Behavioral Portfolio Theory Revisited: Lessons Learned from the Field

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Abstract

We examine the relation between households' wealth and relative risk aversion (RRA) in two different frameworks: the Behavioral Portfolio Theory (BPT) and Merton's consumption and portfolio choice model (CPCM). For this purpose we use the dataset of the German central bank's (Deutsche Bundesbank) Panel on Household Finances-Survey and apply the BPT to field data for the first time. More specifically, we compute households' high aspiration layer that covers households' risky investments and the wealth available for further risky investments. We show that this implementation of the BPT provides a better fit than the CPCM to explain households' financial risk-taking. This means that households consider rather the easier assessable wealth in their high aspiration layer than their difficult to estimate total wealth in the financial decision making process. However, both models are in favor of decreasing RRA, i.e. that households are more likely to generally enter in risky asset markets with rising total wealth (CPCM) or a rising value of their high aspiration layer (BPT). We furthermore show that households' education and financial literacy hardly improve both models' fit. Instead, households with the same level of wealth, education, and financial literacy show a different risk-taking behavior in accordance with their self-assessed risk attitude. Our results are robust to changes in the risk-taking measure.

JEL Classification: D14, D81, G02, G11

Keywords: Household finance, relative risk aversion, behavioral portfolio theory, consumption and portfolio choice model, risk-taking

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This paper uses data from the Deutsche Bundesbank Panel on Household Finances. The results published and the related observations and analysis may not correspond to results or analysis of the data producers.

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Abstract

We examine the relation between households' wealth and relative risk aversion (RRA) in two different frameworks: the Behavioral Portfolio Theory (BPT) and Merton's consumption and portfolio choice model (CPCM). For this purpose we use the dataset of the German central bank's (Deutsche Bundesbank) Panel on Household Finances-Survey and apply the BPT to field data for the first time. More specifically, we compute households' high aspiration layer that covers households' risky investments and the wealth available for further risky investments. We show that this implementation of the BPT provides a better fit than the CPCM to explain households' financial risk-taking. This means that households consider rather the easier assessable wealth in their high aspiration layer than their difficult to estimate total wealth in the financial decision making process. However, both models are in favor of decreasing RRA, i.e. that households are more likely to generally enter in risky asset markets with rising total wealth (CPCM) or a rising value of their high aspiration layer (BPT). We furthermore show that households' education and financial literacy hardly improve both models' fit. Instead, households with the same level of wealth, education, and financial literacy show a different risk-taking behavior in accordance with their self-assessed risk attitude. Our results are robust to changes in the risk-taking measure.

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1 Introduction

The question how households' relative risk aversion (RRA) (see Arrow (1965) and Pratt (1964)) changes with wealth is both crucial for the field of household finance and yet not sufficiently answered (see Guiso/Sodini 2013, p. 1433). Most of the studies analyzing RRA rely on the consumption and portfolio choice model (CPCM) of Merton (1969). Yet, as Statman (2014) points out, standard finance[1] models – like the CPCM – are partially unable to explain households' actual investment behavior. One reason for the divergence between standard finance models and households' actual investment behavior is the standard finance foundation that households are fully rational and design one single portfolio by the rules of mean-variance portfolio theory, which fails to hold true. Shefrin/Statman (2000) develop the Behavioral Portfolio Theory (BPT) with the aim to overcome the shortcomings associated with the standard finance models. According to the BPT investors segregate their portfolio in different layers. Each portfolio layer is associated to an aspiration, while the layer may contain several financial products that contribute to this aspiration. Covariance among the layers is overlooked by the investors.

The BPT's layer approach stands in clear contrast to the CPCM where a household maximizes its utility by keeping all its assets in one mean-variance optimized portfolio. Applied on the relation between households' wealth and RRA, the BPT's key implication is that households rather establish different portfolio layers with individual RRA per layer to reach the layer's investment goal than having one RRA for the entire portfolio as suggested by the CPCM. Due to the important role of the relation between households' RRA and wealth in the economic literature (e.g. for the

[1] Some authors also use the term traditional finance (see, e.g., Ackert 2014 and Bloomfield 2010).

determination of the market price of risk (see, e.g., Campbell 2003)) it is of interest whether the BPT or the CPCM framework better fits households' risk-taking behavior and to which extent the BPT and the CPCM lead to different findings regarding households' RRA. Such an analysis, however, is, to the best of our knowledge, still missing. We close this gap in the literature by deriving a high aspiration layer in the sense of the BPT from household-level field data and assessing the effect of employing this layer instead of households' entire portfolio when deriving households' RRA.

We contribute to the literature on three issues. First, we provide the first implementation of the BPT on field data by deriving a high aspiration portfolio layer covering households' risky investments and the cash(-equivalents) available for investments in risky assets or for consumption. Second, we simultaneously estimate households' RRA in the framework of the BPT and the CPCM and compare and discuss the respective outcomes. Third, we add new insights to the discussion on the suitability of different wealth- and risk-measures in the domain of households' RRA (see, e.g., Paya and Wang (2016) who state that they can find evidence for all three different types of RRA in dependence of the definition of wealth).

The dataset for our analysis consists of 3,565 German households from the first wave of the Panel on Household Finances (PHF)-Survey provided by Deutsche Bundesbank. Stepwise multivariate regression analyses including age and gender of household's financial knowledgeable person (FKP), monthly household income, and households' directly queried risk attitude are used to reveal the explanatory power of the BPT and the CPCM regarding households' RRA. Moreover, we deal with the underlying assumption of Arrow (1965) and Pratt (1964) that all households invest in the market portfolio. According to field data, most households' portfolio can hardly be seen as a clone of the market portfolio (see, e.g., Curcuru et al. 2010, von Gaudecker 2015). Therefore, household's risky asset share is an ambiguously interpretable measure.[2] We tackle this problem by computing the σ (return's standard deviation) of the portfolio layer as additional risk-taking measure to households' risky asset share.

We find that households' risk-taking is more accurately explained by models relying on the BPT than by the CPCM. However, models of both frameworks reveal that – in line with decreasing RRA – households are more likely to generally enter in risky assets when households' wealth rises. The results are robust to households' education and financial literacy, changes in the risk-taking measure, i.e. when risk-taking is measured as the high aspiration layer's σ instead of a portfolio's risky asset share, and households' purpose for saving. Since the BPT framework provides more explanatory power than the standard finance CPCM our findings provide implications for policymakers, practitioners, and researchers alike. They should include the BPT in models on households' financial decision making. An implementation of the BPT, however, should generally consider the social system of the households' domestic country. Therefore, further research with implementations of the BPT in other countries is needed.

The remainder of our study is organized as follows. In Section 2, we review the related literature on the influence of investors' wealth and risk attitude on their actual risk-taking. We describe the PHF dataset provided by Deutsche Bundesbank and our

[2] Consider, e.g., two households A and B where A holds 10 percent stocks and 40 percent bonds whereas B holds 40 percent stocks and 10 percent bonds. Both households have a risky share of 50 percent but a different portfolio risk σ.

methodology in section 3. We present our results and robustness checks in Section 4. Section 5 concludes our analysis.

2 Literature Review

The concepts of absolute and relative risk aversion were first established by Pratt (1964) and Arrow (1965) (see Cohn et al. 1975). Following these concepts and the standard expected utility framework of von Neumann/Morgenstern (1953) the consumption and portfolio choice model of Merton (1969) puts a household's financial risk-taking (measured as household's portfolio risky share) in direct relation to household-specific characteristics and wealth. More specifically, household's portfolio risky asset share ω_h is determined by the term

$$ln\omega_h = \eta lnW_h + \xi_h + \varepsilon_h \quad (1a)$$

where W_h is household's wealth and η the wealth elasticity of ω_h implying either constant (η=0), increasing (η<0), or decreasing (η>0) RRA; ξ_h captures the household's risk preferences and other (partially unobservable) characteristics (e.g. return and risk expectations).[3]

While researchers agree that households' absolute risk aversion is decreasing, i.e. that households place a higher absolute value in risky assets the wealthier the households get, results regarding RRA are ambiguous (see e.g., Guiso/Sodini 2013). Pratt (1964), Arrow (1971), and Siegel/Hoban Jr. (1982) find evidence for increasing

[3] see e.g. Guiso and Sodini (2013) for a detailed review of this strand of literature.

RRA, i.e. a decreasing percentage of wealth invested in risky assets when households get wealthier. Friend/Blume (1975), Brunnermeier/Nagel (2008), and Chiappori/Paiella (2011) state that RRA is independent of households' wealth (constant relative risk aversion). Decreasing RRA – a larger percentage of wealth invested in risky assets with increasing wealth – is found in the studies of Cohn et al. (1975), Morin/Suarez (1983), Riley/Chow (1992), Oehler (1998), Calvet/Sodini (2014), and Oehler et al. (2016). Finally, Paya/Wang (2016) point out that they find evidence for each type of RRA in the cross section of one data set, depending on the wealth measure they use.

The heterogeneous results regarding households' RRA suggest that the the employed standard finance models do not sufficiently capture households' actual investment behavior. One key reason for the divergence between households' actual investment behavior and the investment behavior standard finance models predict is that households underlie bounded rationality, which leads them to use heuristics instead of making fully rational decisions (see e.g., Statman 2014, Oehler/Wendt 2017). E.g., households are assumed to have a mental account that they use for risky investments instead of considering their entire portfolio and total wealth (see e.g. Thaler 1999). Shefrin/Statman (2000) include mental accounting as underlying feature in their behavioral portfolio theory (BPT). The BPT implies that households establish several independent portfolio layers (i.e. mental accounts) with different underlying utility functions, allowing households to act risk seeking in one layer (e.g. buying lottery tickets) while simultaneously acting risk averse in another layer (e.g. by buying insurances). Adapted to an analysis of households' RRA, the main implication of the BPT is to differentiate between those layers. E.g., a study that aims at analyzing households' risk-taking in financial markets should separate households' risky investments and the wealth available for further risky investments from the wealth and assets that households ascribe to other layers. This, however, implies that BPT's high aspiration layer includes only a subsample of the assets captured in the CPCM.

The layer that covers risky investments and the wealth available for further risky investments represents a subset of households' entire portfolio, however, likely with a different RRA than the entire portfolio.[4] For this layer, equation (1a) can be adapted to

$$ln\omega_{h,l} = \eta lnW_{h,l} + \xi_h + \varepsilon_h \quad (1b)$$

where $\omega_{h,l}$ is household's risky share in portfolio layer l and $W_{h,l}$ is the value of household's layer l.

In addition to household's RRA and wealth, households' risk-taking is influenced by household-specific characteristics (denoted as ξ_h in equations 1a and 1b). Kaustia/Luotonen (2016) find that the education, gender, and age of households' FKP as well as households' directly queried risk attitude are the most influential factors regarding households' stock market participation. Their conclusions support former findings that the probability to hold risky assets rises with a higher educational level (e.g. Campbell 2006, Cole/Shastry, 2009), that men are more likely to take financial risk than women (Jianakoplos/Bernasek, 1998; Sundén/Surette, 1998;

[4] Das et al. (2010) point out that a household implicitly determines the RRA of one layer by specifying the layer's aspiration with threshold levels and probabilities (as suggested by the BPT) that are most suitable to reach the household's investment goals.

Barber/Odean, 2001; Croson/Gneezy 2009; Dohmen et al. 2011), and that older people are less likely to invest in risky assets than younger people (Ameriks/Zeldes 2004, Curcuru et al. 2010). The positive relation between households' directly queried risk attitude and their risk-taking was also observed by Bertraut (1998), Dohmen et al. (2011), Halko et al. (2012), Guiso and Sodini (2013), Oehler and Horn (2016), and Oehler et al. (2016) providing support that investor's risk-taking is a function of investors' risk attitude (see Nosic/Weber 2010 and Weber et al. 2013 on the latter concept). However, the inclusion of households' risk attitude as explanatory variable for their risk-taking requires an assessment whether risk attitude is time invariant. This is supported by experimental findings of Harrison et al. (2005), Sahm (2012), Weber et al. (2013), and Wölbert and Riedl (2013).

3 Data and Methodology

Data

We use data from the first wave of the German central bank's (Deutsche Bundesbank) PHF-Survey.[5] The survey includes 3,565 households who were interviewed once in the period from September 14th 2010 to July 15th 2011. The PHF-Survey covers questions about the households' wealth invested in different asset classes and personal data of all household members. One household member is determined as FKP and assumed to be mainly responsible for the household's financial decisions. Information about the FKP includes her age, gender, graduation, professional qualification, and financial literacy (measured by the three questions used in Lusardi/Mitchell 2006). The remaining data is on household-level.

[5] See von Kalckreuth et al. (2012) and Deutsche Bundesbank's homepage (http://www.bundesbank.de/Navigation/EN/Bundesbank/Research/Panel_on_household_finances/panel_on_household_finances.html) for a detailed description of the survey's methodology and the dataset as well as analyses regarding households' balance sheets.

Definition of risky assets and wealth following the BPT and the CPCM

We provide an implementation of the BPT for German households by deriving households' high aspiration layer following Oehler/Horn (2016). The layer includes households' wealth invested in the *money market*, *stocks*, *bonds*, *real estate funds*, *assets of great value* (e.g. bullion coins, collectables), and *other assets* that primarily have an investment character (e.g. money debt towards the household, certificates) as well as households' debts associated with these asset classes (e.g. consumer loans and credit card debts).[6] All previous assets are considered as being risky except the asset class *money market*.

The analysis that builds on the CPCM additionally covers – if applicable – the net wealth of direct investments in *(owner-occupied) residential property*, *value of businesses ran by household members*, *direct investments in firms* that are not listed on a stock exchange, and wealth on *retirement savings accounts* (and comparable products used for retirement savings, e.g. whole life insurances) as well as households' total debts. We consider the *value of businesses ran by household members* and *direct investments in firms* that are not listed on a stock exchange as risky investments (see Paya/Wang 2016 for a similar approach). However, we do not include *(owner-occupied) residential property*, and wealth on *retirement savings accounts* as risky assets since most households' main motivation for an investment

[6] We include households' debts that can be associated with the asset classes of the high aspiration layer because we hold the view that excluding debts may lead to an overestimation of the investable wealth. We are therefore in line with the argumentation of Cohn et al. (1975) who point out that taking into account the percentage of households' net worth invested in risky assets is more consistent with the underlying theory of the Arrow-Pratt measures.

should be a long-term risk reduction, e.g. income hedging with retirement savings account or insuring against increasing rents with residential property.[7]

Due to the complex estimation procedures and the incomplete data (e.g. missing data about diseases or aspects that influence life expectancy) we do not include human wealth in our analysis but control for households' monthly income (which also captures income from pension payments) as household-specific characteristic to proxy differences in households' human wealth.

Linear Regression Model

In addition to the previously described risk-taking and wealth measures, we include household specific characteristics ξ_h in the linear regression models. These characteristics include age (Age_h) and gender ($Male_h$) of household's FKP, the monthly household income ($Income_h$), and households' directly queried risk attitude ($RiskAtt_h$). This risk attitude is measured with a question also used in the US Survey of Consumer Finances about how much financial risk the household is willing to take for a commensurate financial return. The answer is captured with a vector including two dummy variables. The first dummy indicates if a household states to take no financial risk and the second dummy denotes whether a household is willing to take above average financial risk for above average financial returns. Therefore, households that state to be willing to take average financial risk serve as basis (omitted dummy) of the vector. To account for non-linear effects of households' wealth in their life-cycle, we also include the FKP's squared age (${Age^2}_h$). We

[7] In Germany owner occupied residential property is considered as a conservative way of retirement saving and therefore partially sponsored by the government (see Deutsche Bundesbank 2015).

additionally employ a dummy variable that indicates whether at least one child at the age of 16 or younger lives in the household ($Child_h$).

For the purpose of comparing the CPCM and the BPT when deriving households' RRA we use a stepwise cross-sectional regression analysis with four model specifications. The first model specification implements the CPCM and builds on equation (1a). The risk-taking measure ω_h is implemented as percentage of wealth invested in risky assets relative to household's total wealth ($PercentageRisky_{h,CPCM}$) and the independent variable W_h is households' total wealth ($TWealth_h$). The full linear regression model for the CPCM is written in equation (2a).

$$lnPercentageRisky_{h,CPCM} = \beta_0 + \eta lnTWealth_h + \beta_1 * Age_h + \beta_2 * Age^2{}_h + \beta_3 * Male_h + \beta_4 * lnIncome_h + \beta_5 * Child_h + \gamma_1 * RiskAtt_h + \varepsilon \quad (2a)$$

The remaining three model specifications implement the BPT and build on equation (1b). In this three model specifications the independent variable $W_{h,l}$ is the value of households' high aspiration layer ($ValueHAL_h$). The risk-taking measure $\omega_{h,l}$ either is implemented as percentage of wealth invested in risky assets of the high aspiration layer relative to the value of household's high aspiration layer ($PercentageRisky_{h,BPT}$) or as σ of household's high aspiration layer. The σ is computed as $\sigma_{h,3years}$ and $\sigma_{h,4years}$ over a three and four year investment period after the PHF-Survey took place. The full linear regression model for the BPT is written in equation (2b).

$$ln\omega_{h,l} = \beta_0 + \eta lnValueHAL_h + \beta_1 * Age_h + \beta_2 * Age^2{}_h + \beta_3 * Male_h + \beta_4 * lnIncome_h + \beta_5 * Child_h + \gamma_1 * RiskAtt_h + \varepsilon \quad (2b)$$

with $\omega_{h,l}$ as either $PercentageRisky_{h,BPT}$, or $\sigma_{h,3years}$, or $\sigma_{h,4years}$.

To estimate the high aspiration layers' σ we use ETFs as benchmark for the risky asset classes *Stocks, Bonds, Real estate funds,* and *Articles of great value*. Due to the lack of an appropriate benchmark, we exclude the asset class O*ther assets* from the calculations and normalize the sum of the remaining asset classes' percentages in the high aspiration layer to 100 percent. The ETF for each asset class is presented in Table 1. We choose ETFs with underlying indices from Germany due to German investors' significant home or even local bias (see e.g. Oehler et al. 2007 and Baltzer et al. 2015).

Insert Table 1 about here

The regression models of equations (2a) and (2b) apply to the sample of households that are wealthy enough to establish a high aspiration layer with a value of at least 1,000 EUR[8], however, leaving unconsidered whether the household invests in risky assets or not. We first employ the regression models in a logit regression analysis to analyze households' decision to generally invest in risky assets in the context of the CPCM and the BPT. For this purpose, the dependent variable in equations (2a) and (2b) is replaced by a dummy variable that takes the value 1 if a household invests in risky assets and 0 otherwise. We subsequently employ the regression models of equations (2a) and (2b) in a linear OLS regression. If a household does not hold any risky assets, we set $\ln\omega_h$ as -8.1 (which is equal to less than 1 EUR invested in risky assets) to avoid missing values for the full sample analyses.

[8] See, e.g. von Gaudecker (2015) who uses this threshold.

We furthermore provide robustness checks to extract the influence of households' purpose for saving, education and financial literacy and the point in time when the interview took place from our results. In addition, we focus on the subsample of households that actually hold risky assets to estimate to which extent the explanatory power of our models primarily emerges from households' decision to invest/not to invest in risky assets.

4 Results

Descriptive statistics

Of 3,565 households in the sample of the PHF-Survey 1,401 are wealthy enough to establish a high aspiration layer with a value of at least 1,000 EUR. The mean age of these households' FKPs is 58 years (median age: 59 years). 64 percent of the FKPs are male. In 18 percent of the households lives at least one child that is 16 years or younger.

Table 2 contains descriptive statistics of the 1,401 households' risk-taking and wealth. In the framework of the CPCM the households invest 12.6 percent of their total wealth in risky assets, on average. Following our implementation of the BPT the households invest 23.2 percent of their high aspiration layer's value in risky assets. The moderate participation rate in risky assets is the reason for the low mean annualized volatility of households' high aspiration layer which is 3.6 percent for the four year investment period. The households' mean total wealth is about 472,000 EUR and the value of the high aspiration layer is 122,000 EUR on average. The median values are lower for all measures indicating a right-skewed distribution of the measures in the cross-section.

Insert Table 2 about here

Regression analyses

We perform stepwise logit regression analyses using the models from equation (2a) and (2b) to analyze the relation between households' wealth and households' decision to generally engage in risky investments in the CPCM and the BPT framework. For each model specification we first determine the explanatory power of households' characteristics ξ_h regarding households' risk-taking. Thereafter, we compare the explanatory power added when households' total wealth and the value of households' high aspiration layer is included in the regression model. We present the results of the logit regression in Table 3. The regression analyses reveal that the models are able to correctly predict a high percentage of households that invest/do not invest in risky assets. By just using the household-specific characteristics in the CPCM it is possible to correctly forecast whether a household invests in risky assets or not in 71.7 percent of the cases. Adding households' total wealth ($TWealth_h$) as explanatory variable increases the percentage of correct forecasts to 73.2 percent. By using the value of households' high aspiration layer ($ValueHAL_h$) in combination with the set of household specific characteristics as independent variables in the BPT model it is possible to correctly forecast 76.4 percent of the households that do not invest in risky assets and 78 percent of the households that invest in risky assets, leading to 77.2 percent of correct estimates overall. This means that the forecasting probabilities in the BPT model are 4 percentage points higher than in the CPCM model. The regression coefficients for households' total wealth and the value of households' high aspiration layer show that households are more likely to generally invest in risky assets as they get wealthier in both models.

Insert Table 3 about here

We provide findings of the stepwise linear OLS regression analyses using the models from equation (2a) and (2b) in Table 4. As dependent variables we employ $PercentageRisky_{h,CPCM}$, $PercentageRisky_{h,BPT}$, $\sigma_{h,3years}$, and $\sigma_{h,4years}$. Solely including the household-specific characteristics ξ_h without a wealth measure in the linear regression already yields an adjusted R-squared of 24 to 26 percentage points in all four model specifications. This means that households' characteristics explain a very similar percentage of households' risk-taking in both the CPCM and the BPT model. Adding households' total wealth as independent variable in the CPCM model increases the adjusted R-squared by 0.9 percentage points. In contrast, introducing the value of households' high aspiration layer provides an at least 9.4 percentage points higher R-squared in the BPT model. Consequently, the explanatory power – measured as the model's R-squared - of the BPT model, is at least 7 percentage points higher than the explanatory power of the CPCM model. Moreover, the value of the high aspiration portfolio layer explains households' risk-taking in the BPT model more accurately than households' total wealth in the CPCM. Results for models with the high aspiration layer's σ as dependent variable are very similar to the results with the high aspiration layer's percentage of risky assets as dependent variable. The concept of decreasing RRA is supported in all model specifications.

Insert Table 4 about here

Our findings so far show that regression models that are based on the BPT framework provide more explanatory power than regression models based on the CPCM. Moreover, the stepwise approach revealed that the wealth measure in the BPT model, i.e. the value of households' high aspiration layer, adds more explanatory power on top of the household-specific characteristics than households' total wealth in the CPCM. However, results in both frameworks are in favor of a decreasing RRA among households. More specifically, households are more likely to generally invest in risky assets when they get wealthier in both models. Furthermore, households' portfolio risky share and the σ of households' high aspiration layer rise with wealth.

Robustness Checks

Previous studies identified an influence of investors' cognitive capabilities (measured e.g. by their graduation or IQ) and financial literacy on the probability of stock market participation (see e.g. Christelis et al. 2010; Cole and Shastry 2009; Grinblatt et al. 2011 and 2012; Van Rooij et al. 2007). Furthermore Chatterjee et al. (2017) find a relation between households' goals-based saving behavior and risk-tolerance. We first provide ANOVA analyses to figure out if and how these factors influence the risk-taking of the households in our sample before we extend our previous regression models with the relevant factors. The p-values of the ANOVA analyses are presented in Table 5 and show statistically significant differences regarding the risk-taking among households with differently educated FKPs. Descriptive statistics of households' risk-taking subdivided by the graduation and professional qualification of their FKPs[9] show that households' risk-taking increases with the education level of their FKP. For the sake of comparability with previous literature we use the three questions of Lusardi and Mitchell (2006) to measure financial literacy although these questions rather measure pure textbook knowledge than more helpful applied knowledge about financial products (see Oehler et al. 2017 for a detailed discussion on this topic). Our results show that FKPs with different financial literacy build portfolios with different riskiness. However, we do not observe a linear relation between financial literacy and risk-taking. Instead, the risk-taking of households that answered one or two questions in the way that Lusardi and Mitchell (2006) define as correct varies with no clear tendency. Those households that gave three – in the sense of the questions' inventers – correct answers clearly show the highest degree of risk-taking. Furthermore, households that state to save for their own retirement show a slightly higher risk-taking than households that save for larger purchases, emergency situations, or to support their children or grandchildren. The latter difference, however, is hardly statistically significant.

Insert Table 5 about here

Given the statistically significant different risk-taking among households with different graduation, professional qualification, and financial literacy we extend our linear regression models (2a) and (2b) by these three factors. Graduation ($Graduation_{FKP,h}$) and professional qualification ($ProfessionalQualification_{FKP,h}$) are included as ordinal factors. Financial literacy is captured by a dummy variable that is 1, if all three

[9] We do not report these statistics in detail since the following regression analyses show that only few of the factors remain significant when households' wealth is considered.

questions are answered correctly and 0 otherwise ($AllFinLitQuestionsCorrect_h$). The full regression models are as follows:

$$
\begin{aligned}
lnPercentageRisky_{h,CPCM} = \beta_0 + \eta lnTWealth_h + \beta_1 * Age_h + \beta_2 * Age^2{}_h \\
+ \beta_3 * Male_h + \beta_4 * lnIncome_h \\
+ \beta_5 * Child_h + \beta_6 * Graduation_{FKP,h} \\
+ \beta_7 * ProfessionalQualification_{FKP,h} \\
+ \beta_8 * AllFinLitQuestionsCorrect_h + \gamma_1 * RiskAtt_h + \varepsilon
\end{aligned}
\tag{3a}
$$

$$
\begin{aligned}
ln\omega_{h,l} = \beta_0 + \eta lnValueHAL_h + \beta_1 * Age_h + \beta_2 * Age^2{}_h \\
+ \beta_3 * Male_h + \beta_4 * lnIncome_h \\
+ \beta_5 * Child_h + \beta_6 * Graduation_{FKP,h} \\
+ \beta_7 * ProfessionalQualification_{FKP,h} \\
+ \beta_8 * AllFinLitQuestionsCorrect_h + \gamma_1 * RiskAtt_h + \varepsilon
\end{aligned}
\tag{3b}
$$

We perform a logit regression to check if our previous findings on households' decision to generally participate in risky assets are robust to the three control variables. The outcome of the logit regression analysis is presented in Table 6. FKPs' graduation and financial literacy are identified as statistical significant influence factors regarding the decision to invest in risky assets in both the CPCM and the BPT framework. Nevertheless, both models' fit still increases when the wealth measures are added. Furthermore, again the full model of the BPT framework provides a higher percentage of correct estimates and a better fit than the model of the CPCM.

Compared to our previous logit regression the three new factors hardly impact the models' accuracy. Therefore, our previous findings stay robust.

Insert Table 6 about here

We additionally provide results of the linear regression analysis using the models (3a) and (3b) in Table 7. Again, the three additional factors provide only little further explanatory power. Compared to the previous linear regression analyses the R-squared and adjusted R-squared rise between 0.9 and 2.5 percentage points. FKPs' graduation and financial literacy are both statistical significant factors. However, the regression coefficients of the wealth measures – as well as their statistical significance – hardly change compared with the previous analyses and are, therefore, robust to the control variables. Again, results for the risk-taking measures $PercentageRisky_{h,BPT}$, $\sigma_{h,3years}$, and $\sigma_{h,4years}$ are very similar. Furthermore, the full models of the BPT framework still provide more explanatory power than the full model of the CPCM.

Insert Table 7 about here

Since data of the PHF-survey were collected over an 11-month period, we control whether the date of the interview influences our results. For this purpose, we subdivide the dataset according to the quarter when households were interviewed.[10] Again the stepwise regression analyses reveal that the models of the BPT framework provide more explanatory power regarding the relation between households' wealth

[10] See the appendix for the detailed results of these regression analyses.

and risk-taking than the CPCM. Furthermore, models using the risky asset share and the σ of the high aspiration layer as risk-taking measure show similar results. The concept of decreasing RRA is supported in all models. Therefore, our main findings are also robust to the point in time when the survey took place.

Only half of the households that are wealthy enough to establish a high aspiration layer with a value of at least 1,000 EUR actually invest in risky assets. This might entail that a substantial part of the previous regression analyses' explanatory power may arise from the subsample of households with no risky investments. We, therefore, focus on the subsamples of households that actually own risky assets. This subsample covers 787 households in the CPCM framework and 736 households in the BPT framework. The difference between the numbers of households equals the number of households that solely have *businesses ran by household members* and *direct investments in firms* as risky assets. Compared to the full sample, households in these subsamples are on average wealthier. The 787 households of the CPCM sample show a mean (median) total wealth of 644,545 EUR (367,000 EUR) and the high aspiration layer of the 736 households of the BPT sample show a mean (median) value of 203,703 EUR (76,050 EUR).

We perform linear regression analyses to assess the relation between these households' wealth and their risk-taking. The respective results are presented in Table 8. Compared to the previous analysis the explanatory power of both frameworks – measured by the adjusted R-squared of their regression models – considerably decreases by 16 to 31 percentage points depending on the model specification. More specifically, the full model of the CPCM framework provides an adjusted R-squared of 12.4 percent while the adjusted R-squared of the full models in the BPT framework range between 4.5 and 6.1 percent. Furthermore, the relation between households' wealth and their risk-taking turned. In the CPCM model, households' total wealth is negatively correlated with households' risk-taking with a statistical significance at the one percent level. The same holds true in the BPT model when households' risk-taking is measured by the high aspiration layer's σ. In the BPT model, however, a considerable amount of the regression models' explanatory power arises from households' directly queried risk attitude. Households stating to be willing to take above average risk show a higher percentage of risky investments and have portfolio layers with a higher σ than households stating to take average or no financial risk. Likewise, households stating not to be willing to take financial risk show a lower percentage of risky investments and have portfolio layers with a lower σ than the remaining households. Consequently, households' wealth is of particular importance when households' make the decision whether to generally invest in risky assets. Therefore, the models of both frameworks, i.e. CPCM and BPT, considerably loose explanatory power when they are applied solely on households that invest in risky assets.

Insert Table 8 about here

5 Conclusions

This study's aim is to provide new insights on the relation between households' wealth and RRA. For this purpose, we extend the existing literature that commonly employs the standard finance CPCM by providing an implementation of the BPT on field data. A comparison of the two frameworks' explanatory power shows that the implementation of the BPT provides a better fitting approach than the CPCM to explain households' financial risk-taking although the BPT includes only a subsample of the assets captured in the CPCM. However both frameworks yield similar results regarding households' RRA. Our regression analyses show that households' willingness to generally invest in risky asset markets rises with households' wealth, indicating decreasing RRA as in, e.g., Cohn et al. (1975), Morin/Suarez (1983), Riley/Chow (1992), Oehler (1998), Calvet/Sodini (2014), and Oehler et al. (2016). The results are robust to households' education and financial literacy, changes in the risk-taking measure, i.e. when risk-taking is measured as the high aspiration layer's σ instead of a portfolio's risky share, and the point in time when the interview took place. In turn, models employing the high aspiration layer's σ instead of a portfolio's risky share do hardly provide additional explanatory power or different results on households' RRA.

Our findings provide implications for researchers, policymakers, and practitioners alike. Since the models of the BPT provide more explanatory power than the standard finance CPCM researchers should include the BPT in models on households' financial decision making and behavior in financial markets. Extending normative portfolio choice models with behavioral insights could considerably increase the models' explanatory power. Our results show that households consider rather the wealth in their high aspiration layer than their total wealth in the financial decision making process. A possible explanation for this phenomenon is that the value of the high aspiration layer is quickly accessible and assessable (e.g. through online banking and brokerage platforms) and therefore more present to households than their total wealth. The resulting implication for policymakers and regulators is that households are more likely to opt-in in governmental programs that cause an immediate positive effect in households' high aspiration layer than in programs that influence other portfolio layers. It is furthermore interesting for financial advisors that households with the same level of wealth, education, and financial literacy show a different risk-taking behavior in accordance with their self-assessed risk attitude. Therefore, inquiring households' risk attitude and understanding what households actually perceive as financial risk (see, e.g., Zeisberger 2016 on the role of loss probabilities) is necessary for providing financial advice that households appraise as useful (see, e.g., Oehler/Wendt 2017 for a discussion on conditions for good consumer information).

We based our study's methodology on Oehler et al. (2016) and the therein cited studies that already provided starting points for an implementation of the BPT. Such an implementation, however, should to some degree consider the social system of the households' domestic country (see e.g. Badarinza et al. 2016 and Oehler et al. 2017 on country differences regarding the ownership of financial products). We invite further research with implementations of the BPT in other countries. We believe that hierarchical models of both households' portfolio structure – like the BPT – and asset market participation drivers (see, e.g., Kaustia/Luotonen 2016) can provide further valuable insights on related questions regarding households' risk-taking behavior and RRA.

References

Ackert, L. (2014), “Traditional and Behavioral Finance”, in Baker, K., Ricciardi, V. (Eds.), *Investor Behavior*, pp. 25-41.

Arrow, K. (1965), *Aspects of the Theory of Risk-Bearing*, Yrjö Jahnssonin Säätiö, Helsinki.

Arrow, K. (1971): Essays in the Theory of Risk-Bearing, Amsterdam.

Badarinza, C., Campbell, J., Ramadorsai, T. (2016), “International Comparative Household Finance”, *Annual Review of Economics*, Vol. 8, pp. 111-144.

Baltzer, M., Stolper, O. and Walter, A. (2015), “Home-field advantage or a matter of ambiguity aversion? Local bias among German individual investors”, *European Journal of Finance*, Vol. 21 No. 9, pp. 734-754.

Bertraut, C.C. (1998), “Stockholding Behavior of U.S. Households: Evidence from the 1983-1989 Survey of Consumer Finances”, *The Review of Economics and Statistics*, Vol. 80 No. 2, pp. 263-275.

Bloomfield, R. (2010), “Traditional Versus Behavioral Finance”, in Baker, K., Nofsinger, J. (Eds.), *Behavioral Finance*, pp. 23-38.

Brunnermeier, M.K. and Nagel, S. (2008), “Do Wealth Fluctuations Generate Time-Varying Risk Aversion? Micro-Evidence on Individuals’ Asset Allocation”, *American Economic Review,* Vol. 98 No. 3, pp. 713-736.

Calvet, L.E. and Sodini, P. (2014), “Twin Picks: Disentangling the Determinants of Risk-Taking in Household Portfolios”, *Journal of Finance*, Vol. 69 No. 2, pp. 867-906.

Campbell, J. (2003), “Consumption-based asset pricing”, in C. George H. Milton & S. Rene (Eds.), *Handbook of the economics of finance*, Vol. IB, pp.803–887, Elsevier Science, Amsterdam.

Campbell, J.Y. (2006), “Household Finance”, *Journal of Finance,* Vol. 61 No. 4, pp. 1553-1604.

Chatterjee, S., Fan, L., Jacobs, B. and Haas, R. (2017), “Risk Tolerance and Goals-Based Savings Behavior of Households: The Role of Financial Literacy”, *Journal of Personal Finance*, Vol. 16 No. 1, pp. 66-77.

Chiappori, P-A. and Paiella, M. (2011), “Relative Risk Aversion Is Constant: Evidence From Panel Data”, *Journal of the European Economic Association*, Vol. 9 No. 6, pp. 1021-1052.

Christelis, D., Jappelli, T. and Padula, M. (2010), „Cognitive abilities and portfolio choice”, *European Economic Review*, Vol. 54 No. 1, pp. 18–38.

Cohn, R.A., Lewellen, W.G., Lease, R.C. and Schlarbaum, G.G. (1975), “Individual Investor Risk Aversion and Investment Portfolio Composition”, *Journal of Finance*, Vol. 30 No. 2, pp. 605-620.

Cole, S. and Shastry, G.K. (2009), “Smart money: The effect of education, cognitive ability, and financial literacy on financial market participation”, working paper, Harvard Business School, Boston, MA, February 2009.

Curcuru, S., Heaton, J., Lucas, D. and Moore, D. (2010), “Heterogeneity and portfolio choice: theory and evidence”, in Ait-Sahalia, Y. and Hansen, L.P. (Eds.), *Handbook of Financial Econometrics, Vol. I.*, Elsevier, Amsterdam, pp. 337-382.

Deutsche Bundesbank (2015), „German households’ saving and investment behaviour in light of the low-interest-rate environment“, *Deutsche Bundesbank Monatsbericht*, Oktober 2015, pp. 13-31.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. and Wagner, G.G. (2011), “Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences”, *Journal of the European Economic Association*, Vol. 9 No. 3, pp. 522–550.

Friend, I. and Blume, M.E. (1975), “The demand for risky assets”, *American Economic Review*, Vol. 65 No. 5, pp. 900-922.

Grinblatt, M., Keloharju, M. and Linnainmaa, J. (2011), „IQ and stock market participation”, *Journal of Finance*, Vol. 66 No 6. , pp. 2121–2164.

Grinblatt, M., Keloharju, M., and Linnainmaa, J. (2012), „IQ, trading behavior, and performance. *Journal of Financial Economics*, Vol. 104 No. 2, 104, pp. 339–362.

Guiso, L. and Sodini, P. (2013), “Household Finance: An Emerging Field”, in Constantinides, G.M., Milton, H. and Stulz, R.M. (Eds.), *Handbook of the Economics of Finance*, pp. 1397 – 1532, Elsevier Science, Amsterdam.

Halko, M-L., Kaustia, M. and Alanko, E. (2012), “The gender effect in risky asset holdings”, *Journal of Economic Behavior & Organization*, Vol. 83 No. 1, pp. 66– 81.

Harrison, G.W., Johnson, E., McInnes, M.M. and Rutström, E.E. (2005), “Temporal stability of estimates of risk aversion”, *Applied Financial Economics Letters*, Vol. 1 No. 1, pp. 31-35.

Kaustia, M. and Luotonen, N. (2016), “What drives the heterogeneity in portfolio choice? The role of institutional, traditional, and behavioral factors”, paper presented at the 2nd Research in Behavioral Finance Conference, 11 October 2016, Amsterdam, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2845963 (accessed 05 May 2017).

Lusardi, A., Mitchell, O., 2006. Financial literacy and planning: implications for retirement wellbeing. NBER Working Paper No. 17078.

Merton, R. C. (1969), “Lifetime portfolio selection under uncertainty: The continuous-time case”, *Review of Economics and Statistics*, Vol. 51 No. 3, pp. 247–257.

Morin, R.A. and Suarez, A.F. (1983), “Risk aversion revisited”, *Journal of Finance*, Vol. 38 No. 4, pp. 1201-1216.

Nosic, A. and Weber, M. (2010), “How risky do I invest: The role of risk attitudes, risk perceptions and overconfidence”, *Decision Analysis*, Vol. 7 No. 3, pp. 282-301.

Oehler, A. (1998), „Decreasing or Increasing Relative Risk Aversion? [Abnehmende oder zunehmende relative Risikoaversion?]“, *ZBB*, Vol. 10 No. 4, pp. 230-236.

Oehler, A. and Horn, M. (2016), ”Does Households’ Wealth Predict the Efficiency of their Asset Mix? Empirical Evidence”, paper presented at the 2nd Research in Behavioral Conference 2016, Amsterdam and 53rd Meeting of the Eastern Finance Association (EFA), April 5-8 2017, Jacksonville.

Oehler, A., Horn, M. and Wedlich, F. (2016), “Young Adults’ Subjective and Objective Risk Attitude in Financial Decision Making: Evidence from the Lab and the Field”, paper presented at the 53rd Meeting of the Eastern Finance Association (EFA), April 5-8 2017, Jacksonville and the 2017 Behavioural Finance Working Group Conference, June 12-13 2017, London.

Oehler, A., Horn, M., Wendt, S., Reisch, L., Walker, T. (2017), “Young adults and their finances: An international comparative study on applied financial literacy”, *Economic Notes* (forthcoming).

Oehler, A., Rummer, M., Walker, T. and Wendt, S. (2007), “Are Investors Home Biased? Evidence from Germany” in Gregoriou, G.N. (Ed.), *Diversification and Portfolio Management of Mutual Funds,* Palgrave MacMillan, Houndmills, pp. 57-77.

Oehler, A. and Wendt, S. (2017), “Good Consumer Information: The Information Paradigm at its (Dead) End?”, *Journal of Consumer Policy*, Vol. 40, pp. 179-191.

Paya, I. and Wang, P. (2016), “Wealth fluctuations and investment in risky assets: The UK micro evidence on households’ asset allocation”, *Journal of Empirical Finance*, Vol. 38 (Part A, September 2016), pp. 221-235.

Pratt, J.W. (1964), “Risk Aversion in the Small and the Large”, in *Econometrica*, The Econometric Society, pp. 122-136.

Riley Jr., W.B. and Chow, K.V. (1992), “Asset Allocation and Individual Risk Aversion”, *Financial Analyst Journal*, Vol. 48 No. 6, pp. 32-37.

Sahm, C.R. (2012), “How much does risk tolerance change?”, available at http://dx.doi.org/10.1142/S2010139212500206 (accessed at 05 May 2017).

Shefrin, H.M. and Statman, M. (2000), “Behavioral Portfolio Theory”, *Journal of Financial and Quantitative Analysis*, Vol. 35 No. 2, pp. 127-151.

Statman, M. (2014), "Behavioral finance: Finance with normal people", *Borsa Istanbul Review*, Vol. 14, pp. 65-73.

Siegel, F.W. and Hoban Jr., J.P. (1982), "Relative Risk Aversion Revisited", *The Review of Economics and Statistics*, Vol. 64 No. 3, pp. 481-487.

Thaler, R.H. (1999), "Mental Accounting Matters", *Journal of Behavioral Decision Making*, Vol. 12 No. 3, pp. 183-206.

Van Rooij, M., Lusardi, A. and Alessie, R. (2007), "Financial literacy and stock market participation", working paper, National Bureau of Economic Research, Cambridge, MA, October 2007.

Von Gaudecker, H.M. (2015), "How Does Household Portfolio Diversification Vary with Financial Literacy and Financial Advice?", *Journal of Finance*, Vol. 70 No. 2, pp. 489-506.

Von Kalckreuth, U., Eisele, M., Le Blanc, J., Schmidt, T. and Zhu, J. (2012), "The PHF: a comprehensive panel survey on household finances and wealth in Germany", discussion paper, Deutsche Bundesbank, Frankfurt am Main, 2012.

Von Neumann, N. and Morgenstern, O. (1944), *Theory of Games and Economic Behavior,* Princeton University Press, Pinceton, NJ, 1944.

Weber, M., Weber, E.U. and Nosic, A. (2013), "Who takes Risks When and Why: Determinants of Changes in Investor Risk Taking", *Review of Finance*, Vol. 17 No. 3, pp. 847-883.

Wölbert, E. and Riedl, A. (2013), "Measuring Time and Risk Preferences: Reliability, Stability, Domain Specificity", discussion papers, Center of Economic Studies & ifo Institute, Munich, July 2013.

Zeisberger, S. (2016), "Do People Care About Loss Probabilities?", working paper, Institute for Management Research Radboud University, Nijmengen, October 2016.

Table 1: Benchmarks of asset classes

Asset class	Benchmark index	ISIN of ETF
Stocks	DAX30 Performance Index	DE0005933931
Bonds	Barclays Euro Aggregate Bond Index	DE000A0RM447
Real estate funds	Vontobel REITs Low Volatility Performance Index	DE000VT0RLV8
Articles of great value	Solactive Luxury and Lifestyle Index (Total Return)	DE000DR0NUM1

Table 2: Descriptive statistics of the risk-taking and wealth measures (N=1401 households)

Panel A: Risk-taking measures			
	Mean	Med.	Std.
$PercentageRisky_{h,CPCM}$	.126	.013	.234
$PercentageRisky_{h,BPT}$	.232	.045	.302
$\sigma_{h,3years}$	.037	.007	.053
$\sigma_{h,4years}$	.036	.007	.051
Panel B: Wealth measures (in EUR)			
	Mean	Med.	Std.
$TWealth_h$	472,369	250,000	872,577
$ValueHal_h$	122,125	38,310	379,150

Notes: Panel A displays descriptive statistics of the risk-taking measures and Panel B of the wealth measures. For each measure we provide the mean value (Mean), median value (Med.), and standard deviation (Std.).

Table 3: Logit regression analyses with a dummy indicating investment in risky assets as dependent variable

	CPCM (model 2a)		BPT (model 2b)	
$TWealth_h$		.410*** (.058)		
$ValueHAL_h$				.914*** (.068)
ξ_h	Yes	Yes	Yes	Yes
β_0	-14.17*** (1.323)	-13.63*** (1.324)	-12.95*** (1.449)	-16.02*** (1.449)
2-Log-Likelihood	1541	1459	1574	1337
Nagelkerkes R^2	.318	.360	.306	.466
Percentage of correctly estimated non-risky investors	65.3	63.8	70.1	76.4
Percentage of correctly estimated risky investors	76.6	80.4	71.9	78.0
Percentage correct estimates	71.7	73.2	71.0	77.2
N	1401	1401	1401	1401

Notes: We provide regression coefficients, their respective standard errors (in parentheses), 2-Log-Likelihood statistics, Nagelkerkes R^2, and the percentage of correct estimates for the logit regression analysis using the regression models (2a) and (2b). ξ_h captures age (Age_h), squared age ($Age^2{}_h$), and gender ($Male_h$) of household's FKP, the monthly household income ($Income_h$), households' directly queried risk attitude ($RiskAtt_h$), and a dummy variable that indicates whether at least on child at the age of 16 or younger lives in the household ($Child_h$).The symbols ***, **, and * denote statistical significance at the one-, five-, and ten-percent level, respectively. Example: Regressing the risky asset dummy on regression model (2b) with $ValueHAL_h$as wealth measure yields a coefficient of $ValueHAL_h$ of .914 with a statistical significance at the one-percent level and a Nagelkerkes R^2 of .466.

Table 4: Stepwise regression analyses with $PercentageRisky_{h,CPCM}$, $PercentageRisky_{h,BPT}$, $\sigma_{h,3years}$, and $\sigma_{h,4years}$ as dependent variable

Framework	CPCM (model 2a)		BPT (model 2b)					
Dependent variable $\omega_h/\omega_{h,l}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
$TWealth_h$		.235*** (.060)						
$ValueHAL_h$				.983*** (.065)		.681*** (.048)		.679*** (.048)
ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	-20.38*** (1.309)	-20.46*** (1.307)	-21.07*** (1.53)	-21.46*** (1.417)	-17.61*** (1.135)	-17.88*** (1.063)	-17.58*** (1.131)	-17.85*** (1.059)
R^2	.260	.269	.244	.352	.247	.341	.247	.341
R^2 adj.	.256	.265	.241	.349	.243	.337	.243	.337
F-Test	69.86	63.34	64.34	94.66	65.25	89.91	65.29	90.03
N	1401	1401	1401	1401	1401	1401	1401	1401

Notes: We provide regression coefficients, their respective standard errors (in parentheses), R^2, adjusted R^2, and F-statistics for the linear regression analysis using the models of equation (2a) and (2b). ξ_h captures age (Age_h), squared age ($Age^2{}_h$), and gender ($Male_h$) of household's FKP, the monthly household income ($Income_h$), households' directly queried risk attitude ($RiskAtt_h$), and a dummy variable that indicates whether at least on child at the age of 16 or younger lives in the household ($Child_h$).The symbols ***, **, and * denote statistical significance at the one-, five-, and ten-percent level, respectively. Example: Regressing $PercentageRisky_{h,BPT}$ on the regression model with $ValueHAL_h$as wealth measure yields a coefficient of $ValueHAL_h$ of .983 with a statistical significance at the one-percent level and an adjusted R^2 of .349.

Table 5: ANOVA graduation, professional qualification and purpose for saving

	p-values			
	Graduation	Professional qualification	Financial literacy	Purpose for saving
$PercentageRisky_{h,CPCM}$	.000	.000	.000	.087
$PercentageRisky_{h,BPT}$	.000	.000	.000	.036
$\sigma_{h,4years}$	.000	.000	.000	.093

Notes: We provide p-values for between group ANOVAs that analyze the influence of the households' FKPs' graduation, professional qualification, and financial literacy as well as household's purpose for saving on the differences regarding households' $PercentageRisky_{h,CPCM}$, $PercentageRisky_{h,BPT}$, and $\sigma_{h,4years}$. Regarding graduation we consider the groups "lower secondary school", "higher secondary school", "university of applied sciences entrance diploma", and "general university entrance diploma". Regarding professional qualification we consider the groups "no training completed", "currently in training/studying", "vocational training completed", "training at technical/commercial college completed", "university of applied sciences degree", "university degree", "doctorate/postdoctoral qualification". Regarding purposes for saving we consider the groups "larger purchase excl. vehicles", "funds for emergency situations", "old-age provision", and "supporting children or grandchildren". For example, the p-value of .000 shows that there is a statistically significant difference (at least at the 99.9 percent level) regarding the mean values of $PercentageRisky_{h,CPCM}$ between the groups with different graduation.

Table 6: Logit regression analyses with a dummy indicating investment in risky assets as dependent variable

	CPCM (model 3a)		BPT (model 3b)	
$TWealth_h$		.414*** (.060)		
$ValueHAL_h$				.883*** (.070)
$Graduation_{FKP,h}$	.258*** (.076)	.263*** (.079)	.267*** (.076)	.216*** (.083)
$ProfessionalQualification_{FKP,h}$	.019 (.062)	.023 (.064)	.025 (.061)	-.012 (.067)
$AllFinLitQuestionsCorrect_h$	.400*** (.146)	.467*** (.151)	.386*** (.145)	.483*** (.159)
Further households-specific characteristics ξ_h	Yes	Yes	Yes	Yes
β_0	-13.02*** (1.371)	-13.91*** (1.423)	-11.69*** (1.340)	-15.10*** (1.514)
2-Log-Likelihood	1447	1364	1478	1270
Nagelkerkes R^2	.339	.382	.329	.473
Percentage of correctly estimated non-risky investors	64.4	65.4	69.2	75.2
Percentage of correctly estimated risky investors	77.4	79.2	74.1	77.9
Percentage correct estimates	71.8	73.4	71.8	76.7
N	1345	1345	1345	1345

Notes: We provide regression coefficients, their respective standard errors (in parentheses), 2-Log-Likelihood statistics, Nagelkerkes R^2, and the percentage of correct estimates for the logit regression analysis using the regression models (3a) and (3b). ξ_h captures age (Age_h), squared age ($Age^2{}_h$), and gender ($Male_h$) of household's FKP, the monthly household income ($Income_h$), households' directly queried risk attitude ($RiskAtt_h$), and a dummy variable that indicates whether at least on child at the age of 16 or younger lives in the household ($Child_h$).The symbols ***, **, and * denote statistical significance at the one-, five-, and ten-percent level, respectively. Example: Regressing the risky asset dummy on regression model (3b) with $ValueHAL_h$as wealth measure yields a coefficient of $ValueHAL_h$ of .883 with a statistical significance at the one-percent level and a Nagelkerkes R^2 of .473.

Table 7: Stepwise regression analyses with $PercentageRisky_{h,CPCM}$, $PercentageRisky_{h,BPT}$, $\sigma_{h,3years}$, and $\sigma_{h,4years}$ as dependent variable

Framework	CPCM (model 3a)		BPT (model 3b)					
Dependent variable $\omega_h/\omega_{h,l}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
$TWealth_h$		.216*** (.061)						
$ValueHAL_h$				.929*** (.066)		.640*** (.050)		.638*** (.049)
$Graduation_{FKP,h}$	.247*** (.086)	.247*** (.086)	.417*** (.100)	.321*** (.094)	.299*** (.074)	.233*** (.070)	.299*** (.074)	.233*** (.070)
$ProfessionalQualification_{FKP,h}$	.086 (.067)	.086 (.068)	.041 (.079)	-.014 (.074)	.033 (.058)	-.005 (.055)	.033 (.058)	-.005 (.055)
$AllFinLitQuestionsCorrect_h$	.601*** (.164)	.624*** (.165)	.602*** (.192)	.639*** (.179)	.453*** (.142)	.478*** (.134)	.448*** (.142)	.473*** (.134)
Further households-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	-18.91*** (1.368)	-18.98*** (1.366)	-19.57*** (1.596)	-20.52*** (1.491)	-16.45*** (1.185)	-17.11*** (1.119)	-16.43*** (1.181)	-17.08*** (1.115)
R^2	.282	.291	.269	.364	.271	.352	.271	.352
R^2 adj.	.276	.285	.264	.358	.266	.347	.266	.347
F-Test	52.27	49.14	49.15	69.25	49.60	65.86	49.61	65.90
N	1345	1345	1345	1345	1345	1345	1345	1345

Notes: We provide regression coefficients, their respective standard errors (in parentheses), R^2, adjusted R^2, and F-statistics for the linear regression analysis using the regression models (3a) and (3b). ξ_h captures age (Age_h), squared age ($Age^2{}_h$), and gender ($Male_h$) of household's FKP, the monthly household income ($Income_h$), households' directly queried risk attitude ($RiskAtt_h$), and a dummy variable that indicates whether at least on child at the age of 16 or younger lives in the household ($Child_h$).The symbols ***, **, and * denote statistical significance at the one-, five-, and ten-percent level, respectively. Example: Regressing $PercentageRisky_{h,BPT}$ on the regression model (3b) with $ValueHAL_h$as wealth measure yields a coefficient of $ValueHAL_h$ of .929 with a statistical significance at the one-percent level and an adjusted R^2 of .358.

Table 8: Stepwise regression analyses with $PercentageRisky_{h,CPCM}$, $PercentageRisky_{h,BPT}$, $\sigma_{h,3years}$, and $\sigma_{h,4years}$ as dependent variable, conditional on holding risky assets

Framework	CPCM (model 3a)		BPT (model 3b)					
Dependent variable $\omega_h/\omega_{h,l}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
$TWealth_h$		-.391***						
		(.054)						
$ValueHAL_h$				-.046		-.107***		-.107***
				(.035)		(.036)		(.036)
$AboveAverageRisk_h$	.467*	.466*	.467***	.474***	.693***	.709***	.687***	.703***
	(.272)	(.238)	(.176)	(.176)	(.182)	(.181)	(.180)	(.179)
$NoRisk_h$	-.577***	-.610***	-.267***	-.285***	-.273***	-.315***	-.273***	-.315***
	(.121)	(.117)	(.081)	(.082)	(.083)	(.084)	(.082)	(.083)
$Graduation_{FKP,h}$	-.092	-.068	.046	.047	.032	.033	.032	.033
	(.067)	(.065)	(.045)	(.082)	(.046)	(.046)	(.045)	(.045)
$ProfessionalQualification_{FKP,h}$	.107**	.105**	.004	.008	.008	.017	.008	.017
	(.052)	(.051)	(.034)	(.035)	(.035)	(.035)	(.035)	(.035)
$AllFinLitQuestionsCorrect_h$	.358***	.295**	.221**	.223**	.190**	.194**	.183*	.187**
	(.138)	(.134)	(.091)	(.091)	(.094)	(.094)	(.093)	(.093)
Further households-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	-4.76***	-3.57*	-2.42***	-2.35***	-4.12***	-3.96***	-4.13***	-3.97***
	(1.136)	(1.112)	(.767)	(.768)	(.791)	(.789)	(.781)	(.779)
R^2	.077	.137	.057	.060	.064	.076	.064	.076
R^2 adj.	.065	.124	.044	.045	.051	.061	.051	.061
F-Test	6.30	10.85	4.28	4.05	4.82	5.23	4.82	5.25
N	787	787	736	736	736	736	736	736

Notes: We provide regression coefficients, their respective standard errors (in parentheses), R^2, adjusted R^2, and F-statistics for the linear regression analysis using the regression models (3a) and (3b). Further households-specific characteristics in ξ_h captures age (Age_h), squared age ($Age^2{}_h$), and gender ($Male_h$) of household's FKP, the monthly household income ($Income_h$), and a dummy variable that indicates whether at least on child at the age of 16 or younger lives in the household ($Child_h$).The symbols ***, **, and * denote statistical significance at the one-, five-, and ten-percent level, respectively. Example: Regressing $PercentageRisky_{h,BPT}$ on the regression model (3b) with $ValueHAL_h$as wealth measure yields a coefficient of $ValueHAL_h$ of -.046 with no statistical significance and an adjusted R^2 of .045.

Appendix accompanying:

Behavioral Portfolio Theory Revisited: Lessons Learned from the Field

Table A1: Logit regression analyses with a dummy indicating investment in risky assets as dependent variable, by quarter of interview

	Fourth quarter 2010				First quarter 2011				Second quarter 2011			
	CPCM (model 3a)		BPT (model 3b)		CPCM (model 3a)		BPT (model 3b)		CPCM (model 3a)		BPT (model 3b)	
$TWealth_h$		.391*** (.138)				.566*** (.133)				.384*** (.080)		
$ValueHAL_h$				.857*** (.148)				.896*** (.134)				.945*** (.105)
$Graduation_{FKP,h}$	.316* (.166)	.241 (.171)	.308* (.166)	.073 (.184)	.250 (.147)	.279 (.156)	.200 (.145)	.179 (.161)	.264** (.112)	.284** (.115)	.310*** (.112)	.291** (.125)
$ProfessionalQualification_{FKP,h}$	-.045 (.130)	.005 (.134)	.013 (.130)	.098 (.142)	.158 (.119)	.196 (.129)	.152 (.117)	.133 (.129)	-.029 (.090)	-.043 (.092)	-.043 (.089)	-.136 (.099)
$AllFinLitQuestionsCorrect_h$	.210 (.323)	.142 (.337)	-.001 (.329)	-.086 (.359)	.143 (.295)	.265 (.306)	.164 (.295)	.333 (.324)	.564*** (.203)	.665*** (.221)	.582*** (.202)	.757*** (.224)
Further households-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	-15.08*** (2.779)	-17.05*** (2.988)	-14.04*** (2.779)	-18.36*** (3.210)	-10.58*** (2.593)	-10.10*** (2.691)	-9.97*** (2.561)	-12.42*** (2.833)	-13.95*** (2.083)	-14.66*** (2.126)	-12.53*** (2.046)	-16.03*** (2.309)
2-Log-Likelihood	342	322	339	296	401	368	408	350	681	650	703	595
Nagelkerkes R²	.349	.382	.378	.495	.358	.423	.355	.492	.349	.384	.317	.477
Percentage of correctly estimated non-risky investors	64.8	59.0	66.9	72.8	64.3	71.1	66.5	78.4	69.7	69.0	74.6	78.3
Percentage of correctly estimated risky investors	83.2	86.1	80.9	83.5	78.9	81.5	77.4	80.2	73.9	74.8	66.8	74.7
Percentage correct estimates	76.1	75.9	75.2	79.1	72.9	77.3	72.7	79.4	71.9	72.1	70.8	76.5
N	330	330	330	330	384	384	384	384	631	631	631	631

Notes: We provide regression coefficients, their respective standard errors (in parentheses), 2-Log-Likelihood statistics, Nagelkerkes R², and the percentage of correct estimates for the logit regression analysis using the regression models (3a) and (3b). ξ_h captures age (Age_h), squared age ($Age^2{}_h$), and gender ($Male_h$) of household's FKP, the monthly household income ($Income_h$), households' directly queried risk attitude ($RiskAtt_h$), and a dummy variable that indicates whether at least on child at the age of 16 or younger lives in the household ($Child_h$).The symbols ***, **, and * denote statistical significance at the one-, five-, and ten-percent level, respectively. Example: Regressing the risky asset dummy on regression model (3b) on households that were interviewed in the fourth quarter of 2010 with $ValueHAL_h$as wealth measure yields a coefficient of $ValueHAL_h$ of .857 with a statistical significance at the one-percent level and a Nagelkerkes R² of .495.

Table A2: Stepwise regression analyses with $AmountRisky_{h,TW}$ (specification a), $AmountRisky_{h,VSP}$ (specification b), $\sigma_{h,3years}$ (specification c), and $\sigma_{h,4years}$ (specification d) as dependent variable ω_h, by quarter of interview

Panel A: Fourth quarter 2010

Framework	CPCM (model 3a)		BPT (model 3b)					
Dependent variable ω_h/$\omega_{h,l}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
$TWealth_h$		.287** (.143)						
$ValueHAL_h$				.845*** (.139)		.586*** (.105)		.581*** (.104)
$Graduation_{FKP,h}$	.265** (.179)	.216 (.180)	.444** (.204)	.212 (.197)	.292* (.152)	.131 (.149)	.290* (.151)	.130 (.147)
$ProfessionalQualification_{FKP,h}$	.073 (.138)	.103 (.138)	.088 (.157)	.125 (.149)	.080 (.117)	.106 (.112)	.078 (.116)	.104 (.111)
$AllFinLitQuestionsCorrect_h$	.268 (.361)	.184 (.362)	.077 (.412)	-.025 (.391)	.040 (.308)	-.030 (.295)	.040 (.306)	-.031 (.293)
Further households-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	-20.44*** (2.640)	-18.02*** (2.536)	-19.98*** (3.011)	-21.09*** (2.862)	-16.86*** (2.254)	-17.63*** (2.159)	-16.79*** (2.234)	-17.55*** (2.141)
R^2	.282	.296	.292	.365	.297	.360	.298	.360
R^2 adj.	.259	.271	.269	.343	.275	.338	.276	.338
F-Test	12.52	11.90	13.13	16.60	13.51	16.25	13.51	16.25
N	330	330	330	330	330	330	330	330

Notes: We provide regression coefficients, their respective standard errors (in parentheses), R^2, adjusted R^2, and F-statistics for the linear regression analysis using the regression models (3a) and (3b). Further households-specific characteristics ξ_h captures age (Age_h), squared age ($Age^2{}_h$), and gender ($Male_h$) of household's FKP, the monthly household income ($Income_h$), households' directly queried risk attitude ($RiskAtt_h$), and a dummy variable that indicates whether at least on child at the age of 16 or younger lives in the household ($Child_h$).The symbols ***, **, and * denote statistical significance at the one-, five-, and ten-percent level, respectively. Example: Regressing $PercentageRisky_{h,BPT}$ on the regression model (3b) with $ValueHAL_h$as wealth measure yields a coefficient of $ValueHAL_h$ of .845 with a statistical significance at the one-percent level and an adjusted R^2 of .343.

Table A2: Stepwise regression analyses with $AmountRisky_{h,TW}$ (specification a), $AmountRisky_{h,VSP}$ (specification b), $\sigma_{h,3years}$ (specification c), and $\sigma_{h,4years}$ (specification d) as dependent variable ω_h, by quarter of interview (cont'd)
Panel B: First quarter 2011

Framework	CPCM (model 3a)		BPT (model 3b)					
Dependent variable $\omega_h/\omega_{h,l}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
$TWealth_h$		.257** (.126)						
$ValueHAL_h$				.896*** (.126)		.615*** (.095)		.613*** (.094)
$Graduation_{FKP,h}$	.151 (.159)	.159 (.159)	.286 (.188)	.244 (.177)	.216 (.140)	.188 (.133)	.217 (.139)	.188 (.132)
$ProfessionalQualification_{FKP,h}$	.222* (.125)	.221* (.125)	.179 (.148)	.116 (.139)	.130 (.110)	.087 (.105)	.129 (.109)	.086 (.104)
$AllFinLitQuestionsCorrect_h$	.478 (.318)	.558* (.315)	.327 (.377)	.487 (.355)	.250 (.281)	.360 (.267)	.247 (.279)	.357 (.266)
Further households-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	-15.72*** (2.407)	-15.68*** (2.481)	-17.28*** (2.967)	-17.59*** (2.787)	-14.52*** (2.208)	-14.73*** (2.096)	-14.49*** (2.198)	-14.70*** (2.085)
R^2	.310	.329	.289	.374	.284	.357	.285	.358
R^2 adj.	.291	.309	.270	.356	.265	.338	.265	.339
F-Test	16.74	16.33	15.16	20.22	14.81	18.80	14.84	18.84
N	384	384	384	384	384	384	384	384

Table A2: Stepwise regression analyses with $AmountRisky_{h,TW}$ (specification a), $AmountRisky_{h,VSP}$ (specification b), $\sigma_{h,3years}$ (specification c), and $\sigma_{h,4years}$ (specification d) as dependent variable ω_h, by quarter of interview (cont'd)
Panel C: Second quarter 2011

Framework	CPCM (model 3a)		BPT (model 3b)					
Dependent variable $\omega_h/\omega_{h,l}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
$TWealth_h$		.182** (.083)						
$ValueHAL_h$				1.006*** (.097)		.691*** (.072)		.693*** (.072)
$Graduation_{FKP,h}$	.312** (.128)	.316** (.129)	.498*** (.149)	.413*** (.138)	.363*** (.110)	.305*** (.103)	.362*** (.110)	.304*** (.103)
$ProfessionalQualification_{FKP,h}$	.015 (.100)	.007 (.100)	-.061 (.116)	-.155 (.108)	-.046 (.086)	-.110 (.081)	-.045 (.086)	-.109 (.080)
$AllFinLitQuestionsCorrect_h$	.777*** (.231)	.806*** (.233)	.879*** (.269)	.950*** (.248)	.665*** (.199)	.713*** (.186)	.662*** (.198)	.711*** (.185)
Further households-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	-19.26*** (2.116)	-17.01*** (2.066)	-20.76*** (2.467)	-22.02*** (2.282)	-17.52*** (1.823)	-18.38*** (1.706)	-17.52*** (1.822)	-18.38*** (1.704)
R^2	.276	.279	.257	.367	.260	.355	.261	.356
R^2 adj.	.265	.266	.245	.356	.249	.344	.249	.345
F-Test	23.68	21.56	21.45	32.66	21.84	31.02	21.87	31.12
N	631	631	631	631	631	631	631	631