Why Do Wealthier Households Earn Higher Returns? Evidence from the SCF

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Abstract

This thesis studies how different measures of investment returns shape conclusions about the relationship between household wealth and investment performance. Using the 2007–2009 SCF panel, we construct both a benchmark-based expected return (Er) and a realized Dietz return, and estimate household-level alphas following Bach et al. (2020) and Fagereng et al. (2020). The results show that Er suggests a strong wealth–return gradient and produces widely dispersed alphas, whereas the Dietz return yields a weak and statistically insignificant relationship, with alphas tightly clustered around zero once observable characteristics are controlled. These findings indicate that the unobserved heterogeneity in investment performance under an expected-return framework may largely reflect measurement conventions rather than true persistent skill. The thesis therefore highlights that conclusions about return heterogeneity, investment ability, and their contribution to wealth inequality depend crucially on how returns are measured, especially in short panels and during periods of extreme market turbulence.

Keywords: return measurement, expected return, Dietz return, Survey of Consumer Finances, investment heterogeneity, alpha, wealth inequality

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1. Introduction

In recent years, wealth inequality in the United States has continued to widen, bringing attention to a fundamental question in the study of wealth accumulation: why do richer households earn higher investment returns than ordinary families? Theoretical research suggests that even small differences in returns, when compounded over time, can generate extremely concentrated wealth distributions (Benhabib, Bisin, & Zhu, 2011; Gabaix et al., 2016). Piketty (2014) further argues that when the rate of return on capital for the wealthy exceeds the rate of economic growth, this structural gap accelerates the concentration of wealth at the top. Therefore, understanding the heterogeneity of investment returns and its origins is crucial for explaining the evolution of wealth inequality.

High-quality administrative data have provided valuable insights into the relationship between wealth and investment returns. Using Swedish population-wide data, Bach, Calvet, and Sodini (2020) show that wealthy households tend to hold portfolios with greater exposure to systematic risk, leading to higher expected returns, while finding little evidence that the rich exhibit superior investment skill (alpha). In contrast, Fagereng et al. (2020), drawing on Norwegian administrative records, document substantial and persistent return differentials and suggest that alpha may reflect stable, unobserved individual traits or financial sophistication. These two studies provide complementary yet contrasting explanations for why wealthier households earn higher returns, particularly disagreeing on the centrality of "investment skill." This divergence highlights the need for further empirical evidence, especially in the context of the United States.

Compared with the rich administrative datasets available in Nordic countries, micro-level evidence from the United States is more limited in scope. The Survey of Consumer Finances (SCF) provides detailed information on U.S. household portfolios, liabilities, and demographic characteristics. While the SCF has been used widely for various purposes, it has been less frequently applied to examining the underlying sources of return heterogeneity, partly because only two waves allow for a panel structure. Consequently, it remains an open question to what extent differences in investment returns across U.S. households reflect variation in investment skill, differences in risk-taking, or observable behaviors and characteristics.

Building on these gaps, this paper offers an examination of how alternative return measures affect empirical conclusions about return heterogeneity in the United States. Using the 2007–2009 panel of the Survey of Consumer Finances (SCF), we construct two distinct measures of household portfolio performance: a benchmark-based expected return (Er), derived from portfolio weights and asset-class index returns, and a realized Dietz return, which approximates actual performance using non-salary income and end-of-period net wealth. We then apply a consistent regression framework across both return measures to estimate wealth–return relationships and household-level alphas.

A central feature of our approach is that the empirical model is held constantly, while the return measure varies. This design allows us to isolate how much of the observed return–wealth gradient, and the dispersion of estimated investment ability (α), is driven by economic differences versus by the construction of the return measure itself. The comparison is particularly relevant given the short panel and the extreme market conditions during the 2007–2009 financial crisis, which may amplify differences between theoretical and realized returns.

Our findings reveal that conclusions differ sharply depending on the return measure used. When expected returns (Er) are employed, wealthier households appear to earn higher returns and display a wide dispersion of alphas across the wealth distribution. In contrast, when using the Dietz realized return, the wealth–return relationship becomes weak and statistically insignificant, and the distribution of alpha collapses toward zero once observable characteristics are controlled for. This suggests that the apparent "excess performance" of wealthy households under Er is largely mechanical, arising from benchmark-implied returns rather than from persistent investment skill.

Ovearall, by clarifying the role of return measurement, the paper contributes new U.S.-based evidence to a literature shaped primarily by Nordic administrative studies and highlights the need for careful consideration of measurement choices when evaluating wealth inequality and investment heterogeneity.

2. Literature Review

2.1 Why returns matter for wealth inequality

A substantial theoretical literature highlights the central role of heterogeneous investment returns in shaping the distribution of wealth. Early macroeconomic models

(Aiyagari, 1994; Huggett, 1993) focused primarily on labor-income risk and borrowing constraints. However, these frameworks struggled to replicate the extreme concentration observed in modern wealth distributions (De Nardi & Fella, 2017). Subsequent research introduced heterogeneity in returns to wealth as a key mechanism, which can generate fat-tailed steady-state distributions. Benhabib, Bisin, and Zhu (2011) formalize an overlapping-generations model, where idiosyncratic, persistent differences in returns produce a Pareto-shaped upper tail, even without large differences in income. Gabaix et al. (2016) further shows that realistic levels of return volatility can generate both the long right tail and the dynamic evolution of top wealth shares observed in the data. These models collectively show that return heterogeneity may be the dominant driver of top wealth concentration, rather than saving rate differences or labor-income dispersion.

Recent work also emphasizes that micro-level behavioral channels can reinforce differences in returns. For example, households vary systematically in their risk tolerance (Chiappori & Paiella, 2011), financial literacy (Lusardi & Mitchell, 2014), portfolio participation (Campbell, 2006), and access to high-return entrepreneurial opportunities (Quadrini, 2000; Cagetti & De Nardi, 2006). These studies show that heterogeneity in preferences, information, and market access can translate into persistent differences in realized returns and capital accumulation.

In summary, theory consistently predicts that heterogeneous returns, especially when persistent, play a first-order role in determining both the level and dynamics of wealth inequality. These insights motivate extensive empirical research aimed at identifying whether wealthier households indeed earn higher returns, and if so, what mechanisms produce such differences.

2.2 International empirical evidence on return heterogeneity

High-quality administrative data from Nordic countries have led to major advances in documenting return heterogeneity.

Using Swedish nationwide data, Bach, Calvet, and Sodini (2020) find clear scale dependence: wealthier households hold portfolios with greater exposure to systematic risk and therefore earn higher expected returns. Importantly, they find little evidence that rich households generate positive alpha. Instead, higher returns are fully explained by risk exposures and asset composition.

By contrast, Fagereng et al. (2020) use Norwegian administrative records to document large and persistent cross-sectional differences in realized returns. They argue

that part of this heterogeneity reflects stable, unobserved individual traits, potentially financial sophistication or entrepreneurial ability, which implies that some investors may indeed possess "investment skill."

These studies provide complementary but conflicting interpretations of why wealthy households earn higher returns. Reconciling these differences remains an open empirical question, especially in the context of a country with a very different financial system such as the United States.

2.3 Mechanisms behind return heterogeneity

Several mechanisms have been proposed to explain why investment returns vary systematically across households. One explanation focuses on differences in systematic risk exposure, as wealthier households tend to hold more equity-like and market-sensitive assets, leading to higher expected returns (Calvet, Campbell, & Sodini, 2007). A second mechanism emphasizes portfolio composition, particularly participation in equities, mutual funds, and private business assets, which offer higher average returns relative to safer assets. Another strand of research highlights the role of financial literacy and risk tolerance, noting that financially sophisticated households are more likely to participate in high-return asset classes and diversify effectively (Lusardi & Mitchell, 2014). Moreover, wealthier households often enjoy greater access to high-return investments, such as entrepreneurship and private equity, which have historically generated elevated but volatile returns (Moskowitz & Vissing-Jørgensen, 2002).

Besides, different measurements of household investment returns could also influence empirical conclusions about return heterogeneity. Unlike institutional portfolios, household portfolios are difficult to evaluate because most datasets don't have sufficient detailed information on transaction timing, security-level holdings, capital gains, and intra-year cash flows. As a result, researchers might rely on approximations that differ sharply in what they capture. Benchmark-based expected returns, such as those employed by Bach, Calvet, and Sodini (2020), map household portfolio weights to historical asset-class index returns. In contrast, Fagereng et al. (2020) compute realized returns incorporating dividends, interest, capital gains, and borrowing costs, which capture idiosyncratic shocks, liquidity needs, and timing decisions.

Based on these different interpretations, it's interesting to test the return heterogeneity in the U.S. context.

2.4 Return skill versus observable characteristics

A longstanding literature questions whether persistent alpha truly exists, even among professional investors. Fama and French (2010) show that most mutual fund managers fail to generate risk-adjusted excess returns net of fees, while Barber and Odean (2002) show that individual investors often exhibit behavioral biases, such as overconfidence and excessive trading, which reduce rather than enhance performance. If sophisticated institutional investors rarely produce skill-based alpha, it is even less clear whether households possess the ability to do so.

Building on this perspective, several studies argue that what appears to be "investment skill" may instead reflect differences in observable characteristics. For example, risk tolerance and demographic attributes such as age, education, and marital status influence both portfolio choice and long-term outcomes (Guiso & Paiella, 2008). Access to financial advice and intermediate products also varies systematically across households, further blurring the line between skill and resources (Von Gaudecker, 2015).

2.5 Gaps in the U.S. context and our contributions

Compared with Nordic countries, the United States has more limited administrative data that track household-level wealth and investment returns. Consequently, the mechanisms behind return heterogeneity are less well understood in the U.S. context. The Survey of Consumer Finances (SCF) provides exceptionally detailed information on household portfolios. However, its short-panel structure means that it has been used less frequently to analyze the determinants of return differences or to assess the extent to which observable characteristics account for higher returns among wealthier households. Moreover, existing U.S. research has not fully examined how different return measures applied to the same households may generate different conclusions about return heterogeneity.

This paper contributes to the literature by systematically comparing expected returns (Er) and realized Dietz returns within the same empirical framework using the SCF 2007–2009 panel. Our findings reveal that expected returns produce a strong wealth–return gradient and wide alpha dispersion, yet realized returns yield weak wealth effects and tightly clustered alphas once observable characteristics are controlled. This demonstrates that empirical assessments of investment ability and return heterogeneity are highly sensitive to return measurement.

3. Data

3.1 Overview of the SCF

The Survey of Consumer Finance is a representative household financial survey dominated by the U.S. Federal Reserve Board, done every three years since 1983. The survey is conducted by NORC at the University of Chicago, in a dual-frame sample design which enables a more accurate capture of wealth distributions. Additionally, the SCF survey employs multiple imputation to address missing values, with each sample household providing five sets of imputed data. The SCF survey contains comprehensive information on household assets, liabilities, income, and financial behaviors, serving as an essential data source for studying household wealth distribution, financial risk, consumption decisions, and wealth inequality.

The 2007-2009 panel data is used in this thesis, which is an additional longitudinal panel study based on the regular SCF. This dataset was designed to examine the dynamic shifts in U.S. household wealth, debt, and financial behavior during the 2007-2009 global financial crisis.

Variables	Description
WealthRank	Household's percentile rank (0–1) in the survey-weighted distribution of net worth; higher values indicate greater wealth
LEVERAGE	Total Debt / Total Assets
Beta	Risk exposure of each household
MARRIED	Binary variable equal to 1 if the household head is not married and 2 otherwise
W_Stock	Share of total household financial assets invested in stocks
W_Bond	Share of total household financial assets invested in bonds
W_Cash	Share of total household financial assets invested in cash
W_Deposit	Share of total household financial assets invested in deposit
W_Funds	Share of total household financial assets invested in funds

W_RealEstate	Share of total household financial assets invested in stocks
KIDS	The number of kids each household has
INCOME	Household's total pre-tax cash income (U.S. dollars) in the survey year
RISK	Ordinal variable (1–4) indicating willingness to take financial risk; higher values denote lower risk tolerance
IFINPLAN	Dummy variable equal to 1 if the household head has consulted a financial planner or bank advisor about savings or investments, and 0 otherwise
BFINPLAN	Dummy variable equal to 1 if the spouse or partner has consulted a financial planner or bank advisor about savings or investments, and 0 otherwise

Table 1: Descriptive statistics based on the 2007–2009 SCF panel data.
This table shows the main variables and their definitions in the 2007–2009 SCF panel data.

3.2 Other Source of Data

We use the U.S. market index to estimate the returns based on the asset classification according to the SCF survey. We use S&P 500 index for stock returns, ICE BofA US Corporate Index Total Return Index Value for bond returns, 1-Month Treasury Bill Rate for deposit returns, 3-month Treasury Bill Interest Rate for cash returns, and FTSE Nareit All Equity REITs Index for real estate returns.

Following standard practice in both academic research (e.g., Ibbotson and Kaplan, 2000) and the benchmark allocations of balanced mutual funds such as Vanguard and Fidelity, we approximate mutual fund returns using a 60/40 stock–bond portfolio.

3.3 Descriptive Statistics

There are 3,857 families observed for the survey, with each family having 5 imputations. In all, there are 19,285 records in the data set. All the observations are weighted according to the national household distribution.

	count	mean	sd	min	max
Er	5897	0.075	0.185	-0.157	0.280

NETWORTH	7041	12,478,109	56,594,669	1.036	1.32×10^{9}
WealthRank	7041	0.651	0.326	0.010	1.000
Beta	5897	0.560	0.132	0.000	0.640
AGE	7041	53.913	15.278	19.000	95.000
EDUC	7041	14.192	2.700	-1.000	17.000
MARRIED	7041	1.316	0.465	1.000	2.000
KIDS	7041	0.833	1.185	0.000	10.000
LEVERAGE	7041	21.714	26.173	0.000	99.998
RISK	7041	3.003	0.844	1.000	4.000
INCOME	7041	948,034	5,322,745	0.000	1.88×10^{8}
NonSalary Inco	7041	26,996	2,401,502	-1,000,000	1.22×10^{8}
IFINPLAN	7041	0.381	0.486	0.000	1.000
BFINPLAN	7041	0.248	0.432	0.000	1.000
W_Stock	5897	0.116	0.241	0.000	1.000
W_Bond	5897	0.020	0.124	0.000	1.000
W_Deposit	5897	0.051	0.163	0.000	1.000
W_Cash	5897	0.008	0.053	0.000	1.000
W_Funds	5897	0.087	0.202	0.000	1.000
W_RealEstate	5897	0.719	0.357	0.000	1.000
Dietz_r	7041	-0.108	2.597	-185.400	34.168

Table 2: Descriptive statistics based on the 2007–2009 SCF panel data.
This table describes the number, mean, max, and min of the observations of each variable. NonSalary Inco is the non-salary income for each household.

The average expected return (Er) across households is 7.5%, while the realized return (Dietz_r) exhibits a much larger variation, reflecting the severe market turbulence during the global financial crisis. The average household net worth is approximately USD 1.25 million, while the standard deviation reflects significant wealth inequality.

In terms of financial sophistication, only 38% of households reported consulting a financial planner and 25% consulted a bank advisor. From the perspective of asset composition, real estate dominates household portfolios (mean share 72%), followed by stocks (11%) and funds (9%), while bonds, deposits, and cash account for relatively small portions. This distribution reflects the relatively illiquid and housing-centered nature of U.S. household portfolios during this period.

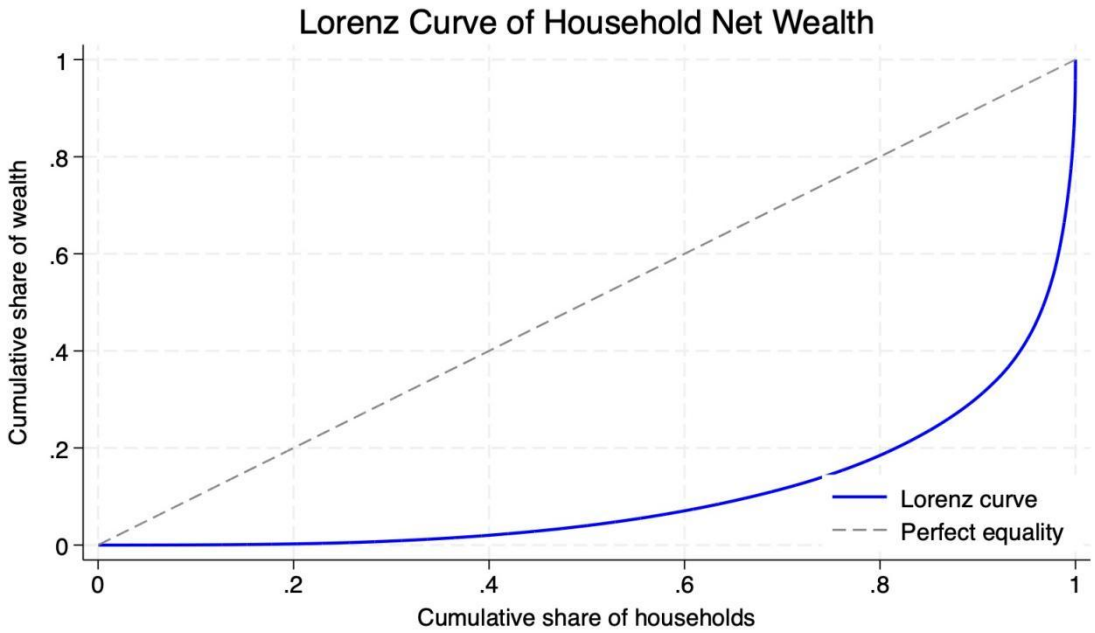


Figure 1: Lorenz Curve of Household Net Wealth.
This figure shows the Lorenz curve for household net wealth in the sample. The curve lies far below the 45-degree line of perfect equality, indicating a highly unequal distribution of wealth.

Figure 1 plots the Lorenz curve of household net worth. The curve deviates sharply from the 45-degree line of perfect equality, which illustrates the extreme concentration of wealth in the upper tail of the distribution. The bottom 80 percent of households hold less than 20 percent of total wealth. In contrast, the top decile captures the majority of aggregate net wealth.

All obs	GE(−1)	GE(0)	GE(1)	GE(2)	Gini
	319.000	1.750	1.677	16.290	0.791

Table 3: Inequality Measures of Household Net Wealth, 2007–2009.
The Gini coefficient of 0.79 and the large upper-tail–sensitive GE(2) index indicate substantial wealth inequality in the U.S. sample, with a small group of high-wealth households holding a disproportionate share of total net wealth.

Table 3 reports several standard measures of wealth inequality for U.S. households during the 2007–2009 sample period. The Gini coefficient of net worth is approximately 0.79, which is an extremely unequal distribution of wealth. Consistent with this pattern, the generalized entropy (GE) indices also point to substantial inequality. GE(0) and GE(1), which are more sensitive to the middle of the distribution, take values around 1.75 and 1.68, respectively. In contrast, GE(2), which places greater weight on the upper tai (16.29), reflects the high concentration of wealth among the richest households. Overall, these inequality measures confirm the highly skewed and heavy-tailed nature of U.S. household net wealth in the SCF panel.

Because high-wealth households are intentionally oversampled in the raw SCF data, the unweighted sample does not accurately represent the true population distribution of U.S. households. To ensure that our analysis reflects the overall structure of wealth in the United States, all subsequent regressions and descriptive statistics are conducted using survey weights.

These weighted shares more accurately capture the wealth structure of the U.S. population and provide a reliable foundation for our subsequent analysis of return differentials and investment behavior across the wealth distribution.

To ensure comparability across years, all monetary variables are deflated to 2009 U.S. dollars using the Consumer Price Index (CPI) from the Bureau of Labor Statistics.

3.4 Household Characteristics Display

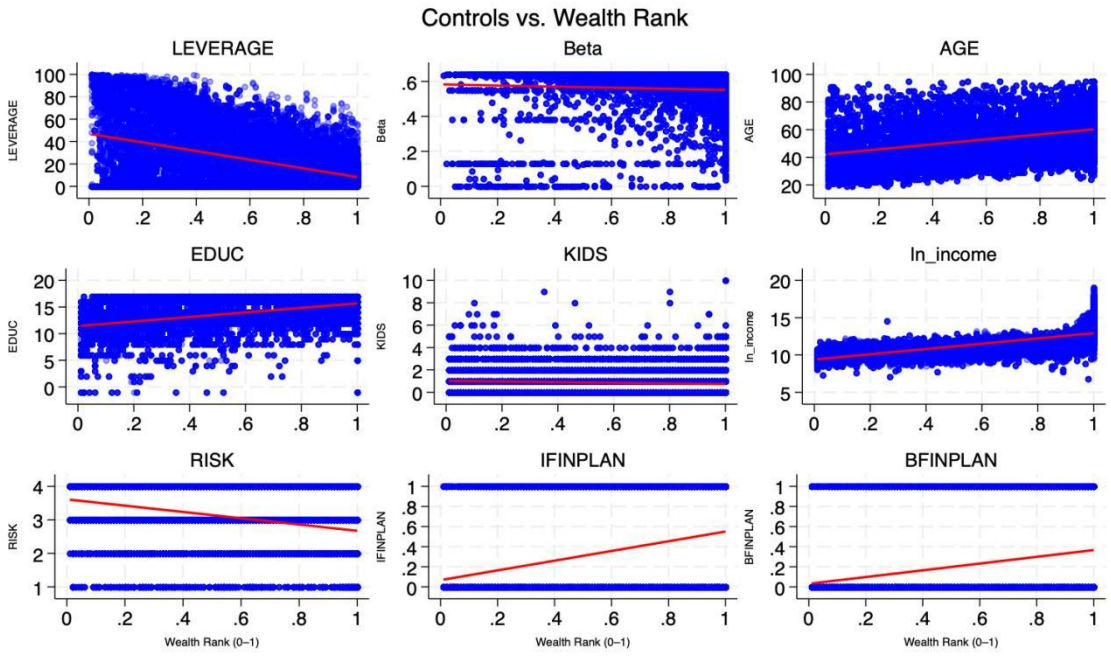


Figure 2: Control Variables Across the Wealth Distribution
This figure plots the relationship between household wealth rank (0–1) and a set of key control variables used in the regression analysis. Each subplot displays raw household-level observations along with a fitted linear trend line.

Figures 2 display the relationship between key household characteristics and the wealth rank (scaled from 0 to 1). From these figures, we can see several systematic patterns.

First, leverage declines markedly with wealth: lower-wealth households exhibit substantially higher debt-to-asset ratios, while high-wealth households maintain relatively low leverage levels. Second, risk exposure (Beta) shows little systematic

variation across wealth ranks, suggesting that differences in market exposure are not mechanically related to household wealth. Age and income both rise gradually with wealth rank, which indicates that wealth accumulation is strongly correlated with life-cycle stages and income levels.

Moreover, education shows a clear positive gradient: households in higher wealth percentiles on average have significantly more years of schooling. This supports the view that human capital and financial sophistication correlate with wealth. Similarly, self-reported financial planning variables, such as informal financial planning (IFINPLAN) and professional financial advice (BFINPLAN), also increase with wealth rank, suggesting greater engagement in financial decision-making among wealthier households. Risk tolerance shows a modest positive slope as well, which means that wealthier households are a little more willing to bear financial risk. However, family size (KIDS) doesn't exhibit a meaningful trend with respect to wealth rank.

Taken together, these patterns demonstrate that wealthier households differ systematically from poorer households along multiple observable dimensions such as education, income, leverage, risk tolerance, and financial planning. These correlations could help us to explain why controlling these characteristics in the regression substantially reduces cross-sectional differences in household alpha.

4.Methodology

This section describes the construction of key variables and the empirical models used to examine the relationship between household wealth and investment returns.

4.1 Expected Return (Er)

In the SCF panel data, we classify household portfolios into six asset categories, which are stocks, cash, bonds, deposits, mutual funds, and real estate. A_i is the total asset value of household i, calculated by the sum of the market values of these six asset classes. The portfolio weight of asset class k for household i is calculated by following formula:

$$w_{ik} = \frac{A_{ik}}{A_i}$$

Unlike Nordic administrative datasets in Bach (2020), which provide detailed information on the specific securities held by each household, the SCF does not contain security-level return data. Therefore, we get the expected return of each asset class from corresponding market returns of the six asset classes which are Erk in the following formula. The expected return of household i's portfolio is computed as a weighted average of expected returns:

$$Er_{it} = \sum_{k=1}^{6} w_{ikt} Er_{kt}$$

This alternative allows us to construct household-level expected returns that reflect both the composition of household portfolios and the returns of each asset category.

4.2 Risk Exposure: Household Beta (β)

To measure the systematic risk exposure of each household, we first estimate asset-class betas using a standard Capital Asset Pricing Model (CAPM) framework. Bach et al. (2020) estimate household-level risk exposure and risk-adjusted performance by first modeling the excess return of each individual asset i at time t using a standard factor-pricing equation:

$$r_{i,t}^{e} = \alpha_i + \beta_i^{'} f_t + u_{i,t},$$

where f_t is a vector of pricing factors, $\beta_i^{'}$ represents the assets' factor loadings, and α captures the asset's risk-adjusted performance. Importantly, the estimation of $\beta_i^{'}$ relies on long historical return series for each asset class, which reduces sampling noise in covariances. Once asset-level parameters are obtained, portfolio-level measures for each household h at time t.

$$\alpha_{h,t} = \sum_i w_{h,i,t} (r_{i,t}^{e} - \beta_i^{'} f_t),$$

$$\beta_{h,t} = \sum_i w_{h,i,t} \beta_i$$

However, we don't have detailed information about each individual asset i which the household had during these years. Thus, it's hard for us to replicate the regression Bach et al. (2020) did. Instead, we use substitutes for returns.

For each asset class k, we perform the following time-series regression:

$$R_{\mathrm{kt}} - R_{ft} = \alpha_k + \beta_k MKT_t + \varepsilon_t$$

R_{kt} is estimated by the monthly return of the asset-class index, R_{ft} is the monthly risk-free rate, and MKT represents the monthly market excess return from the Fama–French U.S. market factor.

We use monthly data from 1980 to 2013 to estimate β_{k} for stocks, bonds, and real estate. The reason why we don't use yearly data as Bach et al. (2020) did is that we would like to have a larger data sample for each regression.

Betas for cash and deposits are set to zero, due to their negligible exposure to market fluctuations. The beta for mutual fund is the weighted average of stock beta and bond beta (60/40). At the household level, we also compute systematic risk exposure by aggregating asset-class betas using household-specific portfolio weights.

The household-level beta is calculated as:

$$\beta_{\mathrm{i}} = \sum_{k=1}^{6} w_{ik}\beta_k$$

Systemic risk at the household level β_{i} is the weighted sum of the β values for each asset class, weighted by household holdings. It's used to compare the systematic risk across the wealth distribution. The Beta variable reported in Table 1&2 is computed using the method described here.

4.3 Realized Return: Dietz Return Rate

As the method Fagereng et al. (2020) used, we compute a realized return with a simplified version of the Dietz (1968) formula. The Dietz return measures change in wealth that occurs during the period, which reflects both beginning-of-period asset holdings and net flows.

In Norwegian administrative datasets used by Fagereng et al. (2020), detailed information on asset flows and intra-year transactions enables them to use an exact implementation of the modified Dietz formula:

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

where y_{it}^{f} is financial income, y_{it}^{r} is real asset income, and y_{it}^{b} is debt costs. They are divided by the sum of gross wealth w_{it}^{g} and the mid-year flows into and out of wealth $F_{it}^{g}/2$.

However, the SCF does not provide detailed intra-year cash-flow information, or the capitalized income components required to estimate. Therefore, we adapted the conceptual structure of Fagereng et al. (2020) to the SCF's data constraints and got a simplified form of realized return. Specifically, we compute the Dietz return for household i as:

$$Dietz_r_{it} = \frac{non-salary\ income_{it} - mortage\ interest_{it}}{gross\ asset_{it}}$$

In this formulation, non-salary income proxies financial and real asset income, such as dividends, interest, rental income, and business income. The denominator only uses end-of-period net assets as a proxy for average invested wealth due to the absence of intra-year flow data.

4.4 Wealthrank Construction

We construct household wealth ranks using the panel structure of the 2007–2009 Survey of Consumer Finances (SCF). Households are ranked according to their net worth, with the SCF-provided survey weights to ensure representativeness of the U.S. population. Specifically, within each implicate we compute the weighted wealth percentile of households which range from 1 to 100. Wealthier people have higher wealth ranks. We follow the SCF's multiple-imputation framework by estimating wealth percentiles separately within each implicate to preserve the appropriate variance structure of the data.

4.5 Empirical Strategy

To examine the relationship between household wealth, portfolio returns, and the mechanisms underlying return heterogeneity, we estimate two regressions following the empirical strategies developed by Fagereng et al. (2020), adapted to the SCF context.

(1) Expected Return on Control Variables

We follow the empirical design of Fagereng et al. (2020) and regress the expected return (Bach et al. (2020)) on a set of household controls:

$$Er_{it} = \alpha + X_{it}\theta + \mu_i + \varepsilon_{it}$$

X_{it} includes demographic variables (age, education, marital status, etc.), balance sheet variables (Log Wealth, Log Income, and leverage, etc.), and detailed portfolio composition controls. This specification evaluates the extent to which expected return differences across households can be explained by observable characteristics. Furthermore, the controls help to get a cleaner α which has fewer factors included.

(2) Dietz Return on Control Variables

Then we change the measure of return as the Dietz return on a set of household controls:

$$Dietz_r_{it} = \alpha + X_{it}\theta + u_i + \varepsilon_{it}$$

It evaluates the extent to which expected return differences across households can be explained by observable characteristics. By comparing the result of this regression and the other one above, we can see the influence of two different measures of returns. Moreover, the controls can also help us to get a cleaner α.

4.6 Construction of Investment Ability (α)

We employ two complementary approaches to estimate household investment ability, following Bach et al. (2020) and Fagereng et al. (2020).

(1) Bach-style α (risk-adjusted excess return)

In Bach et al. (2020)'s approach, alpha is calculated by CAPM model which is $r^e_{i,t} = \alpha_i + \beta_i^{'} f_t + u_{i,t}$, but the obstacle is that we do not have the real return data in SCF, which prevents us from calculating the real excess returns. Moreover, to ensure a more rigorous empirical comparison, we compute alpha in the same manner across both approaches, which is the fixed effect alpha introduced in the next paragraph.

(2) Fagereng-style α (persistent fixed effect)

In Fagereng et al. (2020)'s approach, we estimate individual fixed effects from panel regression 3 to capture persistent investment ability over time. α represents the individual fixed effect, which indicates the time-invariant and sustainable investment ability with wealth, leverage and other observables controlled.

For better comparison, we use the same measure (Fagereng-style α) in our thesis to capture persistent heterogeneity in returns across households.

5.Empirical Analysis

5.1 Beta Regression

	(1) bond	(2) realestate	(3) stock
MktRF	0.132***	0.644***	0.552***
	(0.021)	(0.043)	(0.030)
_cons	0.252***	0.197	0.009
	(0.097)	(0.197)	(0.137)
N	402	402	401
r2	0.090	0.360	0.462

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Results of Beta Regression

This table reports CAPM regressions estimating market betas for bonds, real estate, and stocks using the market excess return (MktRF). All three asset classes exhibit positive and significant exposure to market risk, with the magnitude of beta varying across assets.

Table 4 reports the CAPM regression results for bonds, real estate, and stocks with respect to the market excess return (MktRF). The results indicate that all three asset classes exhibit positive exposure to market risk, though the magnitude of such exposure differs substantially across assets.

The bond portfolio has a significant β of 0.132, which suggests that bond returns are only weakly sensitive to market fluctuations. This low level of systematic risk is consistent with the relatively conservative nature of bond investments. Then, the real estate portfolio exhibits a moderate degree of comovement (0.644) between real estate returns and the overall equity market. The stock returns respond more strongly to market movements (0.552) and therefore carry greater systematic risk.

Regarding the goodness of fit, the R^2 values for the bond, real estate, and stock regressions are 0.090, 0.360, and 0.462, respectively. These values suggest that the explanatory power of the market factor increases progressively across asset classes, with the strongest explanatory effect observed for stocks.

Betas for cash and deposits are theoretically zero. The beta for mutual fund is the weighted average of stock beta and bond beta (60/40), so it's calculated to be 0.384. After that, we compute aggregated betas for each household using household-specific portfolio weights.

5.2 Expected-Return Regression

Table 5 presents regression results based on the Bach model, where the dependent variable is household investment return (Er) and the core explanatory variable is the logarithm of household net wealth (Ln_Wealth). The results indicate that the coefficient for Ln_Wealth is -0.05 ($p < 0.05$), demonstrating high statistical significance. This suggests that during the 2007-2009 financial crisis, higher levels of household wealth were associated with lower overall investment returns.

A possible explanation is that, in the SCF data, the wealthier class exhibits higher risk preferences and invests more heavily in high-risk assets. However, following the 2008 global financial crisis, risk assets suffered more severe influence from the global financial crisis, which led to greater losses in investment returns for the wealthy. Additionally, wealthier households may invest more heavily in high-return private assets which are not traded on public markets. Since these assets are not covered by market indices, their expected returns are not counted in standard calculations, which leads to an underestimation of the wealthier households' expected returns.

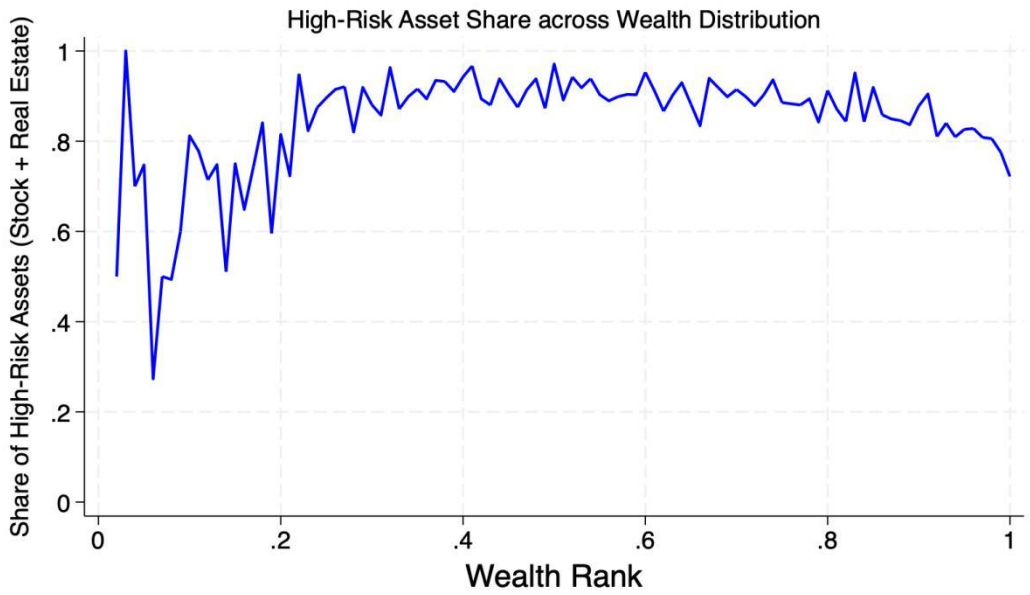


Figure 3: Average Combined High-Risk Asset Index Across Wealth Distribution
This figure shows the average share of high-risk assets, which defined as the combined portfolio weight of stocks and real estate, across the wealth distribution. The share rises markedly with wealth rank, indicating that higher-wealth households allocate a substantially larger portion of their portfolios to riskier asset classes.

We can also see this pattern in figure 3. As wealth rank increases, the proportion of high-risk assets held by households (mean_highrisk = w_Stock + w_RealEstate) rises

significantly. Among high-wealth groups, the share of high-risk assets remains consistently between 80% and 90% over the long term, whereas low-wealth groups exhibit greater volatility and maintain a lower overall proportion. This indicates that the wealthy bear greater market risk, with their asset portfolios more heavily concentrated in volatile investments such as stocks and real estate; the less affluent hold more low-risk assets, such as deposits, cash, or bonds. For the richest households, the line declines slightly. This may reflect the fact that the SCF does not provide extensive detail on high-value assets, such as private equity, which are more commonly held by wealthier individuals.

The data comes from the 2007-2009 panel, which covers the global financial crisis. Stocks and real estate were the most affected asset classes during this period. Moreover, it is shown in figure that wealthier households have lower RISK values, which indicate higher risk tolerance in investment.

Therefore, wealthier households holding more high-risk assets suffered greater losses. During the same period, low-wealth households holding cash, deposits, or bonds experienced smaller shocks; some even benefited from the stable returns of low-risk assets as safe-haven capital flowed in. Consequently, they demonstrated higher average returns or smaller losses during the crisis. Moreover, under individual fixed effect, we get the fixed effect α_i which implies the persistent investment ability other than these observable characteristics.

	(1)	(2)
VARIABLES	Er model	Dietz_r model
Ln_Wealth	-0.050**	-0.005
	(0.024)	(0.014)
LEVERAGE	-0.000	-0.001
	(0.001)	(0.001)
Beta	-0.139	-0.012
	(0.185)	(0.072)
AGE	0.120***	0.003*
	(0.012)	(0.002)
EDUC	-0.038	-0.003
	(0.051)	(0.005)
MARRIED	0.211***	0.025
	(0.072)	(0.020)
W_Stock	0.105*	0.024

	(0.054)	(0.027)
W_Bond	-0.151	0.008
	(0.133)	(0.057)
W_Cash	-0.401	-0.075
	(0.244)	(0.055)
W_Deposit	-0.123	0.023
	(0.107)	(0.042)
KIDS	-0.009	0.001
	(0.012)	(0.007)
Ln_income	-0.033**	0.009
	(0.017)	(0.008)
RISK	0.016	0.002
	(0.011)	(0.008)
IFINPLAN	0.001	-0.001
	(0.014)	(0.008)
BFINPLAN	-0.019	-0.005
	(0.015)	(0.008)
Constant	-5.117***	-0.205
	(1.215)	(0.236)
Observations	5,809	5,809
Individual FE	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Regression Results Using Expected and Realized Returns
This table reports regression results using two alternative return measures: the benchmark-based expected return (Er) and the realized Dietz return (Dietz_r). Column (1) shows that Er produces a negative and significant association between wealth and returns, whereas column (2) shows no significant relationship when using realized returns. After controlling demographic characteristics, leverage, risk preferences, and detailed portfolio composition, most coefficients remain stable, and the wealth effect becomes statistically insignificant under the Dietz measure.

5.3 Dietz Return Regression

This table presents regression results based on the methodology of Fagereng et al. (2020). The model incorporates variables including wealth, risk exposure, leverage, risk preference, income, financial literacy, and investment advisors into a regression analysis of investment returns (Dietz_r). These variables collectively explain observable return differences. The model aims to examine the relationship between wealth and real investment returns while "absorbing" relevant factors, allowing the residual term (individual fixed effects) to reflect genuine persistent capability differences.

A key finding of the Dietz regression model is that the coefficient for the logarithm of wealth (Ln_Wealth) is negative (-0.005). However, this coefficient is not statistically

significant. The divergence between these two results reflects the fundamental differences between the two return measures and the unique macroeconomic environment of our sample period (2007–2009).

Unlike the Bach et al. (2020) approach, which uses market indices as the expected return, this study employs Dietz_r as the return calculating measure. This metric encompasses actual performance, including interest, dividends, rents, and operating income after deducting borrowing costs. These components are particularly crucial for wealthy households, whose portfolios contain high proportions of private enterprises and investment real estate. Given that the sample period spans the global financial crisis, the expected returns are not comprehensive enough to fully capture the actual returns of households at different wealth levels, hence the divergence between expected and actual returns.

It should be noted that although the coefficient for the logarithm of net wealth (Ln_Wealth) in the Dietz regression model is negative, it lacks statistical significance. However, beyond examining the relationship between wealth and real returns, this regression analysis also extracts the individual fixed effect α_i as a core indicator of household sustainable investment capacity by controlling for the systematic impact of observable factors on returns.

5.4 Alpha Patterns Across the Wealth Distribution

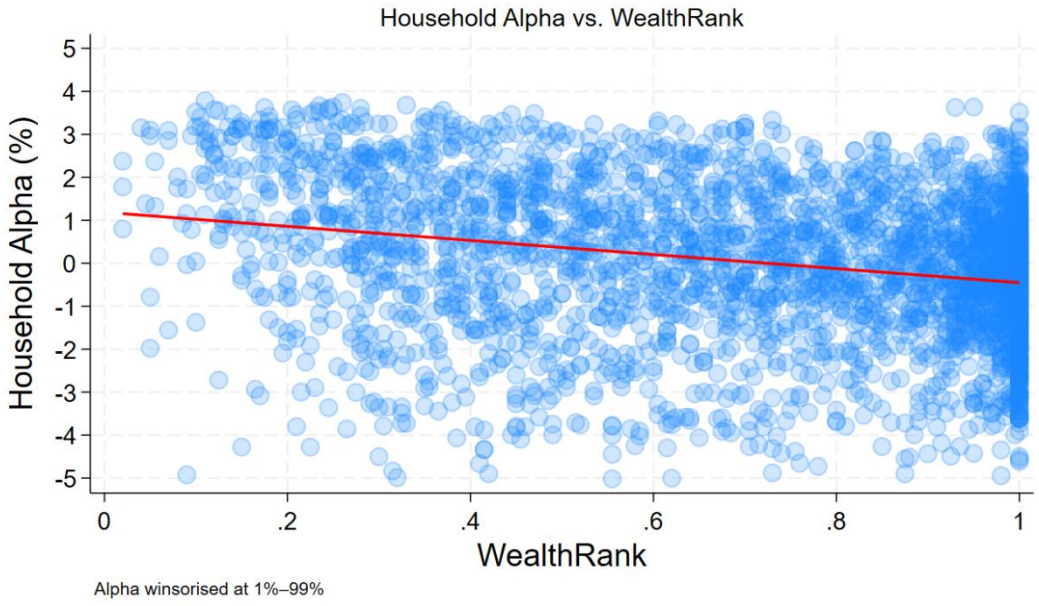


Figure 4: Household Alphas on WealthRank
This figure plots household-level alphas, defined as the fixed effects from the expected-return regression, against wealth rank. The alphas exhibit wide dispersion across the wealth distribution, and although the

fitted line indicates a slight negative association with wealth, most variation reflects household-specific unobserved heterogeneity.

In the Bach et al. (2020) model, wealthier households don't exhibit significant α after systematic risk exposure (β) is controlled, indicating that rich people's investment performance is driven by higher exposure to market risk.

Here Figure 4 plots household-specific alphas, which is constructed as the household fixed effects from the regression of expected portfolio returns on observable characteristics, against households' positions in the wealth distribution. However, different from the result of Bach et al. (2020), the resulting scatter shows substantial dispersion in estimated alpha across households. It reflects large unobserved heterogeneity in returns persists even after controlling for observed demographic and financial characteristics. The fitted trend line slopes slightly downward, which means that higher-wealth households tend to exhibit marginally lower alphas. However, this systematic component is small relative to the overall cross-sectional variability.

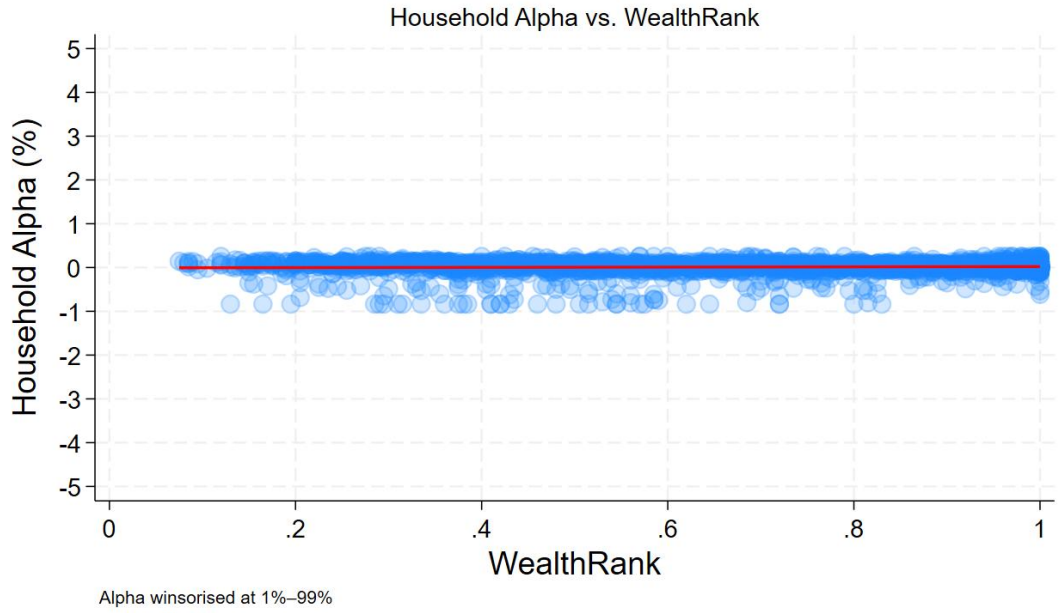


Figure 5: This figure plots household-level alphas against households' wealth ranks. Alpha values are tightly concentrated around zero, and the fitted line shows only a weak negative association, indicating limited systematic variation in unexplained performance across the wealth distribution. Alpha is winsorised at the 1% and 99% levels.

Then we plot the household alphas derived from the fixed effects in the Dietz return regression. Figure 5 shows household-level alphas against households' positions in the wealth distribution. In contrast to the previous graph, the estimates display relatively limited dispersion, with most alphas concentrated between –1% and 1%. It indicates that unexplained variation in realized returns is modest after controlling

observable characteristics. The flat fitted line suggests that household wealth plays little role in explaining residual investment performance, and that the remaining variation largely reflects idiosyncratic household-level factors captured by the fixed effects.

The contrast between the two figures illustrates the fundamental differences between using Er and the Dietz return as measures of household investment performance. The alpha estimates derived from the expected-return specification exhibit substantially greater cross-sectional dispersion. This difference follows directly from the economic nature of the expected return measure. Because Er is constructed mechanically from households' portfolio weights and asset-class benchmark returns, it does not reflect households' actual realized investment experiences. Benchmark returns are uniform across households and do not incorporate substantial idiosyncratic variation in realized asset performance, trading behavior, or risk exposures that characterize real-world household portfolios. As a result, the gap between the model-implied expected return and true household performance is highly heterogeneous. This measurement mismatch could manifest in fixed effects and therefore produce a wide distribution of alpha.

Moreover, theoretical expected returns magnify underlying differences in portfolio composition in a way that realized returns do not. Small divergences in households' portfolio weights, especially in volatile asset classes such as equities and real estate, can translate into large differences in predicted returns when multiplied by benchmark returns, particularly over the 2007–2009 period. Because these predicted differences are not fully explained by observable covariates in the regression, the unexplained component captured by the fixed effects becomes large by construction. Consequently, alpha in the expected-return model reflects both unobserved heterogeneity and model-driven variation from the simplified return construction, which drives the high dispersion in the plot.

Unlike expected returns constructed from benchmark asset-class performance, the Dietz measure captures realized returns that inherently reflect common market conditions faced by all households. During the 2007–2009 period, broad market movements drove most investment outcomes, leaving households with little room to generate meaningfully different realized returns from one another. As a result, once observable characteristics are controlled, the household fixed effects capture only modest residual heterogeneity, leading to a compressed distribution of alpha.

In addition, realized returns are less sensitive to the differences in portfolio composition than theoretical expected returns. Households often hold diversified passive products (e.g., broad mutual funds or index-like retirement accounts), and even those with more concentrated portfolios are exposed to highly correlated market movements. Because households are exposed to similar market movements, their realized returns cannot stray far from the average, which naturally limits the dispersion of unexplained performance. Trading frictions also reduce the scope for households to produce sizable idiosyncratic returns. As a result, alpha calculated from realized returns tends to be less volatile and more concentrated than alpha based on theoretical expected returns.

In addition, the Dietz return figure shows missing observations at the lower end of the wealth distribution, in contrast to the Er-based plot. This gap arises because the computation of the Dietz return requires dividing by household assets. Thus, households with zero or negative asset values must be excluded. Since such cases are disproportionately concentrated among low-wealth households, the lower portion of the wealth rank is mechanically underrepresented. This limitation highlights a drawback of the Dietz return measure: when assets approach zero or become negative, which is common among highly leveraged households, the return measure becomes unstable or economically meaningless. In this respect, the theoretically constructed Er measure is better suited for comparisons across the full wealth distribution, particularly at the bottom tail.

6. Limitations

While our study extends the frameworks of Bach et al. (2020) and Fagereng et al. (2020) to U.S. households using the SCF 2007–2009 panel, several important limitations remain. These limitations mainly arise from the data structure of the SCF and from the methodology simplification.

First, the SCF does not provide detailed portfolio-level asset holdings or transaction information. Unlike the administrative data used by Bach et al. (2020) and Fagereng et al. (2020) which precisely records the security identifiers, trading volumes, and realized returns of each account, the SCF survey reports assets only in broad

categories such as stocks, bonds, real estate. Therefore, it is impossible to accurately estimate β or decompose risk-adjusted returns using SCF data.

Second, the SCF lacks information on alternative and private assets including private equity, hedge funds, and other non-public assets which are proved to be a significant source of high returns for wealthy households. Thus, SCF data may underestimate the true investment performance of high-net-worth families.

Third, since SCF does not record the real cash flows within the year, we can only approximate asset returns using non-salary incomes and calculate actual returns via a simplified Dietz method. This approach assumes uniformly distributed investment timing and overlooks household heterogeneity in transaction timing and liquidity constraints. Consequently, it's hard for us to accurately measure the individual investment ability emphasized by the Fagereng et al. (2020) model.

Finally, the SCF panel data only includes a short time span (2007 & 2009 waves), which makes it difficult to identify the persistence of investment capabilities. In contrast, Fagereng et al. (2020) used 12 years of administrative panel data to distinguish temporary shocks from stable characteristics. Therefore, our fixed-effects estimation has limitations to capture true long-term investment performance.

In summary, the estimated α in this paper should be interpreted as an approximation of investment performance rather than an accurate measure of households' long-term investment skills. Future research could connect SCF with administrative or transaction-level data, or extend to longer-term panel samples, so as to identify structural differences in household investment capabilities more deeply in the U.S. background.

7. Conclusion

This thesis sets out to answer a question: to what extent do different ways of measuring portfolio returns change our understanding of the relationship between household wealth and investment performance? Using the 2007–2009 SCF panel, we compared a benchmark-based expected return (Er) with a realized Dietz return, which was constructed from non-salary income and end-of-period net wealth. Finally, we used both measures to estimate household-level alphas within fixed-effects frameworks.

The comparison reveals that the choice of return measure fundamentally shapes empirical conclusions. When expected returns are calculated by applying asset-class index returns to household portfolio weights, wealth appears to be systematically related to investment performance, and the resulting alpha estimates display cross-sectional dispersion. In this setting, it is easy to interpret wide spreads in alpha as evidence of sizable unobserved heterogeneity in investment ability across households.

However, the picture changes when we turn to the realized Dietz return. Once we proxy actual performance using realized non-salary income and end-of-period wealth, the estimated relationship between wealth and returns becomes weak and insignificant. At the same time, the distribution of household alphas becomes much more compressed, with most fixed effects clustering tightly around zero after controlling personal characteristics. Rather than indicating strong and persistent differences in true investment skill, the residual variation in Dietz-based alpha appears modest and largely idiosyncratic.

Taken together, these results suggest that large apparent differences in alpha under an expected-return framework may partly be an artifact of how returns are constructed, especially when benchmark indices are imposed on heterogeneous household portfolios and the sample period coincides with a major financial crisis. In contrast, realized-return measures incorporate actual income flows and common market shocks, so it tends to mute cross-sectional dispersion and yield a better assessment of persistent "skill." However, the Dietz return could drive missing observations when evaluating households among less wealthier households since these households might have negative or very little net worth.

The thesis also underscores several limitations. The SCF lacks security-level holdings, intra-year transaction data, and detailed information on alternative assets. It forces us to approximate expected returns and to implement a simplified Dietz formula over a short two-period panel. These constraints mean that our alphas should be interpreted as noisy indicators of performance rather than precise measures of long-run investment ability.

Despite these limitations, the main contribution of this study is to demonstrate the importance of return measurement itself. For researchers studying wealth inequality and return heterogeneity, the choice between model-based expected returns and realized returns should not be random since it can change the sign, significance, and dispersion of estimated relationships. Future research could link SCF-style survey data with

administrative or transaction-level records to produce more accurate and detailed measures of household returns. Extending the analysis over longer time horizons would also help distinguish genuine investment skills from patterns that arise due to the construction of return measures.

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Appendix

A. Details of Variables in SCF Data

Variable Name in SCF Data	Variable Description
X716/P716	Current Market Value of Owned Home or Property
X904/P904	The Amount of Debt
X916/P916	Annual Interest Rate on Loans
X3721/P3721	Amount of Certificates of Deposit
X3902/P3902	Value of Saving Bonds
X3915/P3915	Total Market Value of Stocks
X3930/P3930	Value of Cash
X4131/P4131	Nonsalary Earnings
X091018/P091018	Total Marlet Value of Mutual Funds
Y1	Y1: Implicate Case ID For External Users
P42001	Revised Kennickell-Woodburn Consistent Weight

Table 1: Description of Variables in the SCF Data

B. Regressions

VARIABLES	(1) Er model	(2) Dietz_r model
WealthRank	-0.336***	-0.004
	(0.082)	(0.057)
LEVERAGE	-0.000***	-0.000
	(0.000)	(0.000)
Beta	-0.148	-0.127
	(0.171)	(0.092)
AGE	0.118***	0.003
	(0.012)	(0.002)
EDUC	-0.034	0.001
	(0.046)	(0.007)
MARRIED	0.190***	0.013
	(0.064)	(0.020)
W_Stock	-0.005	0.046
	(0.011)	(0.028)
W_Bond	-0.031*	0.081
	(0.016)	(0.096)
W_Cash	0.018*	-0.111
	(0.010)	(0.068)
W_Deposit	0.001	-0.020
	(0.013)	(0.044)
KIDS	-0.018	-0.000
	(0.015)	(0.008)
Ln_Income	0.095**	0.008
	(0.045)	(0.009)
RISK	-0.146	-0.002
	(0.117)	(0.009)
IFINPLAN	-0.385*	-0.010
	(0.232)	(0.011)
BFINPLAN	-0.163	-0.012
	(0.108)	(0.010)
Constant	-5.390***	-0.225
	(1.017)	(0.187)
Observations	6,006	6,006
Individual FE	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2: Regressions of Er/Dietz_r on WealthRank and Other Control Variables

We also conducted Er and Dietz_r regressions on WealthRank instead of Ln_Wealth. During the 2007-2009 short period, the coefficients of WealthRank on Er (-0.329) and Dietz_r (-0.004) are also negative, while the coefficient on Dietz_r is not significant.

	(1)	(2)
VARIABLES	Er	Dietz_r
WealthRank	0.185***	0.185***
	(0.065)	(0.065)
YESFINRISK	0.014	0.014
	(0.026)	(0.026)
LEVRATIO	-0.375***	-0.375***
	(0.094)	(0.094)
IFINPLAN	-0.049*	-0.049*
	(0.027)	(0.027)
BFINPLAN	0.003	0.003
	(0.024)	(0.024)
W_Stock	-0.044**	-0.044**
	(0.020)	(0.020)
W_Bond	0.015	0.015
	(0.016)	(0.016)
W_Deposit	-0.014	-0.014
	(0.017)	(0.017)
W_Cash	-0.098**	-0.098**
	(0.038)+	(0.038)
MARRIED	0.060**	0.060**
	(0.025)	(0.025)
KIDS	0.001	0.001
	(0.016)	(0.016)
Constant	-0.227***	-0.227***
	(0.081)	(0.081)
Time FE	Yes	Yes
Individual FE	Yes	Yes
Observations	19,366	19,366

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Long-term Regressions of Er/Dietz_r on WealthRank

We double check the regression using long term data. We then merged five years' SCF data (2010, 2013, 2016, 2019, and 2022), and adjusted them to 2019 dollars by CPI.

Since the 2010, 2013, 2016, 2019, and 2022 SCF waves do not track the same households over time, we construct pseudo-panel data by grouping households into cohorts (defined by education and birth year), and assigning each household a cohort ID. This allows us to examine the relationship between investment returns and wealth rank using a cohort-based panel structure.

Across both specifications, *WealthRank* remains strongly positive and highly significant, which means that households (or cohorts) with higher positions in the wealth distribution are more likely to earn higher returns on average in the long run.

C. Tables and Figures

WealthRank Range	Weighted Share (%)
0–20%	19.02
20–80%	59.99
80–100%	20.99

Table 4: Weighted Shares in each WealthRank Groups

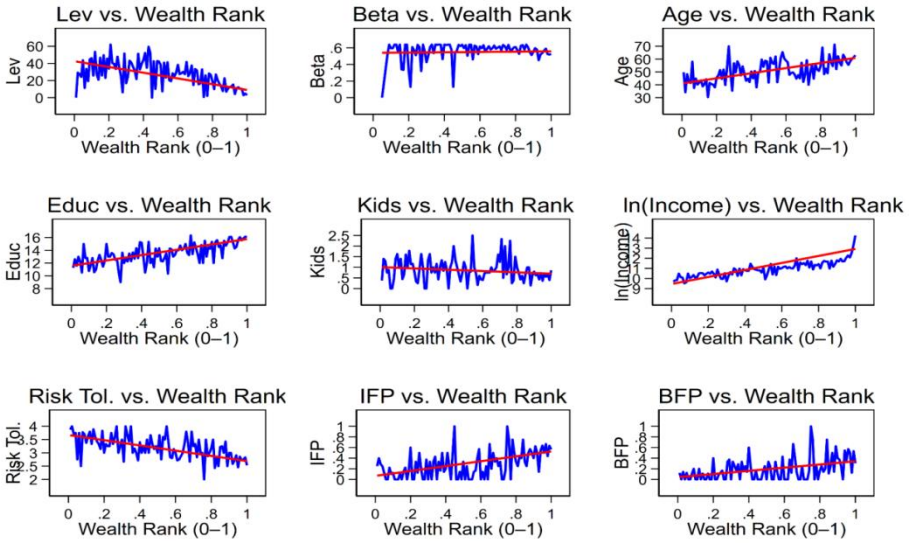


Figure 1: Characteristics on WealthRank

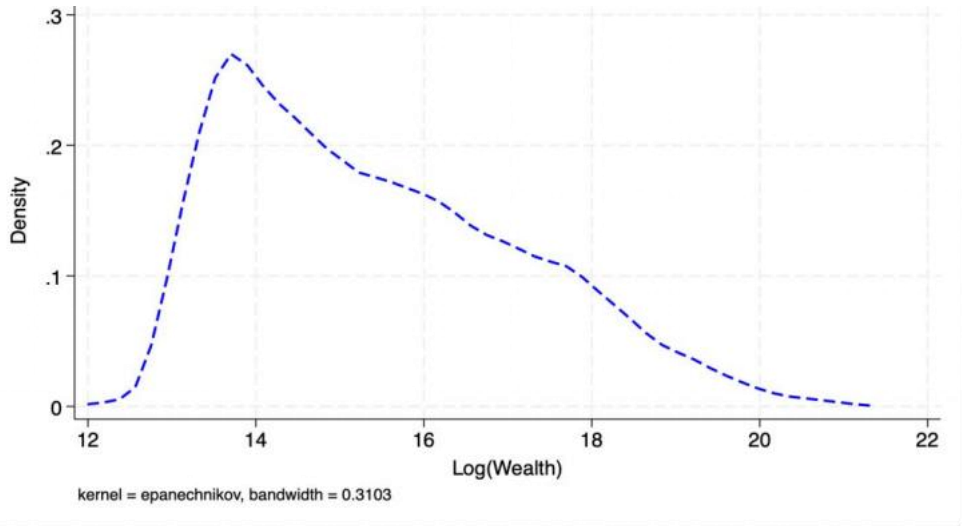


Figure 2: Households distributions on Log(Wealth)

D. AI Disclosure

During the preparation of this thesis, the only AI tool we used was ChatGPT, and solely for supportive, non-substantive purposes. Specifically, the tool assisted us in two areas:

1. **Code review and refinement:** ChatGPT was used to review and improve our code implementations. Its feedback helped us identify potential issues and enhance the accuracy and functionality of the code to better meet the research objectives.
2. **Text revision and improvement:** We used ChatGPT to suggest revisions that improved the clarity, readability, and conciseness of the thesis. These suggestions were carefully evaluated and selectively incorporated to produce a more polished final document.

We critically assessed the outputs to ensure their relevance and appropriateness. Full oversight and control were maintained throughout the writing process, ensuring that the thesis meets rigorous academic standards.