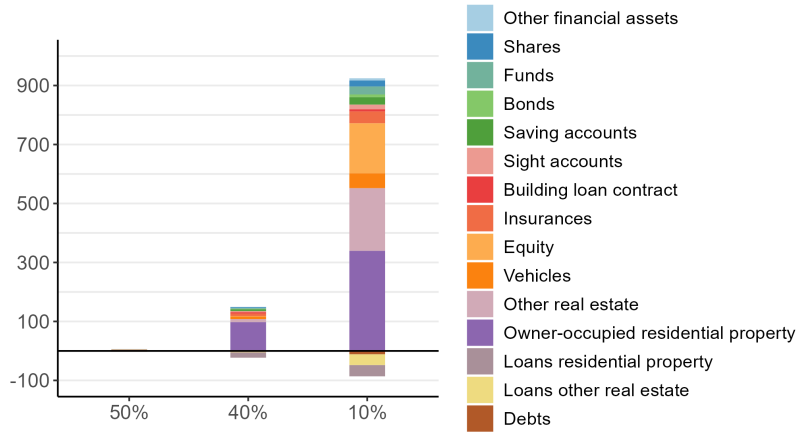
The differences in the ownership of asset classes are also reflected in the average asset portfolios, as illustrated in Figure 3. Figure (a) shows absolute values, which illustrates the unequal distribution of total gross wealth. A person in the bottom half of the population has an average gross wealth of around 6,000€, while a person in the top 10% has an average of around 925,000€.¹⁸

Furthermore, Table 6 displays mean and median gross wealth and income, as well as the first and third quartiles for the different groups. The data indicates that the average monthly income of the upper middle group is higher than that of the bottom 50% group. However, it is important to note that there is substantial overlap in the income ranges, meaning that there are individuals with lower incomes in the upper middle group and those with higher incomes in the bottom 50% group.

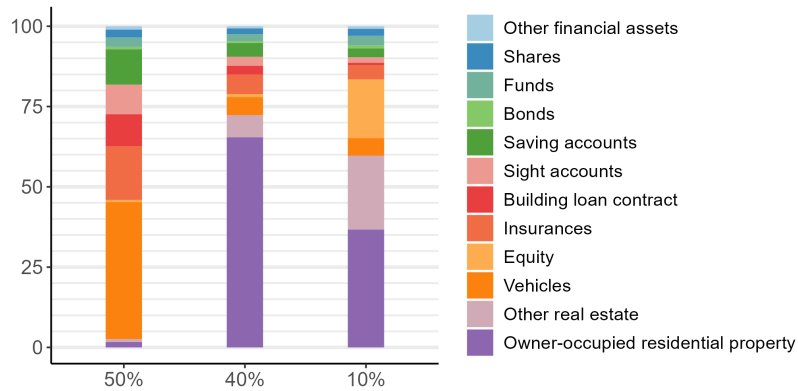
¹⁸All observations were taken into account when calculating the average gross wealth. If only those who have any gross wealth at all are taken into account, the average gross wealth of the bottom half is around 9,500€.

Figure 3: Average asset portfolios by gross wealth groups for 2019

(a) Average asset portfolio (in thousands of euros)



(b) Shares of the average asset portfolios (in %)



Note: This figure shows the type of assets owned by the bottom 50%, upper middle 40%, and top 10% in 1,000 Euros (top pane), and as a share of assets held by the respective group (bottom pane). Table 8 in the appendix presents the absolute average values of the different types of assets per wealth group. Source: SOEP 2019 and ECB (2021).

Table 6: Summary statistics on wealth and income by wealth group in € (in 2019)

(a) Gross wealth

	Q1	Median	Mean	Q3	p90
50%	0 (89.3)	2,000 (127.5)	5,948.1 (130.6)	10,000 (255.1)	19,500 (382.6)
40%	75,500 (2,040.5)	140,000 (2,423.1)	149,383 (1,463)	210,000 (2,550.7)	275,000 (2,295.6)
10%	404,000 (3,825.1)	518,500 (8,670.2)	924,576 (57,316)	758,000 (21,165.6)	1,329,000 (79,052.3)
total	2,000 (204.1)	29,0025 (1,530.6)	155,003 (6,233.7)	173,150 (3,443.7)	338,000 (8,162.9)

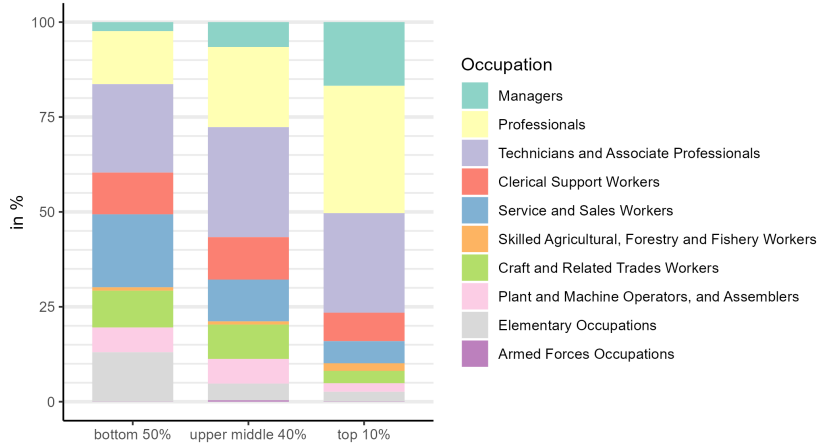
(b) Gross income

	Q1	Median	Mean	Q3
bottom 50%	935 (27.12)	1,875 (26.95)	2,078.2 (23.89)	2,920 (36.85)
upper middle 40%	2,164.63 (42.66)	3,302.86 (38.81)	3,600 (36.58)	4,600.83 (49.16)
top 10%	3,219.02 (103.09)	4,905.25 (117.94)	6,440.9 (253)	7,764.17 (251.52)

Note: This table shows (a) gross wealth owned and (b) gross income received by the individuals located at the first quartile, the median, and the third quartile, and at the mean. For gross wealth it also shows the 90th percentile and the values for the total population, indicating the cut-off scores for the various wealth groups. Standard errors in parentheses. Source: SOEP 2019.

Figure 4 illustrates the distribution of various occupations (according to the ICSO-08 classification) across the asset groups. It shows that elementary occupations and service and sales workers are more likely to be represented in the bottom 50%. Clerical support workers, craft and related trade workers, plant and machine operators are quite equally represented in the lower and middle wealth groups. The highest proportion of technicians and associate professionals is observed in the upper middle 40%, while professionals are most prevalent in the top 10%. Finally, the proportion of managers in the top 10% is considerably higher than in the other two groups.

Figure 4: Distribution of occupations in the different wealth groups (in 2019)



Note: This figure shows the distribution of occupations according to the ISCO-08 classification by wealth group. Source: SOEP 2019.

4.2 Rates of return

The data on asset portfolios and the data on rates of return for different asset classes are employed to estimate the average annual nominal rates of return for each individual as the weighted average of the rates of return of the different asset types. In the analysis here, the variation in the rates of return are thus exclusively due to differences in asset portfolio compositions.

We find rising rates of return across the wealth groups, with an average nominal annual rate on gross wealth of 1% for the bottom 50%, a rate of 5.39% for the upper middle 40% and a rate of 6.3% for the top 10% when all observations are taken into account (see Figure 5a).¹⁹ Furthermore, we incorporate inflation and calculate real rates of return, represented as dots in Figure 5a. The aggregate average returns shown here differ from the returns on the average portfolios of the wealth groups. In particular, there is a larger difference for the bottom 50% due to the observations with a return of 0. The returns on the average portfolios are as follows: 1.9% for the bottom 50%, 5.87% for the next 40% and 6.12% for the top 10%.

In a subsequent step, we adjust the yield for nominal interest expenses on liabilities. We

¹⁹The values are calculated unconditionally, that is including all individuals. Those who do not own a particular asset category naturally have a return of 0 on that asset class. An individual who owns no gross assets is also assigned a return of 0. This applies to a total of 3,844 observations in our sample. The conditional distribution of nominal rates of return (i.e. taking into account only those who own assets) is as follows (the values excluding owner-occupied residential property are shown in brackets): The average nominal unadjusted rate of return across all assets for the bottom 50% is 1.6% (1.55%), for the upper middle 40% 5.39% (2.72%), and for the top 10% 6.29% (4.61%).

calculate the adjusted rate of return on the level of wealth groups based on the calculation of Fagereng et al. (2020) and Bundesbank (2022) as follows:

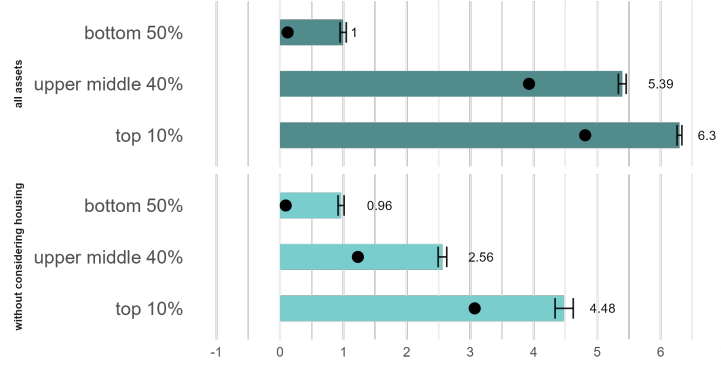
$$r_{net} = r_{gross} - r_{debt} * \frac{Debt}{GrossWealth} \quad (1)$$

where r_{gross} is the average rate of return on gross assets and r_{debt} is the average interest rate on liabilities which is multiplied by the debt-to-asset ratio calculated as the average total debts divided by average total gross wealth. Since the formula is undefined for zero gross wealth and tends towards infinity for observations whose liabilities exceed their assets, we calculate the adjusted rate of return on the level of wealth groups rather than individuals, as does Bundesbank (2022, information through personal correspondence). The adjusted rates of return highlight that the bottom 50% of the population experiences the most substantial decline in absolute rates of return due to the inclusion of interest costs, with the nominal rate of return falling below 0.5% (see Figure 5b). The adjusted nominal rate of return for the upper middle 40% is 5.06% and for the top 10% 6.07%. Adjusting for inflation shows a negative real return of -0.3% for the bottom 50%

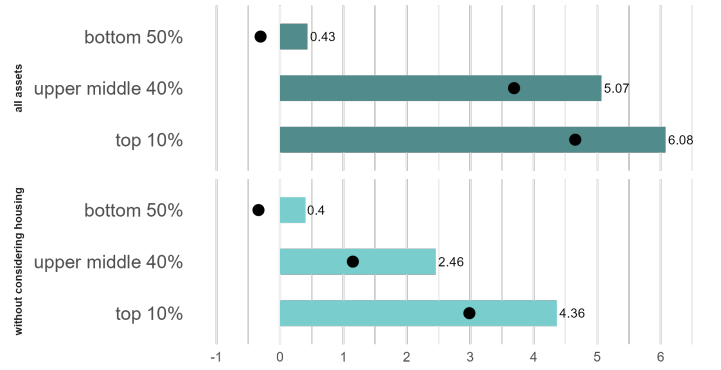
A large part of the observed differences in rates of return, particularly between the bottom half and the middle, can be attributed to the ownership of housing in the middle. When owner-occupied residential property is excluded from the portfolio, the nominal rate of return on gross wealth are 0.96% for the bottom 50%, 2.56% for the upper middle 40% and 4.48% for the top 10% (see the light blue bars in Figure 5). Note, however, that a difference in rates of return between the bottom half and the upper middle 40% of approximately 1.6 percentage points still exists after excluding owner-occupied residential property from the analysis which indicates that financial assets also matter for differential returns. Table 7 in the appendix demonstrates that these results are qualitatively and quantitatively robust to changes in the return data; using only data from Jordà et al. (2019) yields very similar results.

Figure 5: Gross and net rates of return by wealth group

(a) Rate of return on gross wealth



(b) Rate of return on net wealth



Note: This figure shows rates of return on (a) gross and (b) net wealth by wealth group. The bars indicate the nominal rate of return (adjusted for interest costs in the bottom pane), and the dots represent the real rate of return (adjusted for inflation). The 95% confidence intervals are presented for the rate of return on gross wealth. It should be noted that the variance is solely attributable to differences in portfolio composition and is therefore small. Confidence intervals are not displayed for the rate of return on net wealth, as the calculation is based on average values at the level of wealth groups. Source: SOEP 2019, ECB (2021), Bundesbank (2015), Bundesbank (2024a), Bundesbank (2024b), Jordà et al. (2019), and FMH Finanzberatung e.K. (2024).

Overall, our findings align well with previous household-level analyses conducted for Germany. Bundesbank (2022) reports nominal rates of return of slightly over 2% for the lower half of

households, approximately 6% for the upper middle 40%, and about 7% for the top 10%. These rates of return are roughly one percentage point higher than those observed in our individual-level analysis, which can be explained through slight differences in the data basis and the shorter time horizon for returns data from 2009 to 2022. Ederer et al. (2021) estimate a real rate of return of 2.1% for asset-poor households in Germany, defined as those with less than 50% of their gross wealth in their main residence. These rates of return exceeds our calculated real rate of return of 0.5% for the bottom 50%, while their reported rates of return for the home-owning middle class and the business-owning top 5% are lower than those found in our upper half analysis. The main reason is likely the longer time horizon of the interest rates in Ederer et al. (2021), which covers the period 1980 to 2015 and leads to differences in the average annual real rates of return.²⁰

Despite the remarkable consistency with the literature, several caveats should be born in mind. First, the analysis presented here, like the literature, does not take into account regional differences in rates of return on housing, although it is likely to differ substantially. Second, the data in the house price series, on which the return data is based, covers urban areas and does not include properties in rural regions. Another question concerns whether the same rates of return should be applied to shares and corporate assets, where we follow (Jordà et al., 2019, p. 1231).²¹ The application of different rates of return for corporate assets would affect the results, particularly for the top 10% holding a larger share in corporate assets. The assumption of a higher rate of return for private equity than public equity would result in an increase in the average rate of return for this group. Consequently, the current methodology for calculation is conservative since it may underestimate the rate of return for the wealthiest individuals. Regarding the data on the asset portfolios it is important to note this is derived from a survey, which is subject to the typical limitations of such data. For instance, respondents may not have a precise understanding of the value of specific assets they hold, or they may conflate different asset classes, such as corporate assets with shares as part of monetary investments. Finally, it should be noted that the wealth shares within the monetary investments do not originate from the original SOEP data; rather, they were estimated using machine learning. While this is an important innovation of our paper, it may influence our findings.

²⁰Ederer et al. (2021) use average real rates of return published in Jordà et al. (2019), while we access their microdata now available and amplify it with additional data sources.

²¹The empirical evidence is mixed regarding returns on private and public equity. Moskowitz and Vissing-Jørgensen (2002) find that the average returns between 1953 and 1999 on private and public U.S. equities are quite similar. In contrast, Kartashova (2014) find higher private returns between 1999 and 2007 and similar returns in the 2008-2010 period using the same U.S. data. In their analysis on rates of return, Fagereng et al. (2020) detect larger returns when increasing the share in private business, whereas Bach et al. (2020) do not see such risk-adjusted returns on private equity.

4.3 Example groups

Since each wealth group comprises a heterogeneous population, we present examples of individuals below to provide both a more intuitive and a more differentiated picture of different socio-economic groups' wealth composition and rates of return. For each example, we provide the mean wealth, mean income, the first quartile (Q1), the median (Q2) and the third quartile (Q3) of gross income, average annual nominal rate of return, the proportion of this group in our sample, as well as the overall wealth group in which such a person is typically found. Additionally, we display an average asset portfolio.²²

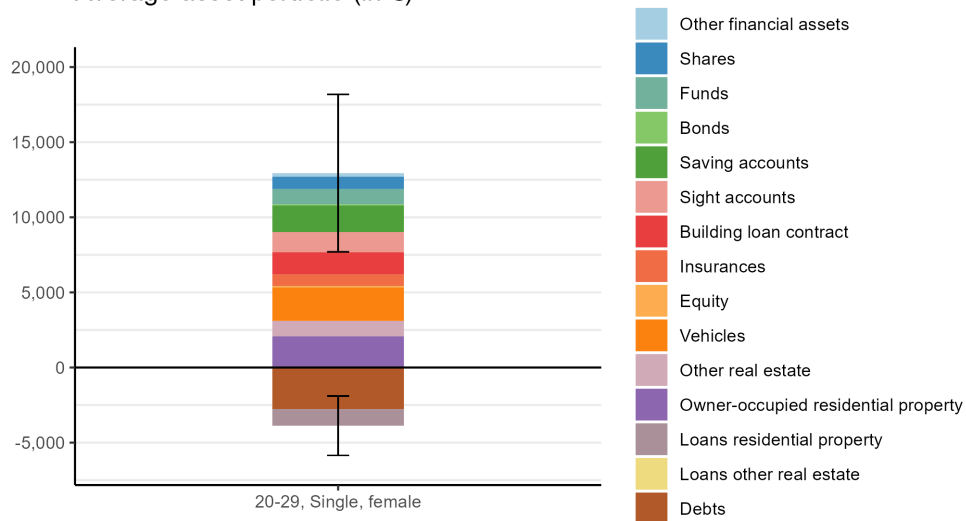
The examples provided can be seen as representative of different wealth groups. Single women in their 20s, young parents with a migration background, single parents, and unemployed men predominantly fall in the lower half of the wealth distribution. Their average nominal rates of return range from about 1.1% for an unemployed man to about 2% for a young parent with a migration background. The average gross wealth for these groups varies from approximately 13,000€ for young single women to approximately 110.000€ for single parents. The portfolio composition also differs between these example groups: young single women have similar-sized shares, while the other three groups have higher shares in owner-occupied residential property. Since these examples are based on socio-demographic characteristics rather than asset groups, their portfolios differ from the previously mentioned wealth groups, where the bottom 50% did not own owner-occupied residential property.

²²A related, nuanced analysis of wealth for slightly different socio-demographic subgroups can be found in the 'Accompanying research on the Sixth Poverty and Wealth Report of the Federal Government' (Kleimann et al., 2019, 313ff).

Example 1: Female Single (20 - 29 years old)

- **Population share:** 1.29%
- **Average wealth 2019:**
 - Gross: 12,973 € (Se: 2,680.9)
 - Net: 9,065.5 € (Se: 2,419.9)
- **Average gross income 2018:**
 - Mean: 1,537.8 € (Se: 97.84)
 - Q1 — Q2 — Q3: 743.58 € — 1,108.33 € — 2,303 €
- **Average nominal rate of return:** 1.36 (Se: 0.16)
- **Shares in wealth groups:**
 - bottom 50%: 90.88%
 - upper middle 40%: 8.32%
 - top 10%: 0.8%

Average asset portfolio (in €)

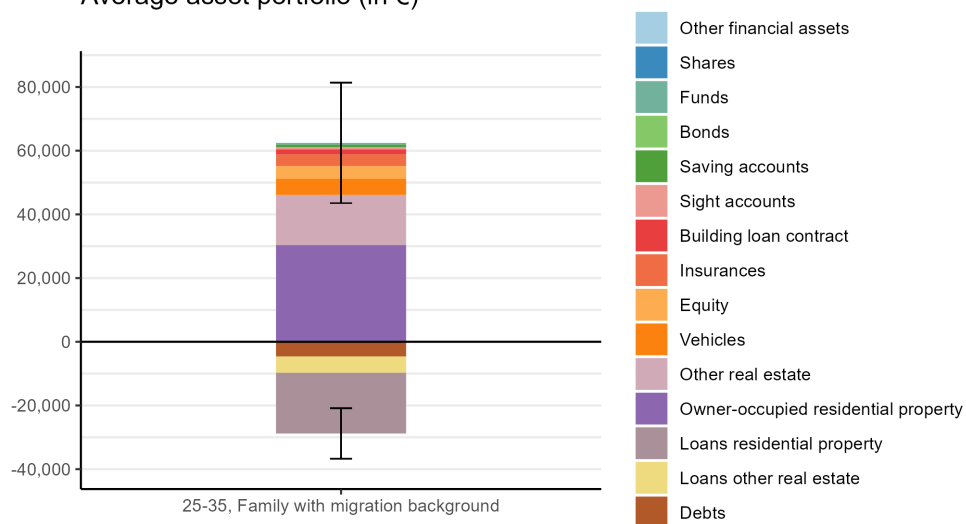


Note: This figure shows the type of assets owned on average by this example group. 95% confidence intervals are presented for total gross assets and total debts. Table 9 in the appendix presents the absolute value. Source: SOEP 2019 and ECB (2021).

Example 2: Parent with partner and child(ren) younger than 18 with migration background (25 - 35 years old)

- **Population share:** 1.65%
- **Average wealth 2019:**
 - Gross: 62,442 € (Se: 9,667.6)
 - Net: 33,641 € (Se: 7,464.1)
- **Average gross income 2018:**
 - Mean: 1,927.7 € (Se: 128.46)
 - Q1 — Q2 — Q3: 729 € — 1,505.33 € — 3090 €
- **Average nominal rate of return:** 1.99 (Se: 0.21)
- **Shares in wealth groups:**
 - bottom 50%: 73.09%
 - upper middle 40%: 22.85%
 - top 10%: 4.06%

Average asset portfolio (in €)

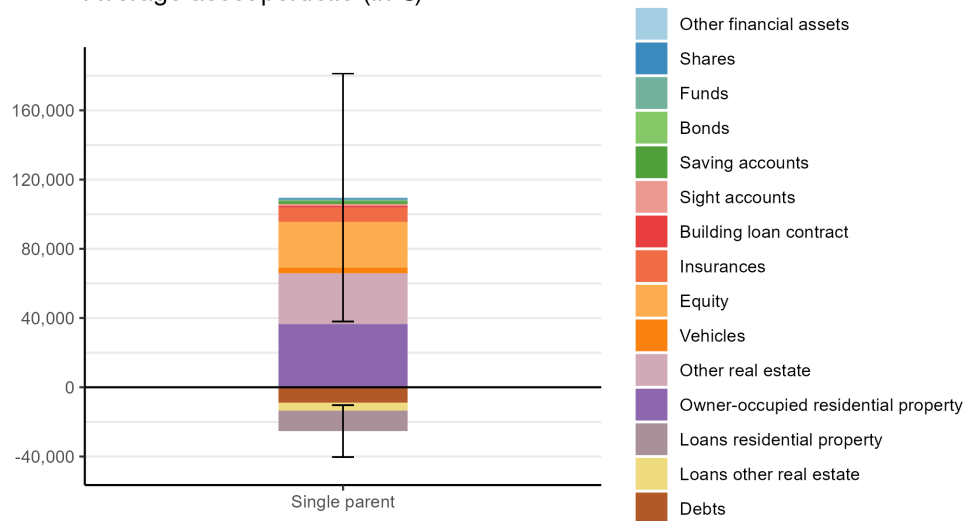


Note: This figure shows the type of assets owned on average by this example group. 95% confidence intervals are presented for total gross assets and total debts. Table 9 in the appendix presents the absolute value. Source: SOEP 2019 and ECB (2021).

Example 3: Single parent with child(ren) younger than 18

- **Population share:** 2.09%
- **Average wealth 2019:**
 - Gross: 109,596 € (Se: 36,565)
 - Net: 84,276 € (Se: 30,233)
- **Average gross income 2018:**
 - Mean: 2,748.6 € (Se: 107.29)
 - Q1 — Q2 — Q3: 1,590.83 € — 2,288 € — 3,368.58 €
- **Average nominal rate of return:** 1.93 (Se: 0.16)
- **Shares in wealth groups:**
 - bottom 50%: 76.11%
 - upper middle 40%: 17.95%
 - top 10%: 5.94%

Average asset portfolio (in €)



Note: This figure shows the type of assets owned on average by this example group. 95% confidence intervals are presented for total gross assets and total debts. Table 9 in the appendix presents the absolute value. Source: SOEP 2019 and ECB (2021).

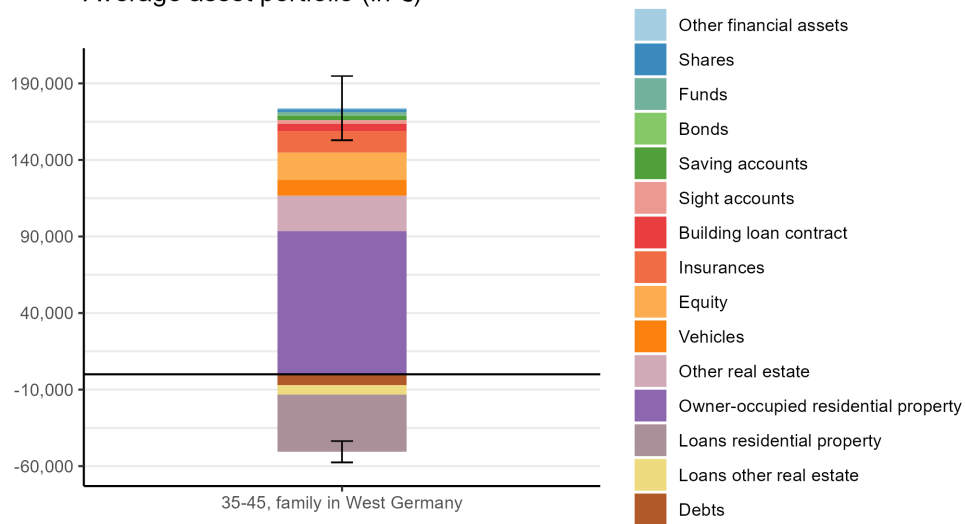
The examples of a parent aged 35 to 45 in West Germany and a person over 70 in a couple in East Germany mostly belong to the upper middle 40% of the wealth distribution, with average nominal rates of return of about 3.8% and 3.4%, respectively. However, the average gross wealth for a parent in West Germany is about 174,000€, compared to only about 64,000€ for the elderly person in East Germany. In both cases, the largest share of their wealth portfolios is in owner-occupied residential property.

A significantly different portfolio composition is observed in the example of a self-employed person in West Germany aged 50-65. This portfolio is primarily made up of equity, followed by owner-occupied residential property and other real estate. The average rate of return for this group is about 5.5%, and their average gross wealth was about 920,000€ in 2019. Moreover, about 46% of this group are in the top 10% of the gross wealth distribution.

Example 4: Parent with partner and child(ren) younger than 18 in West Germany (35 - 45 years old)

- **Population share:** 7.33%
- **Average wealth 2019:**
 - Gross: 173,872 € (Se: 10,700)
 - Net: 123,291 € (Se: 9,604.4)
- **Average gross income 2018:**
 - Mean: 3,388.1 € (Se: 101.21)
 - Q1 — Q2 — Q3: 1,472.83 € — 2,763.21 € 4,190 €
- **Average nominal rate of return:** 3.81 (Se: 0.1)
- **Shares in wealth groups:**
 - bottom 50%: 39.75%
 - upper middle 40%: 48.42%
 - top 10%: 11.83%

Average asset portfolio (in €)

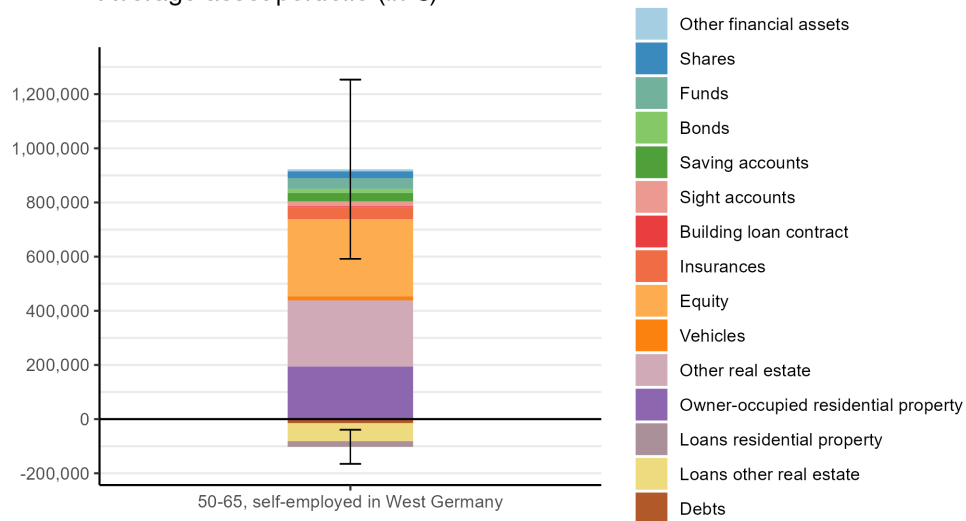


Note: This figure shows the type of assets owned on average by this example group. 95% confidence intervals are presented for total gross assets and total debts. Table 9 in the appendix presents the absolute value. Source: SOEP 2019 and ECB (2021).

Example 5: Self-employed person in West Germany (50 - 65 years old)

- **Population share:** 2.04%
- **Average wealth 2019:**
 - Gross: 922,761 € (Se: 168,936)
 - Net: 820,396 € (Se: 140,258)
- **Average gross income 2018:**
 - Mean: 6,846.1 € (Se: 926.3)
 - Q1 — Q2 — Q3: 1,996.63 € — 3,690.58 € — 7,011.11€
- **Average nominal rate of return:** 5.5 (Se: 0.12)
- **Shares in wealth groups:**
 - bottom 50%: 14.07%
 - upper middle 40%: 40.06%
 - top 10%: 45.87%

Average asset portfolio (in €)

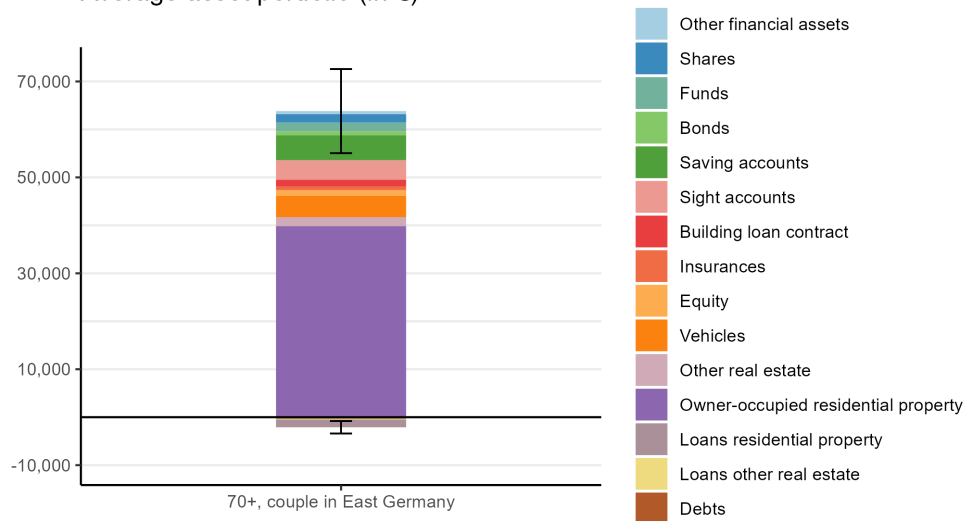


Note: This figure shows the type of assets owned on average by this example group. 95% confidence intervals are presented for total gross assets and total debts. Table 9 in the appendix presents the absolute value. Source: SOEP 2019 and ECB (2021).

Example 6: Person in couple in East Germany (70+ years old)

- **Population share:** 1.72%
- **Average wealth 2019:**
 - Gross: 63,826 € (Se: 4,475.4)
 - Net: 61,724 € (Se: 4,343.6)
- **Average gross income 2018:**
 - Mean: 2,810,9 € (Se: 71.55)
 - Q1 — Q2 — Q3: 2,020.83 € — 2,601.33 € — 3,300.63 €
- **Average nominal rate of return:** 3.44 (Se: 0.17)
- **Shares in wealth groups:**
 - bottom 50%: 45.3%
 - upper middle 40%: 53.44%
 - top 10%: 1.26%

Average asset portfolio (in €)

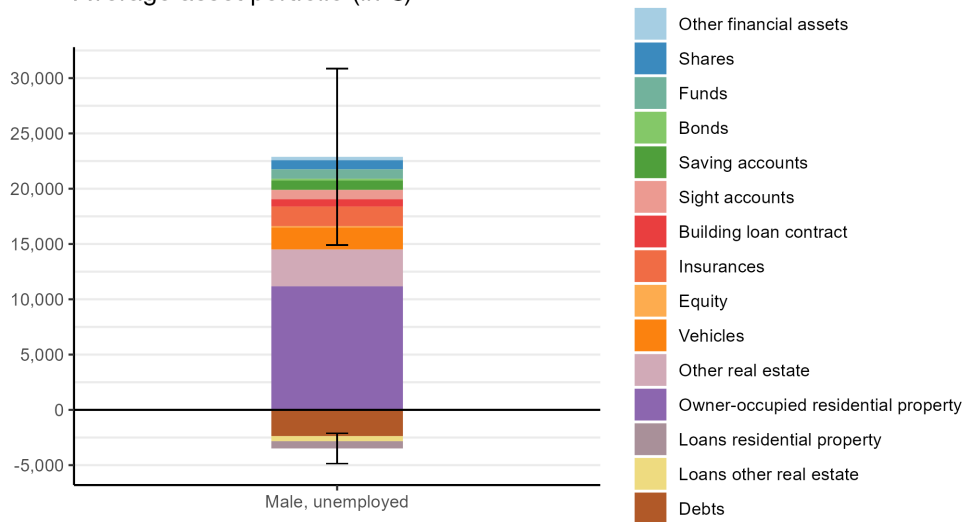


Note: This figure shows the type of assets owned on average by this example group. 95% confidence intervals are presented for total gross assets and total debts. Table 9 in the appendix presents the absolute value. Source: SOEP 2019 and ECB (2021).

Example 7: Male and unemployed person

- **Population share:** 2.44%
- **Average wealth 2019:**
 - Gross: 22,882 € (Se: 4,073.9)
 - Net: 19,393 € (Se: 3,953.7)
- **Average gross income 2018:**
 - Mean: 1,315.4 € (Se: 114.27)
 - Q1 — Q2 — Q3: 560.42 € — 919.42 € — 1,505.33 €
- **Average nominal rate of return:** 1.1 (Se: 0.19)
- **Shares in wealth groups:**
 - bottom 50%: 83.45%
 - upper middle 40%: 15.44%
 - top 10%: 1.11%

Average asset portfolio (in €)



Note: This figure shows the type of assets owned on average by this example group. 95% confidence intervals are presented for total gross assets and total debts. Table 9 in the appendix presents the absolute value. Source: SOEP 2019 and ECB (2021).

5 Conclusion

This paper investigates rates of return on wealth across gross wealth groups by matching individual-level survey data from 2019 (SOEP data combined with ECB (2021) using machine learning) with macroeconomic return data from Jordà et al. (2019), Bundesbank, and FMH Finanzberatung e.K. for detailed asset categories.

For the period from 1995 to 2020, the average nominal rate of return on gross assets for the bottom 50% is 1%, for the upper middle 40% it amounts to about 5.4%, and for the top 10% to 6.3%. After adjusting the nominal rate of return for interest payments on loans and inflation, the average rate of return for the bottom 50% is negative. To the best of our knowledge, the analysis presented here provides the first evidence of differential returns at the personal level for Germany. This discrepancy in returns is due to differences in the portfolio composition. The upper middle group primarily differs from the lower half by possessing owner-occupied residential property, while the top 10% also own other real estate and business assets.

A more nuanced analysis of the wealth groups reveals an unequal distribution of socio-demographic characteristics. For instance, women, individuals with a migration background and young people are more likely to be in the lower half of the wealth distribution. This indicates that certain characteristics structurally predispose individuals to specific positions within the wealth distribution, implying that these characteristics are associated with lower average rates of return. To exemplify this, we present seven distinct groups of individuals. This shows that e.g. young, single women, young parents with a migration background, single parents, and unemployed men are predominantly in the lower half of the wealth distribution with a tendency towards lower returns.

The existing literature identifies different potential explanations for the observed heterogeneity in rates of return. These can be broadly categorised into individual and structural factors. With regard to the former, individual reasons may include a lack of financial education or individual portfolio choice. Structural factors, on the other hand, concern issues such as lower capacities for risk-bearing and for long-duration investment as well as the cost effectiveness of financial advisors and the availability of investment options, which may depend on the level of wealth. The existing empirical literature provides mixed evidence. Although our analysis does not directly address the question of structural versus individual causes, our findings indicate a correlation between the level of wealth and rates of return, which suggest that structural issues linked to the wealth level likely play a role. This conclusion is in line with the development

economics literature on poverty traps.

The investigation conducted in this paper has important political ramifications. If low-income, low-wealth individuals are structurally limited in their investment capacities, as our analysis suggests, then this raises questions about the effectiveness of individual old-age provisioning, especially in comparison to collective welfare systems. Our finding that the rate of return net of cost and inflation is negative for the bottom half of the population further emphasizes this point. Moreover, note that even a positive rate of return might yield low absolute capital income if applied to a (very) low or even negative capital stock, as we observe in our data for the bottom half of the population.

Naturally, several avenues for future research remain open. The individual-level analysis performed here provides a foundation for examining product-side access barriers and costs associated with different asset classes, which would permit a more differentiated picture of returns, rather than the average rates of return assumed here for reasons of data availability. Such an analysis could also facilitate the investigation of structural causes behind portfolio and rate of return differences. Additionally, qualitative research could enrich the findings e.g. by exploring asset categories left out in our analysis like informal loans. Furthermore, qualitative approaches could also be employed to examine in greater detail specific structural differences between wealth groups, such as the possibility to take advantage of financial consulting.

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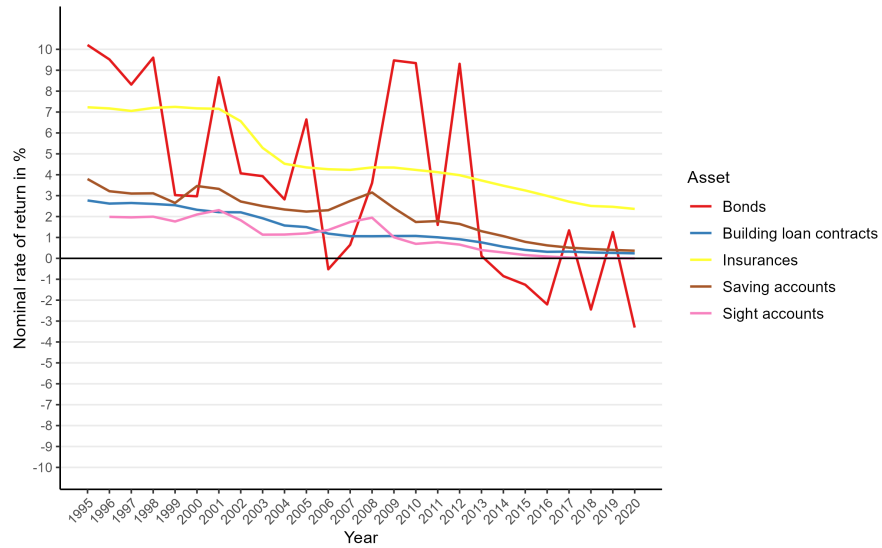
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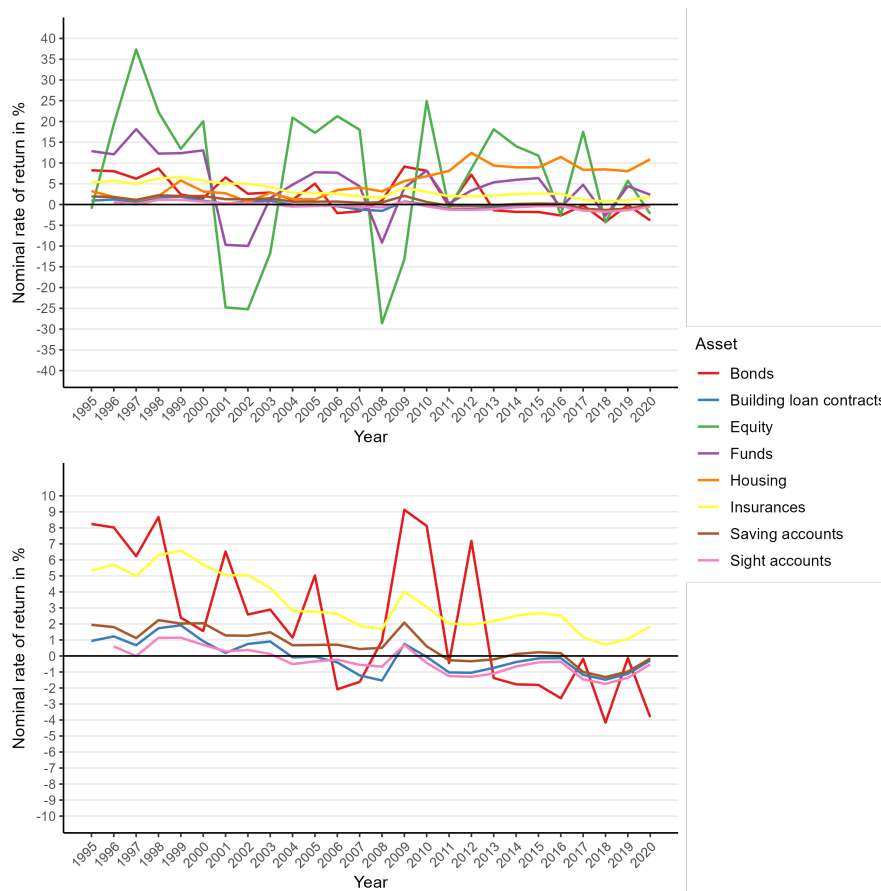
6 Appendix

Figure 6: Annual nominal rates of return by assets (1995-2020)



Note: This figure shows annual nominal rates of return by selected assets from 1995 to 2020. Source: Bundesbank (2015), Bundesbank (2024a), Bundesbank (2024b), and FMH Finanzberatung e.K. (2024).

Figure 7: Annual real rates of return by assets (1995-2020)



Note: This figure shows annual real rates of return by assets from 1995 to 2020. Source: Bundesbank (2015), Bundesbank (2024a), Bundesbank (2024b), Jordà et al. (2019), and FMH Finanzberatung e.K. (2024)

Rates of return from Macrohistory

In this calculation, we match the asset classes and the return data from Macrohistory as follows: we use the housing rate for home ownership and other real estate, the equity rate for business assets, shares and other financial assets, the bond rate for bonds and insurances and the bill rate for saving accounts, sight accounts and building loan contracts. For funds, we use the mean of the average equity and bond rate. We do not assume vehicles to yield a return.

Table 7: Average annual nominal rates of return by wealth group with Macrohistory Data

	All assets	Without owner-occupied housing
bottom 50%	1.11	1.07
upper middle 40%	5.5	2.76
top 10%	6.4	4.71

Note: This table shows average annual nominal rates of return by wealth groups with using only Jordà et al. (2019) data for the rates of return. We use the housing rate for owner-occupied residential property and other real estate, the equity rate for corporate assets, shares and other financial assets, the bond rate for bonds and insurances and the bill rate for saving accounts, sight accounts and building loan contracts. For funds, we use the mean of the average bond and equity rate. Source: SOEP 2019, ECB (2021), and Jordà et al. (2019)

Table 8: Values of average asset portfolios by gross wealth groups for 2019

Asset class	50%	40%	10%
Gross Wealth	5948.10	149382.50	924576.23
Owner-occupied residential property	102.28	97790.75	339549.56
Other real estate	51.14	10233.56	212504.61
Vehicles	2536.40	8453.37	50160.92
Equity	38.74	1359.61	169558.50
Insurances	998.77	9019.56	40234.43
Building loan contracts	589.65	4133.87	7522.01
Sight accounts	550.45	4234.48	15838.45
Saving accounts	654.40	6280.50	25371.55
Bonds	42.25	865.06	8904.29
Funds	176.05	3372.69	27238.30
Shares	146.86	2615.32	20536.06
Other financial assets	61.11	1023.73	7157.91
Total Debts	2612.50	22964.76	86140.16
Loans residential property	13.41	18147.10	38306.82
Loans other real estate	2.89	2036.20	36530.53
Debts	2596.21	2781.46	11302.81

Note: This table presents the absolute values from Figure 3. It should be noted that the values pertaining to monetary investments (sight accounts, saving accounts, bonds, funds, shares and other financial assets) were not directly obtained from the SOEP; rather, they were imputed with the assistance of machine learning and HFCS data. Source: SOEP 2019 and ECB (2021).

Table 9: Values of average asset portfolios by the example groups for 2019

Asset class	1	2	3	4	5	6	7
Gross Wealth	12939.13	62442.24	109595.99	173872.19	922760.70	63825.72	22881.80
Owner-occupied residential property	2071.51	30348.62	36528.49	93462.88	194179.94	39825.79	11171.89
Other real estate	1030.34	15728.23	29321.98	23143.49	244542.49	1879.48	3329.85
Vehicles	2226.26	5129.64	3349.17	10379.90	14364.08	4422.94	1996.00
Equity	100.55	3938.82	26340.85	17802.88	284945.33	1213.11	111.07
Insurances	763.16	3679.47	8202.13	13992.59	44044.62	772.51	1782.11
Building loan contracts	1479.26	1569.41	1103.98	4792.51	3963.51	1394.16	660.96
Sight accounts	1346.26	742.65	1030.16	2429.12	17344.89	4063.27	838.41
Saving accounts	1760.51	744.93	1556.79	2969.39	31866.65	5200.46	845.15
Bonds	82.00	15.13	257.68	357.49	14158.74	827.90	160.02
Funds	1014.50	243.34	856.16	2031.56	39890.31	1821.08	857.09
Shares	827.43	208.05	701.19	1735.29	25838.44	1750.62	824.93
Other financial assets	237.34	93.99	347.41	775.11	7623.21	654.45	304.30
Total Debts	3873.61	28801.26	25319.82	50581.28	102364.89	2102.06	3488.69
Loans residential property	1104.44	19087.56	11877.55	37351.40	21453.95	1658.13	659.41
Loans other real estate	0.00	5117.10	4565.82	6185.84	66198.48	152.71	462.01
Debts	2769.17	4596.59	8876.46	7044.04	14712.46	291.23	2367.28

Note: This table presents the absolute values for the asset portfolios of the seven example groups. It should be noted that the values pertaining to monetary investments (sight accounts, saving accounts, bonds, funds, shares and other financial assets) were not directly obtained from the SOEP; rather, they were imputed with the assistance of machine learning and HFC/S data. Source: SOEP 2019 and ECB (2021).



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