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Behavioural 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 Behavioural Portfolio Theory (BPT) and Merton's consumption and portfolio choice model (CPCM). We apply the BPT to field data for the first time and show that the BPT provides a better fit than the CPCM to explain the financial risk-taking of the households in Deutsche Bundesbank's Panel on Household Finances survey. However, both models indicate decreasing RRA. While households' education and financial literacy hardly improve the fit of either model, households show different risk-taking behaviour in accordance with their self-assessed risk attitude.

Key words: Household finance; Relative risk aversion; Behavioural portfolio theory; Consumption and portfolio choice model; Risk-taking

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1. Introduction

The question how households' relative risk aversion (RRA) (see Pratt, 1964; Arrow, 1965) changes with wealth is crucial for the field of household finance; however, to the present day, sufficient answers remain scarce (e.g., Guiso and Sodini, 2013, p. 1433). Most of the studies analysing RRA rely on the consumption and portfolio choice model (CPCM) by Merton (1969). Yet, as Statman (2014) points out, standard finance[1] models – like the CPCM – are partially unable to explain households' actual investment behaviour.[2] One reason for the divergence between standard finance models and households' actual investment behaviour is the major assumption of the standard finance paradigm that households are fully rational and design one single portfolio by the rules of mean-variance portfolio theory, which fails to hold true. Shefrin and Statman (2000) developed the Behavioural Portfolio Theory (BPT) with the aim of overcoming the shortcomings associated with the standard finance models. According to the BPT, investors segregate their portfolio in different layers. Each portfolio layer is associated with an aspiration, while the layer may contain several financial products that contribute to this aspiration (see Hoffmann *et al.*, 2010 for empirical support regarding the influence of investors' aspiration on their risk-taking). Covariance among the layers is overlooked by the investors.

The BPT's layer approach, at first glance, stands in contrast to the CPCM, where a household maximises its utility by keeping all its assets in one mean-variance optimised portfolio. Only on second glance can the BPT also be seen as a refinement of the CPCM regarding the relation between households' wealth and RRA. The findings of Shefrin and Thaler (1988) show that households are hardly willing to transfer wealth from one portfolio layer to another, although the households' total wealth would stay the same. Additionally, the probability that households spend their credit differs among the portfolio layers. Both findings are more dissent from than consensus with the economic notion of fungibility. Hence, the BPT refines the CPCM by the assumption that households rather establish different portfolio layers with individual RRA per layer than having one RRA for the entire portfolio. Due to

[1]Some authors also use the term traditional finance (e.g., Bloomfield 2011; Ackert, 2014).

[2]See also Guiso and Paiella (2008), who also observe massive unexplained heterogeneity in households' risk-taking in household survey data.

the important role of the relation between households' RRA and wealth in economic literature (such as for the determination of the market price of risk (e.g., Campbell, 2003)), it is of interest whether the BPT or the CPCM framework better fits households' risk-taking behaviour and to what extent the BPT and the CPCM lead to different findings regarding households' RRA. Such an analysis 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 assess the effect of employing this layer instead of households' entire portfolio when deriving households' RRA.

The definition of the high aspiration layer is based on Oehler (2017) and Oehler *et al.* (2018a; 2018b), who assign financial assets of German households to one out of three portfolio layers (i.e., mental accounts) according to the financial goal the assets are suitable for. In accordance with the BPT, the three layers build upon each other in a hierarchical structure. Figure 1 shows the portfolio structure suggested by Oehler *et al.* (2018b). The high aspiration layer is the top layer of the hierarchical structure. It includes the financial assets which households commonly are assumed to engage in after households' basic financial needs (e.g., insurance against financial ruin) are covered with the respective financial products (e.g., liability insurance, disability insurance; highest prioritised goal and basic layer) and after additional financial needs (e.g., to retain a similar level of consumption in the future) are covered by products such as retirement savings accounts (second highest prioritised goal). As a consequence, households are not ultimately reliant on the wealth in the high aspiration layer and could even bear a total loss (e.g., use this wealth for 'speculative' investments). Hence, the high aspiration layer should be the layer which best reflects the influence of wealth on households' risk-taking in financial markets.

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. For this purpose, the analysis relies on data of German households. Due to Germany's social system, which includes comparatively high coverage of background risks such as unemployment and health, households' individual risk management regarding background risks should play a much smaller role for households' asset allocation in the high aspiration layer than in countries with less protective social security systems.[3] 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 Paya and Wang (2016) who state that they can find

[3]See, e.g., Eeckhoudt *et al.* (1996) and Guiso and Paiella (2008) on the influence of background risk on risk-taking behaviour.

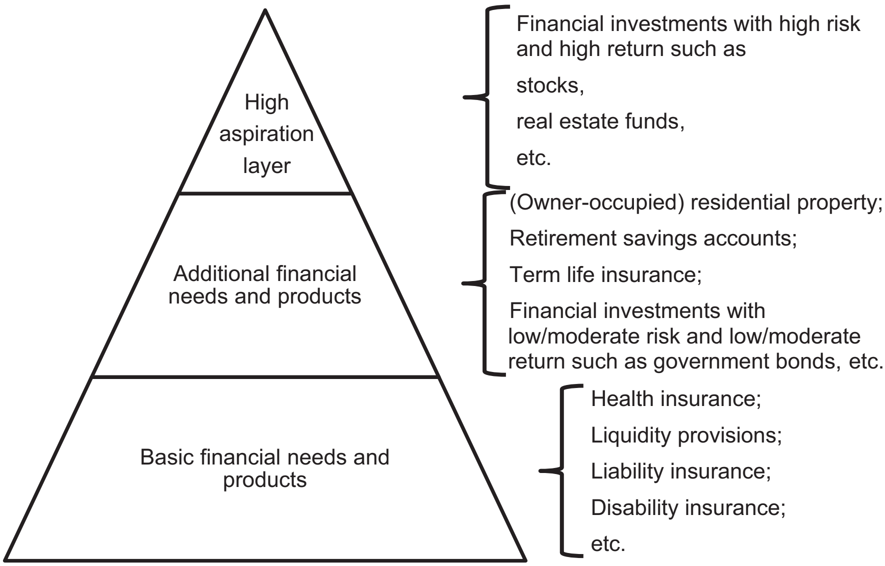

Figure 1 Hierarchical portfolio structure based on Oehler *et al.* (2018b).

evidence for all three different types of RRA depending on 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 the age and gender of the 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 dissonance between, on the one hand, the underlying assumption of Arrow (1965), Pratt (1964) and the CPCM that all households invest in the market portfolio and, on the other hand, field data, which shows that most households' portfolios can hardly be seen as clones of the market portfolio (e.g., Curcuru *et al.*, 2010; von Gaudecker, 2015). The latter makes households' risky asset share an ambiguously interpretable measure,[4] a problem that we tackle with the computation of the portfolio layer's σ (return's standard deviation) as an additional risk-taking measure to households' risky asset share.

We find indications that the BPT provides an approach that better fits households' risk-taking than the CPCM. However, models of both frameworks

[4]Consider, e.g., two households A and B with A holding 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.

reveal that – in line with decreasing RRA – households are more likely to generally enter in risky assets when their respective 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 our findings indicate that the BPT framework provides more explanatory power than the standard finance CPCM, our results provide implications for policymakers, practitioners and researchers alike. In general, including the BPT in models on households' financial decision-making is reasonable and should yield a higher model fit. 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 organised 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 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) (e.g., Cohn *et al.*, 1975). Following their concepts and the standard expected utility framework of von Neumann and Morgenstern (1944), the consumption and portfolio choice model of Merton (1969) puts a household's financial risk-taking (measured as household's risky portfolio share) in direct relation to household-specific characteristics and wealth. More specifically, a household's portfolio risky asset share ω_h is determined by the term

$$ln\omega_h = \eta ln W_h + \xi_h + \varepsilon_h, \tag{1a}$$

where W_h is household's wealth and η the wealth elasticity of ω_h, implying constant ($\eta = 0$), increasing ($\eta < 0$) or decreasing ($\eta > 0$) RRA; ξ_h captures the household's risk preferences and other (partially unobservable) characteristics (e.g., return and risk expectations); and ε_h is an error term.[5]

While researchers agree that households' absolute risk aversion is decreasing, i.e., that households place a higher absolute value in risky assets the wealthier they get, results regarding RRA are ambiguous (e.g., Guiso and Sodini, 2013). Pratt (1964), Arrow (1971) and Siegel and Hoban (1982) find evidence for increasing RRA, i.e. a decreasing percentage of wealth invested in risky assets when households get wealthier. Friend and Blume (1975), Brunnermeier and

[5]See, e.g., Guiso and Sodini (2013) for a detailed review of this strand of literature.

Nagel (2008) and Chiappori and 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 and Suarez (1983), Riley and Chow (1992), Oehler (1998), Calvet and Sodini (2014) and Oehler *et al.* (2018a). Finally, Paya and Wang (2016) point out that they find evidence for different types 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 standard finance models employed do not sufficiently capture households' actual investment behaviour. One key reason for the divergence between households' actual investment behaviour and the investment behaviour standard finance models predict is that households underlie bounded rationality, which leads them to use heuristics instead of making fully rational decisions (e.g., Statman, 2014; Oehler and Wendt, 2017). For example, households are assumed to have a mental account that they use for risky investments instead of considering their entire portfolio and total wealth (e.g., Shefrin and Thaler (1988); see Thaler (1999) regarding mental accounting).

Shefrin and Statman (2000) include mental accounting as an underlying feature in their behavioural 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 in a risk-seeking manner in one layer (e.g., buying lottery tickets) while simultaneously acting in a risk-averse manner in another layer (e.g., buying insurance). Adapted to an analysis of households' RRA, the main implication of the BPT is to differentiate between those layers.[5] Consequently, a study that aims at analysing 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. Hence, the BPT can be seen as a refinement of the CPCM. In addition, splitting up households' total wealth in different portfolio layers also helps to disentangle the influence of the habit channel and the income channel on risk-taking suggested by Liu *et al.* (2016). As households usually assign their income to another mental account than their risky financial assets (see Shefrin and Thaler, 1988), only considering the mental account containing the risky financial assets should isolate the habit channel.

Even though treating assets in separate portfolios is primarily associated with the BPT, the standard finance literature also provides reasons to separate some assets from the household portfolio. As family-owned businesses and owner-

[5]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.

occupied houses are practically indivisible and hardly tradable, these assets may to a certain degree not accord with the underlying assumptions of standard finance portfolio choice models, because of, for example, borrowing constraints when financing a house or business and the associated limitations (also arising from the indivisibility of the assets) for a household's asset allocation and risk diversification (see, e.g., Flavin and Yamashita, 2002 and Moskowitz and Vissing-Jörgensen, 2002). In a more nuanced version of the CPCM that only includes frequently tradable and divisible assets, therefore, a portfolio similar to the one used for the high aspiration layer of the BPT might be considered. Still, some differences, for example regarding assets in retirement saving accounts, might occur, which is one more reason why we see the BPT as a refinement of the CPCM in this study.

Considering the previously mentioned insights from both the behavioural finance and the standard finance literature, we expect that the BPT should better fit households' financial risk-taking than the CPCM.

For the layer that covers risky investments and the wealth available for further risky investments, equation (1a) can be adapted to

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

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 households' RRA and wealth, households' risk-taking is influenced by household-specific characteristics (denoted as ξ_h in equations 1a and 1b). Kaustia *et al.* (2017) 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.[6] Their conclusions support former findings that the probability to hold risky assets rises with the educational level (e.g., Campbell, 2006; Cole *et al.*, 2014), that men are more likely to take financial risks than women (e.g., Jianakoplos and Bernasek, 1998; Sundén and Surette, 1998; Barber and Odean, 2001; Croson and Gneezy, 2009; Dohmen *et al.*, 2011), and that older individuals are less likely to invest in risky assets (e.g., Ameriks and Zeldes, 2004; Curcuru *et al.*, 2010). The positive relation between households' directly queried risk attitude and their risk-taking is also observed by Bertraut (1998), Dohmen *et al.* (2011), Halko *et al.* (2012), Guiso and Sodini (2013), Oehler and Horn (2019) and Oehler *et al.* (2018a), providing support that investor's risk-taking is a function of investors' risk attitude (e.g., Nosic and Weber, 2010; Weber *et al.*,

[6]Kaustia *et al.* (2017) also find that much of the information assigned to the factors sociability (see Hong *et al.,* 2004; Brown *et al.,* 2008), cognitive skills (see Christelis *et al.,* 2010; Grinblatt *et al.,* 2011) and health (see Rosen and Wu, 2004; Edwards, 2008) are already captured by households' directly queried risk attitude, which is why we do not control for these factors.

2013). However, the inclusion of households' risk attitude as an explanatory variable for their risk-taking requires an assessment whether risk attitude is time invariant, a thesis which is supported by experimental findings established by Harrison *et al.* (2005), Sahm (2012), Weber *et al.* (2013) and Wölbert and Riedl (2013).

3. Data and methodology

3.1. Data

We use data from the first wave of the German central bank's (Deutsche Bundesbank) PHF survey.[7] Since the data quality of surveys always depends on the ability/willingness of the interviewed households to provide accurate answers, surveys are considered unsuitable as data sources for certain kinds of econometric analyses.[8] We, however, think that the opposite holds true for an analysis of the relation between households' wealth and RRA. The purpose of such an analysis is to describe households' risk-taking behaviour. Hence, it is rather of interest to capture households' financial risk-taking and wealth in the way the households perceive them than to capture more objective data that substantially differs from the actual determinants of households' financial decisions.[9] Moreover, the PHF survey data can be considered a dataset with only small measurement error. First, the interviews of the PHF survey were conducted by 212 trained interviewers as face-to-face, computer-aided personal interviews, which should almost eliminate the possibility of errors during data collection. Second, Deutsche Bundesbank's comparisons with external statistics show that the PHF dataset does not suffer from selectivity problems. Hence, the dataset is considered as representative of German households.

The survey includes 3,565 households, each interviewed once during the period from 14 September 2010 to 15 July 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 age, gender, graduation, professional qualification and financial literacy (measured by the three

[7]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.

[8]See, e.g., Guiso and Sodini (2013) who describe survey data as 'notoriously inaccurate' (p. 1402).

[9]Please note that, nevertheless, Deutsche Bundesbank of course employed data editing and imputation methods to enhance the consistency within the dataset (see von Kalckreuth *et al.,* 2012).

questions used in Lusardi and Mitchell, 2006). The remaining data is on the household level.

3.2. 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 and Horn (2019). 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 household debts associated with these asset classes (e.g., consumer loans and credit card debts).[10] 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 run 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. The previous assets are not assigned to households' high aspiration layer since they mainly reflect sources of continuous (labour) income of self-employed people and retirement savings.[11] We consider the *value of businesses run by household members* and *direct investments in firms* that are not listed on a stock exchange as risky investments (Paya and Wang (2016) apply 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 in those assets should be a long-term risk reduction, e.g., income hedging with retirement savings account or insuring against increasing rents with residential property.

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.

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[10] *Stocks* and *bonds* also include investments in stock and bond funds as well as ETFs and index funds. 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.

[11] 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).

3.3. 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 the 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_h^2). We 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 a 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 shown in Equation (2a).

$$\begin{aligned} lnPercentageRisky_{h,CPCM} = {} & \beta_0 + \eta lnTWealth_h + \beta_1 * Age_h + \beta_2 * {Age^2}_h \\ & + \beta_3 * Male_h + \beta_4 * lnIncome_h + \beta_5 * Child_h \\ & + \gamma_1 * RiskAtt_h + \varepsilon \end{aligned} \tag{2a}$$

The remaining three model specifications implement the BPT and build on Equation (1b). In these three model specifications, the independent variable $W_{h,l}$ is the value of households' high aspiration layer ($ValueHAL_h$). The risk-taking measure $\omega_{h,l}$ is either implemented as the percentage of wealth invested in the risky assets of the high aspiration layer relative to the value of household's high aspiration layer ($PercentageRisky_{h,BPT}$), or as the standard deviation of the returns (σ) of a 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 shown 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 normalise 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 (e.g., Oehler *et al.*, 2007; Baltzer *et al.*, 2015).

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,[12] however, not considering whether the household invests in risky assets or not. We first employ the regression models in a logit regression analysis to analyse 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 ordinary least squares (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 invested in risky assets) to avoid missing values for the full sample analyses. We choose this approach because we cannot be sure about the reason why a household does not invest in risky assets. Potential reasons are, for example, a (very) high degree of risk aversion, too high (perceived) participation costs in risky asset markets, or a combination of both. Although we only include households that are sufficiently wealthy to establish a high aspiration layer with a value of at least €1,000, their intended investment period may be too short to compensate fixed participation costs. On the other hand, some households may just be too risk averse to invest even a small amount of their wealth in risky assets. Excluding the latter households would skew our results, as these households might invest in risky assets when they get wealthier (assuming that households show decreasing absolute risk aversion). As robustness check, however, we

[12]See, e.g., von Gaudecker (2015) who uses this threshold. The rationale for employing this threshold is the fixed participation costs that households face in risky asset markets. Hence, households need a certain amount of wealth to reasonably invest in risky assets. In turn, this also means that our analysis does not apply to households that are not wealthy enough to participate in risky asset markets. Nevertheless, we assume our analysis representative for the sample of households that is wealthy enough to participate in risky asset markets.

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

exclude all households with no risky investments and focus on the remaining ones to estimate the extent to which the explanatory power of our models primarily emerges from households' general decision to invest/not to invest in risky assets. 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.

4. Results

4.1. 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. The mean age of these households' FKPs is 58 years (median age: 59 years). Sixty-four percent of the FKPs are male. In 18 percent of all households, there is at least one child who is 16 years of age or younger.

Table 2 contains descriptive statistics of the 1,401 households' risk-taking and wealth. In the framework of the CPCM, on average, the households invest 12.6 percent of their total wealth in risky assets. 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 why the mean annualised volatility of households' high aspiration layer is relatively low with a figure of 3.6 percent for the four-year investment period. On average, the households' mean total wealth amounts to €472,000, while the value of the high aspiration layer is €122,000. The median values are lower for all measures indicating a right-skewed distribution of the measures in the cross section, i.e., the high standard deviations of both measures are driven by the high wealth of a few households.

4.2. Regression analyses

We perform stepwise logit regression analyses using the models from Equations (2a) and (2b) to analyse the relation between households' wealth

Table 2
Descriptive statistics of the risk-taking and wealth measures (N = 1,401 households)

	Mean	Med.	Std. dev.
Panel A: Risk-taking measures			
$PercentageRisky_{h,CPCM}$	0.126	0.013	0.234
$PercentageRisky_{h,BPT}$	0.232	0.045	0.302
Consisting of			
Stocks	0.103	0.000	0.202
Bonds	0.056	0.000	0.148
Real estate funds	0.017	0.000	0.074
Articles of great value	0.057	0.000	0.153
$\sigma_{h,3years}$	0.037	0.007	0.053
$\sigma_{h,4years}$	0.036	0.007	0.051
Panel B: Wealth measures (in EUR)			
$TWealth_h$	472,369	250,000	872,577
$ValueHAL_h$	122,125	38,310	379,150

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. dev.).

and households' decision to generally engage in risky investments within the CPCM, as well as the BPT framework. Regarding households' risk-taking, we first determine the explanatory power of households' characteristics ξ_h for each model specification. 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 in 71.7 percent of all 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 four 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, in general, households are more likely to invest in risky assets as they get wealthier in both models. There can be two reasons for this: First, households' decreasing relative risk aversion; second,

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

	CPCM (model 2a)		BPT (model 2b)	
$TWealth_h$		0.410*** (0.058)		
$ValueHAL_h$				0.914*** (0.068)
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	1,541	1,459	1,574	1,337
Nagelkerkes R^2	0.318	0.360	0.306	0.466
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	1,401	1,401	1,401	1,401

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_h^2), 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 one child at the age of 16 or younger lives in the household ($Child_h$). ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Example: Regressing the risky asset dummy on regression model (2b) with $ValueHAL_h$ as wealth measure yields a coefficient of $ValueHAL_h$ of 0.914 with a statistical significance at the 1 percent level and a Nagelkerkes R^2 of 0.466.

participation costs that keep households from investing in the risky asset markets (see Guiso *et al.*, 2003). It is unlikely, however, that the latter reason accounts for the entire effect as we only include households with at least €1,000 of investable wealth.

We provide findings of the stepwise linear OLS regression analyses using the models from Equations (2a) and (2b) in Table 4. We employ $PercentageRisky_{h,CPCM}$, $PercentageRisky_{h,BPT}$, $\sigma_{h,3years}$ and $\sigma_{h,4years}$ as dependent variables. Solely including the household-specific characteristics ξ_h without a wealth measure in the linear regression already yields an adjusted R^2 of 24–26 percentage points in all four model specifications. This means that household characteristics explain a very similar percentage of households' risk-taking in both the CPCM and the BPT models. However, this also means that three-quarters of the variation in risk-taking remains unexplained. The latter finding is consistent with the findings of Guiso and Paiella (2008). Adding households' total wealth as independent variable in the CPCM model increases

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 $\omega_h/\omega_{h,1}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
$TWealth_h$		0.235***						
		(0.060)						
$ValueHAL_h$				0.983***		0.681***		0.679***
				(0.065)		(0.048)		(0.048)
ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	−20.38***	−20.46***	−21.07***	−21.46***	−17.61***	−17.88***	−17.58***	−17.85***
	(1.309)	(1.307)	(1.53)	(1.417)	(1.135)	(1.063)	(1.131)	(1.059)
R^2	0.260	0.269	0.244	0.352	0.247	0.341	0.247	0.341
R^2 adj.	0.256	0.265	0.241	0.349	0.243	0.337	0.243	0.337
F-test	69.86	63.34	64.34	94.66	65.25	89.91	65.29	90.03
N	1,401	1,401	1,401	1,401	1,401	1,401	1,401	1,401

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 equations (2a) and (2b). ξ_h captures age (Age_h), squared age (Age_h^2), 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 one child at the age of 16 or younger lives in the household ($Child_h$). ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Example: Regressing $PercentageRisky_{h,BPT}$ on the regression model with $ValueHAL_h$ as wealth measure yields a coefficient of $ValueHAL_h$ of 0.983 with a statistical significance at the 1 percent level and an adjusted R^2 of 0.349.

the adjusted R^2 by only 0.9 percentage points.[13] This means that households' total wealth hardly provides additional explanatory power regarding households' financial risk-taking when the remaining household-specific characteristics are already considered. In contrast, introducing the value of households' high aspiration layer provides an at least 9.4 percentage points higher R^2 in the BPT model. This means that the value of the high aspiration layer significantly adds explanatory power after household-specific characteristics are considered. Consequently, the R^2 of the BPT model is at least seven percentage points higher than the R^2 of the CPCM model. Even though the CPCM and the BPT models differ in the computation of their dependent variables, which can hamper the comparability of both models regarding their R^2, the results of our stepwise approach indicate that the BPT model explains households' risk-taking better, as the value of the high aspiration layer significantly adds explanatory power while households' total wealth does not. However, as the wealth measures also appear on both sides of the regression equations, the higher R^2 of the BPT model might – from a mathematical point of view – just be a mechanical result of the narrower definition of investable wealth. But even if that was the case, we would not consider this a major flaw because the narrower definition of investable wealth considers the borrowing constraints and the indivisibility of some investments that households actually face. Besides, it seems likely that the higher R^2 of the BPT model is not entirely a mechanical effect of the narrower wealth definition but also further indication for the influence of households' mental accounting on their asset allocation – a phenomenon that has been observed in numerous studies in the behavioural finance literature.

Ultimately, the results so far indicate that the value of households' high aspiration layer matters more than the total wealth when households decide whether to invest in risky assets or not. 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.

So far, our findings indicate that regression models based on the BPT framework provide more explanatory power than regression models based on the CPCM. Moreover, the stepwise approach reveals 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 favour of a decreasing RRA among households. More specifically,

[13]The magnitude of the regression coefficient (0.235) is in line with results of Calvet and Sodini (2014) where the magnitude of the coefficient ranges between 0.196 and 0.231. Paya and Wang (2016) report significantly smaller magnitudes. However, comparisons with these studies need to be treated with caution as they use other datasets and partially different household characteristics in their regression models.

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.

4.3. 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 (e.g., Christelis *et al.*, 2010; Grinblatt *et al.*, 2011; 2012; Van Rooij *et al.*, 2011; Cole *et al.*, 2014). Furthermore, Chatterjee *et al.* (2017) find a relation between households' goal-based saving behaviour and risk tolerance. We first use analysis of variance (ANOVA) to figure out if and how these factors influence the risk-taking of households in our sample before we extend our previous regression models with the relevant factors. The *p*-values of the ANOVA tests 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[14] illustrate 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 instead of the in this context more helpful applied knowledge about financial products (e.g., Oehler *et al.*, 2018b 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 correct answers clearly have the highest degree of risk-taking. Furthermore, households saving 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.

Given the statistically significant different risk-taking by households with different graduation, professional qualification and financial literacy, we extend our linear regression models (2a) and (2b) by the three further 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 takes a value of 1 if all three

[14]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.

Table 5
ANOVA graduation, professional qualification and purpose for saving

	p-values			
	Graduation	Professional qualification	Financial literacy	Purpose for saving
$PercentageRisky_{h,CPCM}$	0.000	0.000	0.000	0.087
$PercentageRisky_{h,BPT}$	0.000	0.000	0.000	0.036
$\sigma_{h,4years}$	0.000	0.000	0.000	0.093

We provide p-values for between-group ANOVAs that analyse 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' and '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 0.000 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.

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 analysis 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 statistically significant 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 CPCM model. Compared to our previous logit regression, the three new factors hardly impact the models' accuracy. Therefore, our previous findings remain robust.

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^2 and adjusted R^2 rise between 0.9 and 2.5 percentage points. FKPs' graduation and financial literacy are both statistically 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.

Since data in 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 accordingly to the quarter when households were interviewed.[15] Again the stepwise regression analyses reveal that the models of the BPT framework provide more explanatory power regarding the relation between households' wealth 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 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 subsample 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 run 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

[15]See Tables A1 and A2 in the Appendix for the detailed results of these regression analyses.

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

	CPCM (model 3a)		BPT (model 3b)	
$TWealth_h$		0.414*** (0.060)		
$ValueHAL_h$				0.883*** (0.070)
$Graduation_{FKP,h}$	0.258*** (0.076)	0.263*** (0.079)	0.267*** (0.076)	0.216*** (0.083)
$ProfessionalQualification_{FKP,h}$	0.019 (0.062)	0.023 (0.064)	0.025 (0.061)	−0.012 (0.067)
$AllFinLitQuestionsCorrect_h$	0.400*** (0.146)	0.467*** (0.151)	0.386*** (0.145)	0.483*** (0.159)
Further household-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	1,447	1,364	1,478	1,270
Nagelkerkes R^2	0.339	0.382	0.329	0.473
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	1,345	1,345	1,345	1,345

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_h^2), 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 one child at the age of 16 or younger lives in the household ($Child_h$). ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Example: Regressing the risky asset dummy on regression model (3b) with $ValueHAL_h$ as wealth measure yields a coefficient of $ValueHAL_h$ of 0.883 with a statistical significance at the 1 percent level and a Nagelkerkes R^2 of 0.473.

(median) total wealth of €644,545 (€367,000) and the high aspiration layer of the 736 households of the BPT sample shows a mean (median) value of €203,703 (€76,050).

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^2 of their regression models – considerably decreases by 16–31 percentage points depending on the model specification. More specifically, the full model of the CPCM framework

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 $\omega_h/\omega_{h,l}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
$TWealth_h$		0.216***						
		(0.061)						
$ValueHAL_h$				0.929***		0.640***		0.638***
				(0.066)		(0.050)		(0.049)
$Graduation_{FKP,h}$	0.247***	0.247***	0.417***	0.321***	0.299***	0.233***	0.299***	0.233***
	(0.086)	(0.086)	(0.100)	(0.094)	(0.074)	(0.070)	(0.074)	(0.070)
$ProfessionalQualification_{FKP,h}$	0.086	0.086	0.041	-0.014	0.033	-0.005	0.033	-0.005
	(0.067)	(0.068)	(0.079)	(0.074)	(0.058)	(0.055)	(0.058)	(0.055)
$AllFinLitQuestionsCorrect_h$	0.601***	0.624***	0.602***	0.639***	0.453***	0.478***	0.448***	0.473***
	(0.164)	(0.165)	(0.192)	(0.179)	(0.142)	(0.134)	(0.142)	(0.134)
Further household-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	−18.91***	−18.98***	−−19.57***	−20.52***	−16.45***	−17.11***	−16.43***	−17.08***
	(1.368)	(1.366)	(1.596)	(1.491)	(1.185)	(1.119)	(1.181)	(1.115)
R^2	0.282	0.291	0.269	0.364	0.271	0.352	0.271	0.352
R^2 adj.	0.276	0.285	0.264	0.358	0.266	0.347	0.266	0.347
F-test	52.27	49.14	49.15	69.25	49.60	65.86	49.61	65.90
N	1,345	1,345	1,345	1,345	1,345	1,345	1,345	1,345

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_h^2), 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 one child at the age of 16 or younger lives in the household ($Child_h$). ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Example: Regressing $PercentageRisky_{h,BPT}$ on the regression model (3b) with $ValueHAL_h$ as wealth measure yields a coefficient of $ValueHAL_h$ of 0.929 with a statistical significance at the 1 percent level and an adjusted R^2 of 0.358.

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 $\omega_h/\omega_{h,l}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
$TWealth_h$		−0.391***						
		(0.054)						
$ValueHAL_h$				−0.046		−0.107***		−0.107***
				(0.035)		(0.036)		(0.036)
$AboveAverageRisk_h$	0.467*	0.466*	0.467***	0.474***	0.693***	0.709***	0.687***	0.703***
	(0.272)	(0.238)	(0.176)	(0.176)	(0.182)	(0.181)	(0.180)	(0.179)
$NoRisk_h$	−0.577***	−0.610***	−0.267***	−0.285***	−0.273***	−0.315***	−0.273***	−0.315***
	(0.121)	(0.117)	(0.081)	(0.082)	(0.083)	(0.084)	(0.082)	(0.083)
$Graduation_{FKP,h}$	−0.092	−0.068	0.046	0.047	0.032	0.033	0.032	0.033
	(0.067)	(0.065)	(0.045)	(0.082)	(0.046)	(0.046)	(0.045)	(0.045)
$ProfessionalQualification_{FKP,h}$	0.107**	0.105**	0.004	0.008	0.008	0.017	0.008	0.017
	(0.052)	(0.051)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
$AllFinLitQuestionsCorrect_h$	0.358***	0.295**	0.221**	0.223**	0.190**	0.194**	0.183*	0.187**
	(0.138)	(0.134)	(0.091)	(0.091)	(0.094)	(0.094)	(0.093)	(0.093)
Further household-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)	(0.767)	(0.768)	(0.791)	(0.789)	(0.781)	(0.779)
R^2	0.077	0.137	0.057	0.060	0.064	0.076	0.064	0.076
R^2 adj.	0.065	0.124	0.044	0.045	0.051	0.061	0.051	0.061
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

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 household-specific characteristics in ξ_h captures age (Age_h), squared age (Age_h^2), and gender ($Male_h$) of household's FKP, the monthly household income ($Income_h$), and a dummy variable that indicates whether at least one child at the age of 16 or younger lives in the household ($Child_h$). ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Example: Regressing $PercentageRisky_{h,BPT}$ on the regression model (3b) with $ValueHAL_h$ as wealth measure yields a coefficient of $ValueHAL_h$ of −0.046 with no statistical significance and an adjusted R^2 of 0.045.

provides an adjusted R^2 of 12.4 percent while the adjusted R^2 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 changes. In the CPCM model, households' total wealth is negatively correlated with households' risk-taking with a statistical significance at the 1 percent level. A further look at the data reveals that this effect is probably driven by the high ratio of house owners in this sample (about 80 percent). They show a significantly lower risky asset share and a significantly higher total wealth than the remaining households on average, the difference being statistically significant at the 1‰ level according to t-tests. This finding is in line with theoretical predictions and empirical results by Flavin and Yamashita (2002) considering the borrowing constraints associated with financing a house. Interestingly, the average value of the high aspiration layers is almost exactly equal for house owners and the remaining households and so is the risky asset share in the high aspiration layers of both groups. Regression results on the BPT model show that the value of the high aspiration layer has no significant influence on the layer's risky asset share in the investor sample. Neither is the regression coefficient significant nor does the value of the high aspiration layer considerably increase the model's R^2. When households' risk-taking is measured by the high aspiration layer's σ, we observe that the regression coefficient of the value of the high aspiration layer is statistically significant at the 1 percent level. We, however, do not consider this relation as being actually significant for the following reasons. Compared to the previous regression analyses, the magnitude of the coefficient is only small and it adds almost no explanatory power in the stepwise approach. As the value of the high aspiration layer is also used as denominator on the left-hand side of the equation, these results hardly allow classifying the relation as significant (for a detailed discussion of this issue, see, e.g., Powell *et al.*, 2009). In contrast, 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 lose explanatory power when they are applied solely on households that invest in risky assets. Additionally, the latter finding indicates that a potential reverse causation between household wealth and the risky asset share (i.e., households with a higher risky asset share become wealthier because of their high return investments) is a minor issue – if it is an issue at all – as households seem to allocate their assets in line with their self-reported risk attitude. If reverse causation were a problem in our dataset, we would observe a stronger relation between household wealth and the risky asset share in our results in Table 8.

5. Conclusions

This study aims at providing 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 indicates that the implementation of the BPT provides a better fitting approach than the CPCM to explain households' financial risk-taking. This result meets our expectations since the BPT includes only a subsample of the assets captured in the CPCM and, hence, can be seen as a refinement of the CPCM. Nevertheless, 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 Cohn *et al.* (1975), Morin and Suarez (1983), Riley and Chow (1992), Oehler (1998), Calvet and Sodini (2014) and Oehler *et al.* (2018a). 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 better fit households' behaviour than the standard finance CPCM, researchers should include the BPT in models on households' financial decision-making and behaviour in financial markets. Extending normative portfolio choice models with behavioural 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 to governmental programmes that cause an immediate positive effect in households' high aspiration layer than in programmes 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 different risk-taking behaviour in accordance with their self-assessed risk attitude. Therefore, inquiring into households' risk attitude and understanding what households actually perceive as financial risk (e.g., Zeisberger, 2016 on the role of loss probabilities) is necessary for providing financial advice that households appraise as useful (for a discussion on conditions for good consumer information, see, e.g., Oehler and Wendt, 2017).

We based our study's methodology on Oehler *et al.* (2018a) and the cited studies therein that already provide 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.*, 2018b 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 (e.g., Kaustia *et al.*, 2017) can provide further valuable insights on related questions regarding households' risk-taking behaviour and RRA.

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Appendix

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)	
$TWealth_h$		0.391***				0.566***				0.384***		
		(0.138)				(0.133)				(0.080)		
$ValueHAL_h$				0.857***				0.896***				0.945***
				(0.148)				(0.134)				(0.105)
$Graduation_{FKP,h}$	0.316*	0.241	0.308*	0.073	0.250	0.279	0.200	0.179	0.264**	0.284**	0.310***	0.291**
	(0.166)	(0.171)	(0.166)	(0.184)	(0.147)	(0.156)	(0.145)	(0.161)	(0.112)	(0.115)	(0.112)	(0.125)
$ProfessionalQualification_{FKP,h}$	−0.045	0.005	0.013	0.098	0.158	0.196	0.152	0.133	−0.029	−0.043	−0.043	−0.136
	(0.130)	(0.134)	(0.130)	(0.142)	(0.119)	(0.129)	(0.117)	(0.129)	(0.090)	(0.092)	(0.089)	(0.099)
$AllFinLitQuestionsCorrect_h$	0.210	0.142	−0.001	−0.086	0.143	0.265	0.164	0.333	0.564***	0.665***	0.582***	0.757***
	(0.323)	(0.337)	(0.329)	(0.359)	(0.295)	(0.306)	(0.295)	(0.324)	(0.203)	(0.221)	(0.202)	(0.224)
Further household-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	−15.08***	−17.05***	−14.04***	−18.36***	−10.58***	−10.10***	−9.97***	−12.42***	−13.95***	−14.66***	−12.53***	−16.03***
	(2.779)	(2.988)	(2.779)	(3.210)	(2.593)	(2.691)	(2.561)	(2.833)	(2.083)	(2.126)	(2.046)	(2.309)
2-log-likelihood	342	322	339	296	401	368	408	350	681	650	703	595
Nagelkerkes R^2	0.349	0.382	0.378	0.495	0.358	0.423	0.355	0.492	0.349	0.384	0.317	0.477
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

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_h^2), 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 one child at the age of 16 or younger lives in the household ($Child_h$). ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, 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 0.857 with a statistical significance at the 1 percent level and a Nagelkerkes R^2 of 0.495.

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

Framework	CPCM (model 3a)		BPT (model 3b)					
Dependent variable $\omega_h/\omega_{h,l}$	$PercentageRisky_{h,CPCM}$		$PercentageRisky_{h,BPT}$		$\sigma_{h,3years}$		$\sigma_{h,4years}$	
Panel A: Fourth quarter 2010								
$TWealth_h$		0.287**						
		(0.143)						
$ValueHAL_h$				0.845***		0.586***		0.581***
				(0.139)		(0.105)		(0.104)
$Graduation_{FKP,h}$	0.265**	0.216	0.444**	0.212	0.292*	0.131	0.290*	0.130
	(0.179)	(0.180)	(0.204)	(0.197)	(0.152)	(0.149)	(0.151)	(0.147)
$ProfessionalQualification_{FKP,h}$	0.073	0.103	0.088	0.125	0.080	0.106	0.078	0.104
	(0.138)	(0.138)	(0.157)	(0.149)	(0.117)	(0.112)	(0.116)	(0.111)
$AllFinLitQuestionsCorrect_h$	0.268	0.184	0.077	−0.025	0.040	−0.030	0.040	−0.031
	(0.361)	(0.362)	(0.412)	(0.391)	(0.308)	(0.295)	(0.306)	(0.293)
Further household-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	−20.44***	−18.02***	−19.98***	−21.09***	−16.86***	−17.63***	−16.79***	−17.55***
	(2.640)	(2.536)	(3.011)	(2.862)	(2.254)	(2.159)	(2.234)	(2.141)
R^2	0.282	0.296	0.292	0.365	0.297	0.360	0.298	0.360
R^2 adj.	0.259	0.271	0.269	0.343	0.275	0.338	0.276	0.338
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

(continued)

Table A2 (continued)

Panel B: First quarter 2011								
$TWealth_h$		0.257**						
		(0.126)						
$ValueHAL_h$				0.896***		0.615***		0.613***
				(0.126)		(0.095)		(0.094)
$Graduation_{FKP,h}$	0.151	0.159	0.286	0.244	0.216	0.188	0.217	0.188
	(0.159)	(0.159)	(0.188)	(0.177)	(0.140)	(0.133)	(0.139)	(0.132)
$ProfessionalQualification_{FKP,h}$	0.222*	0.221*	0.179	0.116	0.130	0.087	0.129	0.086
	(0.125)	(0.125)	(0.148)	(0.139)	(0.110)	(0.105)	(0.109)	(0.104)
$AllFinLitQuestionsCorrect_h$	0.478	0.558*	0.327	0.487	0.250	0.360	0.247	0.357
	(0.318)	(0.315)	(0.377)	(0.355)	(0.281)	(0.267)	(0.279)	(0.266)
Further household-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	−15.72***	−15.68***	−17.28***	−17.59***	−−14.52***	−14.73***	−14.49***	−14.70***
	(2.407)	(2.481)	(2.967)	(2.787)	(2.208)	(2.096)	(2.198)	(2.085)
R^2	0.310	0.329	0.289	0.374	0.284	0.357	0.285	0.358
R^2 adj.	0.291	0.309	0.270	0.356	0.265	0.338	0.265	0.339
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
Panel C: Second quarter 2011								
$TWealth_h$		0.182**						
		(0.083)						
$ValueHAL_h$				1.006***		0.691***		0.693***
				(0.097)		(0.072)		(0.072)
$Graduation_{FKP,h}$	0.312**	0.316**	0.498***	0.413***	0.363***	0.305***	0.362***	0.304***

(continued)

Table A2 (continued)

Panel C: Second quarter 2011

	(0.128)	(0.129)	(0.149)	(0.138)	(0.110)	(0.103)	(0.110)	(0.103)
$ProfessionalQualification_{FKP,h}$	0.015	0.007	−0.061	−0.155	−0.046	−0.110	−0.045	−0.109
	(0.100)	(0.100)	(0.116)	(0.108)	(0.086)	(0.081)	(0.086)	(0.080)
$AllFinLitQuestionsCorrect_h$	0.777***	0.806***	0.879***	0.950***	0.665***	0.713***	0.662***	0.711***
	(0.231)	(0.233)	(0.269)	(0.248)	(0.199)	(0.186)	(0.198)	(0.185)
Further household-specific characteristics ξ_h	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β_0	−19.26***	−17.01***	−20.76***	−22.02***	−17.52***	−18.38***	−17.52***	−18.38***
	(2.116)	(2.066)	(2.467)	(2.282)	(1.823)	(1.706)	(1.822)	(1.704)
R^2	0.276	0.279	0.257	0.367	0.260	0.355	0.261	0.356
R^2 adj.	0.265	0.266	0.245	0.356	0.249	0.344	0.249	0.345
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

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 household-specific characteristics ξ_h captures age (Age_h), squared age (Age_h^2), 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 one child at the age of 16 or younger lives in the household ($Child_h$). ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Example: Regressing $PercentageRisky_{h,BPT}$ on the regression model (3b) with $ValueHAL_h$ as wealth measure yields a coefficient of $ValueHAL_h$ of 0.845 with a statistical significance at the 1 percent level and an adjusted R^2 of 0.343 for the subsample of households interviewed in the fourth quarter 2010.