How Does Household Portfolio Diversification Vary with Financial Literacy and Financial Advice?

HANS-MARTIN VON GAUDECKER *

ABSTRACT

Household investment mistakes are an important concern for researchers and policymakers alike. Portfolio underdiversification ranks among those mistakes that are potentially most costly. However, its roots and empirical importance are poorly understood. I estimate quantitatively meaningful diversification statistics and investigate their relationship with key variables. Nearly all households that score high on financial literacy or rely on professionals or private contacts for advice achieve reasonable investment outcomes. Compared to these groups, households with below-median financial literacy that trust their own decision-making capabilities lose an expected 50bps on average. All group differences stem from the top of the loss distribution.

JEL codes: D14, D12, G11

Keywords: household portfolios, diversification, financial literacy, financial advice.

Economic theory predicts that households will hold their risky assets in the form of a well-diversified portfolio. The extent to which this prediction holds true has important implications for the regulation of consumer financial products, the design of retirement savings

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plans, and the distribution of consumer well-being in general. It is especially significant to know the patterns of underdiversification. If only those households that are particularly savvy in financial matters invested their retirement wealth in a few highly correlated stocks, most policymakers would conclude that this was a rational choice driven, for example, by superior information (van Nieuwerburgh and Veldkamp (2010)). If only the least financially literate households were doing the same thing, however, policymakers would likely conclude that these households were simply making poor decisions. In a similar vein, a regulator’s strategy also depends on whether the underdiversified households rely on professional financial advisers or make their investment choices autonomously.

Little guidance has come from empirical studies, which can be roughly divided into two strands. One strand studies detailed diversification properties using administrative data from Scandinavian countries (Calvet, Campbell, and Sodini (2007, 2009), Grinblatt, Keloharju, and Linnainmaa (2011)). These studies show that—when one accounts for mutual funds on top of stock portfolios—most households reach reasonable investment outcomes, but some may expect a very low rate of return given the amount of risk they take. However, the lack of data on financial literacy and financial advice prevents one from going beyond unconditional distributions of diversification losses with respect to the questions raised above. A second strand employs simple measures of portfolio diversification drawn from household surveys (Bilias, Georgarakos, and Haliassos (2009), Kimball and Shumway (2010), Guiso and Jappelli (2009), Graham, Harvey, and Huang (2009)). In these studies, the data issues are reversed: while covariates are abundant, the diversification properties do not permit a quantitative analysis.

In this paper, I combine the strengths of both approaches and calculate quantitatively meaningful diversification measures for the respondents to a Dutch household survey. In addition to an abundance of background variables, the survey includes detailed information on both financial literacy and the most important source of financial advice. In my analysis, I employ the return loss (Calvet, Campbell, and Sodini (2007)) as the diversification measure. The return loss is the difference between the maximum expected return attainable at a given standard deviation and the actual expected return for a particular portfolio. The unconditional distribution of the annual return loss reveals that it is limited to half a percentage point or less up to the fourth quintile. In its top quintile, it averages 1.8 percentage points, which is large and comparable to previous results.

My main analyses uncover an important interaction of financial literacy and financial advice in the decision-making process. The return loss of households that seek advice either in their private network or from professionals does not vary with financial literacy. Among households making autonomous decisions, the distribution of the return loss looks very similar only if they are endowed with the maximum level of financial literacy. In this group, a decrease in financial literacy of one standard deviation is associated with an increase in return loss by 0.7 percentage points on average. Using quantile regressions I show that these effects stem entirely from very large effects at the upper end of the return loss distribution.
Intrigued by the fact that the outcomes of households relying on professional financial advisers are so similar to those of households relying on recommendations from within their private network looks so similar, I further investigate the differences between these two groups. The use of professional financial advice is associated with an increase in fees paid across the portfolio of 0.3 percentage points. However, the higher fees do not translate into a significantly higher return loss.

This paper is structured as follows. In the first section, I describe the data set and the mean-standard deviation characteristics of households’ portfolios, including the return loss. In Section II, I explore the sources of underdiversification and scrutinize the effects of professional advisers. I then discuss the results. Section III concludes.

I. The Properties of Households’ Portfolios

Our understanding of the empirical characteristics of household portfolios is based on three distinct sources of data: (1) tax registers from Scandinavian countries, (2) online brokers’ databases, and (3) household surveys. Each source has its own advantages and drawbacks. The first two sources usually yield extraordinarily detailed portfolio data, but they do so for highly selective sets of countries and individuals, respectively, and the availability of certain covariates is an issue. In surveys the situation is the opposite: while representative samples with a plethora of background information are available all over the world, information on household portfolios is rather coarse.\footnote{A detailed review of the literature and data sources can be found in the Internet Appendix, available in the online version of the article on the Journal of Finance website.} In this study, I combine several strengths of the various approaches by constructing detailed portfolios for the respondents to the Dutch Central Bank Household Survey (DHS). Linking individual portfolio components to historical return series allows me to calculate diversification statistics that are measured in meaningful economic quantities, mirroring studies based on administrative registers or discount broker data. In this section I establish the usefulness of this approach. In Section II I go beyond previous studies by exploiting the background characteristics present in the DHS data.

A. The DHS Data on Household Portfolios

I use data from the CentERpanel, a Dutch household survey that is administered via the Internet. To avoid selection problems due to lack of Internet access, respondents without a computer are equipped with a set-top box for their television set (and with a TV if they do not have one). Respondents are reimbursed for the cost of using the Internet. The CentERpanel is representative of the Dutch population in terms of observable characteristics. It hosts the...
DHS, which contains particularly detailed information on financial matters. For this reason, these data have been used extensively to describe households’ portfolio choice behavior. Alessie, Hochgürtel, and van Soest (2002, 2004, 2006), Dimmock and Kouwenberg (2010), and Korniotis and Kumar (2011) are excellent examples. The CentERpanel was the role model for the RAND American Life Panel, which has emerged as another workhorse in the area of household financial decision-making (Lusardi and Mitchell (2007), Hung, Parker, and Yoong (2009), Hung and Yoong (2010)).

My analysis is cross-sectional, but to increase the sample size I make use of two waves (2005 and 2006) and adjust all standard errors for clustering within households using standard methods (StataCorp (2013)). Throughout the analysis, I exclude households with less than 1,000 euros in financial assets (8.6% of the sample), which yields an initial sample of 1,604 households. About a third of these hold risky financial assets, defined as shares, various types of funds, bonds, and options. See the Internet Appendix for more details.

A unique feature of the dataset is that individuals are asked to report not only the number of stocks and mutual funds they possess, but also each item's name and the quantity held. I follow the same strategy as (Calvet, Campbell, and Sodini (2007, 2009)) and connect each item to its time series of returns obtained from Datastream or Morningstar. This allows me to estimate the risk-return characteristics of households’ portfolios directly from the data. Importantly, I do not need to invoke any assumptions about the properties of asset classes. Furthermore, I can appropriately account for the covariances between different items’ returns.

While most households’ reports of their portfolio constituents appear to be thorough, I lose about a fourth of risky financial asset holders because of incomplete reports. Fortunately, I cannot detect any bias in terms of observable characteristics when dropping these households. See the Internet Appendix for details. My final sample of households consists of 381 observations.

The households in my sample possess 269 different assets consisting of 99 shares and 170 funds. I observe these assets for more than 11 years on average. The lengths of these return series vary widely, ranging from below six years at the fifth percentile to almost 20 years at the 95th percentile. I conduct all analyses at a monthly frequency, but report annualized results for easier comparability with the literature.

Of the 170 funds, 106 are equity funds. There are about a dozen funds each investing in sovereign bonds, corporate bonds, and real estate, and 28 funds follow a mixed strategy. I also obtain data on the fees of these funds. The fees are about 130 bps on average, with the fifth and 95th percentiles at 33 bps and 187 bps. The Internet Appendix describes the characteristics of the portfolios’ components in more detail.

B. The Mean-Variance Characteristics of Households’ Portfolios

I follow Calvet, Campbell, and Sodini (2007) and assume that assets are priced according to an international CAPM. Directly estimating the expected return of each household’s
portfolio would be problematic because of the short return histories for some assets, and because the time series cover different time spans. I use the MSCI Europe Index to proxy for the efficient market portfolio, which is a natural choice for a member of the Eurozone; results are robust to using the AEX or the MSCI World Index instead. All returns are framed as excess returns over the risk-free rate, which is approximated by the one-month EURIBOR. Before applying the CAPM, I subtract mutual funds’ fees from their gross returns and 30bps from the benchmark index’s returns. This is approximately the cost charged by index funds replicating common benchmarks.

Net of this “fee,” the MSCI Europe Index has an annual excess return of \( \mu_b = 5.77\% \) over the January 1983 to July 2009 period. Together with its standard deviation of \( \sigma_b = 16.7\% \), this implies a Sharpe ratio \( S_b = \mu_b / \sigma_b \) of 35\%. Imposing the CAPM leads to the following regression for all assets \( a \in \{1, 2, \ldots, 269\} \):

\[
r_{a,t}^e = \beta_a \cdot r_{b,t}^e + \varepsilon_{a,t}.
\]

Given the \( \beta \)'s of all assets and the portfolio weights for each household, it is straightforward to calculate the expected return \( \mu_h \) of each household’s portfolio.

To better understand the basic characteristics of household portfolios, it is useful to plot them in the mean-standard deviation plane. Panel A of Figure 1 does this for the pure stock portfolios and reveals a picture of strong underdiversification, which is similar to the findings of Calvet, Campbell, and Sodini (2007) for Sweden and Goetzmann and Kumar (2008) for the U.S.. The mutual fund component of households’ portfolios appears to be much better diversified, as can be seen in Panel B the major part of the distribution lines up right below the efficient frontier. Nevertheless, a substantial fraction of mutual fund portfolios perform significantly worse than the market portfolio at any risk level. Panel C contains the aggregate of stocks and mutual funds and shows that many households reduce the risk of their stock portfolios by additionally investing in mutual funds (of all risky asset owners, 55% own mutual funds only, 18% own stocks only, and 26% own both). Panel C implies that studies forced to focus on stock portfolios (e.g., Grinblatt, Keloharju, and Linnainmaa (2012), Goetzmann and Kumar (2008)) miss an important part of the picture.

The distance to the efficient frontier shrinks a lot more when holdings of safe assets are taken into account in Panel D. Nevertheless, a few outliers with severe losses remain at high levels of risk; a number of households hold portfolios one to two percentage points below the efficient frontier at relatively low levels of risk. Diversification losses of this magnitude will be substantial when accumulated over the life-cycle (Calvet, Campbell, and Sodini (2007),

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2To see this, assume that one observes two assets with identical moments. Data for the first are available in the 2000 to 2005 period and data for the second are available in the 2002 to 2007 period. The first asset would likely have a much lower estimated \( \alpha \) because market conditions were worse during the earlier period. Pricing assets via the CAPM avoids this problem as long as the assets’ correlation structure does not change with market conditions.
A: Stocks portfolios

B: Mutual fund portfolios

C: Risky portfolios

D: Financial portfolios

Figure 1. The mean-standard deviation characteristics of household portfolios.

Source: CentERpanel, Datastream, Euromonitor, own calculations.

Tang et al. (2010)). Detailed descriptions of mutual fund fees and other characteristics of the funds and shares in my sample are provided in the Internet Appendix.

C. The Expected Costs of Underdiversification

A variety of measures are available to reduce the two-dimensional graphs in Figure 1 to a single statistic of diversification losses.\(^3\) The most comprehensive criterion is the return loss, defined by Calvet, Campbell, and Sodini (2007) as the expected return a household loses by not choosing a position on the efficient frontier with the same level of risk as its portfolio. In graphical terms, the return loss is the vertical distance between the efficient frontier and the location of a household’s portfolio in Panel D of Figure 1.

\(^3\)The Internet Appendix describes a number of these measures and provides a detailed comparison with the analysis of Calvet, Campbell, and Sodini (2007).
The first column in Table I shows the average return loss within each quintile of its distribution. Return losses are limited to half a percentage point per year up to the fourth quintile; they reach 1.8 percentage points annually in the highest quintile. As mentioned before, such a number implies a large reduction in wealth when accumulated over the life-cycle.

To get an idea of what contributes to the return loss, it is useful to write it as the product of the expected excess return on the market portfolio (which does not vary across households), the risky asset share $\omega_h$, $\beta_h$, and the relative difference between the Sharpe ratios of the efficient market portfolio and the household’s portfolio:

$$RL_h = \mu_b \cdot \omega_h \cdot \beta_h \cdot \left( \frac{S_b - S_h}{S_h} \right).$$

(2)

High values of $\omega_h$ and $\beta_h$ may be signs of efficient risk-taking; the quantity $(S_b - S_h)/S_h$ measures the loss from underdiversification.

Table I

Return Loss and Its Components by Quintile

The table entries are average values of the statistics denoted in the table header by return loss quintile. Standard errors of the means are in parentheses.

Source: CentERpanel, Datastream, Euroinvestor, own calculations.

<table>
<thead>
<tr>
<th>Return loss quintile</th>
<th>Return loss*</th>
<th>Fraction in risky assets</th>
<th>Beta coefficient</th>
<th>Diversification loss*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowest</td>
<td>0.04</td>
<td>0.08</td>
<td>0.77</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.04)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Second</td>
<td>0.14</td>
<td>0.23</td>
<td>0.83</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Third</td>
<td>0.28</td>
<td>0.43</td>
<td>0.89</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Fourth</td>
<td>0.52</td>
<td>0.54</td>
<td>0.91</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.04)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Highest</td>
<td>1.80</td>
<td>0.60</td>
<td>1.01</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.03)</td>
<td>(0.07)</td>
<td>(0.12)</td>
</tr>
</tbody>
</table>

* The value $(S_b - S_h)/S_h$ becomes extremely high if the expected return on a household’s portfolio $\mu_h$ is close to zero. I therefore winsorize $(S_b - S_h)/S_h$ above at its 95th percentile.
The remaining columns of Table I contain the three terms that vary across households. Of course, the different components do not add up due to Jensen’s inequality, and thus this illustration does not qualify as a decomposition. Nevertheless, it remains useful to get a rough idea of the underlying magnitudes. The risky asset share increases quickly until the middle of the return loss distribution, after which it increases modestly. The $\beta$ coefficient rises almost linearly over the quintiles, so inefficient and efficient risk-taking at least go hand-in-hand on average. The diversification loss is fairly constant in the lower quintiles and increases strongly in the top quintile. It is the only one of the three components of $RL_h$ that is significantly different between the fourth and fifth quintiles of $RL_h$ at the 10% level ($p$-value 0.01). Compared to the lower quintiles, the prime driving force behind the highest return losses thus seems to be uncompensated risk-taking. It is important to note that the average size of the financial portfolio is highest in the top two quintiles of the return loss distribution, that is, losses are not concentrated among small-scale investors.

The results above show that the descriptive results of Calvet, Campbell, and Sodini (2007) can be replicated to a large extent for another country and, more importantly, with a type of data set that is fairly easy to collect anywhere. The greatest advantage of the DHS data, however, lies elsewhere: for the first time, it allows the detailed diversification measures to be related to the covariates the literature deems most important. For example, the Swedish administrative data of Calvet, Campbell, and Sodini (2007, 2009) contain measures of wealth, income, employment, age, household size, education, and immigration status. One of their main findings is that more affluent households invest both more aggressively and more efficiently. The data do not allow one to discern whether this is because wealthy households purchase better advice or whether they are better equipped to make their own financial decisions. The policy conclusions would be very different. In the former case, one would target the supply of investment advice. If investor sophistication is the key, financial education programs could be of help (Tang et al. (2010)). The results in the next section help to better understand such channels.

II. The Sources of Underdiversification

To clarify concepts, it is useful to think of the investment process in terms of a simple production function. The output is a measure of efficient investment, for example, the return loss considered in the previous section. A non-exhaustive list of important inputs identified in the literature includes financial literacy, cognitive ability and education, sources of financial advice, wealth, age, risk aversion, and several others described below. I approximate the production function by a linear equation:

$$Y = X'b + u.$$  

(3)
The investment outcome \((Y)\) is observed and relevant for the household as a whole, but many of the inputs concern individuals. For the latter, I use the answers of the households’ financial decision-makers. First, these are the individuals who answered the questions on financial literacy. Second, Smith, McArdle, and Willis (2010) provide evidence that this approach is sensible – they analyze the correlation between cognitive skills and various economic outcomes for older households separately for each partner and show that numeracy of the financial respondent in the HRS data is by far the most important correlate. My analysis identifies subgroups of the population who are at increased risk of observing inferior investment outcomes. It does not follow without further assumption that changing a covariate would lead to a change in \(Y\) corresponding to my estimates of \(b\).

As seen in the previous section, the diversification loss is close to negligible for a large part of its distribution; losses only become high in the upper tail. For this reason, I estimate equation (3) not only by OLS, but also by means of quantile regressions. An additional benefit of the quantile regression approach is that it provides a direct way to incorporate nonparticipants, since the return loss (2) is well defined for them: \(\omega_h = 0 \text{ or } S_b - S_h = 0\) imply \(RL_h = 0\).\(^4\) I estimate (3) using various sets of covariates. My preferred specification includes financial numeracy, the most important source of financial advice, education, age, and the amount of financial assets. A detailed motivation for this choice of covariates may be found in the Internet Appendix, in which I also precisely describe all variables. Here, I briefly discuss financial numeracy and the most important source of financial advice.

One reason for using the portfolio data from the 2005 and 2006 DHS waves is that detailed financial literacy measures are available for that time. These measures form the basis of van Rooij, Lusardi, and Alessie (2011), and the authors kindly provided me with data and code. My financial numeracy score is based on four simple quiz-like math problems framed in financial terms and a question on the time value of money. Using factor-analytic methods, I extract a continuous index and standardize it to have a mean of zero and a variance of one in the overall sample.\(^5\) The financial numeracy index measures whether individuals possess the necessary skills to perform simple numerical computations in financial matters, which is important for informed financial decision-making. Abstracting from agency problems and potential costs, rational households that realize their lack of investment skills would seek external help. In the DHS data, about a quarter of respondents sought help from professional advisers, while another quarter relied upon the advice of family and friends. The remaining

\(^4\) The typical way to include nonparticipants in a least-squares framework would be to model (3) as a two-part process, first deciding whether to invest in risky assets and then deciding how to invest in them (see Pohlmeier and Ulrich (1995) for such a model in another context and Calvet, Campbell, and Sodini (2007) for an application to portfolio choice). Given that the participation decision has been studied extensively—including with the very data used here (van Rooij, Lusardi, and Alessie (2011))—such an approach seems to be an unnecessary complication.

\(^5\) Except for a minor change in the computation described in the Internet Appendix, this is equivalent to the “basic financial literacy” variable of van Rooij, Lusardi, and Alessie (2011).
half relied on their own financial judgment.

A. Financial Literacy, Financial Advice, and Their Interaction

Table II contains the average return loss by the primary source of financial advice and a median-split of financial numeracy. The first cell contains individuals who decide by themselves and have fairly low financial numeracy. This group loses about one percentage point per year in expected returns compared to investing in the efficient portfolio with the same level of risk. This value is twice as much as the average of the remaining categories, and it is the only entry that is significantly higher than the average of the others. The importance of this interaction effect holds throughout the more formal analyses in this section.

Table II
Average Return Loss of Risky Asset Holders by Financial Numeracy and The Primary Source of Financial Advice

The number of observations is 274. The return loss measures the expected return per year (in percentage points) that is forgone by not investing in the efficient portfolio with the same standard deviation of a household’s portfolio. See Section I.C for its definition.

Source: CentERpanel, Datastream, Euroinvestor, own calculations.

<table>
<thead>
<tr>
<th>Primary source of financial advice</th>
<th>Fin. numeracy &lt; median Mean (S.E.)</th>
<th>Fin. numeracy ≥ median Mean (S.E.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-decider</td>
<td>1.00 (0.24)</td>
<td>0.56 (0.08)</td>
</tr>
<tr>
<td>Professional adviser</td>
<td>0.51 (0.21)</td>
<td>0.33 (0.04)</td>
</tr>
<tr>
<td>Family / friends</td>
<td>0.46 (0.26)</td>
<td>0.53 (0.12)</td>
</tr>
</tbody>
</table>

The first column of Table III reports the results for an OLS regression of the return loss on my preferred set of covariates in the sample of participants. Financial numeracy does not have an effect for those who seek professional advice: the coefficient in the first row is essentially zero (just one basis point per year) and is precisely estimated (the 95% confidence interval ranges from -8 bps to 9 bps). There is no significant difference from those who rely on their network of family and friends: both the dummy and the interaction term with financial numeracy are small and insignificant, although the standard errors are a bit higher. The dummy for deciding on the basis of self-collected information takes a large and significant effect.

6The value for high-numeracy households that rely on professional advice is significantly lower than that for the others. However, this result does not survive a change in the definition of fees; see Section II.B.
significantly positive value – those who rely on their own judgment with a financial numeracy score of zero incur a return loss that is 53 bps higher on average than the return loss of those who rely on professional advice. The negative interaction term shows that this effect is much worse if the financial numeracy index takes on values below zero. It almost exactly cancels out for those who achieve the highest financial numeracy score of 0.64 (note that the distribution is left-skewed). These households are estimated to incur an insignificant extra return loss of $53 \text{bps} - 68 \text{bps} \times 0.64 = 9 \text{bps}$ on average, compared to those who seek advice from professionals or family/friends and have a financial numeracy score of zero. The coefficients on all other covariates are insignificant and much smaller than those for financial numeracy and advice.

The results of the quantile regressions shown in the remaining columns of Table III demonstrate that the averages are entirely driven by effects in the top third of the return loss distribution. None of the percentiles varies much with the level of financial numeracy among those who seek professional advice. Again, the results are similar for those who turn to family and friends, except for the point estimates at the top of the return loss distribution. The interesting results are again concentrated among those who rely on their own financial judgment. All else equal, their 90th percentile of the return loss is 145 bps higher if they have a financial numeracy index of zero. Again, the effect becomes much worse for those with negative financial numeracy index values and reduces to 50 bps for those with the maximum financial numeracy score. The same pattern holds for the 70th percentile with substantially smaller magnitudes. The variation of the coefficients across the quantiles is important because it shows that (a) most households achieve reasonable investment outcomes regardless of their characteristics and (b) the worst outcomes are concentrated among those who neither seek any form of personal advice nor have a high level of numerical skills as applied to financial matters.

The estimates reported in Table III are valid for the sample of participants in risky asset markets, but they may be different for the general population. Quantile regressions on the entire sample show that there does not seem to be a financial numeracy effect for those who seek others’ advice at the 75th, 80th, 85th, 90th, or 95th percentiles. Again, there is no difference between the two groups seeking external advice and there is no relation with financial numeracy among these households. Those taking autonomous decisions with a financial literacy score of zero incur a consistently higher return loss at every quantile considered, reaching a magnitude of 72 bps at the 95th percentile. The interaction effect is small and mostly insignificant over the first four quantiles considered; for the 95th percentile, the previous interpretation continues to hold. Larger financial wealth is associated with higher return loss across the distribution. This contrasts with a fairly precise zero in the sample of participants. While these differences are not significant, they nicely illustrate the

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7See Table IA.X in the Internet Appendix. Note that the estimator requires the quantile to be strictly positive for all population groups. I thus limit attention to fairly high percentiles.
Table III  
Contributors to Return Loss

The dependent variable is the return loss as a percentage of total financial assets; see Section I.C for details. The number of observations is 274. The OLS regression is estimated on both waves of data and standard errors are clustered at the household level. The quantile estimates are based on a cross-section. All regressions use sampling weights; standard errors are in parentheses. The adjusted $R^2$ of the OLS regression is 0.11.  
Source: CentERpanel, Datastream, Euroinvestor, own calculations.

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>$p_{10}$</th>
<th>$p_{30}$</th>
<th>$p_{50}$</th>
<th>$p_{70}$</th>
<th>$p_{90}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prof. advice × fin. numeracy</td>
<td>0.01</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.05</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.07)</td>
<td>(0.16)</td>
<td>(0.43)</td>
</tr>
<tr>
<td>Financial advice: Family/friends</td>
<td>0.10</td>
<td>0.01</td>
<td>-0.04</td>
<td>-0.01</td>
<td>-0.02</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.03)</td>
<td>(0.05)</td>
<td>(0.11)</td>
<td>(0.24)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>Advice fam./friends × fin. numeracy</td>
<td>0.14</td>
<td>0.05</td>
<td>0.06</td>
<td>0.14</td>
<td>0.21</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.04)</td>
<td>(0.07)</td>
<td>(0.13)</td>
<td>(0.29)</td>
<td>(0.80)</td>
</tr>
<tr>
<td>Financial advice: Own judgment</td>
<td>0.53***</td>
<td>0.00</td>
<td>0.02</td>
<td>0.02</td>
<td>0.34*</td>
<td>1.45***</td>
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<td></td>
<td>(0.19)</td>
<td>(0.02)</td>
<td>(0.04)</td>
<td>(0.08)</td>
<td>(0.18)</td>
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<td>(0.07)</td>
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<td>0.09</td>
<td>0.00</td>
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<td>(0.09)</td>
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<td>(0.54)</td>
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<td>-0.03</td>
<td>-0.05</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.06)</td>
<td>(0.18)</td>
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<td>Constant</td>
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<td>0.45</td>
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<td></td>
<td>(0.80)</td>
<td>(0.09)</td>
<td>(0.16)</td>
<td>(0.30)</td>
<td>(0.69)</td>
<td>(1.91)</td>
</tr>
</tbody>
</table>

varying interpretations in the two samples. The point estimates in Table III imply that participating households with high financial wealth incur similar return losses conditional on the other covariates. In the full sample, another effect dominates: participation is much more prevalent among the wealthy and they thus incur higher return losses.

These results are robust to a number of other specification choices, which I document in the Internet Appendix. Most importantly, there does not seem to be much of a relation between return loss and financial knowledge; including the latter as a regressor changes neither the magnitude nor the significance of my findings. The same holds for various other
covariates. When considering other measures of diversification loss, the same basic patterns emerge, although they are not always significant.

**B. A Detailed Analysis of Professional Financial Advice**

The effects of financial advice have received a lot of attention over the last several years. Inderst and Ottaviani (2012) provide an overview of the regulation side of the market and a theoretical framework; recent empirical papers on the behavior of financial advisers (e.g., Mullainathan, Noeth, and Schoar (2012)) and properties of portfolios managed by advisers (e.g., Kramer (2012), Hackethal, Haliassos, and Jappelli (2012)) show a rich variety of behavioral patterns. The general theme that appears to emerge is that advisers react to the typical incentive structure in the expected way by recommending high-fee products. Evidence on how this translates into investment outcomes is less clear-cut. My data offer a unique opportunity to complement the above studies by investigating whether the same patterns hold for the general population and whether they vary with financial literacy.

Before turning to these questions, I consider the decision to seek professional advice. For example, Collins (2012) argues that financial advice and financial literacy are complements because more literate individuals have a higher propensity to receive professional advice in his data. I thus regress the decision to turning to professional financial advisers on financial numeracy and the same controls as in Table III. The amount of financial wealth is the only variable that is economically and statistically significant. In particular, the effect of financial numeracy is small and insignificant. This is not too surprising in light of the descriptive statistics, which show that financial numeracy is lowest among those who turn to family and friends for advice and highest among those who rely on their own judgment. In the sense of Collins (2012), professional financial advice and financial numeracy are thus neither complements nor substitutes in my data. In addition, the picture is more complicated because the group that does not seek professional financial advice is made up of two very distinct subpopulations.

In the next step, I regress the fees paid as a percentage of the entire portfolio on financial numeracy, financial advice, their interaction, financial knowledge, and a number of control variables. I relegate the full set of results to the Internet Appendix, as they are very easy to summarize: average fees paid are about 70 bps per year, and they rise by another 30 bps for those who rely on professional financial advice. This is the only effect that is statistically significant. Neither financial numeracy nor financial knowledge play any role.

When analyzing the relation between professional financial advice and expected investment outcomes, the treatment of mutual fund fees deserves special attention because of professional advisers’ typical incentive structures. There are at least three different ways.

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8See the Internet Appendix. This pattern is also confirmed in multinomial logit regressions with the same controls. The only case in which financial numeracy becomes significant there is a negative relation with turning to family and friends for advice.
to deal with fees in the return loss calculations. My analysis so far assumes that after-fee
returns obey the CAPM. One could also completely ignore them, as Calvet, Campbell, and
Sodini (2007) do in their main analysis. The fact that fees are not return-dependent means
that both of these procedures will lead to relatively similar results.9 Both procedures corre-
spond to fairly favorable views on active fund management. The opposite standpoint taken
by many economists—that there is no way to beat an efficient market in terms of expected
returns—can be achieved by ignoring fees in the CAPM implementation and adding them
to the return loss ex post.

When rerunning the analysis of Table II—a cross-tabulation of the average return loss
by source of advice and financial numeracy—under the latter approach, the number in the
first cell rises by 35 bps to 1.35 percentage points, while all other numbers are at around
0.8 percentage points.10 In Table IV, I repeat the analysis from Table III with fees added
to the return loss. My previous results are essentially unchanged. If anything, small dif-
fences between the two types of external advice emerge around the middle of the return
loss distribution at low levels of financial literacy. Hence, even though professional advisers
clearly recommend portfolios with higher average fees, the effects on the resulting portfolio
characteristics are small compared to the impact of underdiversification.

C. Discussion

My results show that the largest losses resulting from underdiversification are incurred
by those who neither seek external help with their investments nor have good skills in basic
numerical operations and concepts. Perhaps the most convincing interpretation of this pat-
tern is overconfidence: The individuals with the highest risk of incurring large return losses
trust their own capabilities more than those of others, and they appear to overestimate the
former. Consistent with this interpretation, self-rated financial knowledge among individuals
with below-median financial numeracy is highest among those who rely on their own finan-
cial judgment.11 Coming back to the motivating question at the very end of Section I, the
lower return losses among the financially wealthy may be explained by a lower prevalence of
households with low financial literacy that rely exclusively on their own judgment.12

These results help answer the question posed by Korniotis and Kumar (2013) of whether
portfolio distortions reflect superior information or psychological biases. Van Nieuwerburgh
and Veldkamp (2010) recently provide a theoretical rationale for the former in the sense

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9To see this, note that in a restriction-free decomposition of total portfolio risk into its idiosyncratic
and systematic components (i.e., adding a constant to the basic CAPM regression (1); see also the Internet
Appendix), both will yield identical results. Forcing the regression line through the origin breaks the identity,
but the results will still be similar in many cases.

10See the Internet Appendix.

11See the Internet Appendix.

12See the Internet Appendix.
Table IV
Contributors to Return Loss, with Fees Added to The Return Loss Ex Post

The dependent variable is the return loss as a percentage of total financial assets (adding mutual fund fees ex post to the return loss); see Sections I.C and II.B for details. The number of observations is 274. The OLS regression I estimated on both waves of data and standard errors are clustered at the household level. The quantile estimates are based on a cross-section. All regressions use sampling weights; standard errors are in parentheses. The adjusted $R^2$ of the OLS regression is 0.10.

Source: CentERpanel, Datastream, Euroinvestor, own calculations.

<table>
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<tr>
<th></th>
<th>OLS</th>
<th>P10</th>
<th>P30</th>
<th>P50</th>
<th>P70</th>
<th>P90</th>
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<td>0.12</td>
<td>0.17</td>
<td>0.21</td>
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<td>(0.04)</td>
<td>(0.08)</td>
<td>(0.09)</td>
<td>(0.19)</td>
<td>(0.54)</td>
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<td>Financial advice: Family/friends</td>
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<td>0.05</td>
<td>-0.18</td>
<td>-0.23*</td>
<td>-0.28</td>
<td>-0.13</td>
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<td>(0.12)</td>
<td>(0.14)</td>
<td>(0.30)</td>
<td>(0.84)</td>
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<td>Advice fam./friends × fin. numeracy</td>
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<td>0.13</td>
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<td>0.35</td>
<td>0.73</td>
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<td>(1.01)</td>
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<td>-0.08</td>
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<td>(0.10)</td>
<td>(0.22)</td>
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<td>-0.42***</td>
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<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.15)</td>
<td>(0.43)</td>
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<td>0.09</td>
<td>0.11</td>
<td>0.10</td>
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<td>(0.10)</td>
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<td>(0.56)</td>
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<td>0.18*</td>
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<td>0.23**</td>
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<td>-0.37</td>
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<td>(0.12)</td>
<td>(0.24)</td>
<td>(0.69)</td>
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<td>Age 65+</td>
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<td>0.57***</td>
<td>0.53*</td>
<td>-0.11</td>
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<td>(0.11)</td>
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<td>(0.27)</td>
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<td>-0.09**</td>
<td>-0.07</td>
<td>-0.01</td>
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<td>(0.03)</td>
<td>(0.04)</td>
<td>(0.08)</td>
<td>(0.23)</td>
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<td>Constant</td>
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<td>1.32***</td>
<td>1.34</td>
<td>1.94</td>
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<td>(0.34)</td>
<td>(0.41)</td>
<td>(0.86)</td>
<td>(2.41)</td>
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that if information about returns is specific to a stock (industry), investors will hold a less than perfectly diversified portfolio in order to exploit their informational advantage. My results are consistent with such an explanation for portfolios in the middle-upper region of the return loss distribution. However, the basic pattern behind the highest return losses makes it unlikely that superior information is the driving force behind the choice of portfolios. Similar arguments hold for other explanations of low diversification as a rational strategy, for example, Roussanov’s (2010) “beat the Jones” argument. Rather, as suggested by Kimball
and Shumway (2010), my results are more likely to reflect investment mistakes.

In this respect, the consequences of low financial literacy have received a lot of attention recently, especially from the policy side (e.g., Lusardi (2010)). My results suggest that the majority of Dutch households reach reasonably effective investment outcomes in terms of the risk-return trade-off, regardless of their level of financial literacy. Many of them achieve this by choosing a very low level of risk, others by turning to external help. Both strategies are consistent with a rational response to poor self-perceived investment skill.\(^\text{13}\)

That the factor measuring financial-numerical skill turns out to be much more important than financial knowledge suggests that increasing the latter would not do much for portfolio outcomes. The nature of the questions in van Rooij, Lusardi, and Alessie’s (2011) basic financial literacy index—mostly simple math quizzes worded in financial terms, which is why I use the term “financial numeracy”—suggests an interpretation as a subcomponent of cognitive functioning. Cognitive ability has also been shown to correlate strongly with the decision to participate in the stock market (Christelis, Jappelli, and Padula (2010)). It becomes increasingly difficult to compensate for low levels of cognitive skills after reaching adolescence (e.g., Cunha, Heckman, and Schennach (2010) and the references therein). Influencing current generations via this channel thus seems difficult; however, this suggests another reason why early interventions to improve the skills of disadvantaged children may be hugely beneficial. This assessment is also in line with the findings of Agarwal and Mazumder (2013) and Grinblatt, Keloharju, and Linnainmaa (2011, 2012), who show that various financial mistakes are correlated with broad measures of cognitive functioning drawn from military qualification tests.

This leaves the second channel, namely, helping individuals receive competent financial advice. Note, however, that my estimates do not necessarily yield the causal effect of mandating advice. Indeed, in the experiments of Hung and Yoong (2010) only solicited advice has an effect on portfolio performance while unsolicited advice is ignored by investors. Nevertheless, expanding the availability of external guidance seems to be the most promising route. Academic economist’s typical advice of investing in low-fee index funds competes with many attempts to guide household’s behavior where the form of the message is designed by professional marketing forces and its content is not necessarily adapted to suit to the needs of consumers (Inderst and Ottaviani (2009)). Further research on how regulation can help shape correctly incentivized marketing forces seems very promising in this light (also see Campbell at al. (2011) for an elaboration of this point).

An additional point to keep in mind is that my analysis has not included the costs associated with portfolio turnover. If professional advisers suggest mutual funds with higher loads and / or induce higher turnover rates, both of which would be consistent with typical

\(^{13}\)Corroborative evidence comes from Choi, Laibson, and Madrian (2010), who show that the (self-reported) likelihood of changing one’s mind after consulting an investment adviser is highest for those who make poor experimental investment decisions.
incentive structures, the results might be very different. The evidence on portfolio turnover is mixed. Analyzing two samples of customers from an online broker and a bank, Hackethal, Haliassos, and Jappelli (2012) find that monthly turnover is roughly the same for all bank customers regardless of who manages the account. In contrast to this, turnover for professionally managed accounts is twice as high among the online broker’s customers.

The Internet Appendix reports the results of some back-of-the-envelope calculations that may shed light on the potential magnitudes. The analysis is crude for two reasons. First, I was only able to obtain data on loads for roughly one-third of the funds in my sample and ended up imputing the remaining ones. Second, I do not observe portfolio rebalancing in the data. I thus assume an annual turnover rate of 60%, which is roughly in line with the numbers reported by Hackethal, Haliassos, and Jappelli (2012). Assigning this rate to all households, no results are changed except for the scaling baseline values of the return loss. So again, the effect of professional advisers recommending products with high fees does not seem to be a major factor. If I assign a 60% turnover rate to households relying on professional advice and 30% to everybody else, notable differences emerge. In particular, the average return loss of all households relying on professional advice would be in the same range as those of self-deciders with low numeracy, about half a percentage point higher than those in other groups. To resolve this ambiguity, future research should strive to collect a comprehensive data set containing detailed trading behavior in addition to the variables available in this study.

Switching from wishful thinking to the reality of typically available information, most data sets used in the area of household finance do not contain nearly as much detail as the DNB Household Survey or the Scandinavian tax registers. Consequently, the question of how to make the most of limited data is of interest to a large number of researchers (see also Calvet, Campbell, and Sodini (2009)). In Section IV of the Internet Appendix, I demonstrate that the detailed portfolio diversification measures constructed in this paper are needed to uncover the detailed patterns described here. Among the commonly constructed proxies (e.g., those computed in Bilias, Georgarakos, and Haliassos (2009), Graham, Harvey, and Huang (2009), Guiso and Jappelli (2009), or Kimball and Shumway (2010)), the fraction of the risky portfolio invested in mutual funds divided by the number of directly held shares (Guiso and Jappelli (2009)) has the highest correlation with the appropriate measure computed here.

III. Conclusions

Detailed portfolio information can be obtained fairly easily from survey respondents. I show that analyzing the diversification properties yields results that are very similar to previous analyses on administrative records. This is important for a wide range of future research on household portfolios because until now, comprehensive and quantitatively meaningful analyses of portfolio diversification have been limited to Scandinavian countries. A
big advantage of the survey data is that it adds a wide range of covariates waiting to be analyzed that are not available in administrative data sets.

My results show that the largest losses resulting from underdiversification are incurred by those who neither turn to external help with their investments nor have good skills in basic financial-numerical operations and concepts. The effects are strong enough to drive average coefficients and are robust to controlling for a number of covariates, including education level, age, financial knowledge in various forms, attitude to financial risk-taking, measures of wealth, and household income. A plausible interpretation of this pattern is overconfidence. The pattern also suggests that underdiversification most often reflects investment mistakes as opposed to optimal strategies. My results suggest that both financial numeracy and increasing the uptake of financial advice—be it from private contacts or professionals—are potential starting points for policies seeking to reduce welfare losses from inferior investment strategies.
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