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Do Financial Advisors Have Different Beliefs than Lay People?

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Abstract

We conduct a web-based experiment in which we elicit the recommendations of professional and lay advisors on the risky portfolio share of randomly assigned vignettes of investors. Both professionals and lay advisors respond to investor characteristics broadly in agreement with portfolio theory, but they are also influenced by their own characteristics and portfolios. Professionals tend to respond more than lay advisors to investor characteristics, but also to their own risk aversion and income. Allowing for unobserved heterogeneity and estimating the distribution of advice through Bayesian methods, we find that professionals tend to recommend more limited risk exposure to older college educated groups compared to their peers, while they recommend young, lower-educated individuals to include more stocks than what their peers and elders would recommend.

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1 Introduction

Household portfolios have evolved considerably over the past decades, from simple combinations of a bank account and possibly a house to modern complex portfolios involving a variety of taxable financial instruments and mutual fund accounts, tax-deferred retirement accounts, consumer and mortgage debt instruments, real estate, and (for some) private businesses. These developments were inspired by financial innovation, the demographic transition, and technological improvements, but they occur against a background of widespread financial illiteracy (Lusardi and Mitchell 2024). The nature of advice given to households by their peers and by professionals is thus of great relevance, motivating a significant number of studies in household finance (Gomes et al. 2021). The negative, on average, findings on the influence of financial advice have typically been attributed to bad incentive schemes and the conflicts of interest they entail, while they have also raised the question of the distribution of heterogeneous professional advice. Regulation has responded by introducing "fee only" advisors, who are not allowed to sell what they recommend. Such developments point to the need to understand the heterogeneous beliefs of professional advisors regarding optimal risk taking and to compare them to those of different peer groups that could provide advice to households regarding their risk exposure. Our study is, to the best of our knowledge, the first to examine and compare how beliefs of heterogeneous professional and lay advisors about the appropriate risk exposure of potential advice recipients depend on recipient characteristics and on the advisor's own characteristics and portfolio risk. This in turn allows us to estimate the distribution of financial advice provided to investors by different groups of potential advisors, whether professionals or peers.

We conduct our study in Germany, a high-income country with a direct stock market participation rate of 15.40% and 20.6% participation in mutual funds,[1] where interest in professional financial advice is prevalent. There is evidence that, if they do invest, the majority of Germans rely on financial advisors: 67% of participants in a survey of Union Investment and Forsa (2018) stated that they rely on their advisors to find alternative investment opportunities in a low interest rate environment. The need for advice is also considerable: 40% of participants stated that they have insufficient knowledge in matters of investment and 48% are not aware that stock investments yield the highest long-term expected returns. Those who seek advice expect advisors to provide custom, rather than one-size-fits-all advice: 97% of participants in a survey among 1,026 German adults (Net Fonds and Toluna 2015) expect financial advisors to tailor recommendation to their individual situation and personal needs.

We present both professional and lay advisors with randomly assigned vignettes of investors and elicit their recommendations on the risky portfolio share for retirement saving without offering them incentives related to the type of advice they provide. This approach serves three purposes. First, to examine professional advice that reflects the professionals' beliefs rather

1. This is above average in the Eurozone (10.9% and 12.9%, respectively), but lower than in the US, where direct stockholding rose from 15% to 19% between 2019 and 2022, while combined direct and indirect stock market participation rose from 53% to 58% (ECB July 2023; FRB October 2023).

than their incentive structure, which has been the object of recent regulations. Second, to avoid complications arising from endogenous matching between advisors and their clients, including the known aspect of the current system that advisors tend to be matched with older, wealthier and more experienced investors and we do not observe what professionals believe about the appropriate risk exposure of others. Third, our approach elicits beliefs without subjecting especially professional advisors to the pressure of catering to preconceptions or prior choices of their customers in order to gain their business.[2] The similar elicitation procedure for lay people who have basic knowledge of financial matters reflects heterogeneous beliefs of lay advisors. We present estimation results on the coefficient patterns, and we then employ Bayesian methods that allow for observed and unobserved advisor heterogeneity to estimate distributions of beliefs for relevant advisor groups and investor types.

Our first set of Tobit estimates, from regressing the recommended risky portfolio share only on advisor characteristics, imply that professional advisors tend to recommend a lower allocation to risky assets than lay advisors do, in the order of about 4.5 percentage points. Older and more risk tolerant advisors, as well as those who are more optimistic about expected returns over a 10-year horizon, tend to recommend higher exposures. Controlling for their characteristics, advisors are influenced by their own risk allocations: those who state that they are exposed to more risk in their own financial portfolios tend to recommend higher exposures for others. This is consistent with recent findings on professional advisor beliefs in Linnainmaa et al. (2021) and extends those to lay advisors. Such active recommendation behavior of the latter could contribute a further peer effect leading to observed similarity of portfolios, in addition to the usually emphasized channels of learning and imitation.

Controlling for investor characteristics presented to advisors in the vignettes hardly affects the magnitudes or the significance pattern of the marginal effects of advisor characteristics. Nevertheless, advisors, both professional and lay, systematically tailor their advice to investor characteristics, even though there is no recipient pressure in our study. The direction of these portfolio recommendations is quite consistent with what current portfolio models imply. Advisors recommend higher risk exposures for investors with larger net resources, in the form of higher income, wealth or lower debt, but they tend to moderate their recommendation when the amount to be invested is larger. Advisors also recommend less risk for the more risk averse, for older individuals, and for novices in the stock market, while they are not being systematically influenced by the investor's educational attainment or marital status.

When we expand the analysis of observed heterogeneity of advisors to include interaction terms between the status of professional advisor and the investor characteristics in the vignettes, we find that the shift parameter in professional advice is no longer significant: the moderating effect of professional advice on the risky portfolio share is to be traced fully to how professional advisors respond, relative to lay advisors, both to investor characteristics and to their own. Professional advisors tend to moderate their recommendations more with

2. The innovative paper of Mullainathan et al. (2012), which sent mystery shoppers to financial advisors for a first visit in order to elicit their financial advice found considerable catering of this type.

respect to investor's age and risk tolerance than lay people do, while they stand ready to recommend higher risky shares for people with greater stock market experience. Professional advice is unresponsive to the size of the planned investment, and the observed negative effect in the overall sample emanates solely in lay advice. Surprisingly, professional advisors are not only more responsive to their own risk tolerance when recommending risky portfolio shares for others, but also to their own income.

We then allow for unobserved advisor heterogeneity, in addition to observed heterogeneity, by using a Bayesian hierarchical Tobit model. We consider different options that a potential investor has, such as asking a professional advisor, or a peer with similar education and labor income status, or a family member or peer that is more senior (in the case of young investors) or younger (in the case of older investors). We employ the collection of posterior distributions characterizing the recommendations of different advisors conditional on investor characteristics in order to illustrate the range and distribution of advice investors would obtain from these different groups of advisors. We focus on three potentially interesting types of advice recipients, namely a wealthy retiree, a wealthy person in the latter half of their career, and a young low-earner without college education, but other cases can also be considered.

We find that professionals not facing conflict of interest are likely to be recommending more limited risk exposure to college educated groups above 50 years compared to their peers, while they would tend to encourage young, lower-educated individuals to include stocks in their financial portfolio to a greater extent than what their peers and their elders would recommend. The distribution of professional advice to the young group is shifted further to the right for professional advisors with high risk tolerance in their own investments, as evidenced by their own portfolios or by their behavior in the bomb game. These findings suggest that the current pattern of access to financial advice documented in the literature, namely the greater tendency of older, wealthier individuals rather than of young, low-income ones to be matched with professional advisors, does not favor stock market participation, even in the absence of conflicts of interest. Put differently, the tendency of the young to talk to their peers and of the older investors to talk to professional advisors is likely to generate lower risky portfolio share recommendations than the advice the respective groups would be likely to receive from alternative sources.

Our study contributes to two strands of literature, on financial advice and on peer effects. Both the theoretical and the empirical literature on financial advice have shown that conflict of interest in the professional provision of advice can result in inferior Sharpe ratios and misselling to clients (for a survey of early contributions, see Inderst and Ottaviani (2012), and for a recent one stressing recent literature and supply-side aspects, see Reuter and Schoar (2024)). Chalmers and Reuter (2020) study changes in the Oregon University System Retirement Plan and find that, in the absence of brokers and presence of Target Date Funds (TDFs), new participants with high predicted demand primarily invest in TDFs, which offer similar market risk but higher Sharpe ratios than the portfolios the brokers recommend. Andries et al. (2024) find that depriving advisors of information on their clients' assets that appreciated and depreciated in value reduces the incidence of the disposition effect in their clients' accounts, and that the result is driven by clients who contact their advisors more often. Choi (2022) compares the advice given in nearly 50 popular 'personal finance' books to insights derived from normative economic theory. He finds that advice is frequently driven by fallacies, but it addresses the limited willpower of individuals. Various such books recommend that longer-term money be more heavily invested in equities, that portfolios should get more conservative with age, and that any money that may be spent in the near term not be invested in stocks. Schoar and Sun (2024) conduct an experiment to study how recipients of advice react to active versus passive advice and how this reaction relates to their financial literacy.

In an early analysis of how professional advice responds to client characteristics, Mullainathan et al. (2012) conduct an audit study on the first meeting of randomly assigned "mystery shoppers" with professional financial advisors. They find that advisors catered to detrimental mistakes such as return chasing and tilted even passive low cost portfolios towards inefficient, actively managed high-cost products. More recent research has found similarity of portfolios of financial advisors to those of their clients. Foerster et al. (2017) use Canadian data and find that advisors respond particularly to clients' risk tolerance and age, but advisor fixed effects explain one and a half times as much of the variation that is explained jointly by all client characteristics. Some studies infer professional advisor beliefs from their actions on their own accounts and compare them to those of their clients, which presumably reflect the advice they provide to the latter. Linnainmaa et al. (2021) find that professional advisors themselves prefer high-cost funds, churning, return chasing, and they underperform passive benchmarks roughly as much as their clients do, even after they leave the financial industry. In a different context of professional advice, Levitt and Syverson (2008) found that real estate agents advise others to sell their homes quickly, but when it comes to their own homes, they sell them more slowly and at a higher price.

Our study takes a different approach to uncovering beliefs, namely that of asking advisors directly what they believe random individuals should do, and it compares those beliefs to similarly elicited beliefs of lay people. This has the advantage of overcoming issues of endogenous matching of professionals to clients and pressure to cater to customer biases, and it allows us to observe advisor beliefs even regarding people who are not their usual clients. Our focus is on comparing the so-elicited professional advisor beliefs with those of lay advisors of different characteristics and relevance to the individual potential investor.

d'Astous et al. (2022) elicit professional advisors' choices for client vignettes from a set of options predefined by the researcher. The authors present highly qualified professional financial advisors in Canada with a survey that includes repeated client vignettes, and they elicit their detailed recommendations regarding retirement savings, annuities, long-term care risk, and an arbitrage involving investment fees by asking them to choose a detailed option from a predefined set. They use multinomial logit estimation and test for the presence of four biases in professional recommendations.[3] They find that, on average, professional advice

3. The biases are: a client gender bias, an increased likelihood of recommending a product that the client is

responds to the relative costs and benefits of different options in ways consistent with theory, but that there is support for all four biases in professional advice. Our study also finds that advisors respond to vignette characteristics in ways broadly consistent with theory, but it has a different focus, namely to compare the beliefs of professionals on risk exposure to those of different peer types.

Moreover, our study contributes to the rapidly growing body of literature examining the influence of peer effects on household financial behavior. These have been traced to factors such as asset holding of peers (Duflo and Saez 2002), sociability (Hong et al. 2004), stock market successes of neighbors (Kaustia and Knüpfer 2012), information on a new asset from peers (Banerjee et al. 2013; Bursztyn et al. 2014), business and economics education of neighbors (Haliassos et al. 2020), and prevalence of stock market knowledge and participation among trusted peers (Arrondel et al. 2022). While existing studies provide evidence of information and knowledge transfer, in addition to some form of imitation, they do not allow direct observation of peer beliefs and advice regarding the ideal level of risk exposure, let alone a comparison of those to the corresponding beliefs of a professional advisor.

2 Experimental design and data

In a web-based survey, we collected data on the risky asset share portfolio allocation recommendations on long-term retirement investments. We recruited participants from two groups – independent financial advisors (professional advisors) and regular "people from the street" (lay advisors). In April 2015, we approached 10,000 independent, non-bank advisors directly by mail. Their postal addresses were obtained from the register of finance and insurance brokers, which is publicly accessible and provided by the German chamber of commerce.[4] The survey for professionals ran from 13 April to 27 April 2015. Around 800 visits resulted in 424 full responses. The complementary survey among non-professionals, recruited by a market research service, ran from 15 April to 5 Mai 2015 and produced 450 complete responses. Professional advisors were promised access to the results of a set of questions regarding the industry of independent financial advice and a comparison of their recommendation behavior to that of other advisors. Non-professionals were compensated by the market research service

supposed to have asked about, a familiarity bias, which they define as the tendency to recommend products that the professionals or their spouses own or are licensed to sell, and a bias based on compensation scheme.

4. https://www.vermittlerregister.info/

provider (with an amount of the order of € 6).

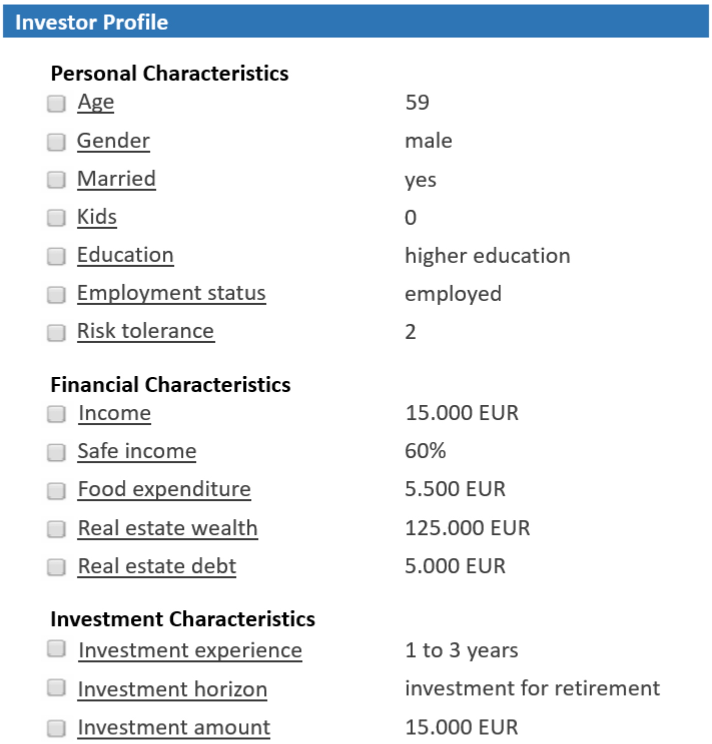
Table 1
Experiment set-up

Section #	Question section title
1.	Screening / Financial literacy (only lay advisors)
2.	Elicitation of return expectations
3.	Elicitation of risk preferences
4.	Portfolio experiment: Allocations for household profiles (Five per advisor)
5.	Elicitation of participant demographics

The general setup of the portfolio experiment is illustrated in Table 1. The lay advisor group was screened for age and a financial literacy questionnaire to include only participants capable of expressing basic opinions and beliefs on investment decisions. Lay advisors had to be at least 25 years old, answer three simple questions measuring financial literacy correctly, and ascertain their willingness and (subjective) ability to make basic investment decisions. Out of 6507 logins to the survey, 696 passed the admission and completed the survey, 450 participants completed the questionnaire with valid entries. We excluded, for example, obviously erroneous or "automatic" entries that included only "0" in all numerical answers. The rest of the experiment was almost identical for both groups. First, we elicited return expectations and risk preferences, then participants were asked to give an optimal portfolio allocation recommendation for five virtual clients. After seeing the last profile, participants stated their own optimal and actual allocation as well as information on their own demographic and financial situation.

Advisors, both professional and lay, were shown the following screen with a list of 14 investor characteristics as part of the vignette:

Figure 1
Household profile display



Notes: The screenshot above shows a household profile as presented to participants during the experiment. Each characteristic provides a detailed description when hovering over it with the mouse.

Respondents were asked to check the box on the left of each vignette characteristic to indicate which characteristics they considered applicable. The results of this exercise are shown in Table 2. Professional advisors tend to tick more boxes, but both groups put investor age, income, risk tolerance, and investment amount high up on the list.

Table 2
Profile characteristics check-boxed in experiment
The table reports the advisor group-specific fraction of participants that checked the corresponding household characteristic (in rows) during the portfolio experiment. The last line states the fraction of participants that checked any box.

	Prof. Adv.	Lay Adv.
Age	0.75	0.51
Income	0.71	0.56
Risk Tolerance	0.69	0.44
Investment Amount	0.64	0.47
Investment Exper.	0.60	0.35
Safe Income	0.54	0.44
Real Estate Wealth	0.48	0.30
Self Employed	0.46	0.40
Real Estate Debt	0.44	0.26
College	0.42	0.27
Food Expenditure	0.39	0.27
Married	0.37	0.24
Kids	0.27	0.20
Male	0.08	0.09
Checked Any	0.82	0.77

Virtual client profiles

The core of our experiment is the portfolio allocation task. Before the allocation task, a comprehensive description of each demographic household characteristic was provided. Each description could be reviewed by the participant when hovering over it with the mouse pointer during the allocation task. Each participant was provided with five hypothetical investor profiles. Each hypothetical investor was presented to participants in the form of a table with information on 14 characteristics (see Figure 1 for an example). For a first indicator of what characteristics enter the participants' decision rule, they were asked to check boxes next to the characteristics for at least the first profile. Around 80% of participants checked at least one box. (Table 2 shows the percentage of participants that selected each characteristic.) Finally, participants had to state the euro amount that they felt represented optimal allocation to risky assets, while the percentage portfolio weights were calculated and displayed next to the entry box in real time.

The virtual client profiles were combined efficiently to maximize information for a linear regression model. This was achieved by utilizing the R-package "algdesign". With 14 variables it is not possible to generate a full factorial design matrix even with very parsimonious discretization. Therefore, we generated two million randomly drawn profiles from which the algorithm selected sets of five profiles for each participant. Income, financial wealth and real estate wealth were randomly generated to match a distribution similar to the data in the German Socio Economic Panel (GSOEP) for households with wealth exceeding €10,000. Summary statistics on the profiles shown to professionals and lay advisors are presented in Table 3. Comparing means, and quantiles which are not shown in the table, both groups have faced a similar distribution of client profiles. Only the average investment amount shown to professional advisors is somewhat higher due to the random sampling.

Table 3
Household profiles - summary statistics on demographic variables
The table collects summary statistics on household profiles shown to participants during the portfolio allocation task. The first two sets of columns report statistics separately for the advisor groups. The last two columns show the overall mean and standard deviation. Statistics in rows one to five provide information on the investment amount down to food spending and is shown in thousand euro. Safe income is a fraction (of total income). All other variables except for the number of kids, risk tolerance, and age are binary indicators.

	Profess. Advisor				Lay Advisor				Overall	
	N	Mean	Min	Max	N	Mean	Min	Max	Mean	SD
Inv.Amount	2105	113.7	10	1000	2250	106.4	10	1000	109.9	199.6
Income	2105	43.8	5	150	2250	42.7	5	150	43.3	32.1
RE.Wlth	2105	217.0	0	1500	2250	209.7	0	1500	213.2	283.2
RE.Dbt	2105	17.0	0	400	2250	15.9	0	350	16.4	39.9
Food Expnd.	2105	13.1	1	72	2250	12.9	1	71	13.0	11.2
Safe Inc.	2105	85.4	50	100	2250	86.0	50	100	85.7	18.6
RiskTol.Prov.	2105	0.8	0	1	2250	0.8	0	1	0.8	0.4
RiskTol.	2105	2.4	0	5	2250	2.4	0	5	2.4	1.8
Inv.Exp.<1yr	2105	0.3	0	1	2250	0.3	0	1	0.3	0.5
Inv.Exp.>3yrs	2105	0.3	0	1	2250	0.3	0	1	0.3	0.5
Age	2105	45.5	20	75	2250	45.4	20	75	45.5	15.8
Male	2105	0.5	0	1	2250	0.5	0	1	0.5	0.5
Married	2105	0.7	0	1	2250	0.7	0	1	0.7	0.4
Kids	2105	1.5	0	4	2250	1.6	0	4	1.6	1.5
Prof.Train.	2105	0.2	0	1	2250	0.3	0	1	0.2	0.4
ALevels	2105	0.3	0	1	2250	0.3	0	1	0.3	0.4
College	2105	0.3	0	1	2250	0.3	0	1	0.3	0.4
Retired	2105	0.1	0	1	2250	0.1	0	1	0.1	0.3
SelfEmpl.	2105	0.1	0	1	2250	0.1	0	1	0.1	0.3

Participants

We refer to the two groups of participants as "professional advisors" (independent advisors that received an invitation via mail) and "lay advisors" ("people from the street", recruited by a market research firm). The latter sample was screened against individuals that are not interested in investments or fail to pass a basic financial literacy test. We compare the participant groups in Table 4. We see that around 90% of professional financial advisors are male, compared to almost 60% of lay advisors. Professionals advisors are richer and more risk tolerant, but hold similar return expectations with respect to stock investments. The most salient difference is in the share of risky assets. Professionals hold 52% while the share of risky assets in the lay advisors' portfolio represents an average of only 32%.

Table 4
Participant demographics
The table reports summary statistics on participating advisors. The first two sets of columns report statistics separately for both advisor groups. The last two columns show the overall mean and standard deviation. Male and college are binary indicators, income and wealth are in thousand euro, and current allocation is the advisors' own private risky asset share in percent. Return expectations are beliefs on an average annual return above 10% in percentage probabilities. The risk tolerance is measured via the "bomb-game" on a scale from 1 to 99 and patience from 1 to 10.

	Profess. Advisor				Lay Advisor				Overall	
	N	Mean	Min	Max	N	Mean	Min	Max	Mean	SD
Age	421	46.3	23	72	450	47.0	25	76	46.7	11.9
Male	421	0.9	0	1	450	0.6	0	1	0.8	0.4
College	421	0.4	0	1	450	0.5	0	1	0.5	0.5
Income	421	70.0	13	250	450	43.5	5	250	56.3	39.8
RE.Wlth	421	310.6	0	3000	450	117.5	0	3000	210.8	463.5
Fin.Wlth	421	124.8	5	1000	450	61.4	5	1000	92.0	163.6
Curr.Alloc	421	52.7	0	100	450	30.2	0	100	41.1	32.1
Ret.Exp.10yrs	421	23.4	0	95	450	20.9	0	99	22.1	20.5
Ret.Exp.1yr	421	22.5	0	90	450	22.9	0	99	22.7	20.0
RiskTol.	421	41.6	1	99	450	34.6	1	99	38.0	25.8
Patience	421	6.3	1	10	450	6.2	1	10	6.2	2.1

3 Model development

In this section, we develop our model. First, we derive the portfolio allocation rule from basic theory in section 3.1. We then discuss Bayesian inference for our econometric model in section 3.2, where we also present the basics of the corresponding Markov-Chain-Monte-Carlo (MCMC) sampler.

3.1 The portfolio allocation rule

To specify a structural estimation equation, we start from a simple asset allocation rule used by King and Leape (1998).[5] It defines the optimal risky asset portfolio share α_h of household h given its net worth W_h, (absolute) risk aversion A_h, and the risk σ^2 adjusted expected return of the risky asset ER in excess of the riskless return R_f.

$$\alpha_h = \frac{1}{A_h W_H}\frac{ER - R_f}{\sigma^2} \tag{1}$$

Substituting the relative risk aversion $\gamma_h = A_h \cdot W_h$ gives:

$$\alpha_h = \frac{1}{\gamma_h}\frac{ER - R_f}{\sigma^2} \tag{2}$$

Taking logs, the above equation can be expressed as:

$$\ln \alpha_h = \beta_0 - \ln \gamma_h \tag{3}$$

with

$$\beta_0 = \frac{ER - R_f}{\sigma^2}, \quad \gamma_h = A_h W_H$$

A known or perceived risk-adjusted risky asset excess return can be represented by a constant β_0. As a result, the risky asset share only depends on this constant and a measure of household specific risk aversion, γ_h. King and Leape (1998) propose a linear approximation for $\ln \gamma_h$. They assume that the household's risk-taking potential depends on observable household characteristics $\boldsymbol{x}_h$ of length d_h that include for example a household's net worth W_h among other variables.[6] Accordingly, we replace $\ln \gamma_h$ with the following term (u_h captures unobservable household characteristics).

$$\ln \gamma_h = \boldsymbol{x}_h' \boldsymbol{\beta} + u_h \tag{4}$$

Combining (3) and (4) results in a simple estimation equation of the risky asset demand with error term $\epsilon_h = u_h + e_h$, capturing unobserved household characteristics via u_h and the remain-

5. King and Leape (1998) derive the given demand equation for a risky asset and household h, extending a conventional portfolio choice model to capture observed differences in portfolio compositions. They explicitly incorporate the impact of differences in tax rates amongst assets and households and aim at estimating the joint discrete continuous choice of asset holding and portfolio fraction in a multi-assets environment. They provide a very good example concerning the estimation of the determinants of asset demand. We will follow their approach, abstracting from taxes in our general example, altering notation to avoid confusion, and focusing on a two asset case with a risky and a riskless asset.

6. There is substantial evidence that individual risk aversion depends not only on the financial situation (see e.g. Calvet and Sodini (2014)) but also on demographic variables. For example, risk aversion has been found to increase with age (e.g. Luigi Guiso and Monica Paiella (2008), Barsky, Robert B, et al (1997)) and decrease with the level of education (Vissing-Jorgensen (2002), Charlotte Christiansen et al. (2008)).

ing estimation error through e_h

$$\ln \alpha_h = \beta_0 + \boldsymbol{x}_h' \boldsymbol{\beta} + \epsilon_h \tag{5}$$

From this point on we use $y = \ln(\alpha)$ to simplify notation:

$$y_h = \beta_0 + \boldsymbol{x}_h' \boldsymbol{\beta} + \epsilon_h \tag{6}$$

Modeling portfolio allocation rules of financial advisors

Now we incorporate the role of financial advisors into the household risky asset demand function to derive an optimal portfolio allocation rule. We want to model the advisor's beliefs about the optimal baseline allocation and the risk-taking potential of a client conditional on the characteristics $\boldsymbol{x}_h$. Allowing for the case that different advisors follow different portfolio allocation rules to map household characteristics into a risky asset share, we anticipate two sources of heterogeneity. First, a shift in the baseline risky asset allocation, that could be caused for example by differences in perceptions regarding excess returns, which can also vary across advisors depending on their observable characteristics. This is easily represented by vector $\boldsymbol{x}_a$ of advisor characteristics; each variable in the vector of advisor characteristic is denoted by $x_{a,j}$ with index $j = 1, ..., d_a$. Second, variation on how certain "advisee" characteristics should influence the recommended risky asset share across advisors is introduced into our model through observed and unobserved slope heterogeneity.

In principle, we can capture observed heterogeneity by interacting the entire set of household variables in $\boldsymbol{x}_h$ with each of the advisor characteristics $x_{a,j}$ in $\boldsymbol{x}_a$ resulting in $\boldsymbol{x}_h \times \boldsymbol{x}_a$.[7] Together with the vector of advisor characteristics this forms a vector of variables for observed fixed effects x_{ah}^f. Since the difference between professional and lay advisors is of particular interest to us, we also interact all remaining advisor characteristics $\boldsymbol{x}_{a,-pro}$ with the professional dummy $\boldsymbol{x}_{a,pro}$:

$$\boldsymbol{x}_{ah}^f = \left[\boldsymbol{x}_a \ , \ \boldsymbol{x}_{a,-pro} \cdot \boldsymbol{x}_{a,pro} \ , \ \underbrace{\boldsymbol{x}_h \cdot x_{a,1} \ , \ \boldsymbol{x}_h \cdot x_{a,2} \ , \ \dots \ , \ \boldsymbol{x}_h \cdot x_{a,d_a}}_{x_h \times x_a} \right] \tag{7}$$

Appending $\boldsymbol{x}_{ah}^f$ by an intercept and the vector of household characteristics, i.e., $[1 \ , \ \boldsymbol{x}_h \ ]$, we could estimate one large pooled regression, clustering standard errors at the advisor level to account for dependence between recommendations by the same advisor. An alternative approach first estimates the regression in (8) for each advisor independently, and then regresses estimated regression coefficients on $\boldsymbol{x}_a$ (see (9)).

7. We use the the symbol "×" in $\boldsymbol{x}_h \times \boldsymbol{x}_a$, similar to the Cartesian product, to symbolize that the columns in $\boldsymbol{x}_h \times \boldsymbol{x}_a$ are equal to the set of all non-redundant multiplied pairs of variables $a \ in \ A = \boldsymbol{x}_a$ and $b \ in \ B = \boldsymbol{x}_h$ $: \ A \times B = \{(a \cdot b) | a \in A \ and \ b \in B\}$.

$$\boldsymbol{y}_{ah} = \boldsymbol{x}'_h \boldsymbol{\beta}_a + \varepsilon'_{ah} \text{ with } \varepsilon'_{ah} \sim \mathcal{N}(0, \sigma^2_{\varepsilon'}) \tag{8}$$

$$\boldsymbol{\beta}_a = \bar{\boldsymbol{\beta}} + \Lambda \boldsymbol{x}_a + \boldsymbol{\zeta}_a, \ \boldsymbol{\zeta}_a \sim N(0, V_\zeta)) \tag{9}$$

The advantage of the former approach is that it delivers statistically reliable estimates of systematic links between observed advisor characteristics and investment recommendations, including of interactions between advisor and household characteristics. The advantage of the latter approach is that it measures observed heterogeneity between advisors via Λ (again including interactions) as well as unobserved heterogeneity, i.e., beyond what can be explained by $\boldsymbol{x}_a$ via $\{\zeta_a\}$ and V_ζ. Also note that it is natural to think about unobserved heterogeneity measured by $\{\zeta_a\}$ in (9) as reflecting the moderating effects Λ^m of (a likely large set of) missing advisor covariates $\boldsymbol{x}^m_a$, i.e., $\{\zeta_a\} = \Lambda^m \boldsymbol{x}^m_a$.

However, our design does not lend itself to this two-step estimation approach because we obtain only a small amount of likelihood information from each advisor. Thus, independent estimates of $\boldsymbol{\beta}_a$ from each advisor's observations are noisy or not even likelihood-identified. Hence we jointly estimate Equations 8 and 9 using a fully Bayesian approach to estimation (e.g., Geweke 2005; Rossi et al. 2005).

3.2 Measuring observed and unobserved heterogeneity – A hierarchical Bayesian Tobit Model

We next explain how we jointly estimate Equations 8 and 9 in a fully Bayesian manner when Equation 8 corresponds to a Tobit model that accounts for the fact that observed risky asset share recommendations cannot be smaller than zero or larger than 100% in our data. Equation 10 depicts the likelihood of an individual advisor's recommendations, where Φ and ϕ denote the cumulative density and the density functions of a standard normal distribution, respectively, and $I(\textbf{arg})$ is the indicator function that evaluates to one if **arg** is true and else to zero.

$$\ell(\boldsymbol{\beta}_a, \sigma) = \prod_{h=1}^{T} \left(\Phi \left(\frac{-\boldsymbol{x}'_h \boldsymbol{\beta}_a}{\sigma} \right) \right)^{I(y_{ah}=0)} \left(\frac{1}{\sigma} \varphi \left(\frac{y_{ah} - \boldsymbol{x}'_h \boldsymbol{\beta}_a}{\sigma} \right) \right)^{I(0<y_{ah}<1)} \left(\Phi \left(\frac{\boldsymbol{x}'_h \boldsymbol{\beta}_a - 1}{\sigma} \right) \right)^{I(y_{ah}=1)} \tag{10}$$

The first factor on the right-hand side of Equation 10 is the likelihood of recommending a zero risky asset share to client h as per client characteristics encoded in $\boldsymbol{x}_h$ and advisor a's reaction to these ($\boldsymbol{\beta}_a$). The second factor is the likelihood of observing an interior risky asset share recommendation y_{ah} where $0 < y_{ah} < 1$, again given client characteristics and an advisor's reaction function. Finally, the last factor can be interpreted as the likelihood of recommending a partially leveraged investment in risky assets, i.e., $y_{ah} > 1$, had this been possible.

The Tobit likelihood of an individual advisor's recommendations in Equation 10 is nonlinear in parameters. Hence, Metropolis-Hastings steps become necessary to generate draws from the posterior implied by the product of the Tobit likelihood in Equation 10 and the conditionally multivariate normal hierarchical prior for $\boldsymbol{\beta}_a$ specified in Equation 9.

Our estimation algorithm relies on data augmentation, circumventing Metropolis-Hastings sampling, and the tuning of proposal densities Metropolis-Hastings sampling requires. Instead of evaluating the likelihood in Equation 10, we follow Chib (1992) and augment unobservable censored data according to Equation 11. In this equation, $TN(\mu, \sigma, a, b)$ denotes a normal distribution with mean μ and standard deviation σ, constrained to values in the interval $[a, b]$. The notation $\delta()$ is for the Dirac delta function that gives rise to a distribution for $y_{ah}*$ that concentrates all mass at the observed value y_{ah} for observed y_{ah} in between zero and one.

$$y^*_{ah} \sim \begin{cases} TN(\boldsymbol{x}'_h\boldsymbol{\beta}_a, \sigma, -\infty, 0) & \text{if} \quad y_{ah} = 0 \\ \delta(y^*_{ah} - y_{ah}) & \text{if} \quad 0 < y_{ah} < 1 \\ TN(\boldsymbol{x}'_h\boldsymbol{\beta}_a, \sigma, 1, \infty) & \text{if} \quad y_{ah} = 1 \end{cases} \tag{11}$$

We can proceed as with a classical linear random coefficients model, conditional on the complete data $\{y^*_{ah}\}$. Thus our Markov-Chain-Monte-Carlo (MCMC) algorithm can be summarized as follows:

Algorithm 1 MCMC algorithm

1. Initialize $\{\boldsymbol{\beta}_a\}_{a=1}^N$ and σ
2. Update hierarchical prior parameters $\boldsymbol{\Lambda}$ and V_ζ conditional on $\{\boldsymbol{\beta}_a\}_{a=1}^N$
3. For $a = 1, \ldots, N$,
    - augment unobservable censored data $\{y^*_{ah}\}_{h=1}^T$ based on Equation 11
    - based on complete data $\{y^*_{ah}\}_{h=1}^T$, update $\boldsymbol{\beta}_a$ in a conditionally conjugate regression model (Equation 8) with prior mean $\boldsymbol{\Lambda}\boldsymbol{x}_a$ and prior variance-covariance V_ζ
4. Update σ conditional on complete data $\{\{y^*_{ah}\}_{h=1}^T\}_{a=1}^N$ and $\{\boldsymbol{\beta}_a\}_{a=1}^N$

»»Repeat steps 2. to 4. until convergence from initial values and continue for 10,000 iterations for reliable posterior inference.

4 Results

4.1 Observed heterogeneity

This section employs Tobit regressions estimated using maximum likelihood with appropriately clustered standard errors to investigate observed heterogeneity in risky asset share recommendations. Observed heterogeneity refers to systematic differences in risky asset share recommendations as a function of advisor and investor characteristics and their interactions. We first follow this standard inference approach because of its familiarity and later leverage our Bayesian hierarchical Tobit model for a full account of heterogeneity in risky asset share recommendations.

We report inferred relations between recommended shares of total financial wealth to be invested in risky financial assets for retirement purposes and different subsets of advisor and investor characteristics in Table 5.[8] These Tobit estimates respect both the no-short-sales constraint and the constraint of not borrowing at the riskless rate to invest in risky financial assets.

The first column reports coefficient estimates on a number of advisor characteristics, without any further controls. Results give a first impression of the influence of advisors' own characteristics on the recommendations they provide. We find that, controlling for other own characteristics, professional advisors tend to be more conservative in their recommendations on the risky portfolio share than lay advisors, and this result is strongly statistically significant. Conditional on professional or lay status, older and more risk tolerant advisors tend to recommend higher exposure to financial risk for others. Not surprisingly, given the role of expected excess returns in determining the optimal portfolio share also shown in the model, advisors who have higher long term (10-year) return expectations are likely to recommend greater risk exposures. Strikingly, and controlling for all other characteristics including professional advisor status, advisors who are themselves more exposed to risk in their own financial portfolios tend to recommend higher exposures for others. This, and some of our following results, shed light on the channel of the key finding in Linnainmaa et al. (2021), namely that advisor portfolios are similar to their clients' portfolios. The authors interpret their finding by arguing that advisor portfolios reflect their own beliefs, these beliefs shape recommendations to clients, and recommendations influence actual client portfolios. We show that the elicited beliefs of professionals about what others should do are indeed influenced by their own characteristics and portfolios, which supports their assumed channel. We also find that this is true of lay advisors.

Table 6 reports average marginal effects. We find that, controlling for all other own characteristics, professional advisors tend to recommend a risky portfolio share that is lower by about 4.5 pp compared to lay advisors. A one percent increase in the advisor's own risky share is associated with a 2.9 pp increase in the recommended risky share.

This result also points to a further potential channel for recent findings in social household finance. Such findings suggest that peers are influenced by the stockholding behavior of those with whom they likely interact (Kaustia and Knüpfer 2012; Gomes et al. 2021). The literature has stressed observation, mimicking, information, and envy mechanisms as operating among peers. Our findings here suggest the potential for a further channel to be operative, namely direct portfolio recommendations from peers, based on their own portfolio.[9] We will exam-

8. The following variables are transformed by taking their inverse hyperbolic sign (IHS): Advisee Investment Amount, Income, Real Estate, Real Estate Debt, Food Expenditure; Advisor Income, Real Estate Wealth, Financial Wealth, Current Stock Allocation.

9. Note that this is not inconsistent with the finding that people tend to discuss their own portfolio with only a limited subset of their social circle (Arrondel et al. 2022). Portfolio recommendations do not require (accurate)

ine below the estimated distributions of such portfolio recommendations, depending on the characteristics of the recommending group and on those of the advice recipient.

What could lie behind recommendations influenced by one's own portfolio? Where do beliefs that this is the best advice come from? For professional advisors, such dependence has typically been interpreted as familiarity bias: professional advisors are more likely to recommend what they know best, and holding an asset is a good way to acquire knowledge of it. To the extent that lay advisors tend to know less about finances in general than financial advisors do, one might expect familiarity bias to be even stronger among lay people: they just communicate to peers what they know because they are doing it. Behavioral biases, such as overconfidence, could exacerbate the effect of own portfolio composition on advice given to peers. We will examine below for which group this tendency is greater.

A further channel, relevant for the literature on external habits and comparison or status effects, could emanate from concerns about relative consumption (dating back to Duesenberry (1949) or status, proxied by relative wealth (Roussanov 2010). This process does not need to be one-way, taking the peers' portfolios as given and trying to adapt to them. Peers can also attempt to influence the portfolios of others by recommending to them portfolios similar to their own. This can provide a further reason for wealth co-movement across peers.

The second column of Table 5 omits advisor characteristics and focuses instead on customer characteristics, as described to the advisors in the presented vignettes. This gives us a first impression of how customer characteristics are related to the recommendations of both types of advisors taken together, and it is reported here for reference.

More relevant for our understanding is column (3), which combines advisor and customer characteristics, as the latter are described in the vignettes. Professional advisors continue to provide more conservative risky portfolio allocations, regardless of the advisee features presented in the vignettes, in the absence of interaction terms between characteristics and professional advisor status. The estimated coefficient in Table 5 is only slightly lower. Older, more optimistic and more risk tolerant advisors are still found to recommend greater financial risk exposure, controlling for vignette characteristics and professional or lay status. Most strikingly, the influence of the advisor's own risk exposure remains very similar, both in terms of coefficient estimate and of marginal effect, even after controlling for advisee characteristics.

Beyond being influenced by their own portfolios and characteristics, advisors do tailor their recommendations to a number of customer characteristics described in the vignettes. Advice recipients with higher resources, in the form of income, real estate wealth, and lower debt outstanding, are encouraged to expose themselves more to risk. Marginal effects are particularly sizeable for the level of income and for the share of recipient income that is safe. The direction of recommended adjustments in the risky portfolio share is consistent with our standard models of saving and portfolio choice. Yet, when presented with greater total financial wealth to be invested (the 'investment amount'), advisors reduce the recommended risky portfolio share. On the face of it, this may look surprising, as both financial and real wealth are part of

disclosure of one's own portfolio.

total net wealth. Yet, a negative dependence of the optimal risky portfolio share on the level of financial wealth, for *given* permanent income, is a feature of the standard portfolio model (Haliassos and Michaelides 2003; Cocco et al. February 2005; Gomes and Michaelides 2005), as well as of the non-homothetic model with necessities and luxuries (Wachter and Yogo 2010).

These tendencies of advisors are not incosistent with this set of now standard portfolio models, even though we cannot presume that our advisors are aware of them. The higher investment amount implies that the risky portfolio share influences the riskiness of consumption more for given permanent income (as the latter is captured by current customer income and the safe share of income, as well as demographics). On the other hand, for given investment amount, higher current income and safer future income tend to be related to higher permanent income. To an increase in those variables, advisors respond by raising the recommended risky share. In a standard, homothetic model, such a reaction can be justified with reference to the now lower ratio of financial wealth to permanent income. In a non-homothetic model, as that of Wachter and Yogo (2010), this direction of portfolio share adjustment is not unambiguous, as the lower wealth to permanent income ratio is set against a conflicting one, namely that people with higher permanent income tend to be risking luxuries rather than necessities, and thus to be less concerned about jeopardizing consumption. The finding that both professional and lay advisor beliefs on how these key factors should affect portfolios, in the absence of pressure to cater to advisee prejudices or prior investments, tend to be broadly consistent with theory is new, to the best of our knowledge.

Advisors, lay and professional, respond to the level of customer risk aversion declared in the vignette, recommending less exposure to the more risk averse. Interestingly, the mere provision of the customer risk tolerance to the advisor discourages advisors in their recommendation for the risky financial share, controlling for the level of the stated risk aversion. This suggests a salience effect: the mere inclusion of risk preferences in the information provided to the advisor likely stresses the importance of risk exposure for the requested advice.

We find that advisors also moderate their risk-taking recommendations to older individuals, even controlling for the advisees' financial and real wealth and current income. This is consistent with standard economic models, homothetic and non-homothetic: older individuals have a higher ratio of non-human to human wealth, and a risky portfolio exposes them to consumption risk more than it does to younger counterparts (Cocco et al. February 2005). In addition, there is a more limited horizon over which to spread shocks to consumption from an adverse shock to financial wealth - an issue that Gollier termed 'time diversification' (Gollier 2001). In Table 6, we see substantial marginal effects of moving to progressively higher age bands, with the over 65 being recommended on average a risky portfolio share that is 23 pp lower than the under 35 investors. Advisors do not react significantly to other important determinants of household permanent income, such as the customer's education level and marital status, although recommendations do respond weakly to the number of children in the household.

For given remaining customer characteristics, advisors tend to moderate their risky share recommendations for novices in the stock market, namely people who have investor experience of less than a year, by about 2 pp, while they do not systematically recommend greater risk taking for those who have more than three years of experience. This is consistent with advisors perceiving a learning curve for new adopters, without assuming that it lasts forever.

Do professional advisors systematically respond differently to their own or clients' characteristics than do lay advisors? Column (4) of Table 5 incorporates all the controls included in (3) plus interaction terms between professional advisor status and each customer characteristic reported in the vignette. Interestingly, the shift dummy variable for professional advisor status becomes insignificant: the greater tendency of professional advisors to recommend lower financial risk taking found in the previous specifications can be fully explained by their differential reaction to customer characteristics relative to that of lay advisors. The sign and pattern of significance of the variables already included in (3) remain the same, with the exception of the advisor's own risk tolerance, which now becomes statistically insignificant for portfolio recommendations. Interestingly, the advisor's age and own portfolio composition continue to be significantly and positively correlated with the risky share recommendation: older and more risk-exposed advisors tend to recommend riskier financial portfolios, without any significant difference between professionals and lay people.

The interaction term analysis in Table 5 is quite revealing. Professionals are more responsive to their own risk tolerance when recommending a risky portfolio share to others, in comparison to lay people. They are also more responsive to their own income, moderating their advice as their income goes up. As professional advisors do not face any perverse financial incentives in this experiment, this may be reflecting a projection on others of their own more limited need to generate wealth through higher returns.

A further important issue is whether professional advisors tend to respond more to customer characteristics and in the direction of what theory prescribes, compared to lay advisors. The interaction term estimates suggest that professional advisors tend to moderate their recommended risky shares more with customer age than lay advisors do.

Further, professional advisors respond more to declared risk tolerance of the customers, by increasing their risky share recommendation further than lay advisors do. They make similar provision for limited investor experience (under one year) as lay advisors make, but they are ready to raise their recommended risky share to those who have more than 3 years experience, unlike lay advisors.

On the other hand, professional advisors hardly reduce the risky portfolio recommendation when faced with a higher level of customer financial wealth (amount to be invested). Thus, the moderation found in the overall sample masks a difference between professional and lay advisors, with the former not taking into account on average that a lot is at stake when financial wealth is higher.

Interestingly, we do not find a significant difference in responsiveness of professional advisors to the income level, income risk (share of safe income), real estate assets or debt of customers. The overall response of the advisor sample to these factors is in the direction implied by theory, and accessing a professional advisor does not deliver any additional movement in those directions.

Table 6 provides a different, but consistent, perspective to the comparison of professional and lay advisors by showing average marginal effects. Column (4) presents estimates for lay advisors, and column (5) for professionals. We see, for example, that lay advisors tend to moderate the recommended risky portfolio share by 2.6 pp when the investment amount goes up by one percent, compared to an insignificant effect for professional advisors. We register a substantially larger positive response of lay, compared to professional, advisors to customer income (7.9 versus 5.9 pp) and to real estate wealth. Professional advisors exhibit greater responsiveness to customer risk tolerance (6.2 versus 4.2 pp), but estimated differences in responsiveness are greatest with regard to customer age: the over 65 receive from professional advisors a recommendation lower than that of the youngest by 34 pp, whereas the corresponding figure for lay advisors is only 13.2 pp.

Table 5
Tobit regression of the recommended risky share on client profile and participant characteristics
The table shows regression coefficients to check for significant differences in interaction terms, and p-values in parentheses. The dependent variable is the recommended risky asset share in percentage points. Lower and upper bound are 0 and 100 respectively. Client profile characteristics Inv.Amount-Food.Exp and advisors characteristics Income-Curr.Alloc are also transformed by inverse hyperbolic sine (IHS). Model 1 regresses only on advisor characteristics; model 2 on client characteristics; model 3 regresses on both sets; model 4 adds interactions of a professional dummy with client characteristics.

	(1)	(2)	(3)	(4)
a.Prof.Adv.	-4.454^{***}		-4.279^{***}	43.416
	(0.003)		(0.004)	(0.155)
a.Age	0.179^{***}		0.179^{***}	0.226^{***}
	(0.002)		(0.002)	(0.003)
a.Male	1.889		1.743	0.963
	(0.211)		(0.244)	(0.595)
a.College	−1.465		−1.070	−2.574
	(0.234)		(0.384)	(0.164)
a.Income	0.393		0.438	2.052
	(0.754)		(0.726)	(0.223)
a.RE.Wlth	−0.120		−0.103	−0.070
	(0.336)		(0.397)	(0.665)
a.Fin.Wlth	−0.448		−0.348	−0.309
	(0.407)		(0.519)	(0.687)
a.Curr.Alloc	2.918^{***}		2.860^{***}	2.889^{***}
	(0.000)		(0.000)	(0.000)
a.Ret.Exp.10yrs	0.083^{**}		0.070^{**}	0.096
	(0.019)		(0.047)	(0.108)
a.Ret.Exp.1yr	0.042		0.057	0.064
	(0.248)		(0.119)	(0.241)
a.RiskTol.	0.060^{**}		0.058^{**}	0.006
	(0.013)		(0.017)	(0.878)
a.Patience	−0.260		−0.207	0.075
	(0.382)		(0.485)	(0.863)
c.Inv.Amount		-1.428^{***}	-1.490^{***}	-2.650^{***}
		(0.000)	(0.000)	(0.000)
c.Income		7.103^{***}	7.102^{***}	7.885^{***}
		(0.000)	(0.000)	(0.000)
c.RE.Wlth		0.284^{***}	0.278^{***}	0.337^{***}

Table 5 – continued from previous page

	(1)	(2)	(3)	(4)
		(0.000)	(0.000)	(0.002)
c.RE.Dbt		−0.260***	−0.253***	−0.255**
		(0.001)	(0.002)	(0.017)
c.Food Expnd.		−0.494	−0.504	−0.529
		(0.452)	(0.442)	(0.553)
c.Safe Inc.		7.161***	6.879***	7.603**
		(0.001)	(0.001)	(0.010)
c.RiskTol.Prov.		−13.860***	−13.779***	−13.760***
		(0.000)	(0.000)	(0.000)
c.RiskTol.		5.133***	5.102***	4.248***
		(0.000)	(0.000)	(0.000)
c.Inv.Exp.<1yr		−1.871*	−2.042**	−3.214**
		(0.053)	(0.033)	(0.016)
c.Inv.Exp.>3yrs		1.339	1.375	−0.295
		(0.158)	(0.146)	(0.814)
c.Age>=35<50		−6.578***	−6.443***	−4.167***
		(0.000)	(0.000)	(0.007)
c.Age>=50<65		−16.174***	−16.087***	−10.070***
		(0.000)	(0.000)	(0.000)
c.Age>=65		−23.978***	−22.959***	−13.217***
		(0.000)	(0.000)	(0.000)
c.Male		0.729	0.821	1.310
		(0.333)	(0.274)	(0.182)
c.Married		−0.924	−0.917	−0.132
		(0.289)	(0.290)	(0.912)
c.Kids		−0.538*	−0.531*	−0.901**
		(0.059)	(0.060)	(0.016)
c.Prof.Train.		−1.229	−1.245	−1.953
		(0.251)	(0.242)	(0.173)
c.ALevels		−0.365	−0.273	−1.334
		(0.746)	(0.808)	(0.350)
c.College		1.213	1.092	0.635
		(0.284)	(0.329)	(0.680)
c.Retired		−2.478	−3.234	−5.618*
		(0.369)	(0.228)	(0.096)
c.Self Empl.		−1.847	−1.910	−0.839
		(0.203)	(0.181)	(0.653)
a.Prof.Adv. × a.Age				−0.145

Table 5 – continued from previous page

	(1)	(2)	(3)	(4)
				(0.192)
a.Prof.Adv. × a.Male				2.240
				(0.480)
a.Prof.Adv. × a.College				3.171
				(0.202)
a.Prof.Adv. × a.Income				−4.354*
				(0.066)
a.Prof.Adv. × a.RE.Wlth				−0.061
				(0.802)
a.Prof.Adv. × a.Fin.Wlth				0.318
				(0.762)
a.Prof.Adv. × a.Curr. Alloc				−0.245
				(0.786)
a.Prof.Adv. × a.Ret.Exp.10yrs				−0.055
				(0.450)
a.Prof.Adv. × a.Ret.Exp.1yr				−0.038
				(0.592)
a.Prof.Adv. × a.RiskTol.				0.104**
				(0.033)
a.Prof.Adv. × a.Patience				−0.594
				(0.314)
a.Prof.Adv. × c.Inv.Amount				2.448***
				(0.001)
a.Prof.Adv. × c.Income				−2.013
				(0.153)
a.Prof.Adv. × c.RE.Wlth				−0.137
				(0.353)
a.Prof.Adv. × c.RE.Dbt				−0.025
				(0.874)
a.Prof.Adv. × c.Food Expnd.				0.370
				(0.772)
a.Prof.Adv. × c.Safe Inc.				−2.041
				(0.627)
a.Prof.Adv. × c.RiskTol.Prov.				−0.753
				(0.791)
a.Prof.Adv. × c.RiskTol.				1.949***
				(0.007)
a.Prof.Adv. × c.Inv.Exp.<1yr				2.805

Table 5 – continued from previous page

	(1)	(2)	(3)	(4)
				(0.134)
a.Prof.Adv. × c.Inv.Exp.>3yrs				4.115**
				(0.027)
a.Prof.Adv. × c.Age>=35<50				−4.658**
				(0.032)
a.Prof.Adv. × c.Age>=50<65				−12.726***
				(0.000)
a.Prof.Adv. × c.Age>=65				−21.022***
				(0.000)
a.Prof.Adv. × c.Male				−1.125
				(0.452)
a.Prof.Adv. × c.Married				−1.784
				(0.299)
a.Prof.Adv. × c.Kids				0.720
				(0.191)
a.Prof.Adv. × c.Prof.Train.				1.168
				(0.579)
a.Prof.Adv. × c.ALevels				1.913
				(0.387)
a.Prof.Adv. × c.College				0.743
				(0.736)
a.Prof.Adv. × c.Retired				5.687
				(0.291)
a.Prof.Adv. × c.Self Empl.				−2.461
				(0.384)
var(e.profPercPntAlloc)	944.591***	819.268***	779.447***	757.238***
	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R^2	0.004	0.020	0.025	0.028
Observations	4355	4355	4355	4355

Table 6
Tobit regression of the recommended risky share - Marginal Effects

The table shows marginal effects to check for significant differences in interaction terms, and p-values in parentheses. The dependent variable is the recommended risky asset share in percentage points. Lower and upper bound are 0 and 100 respectively. Client profile characteristics Inv.Amount-Food.Exp and advisors characteristics Income-Curr.Alloc are also transformed by inverse hyperbolic sine (IHS). Model 1 regresses only on advisor characteristics; model 2 on client characteristics; model 3 regresses on both sets. Columns 4 and 5 report marginal effects separately for the lay and the professional sample, respectively.

	(1)	(2)	(3)	(4)	(5)
a.Prof.Adv.=0				0.000	0.000
				(.)	(.)
a.Prof.Adv.=1				-3.481^{***}	-3.481^{***}
				(0.008)	(0.008)
a.Prof.Adv.	-3.903^{***}		-3.754^{***}		
	(0.003)		(0.004)		
a.Age	0.157^{***}		0.157^{***}	0.202^{***}	0.070
	(0.002)		(0.002)	(0.003)	(0.318)
a.Male	1.656		1.529	0.861	2.755
	(0.211)		(0.244)	(0.595)	(0.218)
a.College	−1.284		−0.939	−2.300	0.513
	(0.233)		(0.383)	(0.164)	(0.719)
a.Income	0.344		0.384	1.833	−1.979
	(0.754)		(0.726)	(0.222)	(0.166)
a.RE.Wlth	−0.105		−0.091	−0.063	−0.113
	(0.336)		(0.397)	(0.665)	(0.474)
a.Fin.Wlth	−0.393		−0.305	−0.276	0.008
	(0.407)		(0.519)	(0.687)	(0.989)
a.Curr.Alloc	2.557^{***}		2.509^{***}	2.582^{***}	2.274^{***}
	(0.000)		(0.000)	(0.000)	(0.000)
a.Ret.Exp.10yrs	0.072^{**}		0.062^{**}	0.086	0.035
	(0.018)		(0.046)	(0.107)	(0.333)
a.Ret.Exp.1yr	0.037		0.050	0.057	0.022
	(0.248)		(0.118)	(0.241)	(0.588)
a.RiskTol.	0.053^{**}		0.051^{**}	0.005	0.094^{***}
	(0.012)		(0.017)	(0.878)	(0.000)
a.Patience	−0.228		−0.181	0.067	−0.446
	(0.382)		(0.485)	(0.863)	(0.194)
c.Inv.Amount		-1.252^{***}	-1.308^{***}	-2.368^{***}	−0.173

Table 6 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
		(0.000)	(0.000)	(0.000)	(0.687)
c.Income		6.226***	6.230***	7.046***	5.050***
		(0.000)	(0.000)	(0.000)	(0.000)
c.RE.Wlth		0.249***	0.244***	0.301***	0.172**
		(0.000)	(0.000)	(0.002)	(0.049)
c.RE.Dbt		−0.228***	−0.222***	−0.227**	−0.241**
		(0.001)	(0.002)	(0.017)	(0.019)
c.Food Expnd.		−0.433	−0.442	−0.473	−0.137
		(0.452)	(0.442)	(0.553)	(0.862)
c.Safe Inc.		6.276***	6.035***	6.794**	4.783*
		(0.001)	(0.001)	(0.010)	(0.063)
c.RiskTol.Prov.		−12.148***	−12.088***	−12.296***	−12.480***
		(0.000)	(0.000)	(0.000)	(0.000)
c.RiskTol.		4.499***	4.476***	3.796***	5.329***
		(0.000)	(0.000)	(0.000)	(0.000)
c.Inv.Exp.<1yr		−1.640*	−1.791**	−2.872**	−0.352
		(0.053)	(0.033)	(0.016)	(0.756)
c.Inv.Exp.>3yrs		1.174	1.206	−0.264	3.285***
		(0.158)	(0.146)	(0.814)	(0.005)
c.Age>=35<50		−5.766***	−5.653***	−3.724***	−7.589***
		(0.000)	(0.000)	(0.007)	(0.000)
c.Age>=50<65		−14.177***	−14.113***	−8.998***	−19.603***
		(0.000)	(0.000)	(0.000)	(0.000)
c.Age>=65		−21.017***	−20.142***	−11.811***	−29.443***
		(0.000)	(0.000)	(0.000)	(0.000)
c.Male		0.639	0.720	1.170	0.159
		(0.333)	(0.274)	(0.182)	(0.870)
c.Married		−0.810	−0.805	−0.118	−1.647
		(0.289)	(0.290)	(0.912)	(0.120)
c.Kids		−0.472*	−0.466*	−0.805**	−0.156
		(0.058)	(0.059)	(0.016)	(0.654)
c.Prof.Train.		−1.078	−1.092	−1.745	−0.675
		(0.251)	(0.242)	(0.173)	(0.611)
c.ALevels		−0.320	−0.239	−1.192	0.498
		(0.746)	(0.808)	(0.350)	(0.731)
c.College		1.063	0.958	0.567	1.185
		(0.284)	(0.329)	(0.680)	(0.384)
c.Retired		−2.172	−2.838	−5.020*	0.059

Table 6 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
		(0.369)	(0.228)	(0.097)	(0.987)
c.Self Empl.		−1.619	−1.676	−0.750	−2.838
		(0.203)	(0.181)	(0.653)	(0.120)
Pseudo R2					
Obs.					

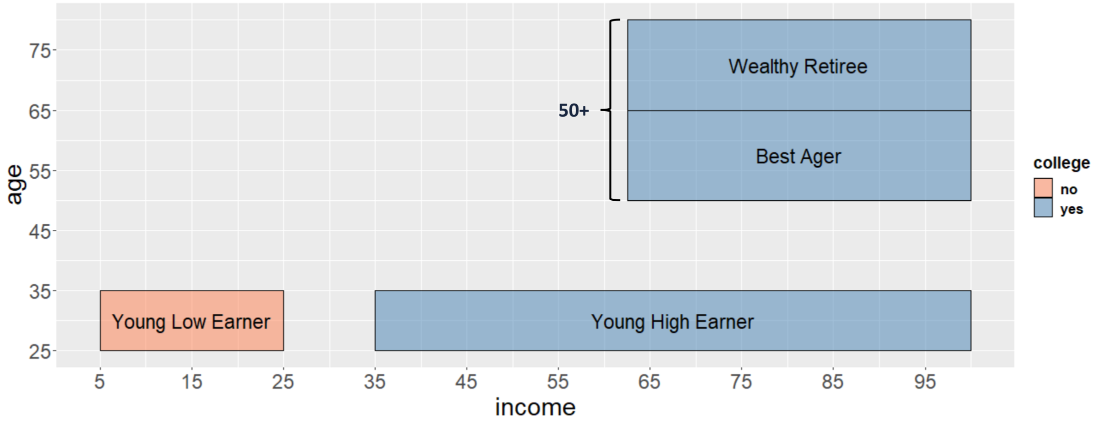
5 The Distribution of Predicted Advice – accounting for observed and unobserved heterogeneity

In this section, we finally leverage our ability to account for both observed and unobserved advisor heterogeneity in risky asset share recommendations conditional on investor characteristics afforded by the hierarchical Bayesian Tobit model introduced in section 3.2.[10] Specifically, we use the collection of posterior distributions characterizing the recommendation behavior of different advisors conditional on investor characteristics to illustrate the distributions of risky asset share recommendations different investors face from different advisor subpopulations. These distributions can be interpreted as describing the disribution of possible outcomes of a specific investor approaching an advisor based on (a subset of) observable characteristics, e.g., seeking advice from a professional advisor versus a layperson or seeking advice from someone with a similar or a more distant demographic profile than the respective investor.

To fix ideas further, we consider three types of investors, graphically represented in Figure 2. Two of the types have college education, while the third does not. Beyond education, the types differ in terms of the combination of age and income. The two college graduates we consider are: a "wealthy retiree", aged at least 65 and earning income of at least € 62,500; and a "wealthy 50-65" in the same income range but aged between 50 and 65 years. The investor without college education is aged between 25 and 35 years and earns between € 5,000 and € 25,000 annually. The characteristics of potential advisors are chosen so as to illustrate the distribution of advice received by likely (homophily-based, i.e., similar) peers or by an older group (e.g., parents or more experienced acquaintances, a "50+" group in Figure 2) or even a younger group (one's adult children and their peers, a "young high earner" in Figure 2), as well

10. In Appendix A Table A.3, we compare the marginal effects that we reported earlier (Table 6 column (3)) to those obtained from the hierarchical Bayesian Tobit model. Generally, the results match. An exception is that investor professional training turns out to be significant in the hierarchical Tobit estimation but insignificant in standard Tobit estimation. The point estimates are both negative. Regarding the interactions between the professional advisor status and investor characteristics we again find strong agreement across models (see Table 5 column (4) and Table A.2). There are two cases where standard Tobit yields insignificant estimates, while hierarchical Tobit yields estimates credibly different from zero. According to hierarchical Tobit, professional advisors tend to reduce their recommended risky share more as customer income goes up, while they tend to increase it more for customers with less than one year of investor experience. Finally, Table A.7 documents agreement between the main advisor effects reported in Table 5 column (1) and the corresponding estimates from the hiearchical Bayesian Tobit model.

Figure 2
Overview of client/ peer types



Notes: Peer types are defined based on three most relevant variables - age, income, and education (college vs. no degree). 50+ group is defined through combination of groups Wealthy 50-65 and Wealthy Retiree. Income is measured in thousands of euro.

as by professional advisors. Results are indicative of patterns, but they could be made more precise if information on the specific peers of an investor were available.

Table 7
Description of client profiles

	YLE	WR	W50-65
c.Inv.Amount	10000	90000	90000
c.Income	20000	40000	80000
c.RE.Wlth	0	250000	250000
c.RE.Dbt	0	0	0
c.Food Expnd.	6000	13013	15500
c.Safe Inc.	1	1	1
c.RiskTol.Prov.	1	1	1
c.RiskTol.	[1,3,5]	[1,3,5]	[1,3,5]
c.Inv.Exp.<1yr	1	0	0
c.Inv.Exp.>3yrs	0	0	1
c.Age>=35<50	0	0	0
c.Age>=50<65	0	0	1
c.Age>=65	0	1	0
c.Male	1	1	1
c.Married	0	1	1
c.Kids	0	2	2
c.Prof.Train.	0	0	0
c.ALevels	0	0	0
c.College	0	1	1
c.Retired	0	1	0
c.Self Empl.	0	0	0

Notes: YLE stands for Young Low Earner, WR for Wealthy Retiree, and W50-65 for Wealthy 50-65.

For a given client type h with household characteristics x_h, we compute predicted risky asset share recommendations y_{ah} for each adviser a of a given peer type (see Equation 8). To integrate out uncertainty, predicted risky asset share recommendations are computed at each draw of advisor a's reaction function β_a. We then censor the results that are smaller than 0 and larger than 1. All predictive values for a given peer type form a distribution of predicted risky asset share recommendations for client h with client characteristics in x_h. Next, we will analyze such distributions by client and peer type and compare those to distributions of professional advice. [11]

5.1 Advice to a Young Low-income Person

Consider first the young low earner without college education (YLE) who chooses to discuss finances with a peer (in terms of age, educational attainment, and income range) and randomly meets a member of that peer group. Figure 3 plots in black the model-predicted distribution of risky portfolio share recommendations that a young low earner would receive from a peer, depending on the level of risk tolerance the YLE declares to that peer. Regardless of the declared risk tolerance, the YLE may receive the full range of advice, from investing 0% to 100% of the intended wealth amount in the risky asset. The black vertical dotted line represents the median level of recommended portfolio share, and this responds to the declared risk tolerance: it is about 25% for a YLE with low risk tolerance and reaches about 50% for one with high risk tolerance. The single most popular peer recommendation to a YLE with low risk tolerance is to stay out of the stock market, with about 2.5% of peers offering this advice. The share of peers giving this advice goes down for higher declared risk tolerance of the YLE, but a small fraction of peers does give this advice even to the YLE with high risk tolerance. At the other extreme, the predicted share of peers who recommend to the YLE to invest all of the available wealth amount in risky stocks is negligible.

How does the predicted advice from peers compare to the advice that the same YLE would receive from the "50+", namely a group of laymen aged 50 years or older, with income more than € 62,500 and a college education? Interestingly, the share of the 50+ who would discourage the YLE from stock market participation is consistently lower than that of peers, regardless of the YLE's risk tolerance, but it does respond to risk tolerance. The predicted median advice from the 50+ is always higher than that from peers, although less so for the more risk tolerant investors. Furthermore, any risky share above the median recommendation of peers is more likely to be recommended by the older group than by the group of peers, regardless of the level of risk tolerance considered.

In the additional analysis reported in Appendix A, we have considered the role of the advisor's stock market experience (of more more than 3 years) in the predicted distribution of advice given by the 50+ group (see Figure A.1). The only notable difference is that this experienced group is predicted to be less likely to recommend very high exposures to stocks

11. For now, all professional advisers represent one type. We further explore heterogeneity in professional advice in Appendix A.

than the overall 50+ group, at a level comparable to peers. In a second exercise, we split the sample of the 50+ into its two subsets, using 3 years of experience as the cutoff (see Figure A.2). Interestingly, the predicted tendency of the two groups to recommend non-participation in the stock market is similar, for all levels of investor risk tolerance. However, when it comes to high risk exposures, the more experienced group is less likely to recommend them than the less experienced group. Unlike the less experienced 50+, those who are more experienced are typically not predicted to be recommending full portfolio specialization in stocks.

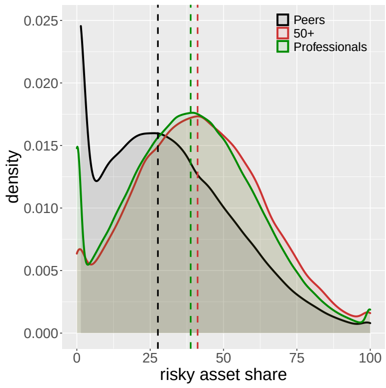
How do these two sources of advice compare to the advice given by professional advisors? The predicted distribution of professional advice is represented by the green color. The median professional advice is predicted to be higher than that of peers in all cases, and above that of the 50+ for medium and high risk tolerance. Professionals are predicted to be less likely to recommend non-participation in the stock market compared to the YLE's peers. They register more conservatism than the 50+ in this respect only in the case of the YLE with a low risk tolerance. Otherwise, the professional advice likely to be given to the YLE with low risk tolerance is predicted to follow a very similar distribution to that of the 50+ group. For the medium- and high-risk-tolerance investors, professional advisors are more likely to recommend a risky portfolio share greater than 50% than either of the two lay groups.

We further examine whether and how the professional advisors' own portfolio composition and independently elicited risk tolerance affect the distribution of advice that a YLE would be likely to receive. Figure A.4 shows the results of splitting the sample of advisors by whether they have an own risky portfolio share of less or more than 50%: the former are called "low-allocation" and the latter "high-allocation" advisors. We observe a rightward shift in the overall distribution of professional advice as their own risk exposure increases, with no noticeable change in the shape of the distribution of advice. Interestingly, the shifts are comparable regardless of the vignette investor's risk preferences. In addition to an increase in the median professional advice when it is given by advisors with higher own-risk exposure, we observe a significant decrease in the discouragement of stock market participation for highly risk-averse investors and an increase in the incidence of recommended full specialization in stocks for investors with high risk tolerance.

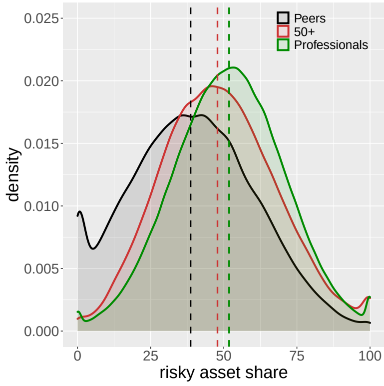
While the existing literature typically uses the risky share of professional advisors' own portfolios as an indicator of advisors' risk preferences, we can also examine this issue directly by using the level of risk tolerance elicited from professional advisors. We split the sample of professionals based on their score in the bomb game: we call professional advisors with a score between 1 and 49 "low risk tolerance", while the rest (50-100) are called "high risk tolerance" advisors. Figure A.7 shows analogous rightward shifts and changes in the propensity to recommend non-participation and full portfolio specialization when we compare low to high risk tolerance professional advisors as when we use their portfolio risk exposure.

The overall impression from this first set of graphs is that young low earners with low education are likely to be getting more conservative advice regarding the stock market if they choose to discuss their financial matters with their peers than with elder lay people with higher

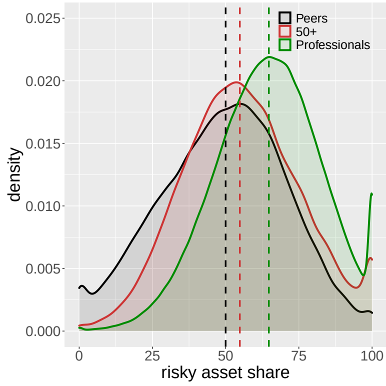
Figure 3
Distributions of predicted risky asset share recommendations for Young Low Earner



(a) Low risk tol



(b) Medium risk tol



(c) High risk tol

Notes: Peers are selected among laymen based on age (35 years and younger), income ($\leq$ €25, 000), and education (no college degree). 50+ group is selected among laymen based on age (50 years and older), income ($\geq$ €62, 500), and education (college degree). Professionals are all of the professional advisors.

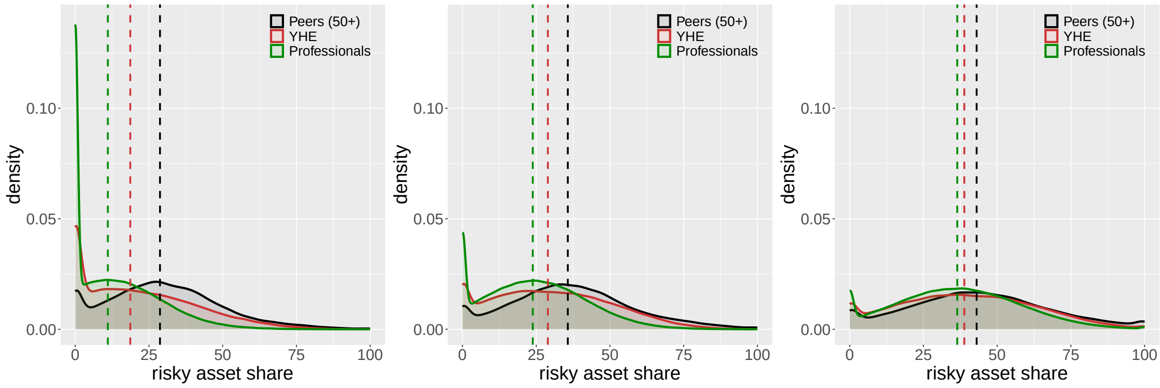
income. Professional advisors are predicted to be more responsive to the risk tolerance levels declared by the YLE and more likely to be encouraging significant stock exposure than either peers or the 50+, except for the YLE with low risk tolerance, where their predicted distribution of advice mimics that of the 50+ quite closely. The tendency of professionals to recommend high risk exposure is more pronounced amonng those who are more risk tolerant, as evidenced either by their portfolio risk exposure or by their responses in the bomb game. In view of the observed homophily in peer group formation and the empirically established limited tendency of YLE groups to access financial advice, these findings are consistent with peer influences being relevant for the limited stock market participation and exposure of the young with lower incomes and lower education.

5.2 Advice to a College-educated Wealthy Retiree

We next turn to college graduates, starting from the case of a "Wealthy Retiree" (WR), as this was described in Figure 2. We can see horizontally aligned predicted distributions of advice in Figure 4, while Figure 5 magnifies the graphs to show detail. We consider three types of advisors: professional advisors (as before), a group of peers now widened to include also some younger ages (starting at 50 years), and a group of "young high earners" aged below 35 years, who are college educated and earn no less than €35,000. This younger group is supposed to illustrate the WR's successful children and/or their peers, while the choice of the 50+ recognizes that WR may well be talking not only to fellow retirees but also to successful people at the later stage of their working career.

The reason for the poor visibility in Figure 4 is the very pronounced tendency of professional advisors to recommend non-participation in the stock market to the WR with low risk

Figure 4
Version 1: Distributions of predicted risky asset share recommendations for 'Wealthy Retiree'



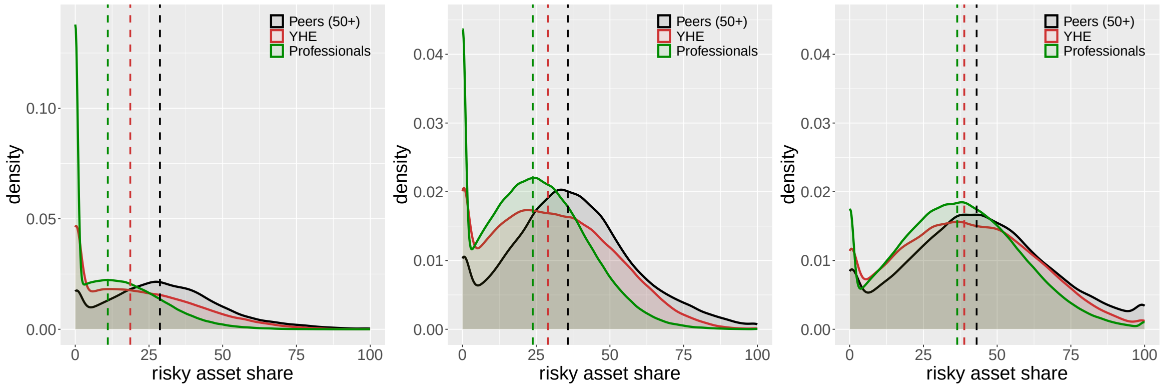
(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Peers (50+) group is selected among laymen based on age (50 years and older), income ($\geq$ €62, 500), and education (college degree). Young high earner (YHE) group is selected among laymen based on age (35 years and younger), income ($\geq$ €35, 000), and education (college degree). Professionals are all of the professional advisors.

tolerance. This is significantly moderated when the WR declares medium or high risk tolerance. The overall impression is that professionals tend to give more conservative advice on risky portfolio exposure to the WR, regardless of the declared risk tolerance. The median of the predicted risky portfolio share recommendations of the three groups does respond positively to declarations of higher risk tolerance, but in all cases, the professional advisor median recommendation is the lowest among the three advisor groups, with the highest always being that of peers. The distance between the predicted median recommendations shrinks as declared risk tolerance goes up, and none of the three groups has predicted median advice above the 50% threshold. We also see that the shares of professional advisors that recommend risky portfolio shares at the upper end of the spectrum are smaller than those of the other two groups, even when the WR declares high risk tolerance. It is also interesting that the young high earners are predicted to be more conservative in their advice to the WR than the retiree's peers. Figures A.5 and A.8 show how greater own risk exposure and risk tolerance of professional advisors shift the respective distributions of advice to the right, analogous to what we found for the case of a young low earner.

Overall, perhaps the key takeaway from considering this case is that a wealthy retiree is likely to be getting more conservative advice on risky portfolio exposure from financial advisors free of conflict of interest than from a member of the peer circle, despite heterogeneity in advice. This is all the more relevant, as the empirical literature identifies wealthier, older, and more experienced people as the ones more likely to be seeking financial advice. Reducing risky portfolio shares with age is also consistent with theory highlighting reduced opportunities to absorb shocks over time and limited human wealth relative to financial wealth.

Figure 5
Version 2: Distributions of predicted risky asset share recommendations for 'Wealthy Retiree'



(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Peers (50+) group is selected among laymen based on age (50 years and older), income (≥ €62,500), and education (college degree). Young high earner (YHE) group is selected among laymen based on age (35 years and younger), income (≥ €35,000), and education (college degree). Professionals are all of the professional advisors.

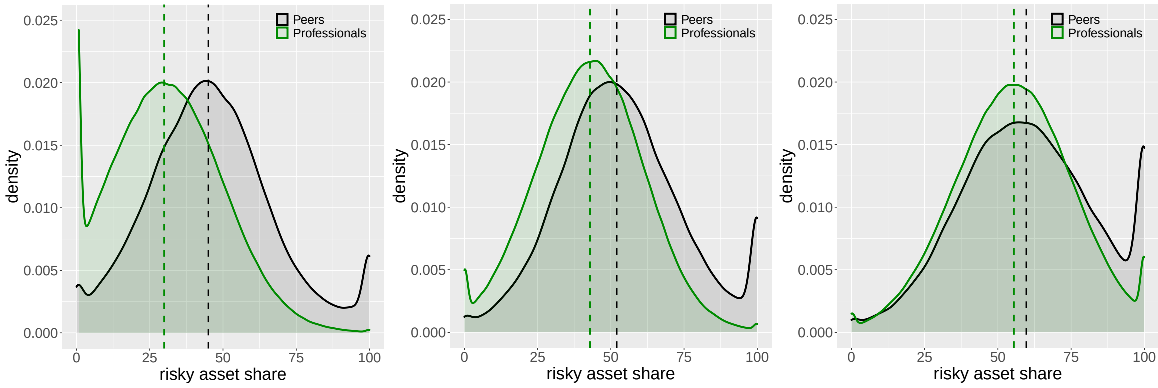
5.3 Advice to a High-Income Older Individual

In the third case, we focus on the advice given to a high-income person in the later part of working life (50-65 years old) with college education, whom we will call "Wealthy 50-65" (W50-65). As these individuals are at their financial prime, we will be comparing the advice they would be getting from professional advisors acting on their beliefs to that from their peers, namely other "Wealthy 50-65". Figure 6 displays the results. The main takeaway for this case is that, even when the full range of possible financial advice is considered, a W50-65 can expect to get more conservative recommendations for risk exposure from a randomly chosen professional acting without conflict of interest than from a randomly chosen peer. Differences in the distribution of predicted advice are small, though, if the W50-65 has declared high risk tolerance.

Specifically, the median predicted risky portfolio recommendation from professionals is below that from peers for all three degrees of declared risk tolerance, and the difference between the two diminishes with declared tolerance. Professionals are more than five times as likely to recommend non-participation to a W50-65 with low risk tolerance, but there is no differential tendency when it comes to high declared risk tolerance, as both professionals and peers are very unlikely to give this recommendation to W50-65. For the cases of low and medium risk tolerance of W50-65, the predicted distribution of advice for professionals is essentially similar to that of peers but shifted to the left. This increased tendency of professionals to recommend lower risky portfolio exposures compared to peers is hardly noticeable with reference to a W50-65 who declares high risk tolerance.

When we split the group of peers into those with more and those with less experience, using

Figure 6
Distributions of predicted risky asset share recommendations for Wealthy 50-65



(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Peers are selected among laymen based on age (between 50 and 65 years), income ($\geq$ €62, 500), and education (college degree). Professionals are all of the professional advisors.

3 years as the cutoff (see Figure A.3 in Appendix A), we find that there is little difference in the median predicted advice, but there is greater mass of less experienced peers recommending high exposure (above 75% or so) and smaller mass who make below-median predicted recommendations.[12] Figures A.6 and A.9 show how greater own risk exposure and risk tolerance of professional advisors shift the respective distributions of advice to the right, analogous to what we found for the previous two cases.

All in all, recognizing heterogeneity in financial advice coming from professional advisors and different peer groups, we find that professionals acting on their beliefs rather than facing conflict of interest are likely to be recommending more limited risk exposure to college educated groups above 50 years compared to their peers, while they would tend to encourage young, lower-educated individuals to include stocks in their financial portfolio to a greater extent than what their peers and their elders would recommend. In view of the known greater tendency of older, richer, more educated people to be matched with professional financial advisors, our findings suggest that, the current pattern of access to financial advice, combined with the trend towards fee-only advice that minimizes conflict of interest, is geared towards discouraging overall stock market participation and exposure. Finding ways to match the less wealthy young to professional financial advisors could help mitigate this tendency.

12. The predicted share of peers recommending full portfolio specialization in stocks is about the same, except for recommendations to high-risk tolerance individuals, where the less experienced are also less conservative advisors.

Table 8
Summary statistics of distributions of predicted risky asset share recommendations across different advisor groups

		YLE			WR			W50-65	
		Peers	50+	Profess-ionals	Peers (50+)	YHE	Profess-ionals	Peers	Profess-ionals
low risk tol	min	0	0	0	0	0	0	0	0
	1Q	11.27	25.78	23.55	16.14	4.65	0.00	31.47	16.41
	Median	27.63	41.16	38.80	28.74	18.66	11.05	45.02	29.94
	Mean	30.03	41.82	39.35	30.02	21.75	14.08	46.04	30.50
	3Q	45.20	56.79	54.15	41.90	34.47	23.10	58.72	43.31
	max	100	100	100	100	100	100	100	100
	sd	22.82	21.97	21.86	19.27	18.93	14.19	21.68	18.88
	IQR	33.93	31.01	30.60	25.76	29.82	23.10	27.26	26.90
medium risk tol	min	0	0	0	0	0	0	0	0
	1Q	23.34	34.51	38.95	22.60	14.19	11.50	39.01	30.26
	Median	38.65	47.84	51.81	35.72	28.96	23.83	51.99	42.87
	Mean	39.09	48.69	51.74	36.85	30.26	24.68	53.28	42.71
	3Q	53.93	61.80	64.52	49.58	44.62	36.07	66.24	55.10
	max	100	100	100	100	100	100	100	100
	sd	21.53	19.87	18.81	20.74	20.15	16.89	21.15	18.28
	IQR	30.59	27.29	25.57	26.97	30.44	24.57	27.23	24.84
high risk tol	min	0	0	0	0	0	0	0	0
	1Q	34.11	41.64	52.31	27.00	22.14	21.91	44.30	41.81
	Median	50.00	54.86	64.76	43.05	38.86	36.46	59.73	55.46
	Mean	48.93	55.62	64.33	43.84	39.59	36.98	60.27	55.30
	3Q	64.18	68.96	76.83	59.60	56.02	51.13	76.43	68.97
	max	100	100	100	100	100	100	100	100
	sd	21.37	19.99	17.86	23.99	23.11	20.90	22.73	19.96
	IQR	30.06	27.31	24.52	32.60	33.88	29.22	32.13	27.16

Notes: IQR stands for interquartile range, YLE for young low earner, WR for wealthy retiree, and W50-65 for wealthy 50-65.

6 Conclusions

Our study presents both professional and lay advisors with randomly assigned vignettes of investors and elicits their beliefs directly, in the form of recommendations about the risky portfolio share for retirement savings. We do not offer them incentives related to the type of advice they give, so as to elicit their beliefs, and we are able to examine what they believe is best even for custormers they would not normally meet. The study then examines how the beliefs of professional and lay advisors relate to the advisors' own characteristics and those of the investors described in the vignettes. It also compares how the beliefs of the two sources of advice respond to their own and the recipient's characteristics. Finally, it derives distributions of advice based on beliefs from relevant advisor groups for an indicative set of investor types. To the best of our knowledge, we are the first to contribute such results to the literature.

We find that both professional and lay advisors are influenced by their own characteristics and the riskiness of their portfolios when expressing their beliefs about what others should do. They also respond to the characteristics of investors described in the vignettes, broadly in line with prevailing portfolio theories, with professionals more responsive to a number (though not all) of investor characteristics than lay advisors.

When we allow for both observed and unobserved advisor heterogeneity and derive the distribution of beliefs from particular advisor groups of interest, a number of findings emerge. Young low-earners with low education are likely to be getting more conservative portfolio advice if they choose to discuss financial matters with their peers than with elder people. If they approach financial advisors expressing their beliefs, they are more likely to be advised to adopt a higher risky portfolio share, compared to the recommendations they would obtain from their peers or from their lay elders. A college-educated wealthy retiree, on the other hand, is likely to receive more conservative advice on risky portfolio exposure from a professional advisor acting on belief than from either a peer or a young high-earner. In fact, the retiree's age-education peers are predicted to be less conservative in their advice to the wealthy retiree than the young high earners. Similarly, a wealthy person in the age range of 50 to 65 can expect to get more conservative advice from a randomly chosen professional acting without conflict of interest than from a randomly chosen peer. Differences in the distribution of predicted advice are small if the investor has declared high risk tolerance.

Overall, our study finds that the beliefs of both knowledgeable peers and professionals on the optimal risky portfolio exposure of different types of investors tend to be consistent with broad portfolio theory, but they do differ between them. Professionals' beliefs tend to respond more to the characteristics of investors than those of lay people. If regulation and incentives are successful in generating financial advice that reflects the professionals' own beliefs and in matching professionals with households that need them most, then we can expect a greater increase in stock market participation than that likely to be produced by peer advice to these groups alone.

Bibliography

Andries, Marianne, Maxime Bonelli, and David Sraer. 2024. "Financial Advisors and Investors' Bias". *Working Paper.*

Arrondel, L., H. Calvo-Pardo, C. Giannitsarou, and M. Haliassos. 2022. "Informative Social Interactions". *Journal of Economic Behavior and Organization* 203:246–263.

Banerjee, Abhijit, Arun G Chandrasekhar, Esther Duflo, and Matthew O Jackson. 2013. "The diffusion of microfinance". *Science* 341 (6144): 1236498.

Barsky, Robert B, et al. 1997. "Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study". *The Quarterly Journal of Economics, MIT Press* 112 (2): 537–579.

Bursztyn, Leonardo, Florian Ederer, Bruno Ferman, and Noam Yuchtman. 2014. "Understanding Mechanisms Underlying Peer Effects: Evidence From a Field Experiment on Financial Decisions". *Econometrica* 82 (4): 1273–1301. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA11991. https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA11991.

Calvet, Laurent E., and Paolo Sodini. 2014. "Twin Picks: Disentangling the Determinants of Risk-Taking in Household Portfolios". *The Journal of Finance* 69 (2): 867–906.

Chalmers, John, and Jonathan Reuter. 2020. "Is Conflicted Investment Advice Bbetter than No Advice?" *Journal of Financial Economics* 138 (2): 366–387. https://www.sciencedirect.com/science/article/pii/S0304405X20301537.

Charlotte Christiansen, Juanna Schrøter Joensen, and Jesper Rangvid. 2008. "Are Economists More Likely to Hold Stocks?" *Review of Finance, European Finance Association* 12 (3): 465–496.

Chib, Siddhartha. 1992. "Bayes inference in the Tobit censored regression model". *Journal of Econometrics* 51 (1): 79–99. https://www.sciencedirect.com/science/article/pii/030440769290030U.

Choi, James J. 2022. "Popular Personal Financial Advice versus the Professors". *Journal of Economic Perspectives* 36 (4): 167–92. https://www.aeaweb.org/articles?id=10.1257/jep.36.4.167.

Cocco, João F., Francisco J. Gomes, and Pascal J. Maenhout. February 2005. "Consumption and Portfolio Choice over the Life Cycle". *The Review of Financial Studies* 18, number 2 (): 491–533. eprint: http://oup.prod.sis.lan/rfs/article-pdf/18/2/491/24421441/hhi017.pdf. https://doi.org/10.1093/rfs/hhi017.

d'Astous, Philippe, Irina Gemmo, and Pierre-Carl Michaud. 2022. "The Quality of Financial Advice: What Influences Client Recommendations?" *NBER Working Paper* No. 30205.

Duesenberry, James. 1949. *Income, Saving, and the Theory of Consumer Behavior.* Harvard University Press.

Duflo, Esther, and Emmanuel Saez. 2002. “Participation and investment decisions in a retirement plan: the influence of colleagues’ choices”. *Journal of Public Economics* 85 (1): 121–148. https://ideas.repec.org/a/eee/pubeco/v85y2002i1p121-148.html.

ECB. July 2023. *The Household Finance and Consumption Survey, Wave 2021 Statistical tables.* Technical report. European Central Bank.

Foerster, S., J. T. Linnainmaa, B. T. Melzer, and A. Previtero. 2017. “Retail Financial Advice: Does One Size Fit All?” *The Journal of Finance* 72 (4): 1441–1482.

FRB. October 2023. *Changes in US Family Finances from 2019 to 2022: Evidence from the Survey of Consumer Finances.* Technical report. Federal Reserve Board.

Geweke, John. 2005. *Contemporary Bayesian Econometrics and Statistics.* J. Wiley & Sons.

Gollier, Christian. 2001. *The economics of risk and time.* Cambridge, Mass: MIT Press. http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=62736.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai. 2021. “Household Finance”. *Journal of Economic Literature* 59 (3): 919–1000.

Gomes, Francisco, and Alexander Michaelides. 2005. “Optimal Life-Cycle Asset Allocation: Understanding the Empirical Evidence”. *Journal of Finance* 60 (2): 869–904. https://ideas.repec.org/a/bla/jfinan/v60y2005i2p869-904.html.

Haliassos, Michael, Thomas Jansson, and Yigitcan Karabulut. 2020. “Financial Literacy Externalities”. *The Review of Financial Studies* 33 (2): 950–989. https://doi.org/10.1093/rfs/hhz076.

Haliassos, Michael, and Alexander Michaelides. 2003. “Portfolio Choice and Liquidity Constraints”. *International Economic Review* 44 (1): 143–177. https://ideas.repec.org/a/ier/iecrev/v44y2003i1p143-177.html.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein. 2004. “Social Interaction and Stock-Market Participation”. *The Journal of Finance* 59 (1): 137–163. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2004.00629.x. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2004.00629.x.

Inderst, Roman, and Marco Ottaviani. 2012. “Financial Advice”. *Journal of Economic Literature* 50 (2): 494–512. http://www.aeaweb.org/articles?id=10.1257/jel.50.2.494.

Kaustia, Markku, and Samuli Knüpfer. 2012. “Peer performance and stock market entry”. *Journal of Financial Economics* 104 (2): 321–338. https://ideas.repec.org/a/eee/jfinec/v104y2012i2p321-338.html.

King, Mervyn A., and Jonathan I. Leape. 1998. “Wealth and portfolio composition: Theory and evidence”. *Journal of Public Economics* 69 (2): 155–193.

Levitt, Steven D., and Chad Syverson. 2008. “Market Distortions When Agents Are Better Informed: The Value of Information in Real Estate Transactions”. *The Review of Economics and Statistics* 90 (4): 599–611. eprint: https://direct.mit.edu/rest/article-pdf/90/4/599/1615028/rest.90.4.599.pdf. https://doi.org/10.1162/rest.90.4.599.

Linnainmaa, Juhani, Brian Melzer, and Alessandro Previtero. 2021. "The Misguided Beliefs of Financial Advisors". *Journal of Finance* LXXVI (2): 587–621.

Luigi Guiso and Monica Paiella. 2008. "Risk Aversion, Wealth, and Background Risk". *Journal of the European Economic Association, MIT Press* 6 (6): 1109–1150.

Lusardi, Annamaria, and Olivia Mitchell. 2024. "The Importance of Financial Literacy: Opening a New Field". *NBER Working Paper* Nr. 31145.

Mullainathan, Sendhil, Markus Noeth, and Antoinette Schoar. 2012. *The Market for Financial Advice: An Audit Study.* NBER Working Papers 17929. National Bureau of Economic Research, Inc. https://ideas.repec.org/p/nbr/nberwo/17929.html.

Net Fonds and Toluna. 2015. "Servicemonitor Finanzen: Industry Study", https://service.netfonds.de/marketing/pdf/Studie_Servicemonitor_B2C_2015.pdf.

Reuter, Jonathan, and Antoinette Schoar. 2024. "Demand-side and Supply-side Constraints in the Market for Financial Advice". *NBER Working Paper No. 32452.*

Rossi, Peter E., Greg M. Allenby, and Robert Edward McCulloch. 2005. *Bayesian statistics and marketing.* J. Wiley & Sons.

Roussanov, Nikolai. 2010. "Diversification and Its Discontents: Idiosyncratic and Entrepreneurial Risk in the Quest for Social Status". *Journal of Finance* 65 (5): 1755–1788. https://ideas.repec.org/a/bla/jfinan/v65y2010i5p1755-1788.html.

Schoar, Antoinette, and Yang Sun. 2024. "Financial Advice and Investor Beliefs: Experimental Evidence on Active vs. Passive Strategies". *NBER Working Paper No. 323001.*

Union Investment and Forsa. 2018. "Anlegerbarometer Q2", https://unternehmen.union-investment.de/startseite-unternehmen/presseservice/pressemitteilungen/alle-pressemitteilungen/2018/Studie--Anlegerbarometer---zweites-Quartal-2018.html.

Vissing-Jorgensen, Annette. 2002. "Limited Asset Market Participation and the Elasticity of Intertemporal Substitution". *Journal of Political Economy* 110 (4): 825–853.

Wachter, Jessica A., and Motohiro Yogo. 2010. "Why Do Household Portfolio Shares Rise in Wealth?" *Review of Financial Studies* 23 (11): 3929–3965. https://ideas.repec.org/a/oup/rfinst/v23y2010i11p3929-3965.html.

Appendix A - Bayesian hierarchical Tobit results

1 Estimation Results

Table A.1
Bayesian Hierarchical Tobit - mu
Average advisor reaction to changes in client characteristics (statistics are over draws for mu of the mixture of normals)

	mean	median	$q_{0.025}$	$q_{0.975}$	p-value
const	−5.669	−5.908	−7.950	−2.721	0.000
c.Inv.Amount	−1.551	−1.562	−2.130	−0.943	0.000
c.Income	6.909	6.891	5.681	8.090	0.000
c.RE.Wlth	0.241	0.239	0.099	0.392	0.000
c.RE.Dbt	−0.240	−0.241	−0.384	−0.085	0.004
c.Food Expnd.	−0.685	−0.683	−1.806	0.462	0.308
c.Safe Inc.	5.283	5.142	3.057	7.796	0.000
c.RiskTol.Prov.	−15.109	−15.064	−17.650	−12.953	0.000
c.RiskTol.	5.547	5.557	4.960	6.113	0.000
c.Inv.Exp.<1yr	−2.463	−2.330	−4.518	−1.151	0.000
c.Inv.Exp.>3yrs	1.364	1.362	−0.640	3.100	0.145
c.Age>=35<50	−5.675	−5.771	−7.454	−3.499	0.000
c.Age>=50<65	−16.201	−16.170	−18.125	−14.286	0.000
c.Age>=65	−18.007	−18.137	−21.442	−14.713	0.000
c.Male	0.313	0.230	−0.958	1.981	0.771
c.Married	−1.040	−1.024	−2.493	0.220	0.141
c.Kids	−0.627	−0.621	−1.181	−0.105	0.012
c.Prof.Train.	−1.818	−1.706	−3.368	−0.538	0.005
c.ALevels	−0.309	−0.370	−1.636	0.999	0.685
c.College	0.071	0.055	−1.285	1.464	0.939
c.Retired	−8.057	−8.047	−11.905	−4.139	0.000

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Table A.1 – continued from previous page

	mean	median	$q_{0.025}$	$q_{0.975}$	p-value
c.Self Empl.	−1.145	−0.962	−3.467	0.832	0.415

Table A.2
Bayesian Hierarchical Tobit - Λ
Coefficients on the interaction of the professional advisor dummy with client characteristics (statistics are over draws for Λ)

	mean	median	$q_{0.025}$	$q_{0.975}$	p-value
const	−3.606	−3.991	−7.254	1.501	0.135
c.Inv.Amount	2.357	2.343	1.154	3.601	0.000
c.Income	−1.963	−1.965	−3.952	−0.084	0.037
c.RE.Wlth	−0.121	−0.122	−0.405	0.173	0.397
c.RE.Dbt	−0.038	−0.039	−0.335	0.286	0.801
c.Food Expnd.	0.266	0.241	−1.574	2.450	0.787
c.Safe Inc.	−1.992	−2.185	−5.962	3.944	0.381
c.RiskTol.Prov.	−1.323	−1.452	−5.143	3.543	0.491
c.RiskTol.	2.086	2.081	1.006	3.202	0.003
c.Inv.Exp.<1yr	3.376	3.257	0.148	6.537	0.033
c.Inv.Exp.>3yrs	3.797	3.864	1.151	6.170	0.000
c.Age>=35<50	−5.027	−5.150	−8.470	−0.825	0.013
c.Age>=50<65	−12.164	−12.124	−15.076	−9.098	0.000
c.Age>=65	−18.505	−18.981	−24.064	−9.458	0.000
c.Male	−1.508	−1.455	−4.036	0.900	0.201
c.Married	−2.000	−2.012	−4.588	0.690	0.171
c.Kids	0.440	0.450	−0.637	1.552	0.429
c.Prof.Train.	0.854	0.709	−2.412	4.572	0.677
c.ALevels	2.428	2.820	−2.072	6.393	0.325
c.College	1.089	0.934	−2.157	4.426	0.536
c.Retired	2.209	2.538	−3.882	7.685	0.549
c.Self Empl.	−4.331	−3.874	−9.587	0.323	0.071

Table A.3
Standard Tobit Regression vs Bayesian Hierarchical Tobit - Average Marginal Effects
Column 1 reports average marginal effects for Standard Tobit Regression that regresses on advisor and client characteristics; columns 2 and 3 report average marginal effects for Standard Tobit Regression separately for the lay and the professional sample, respectively; model 4 reports average marginal effects for Bayesian Hierarchical Tobit; columns 5 and 6 report marginal effects for Bayesian Hierarchical Tobit separately for the lay and the professional sample, respectively

	(1)	(2)	(3)	(4)	(5)	(6)
c.Inv.Amount	-1.308^{***}	-2.368^{***}	-0.173	-1.383^{***}	-2.394^{***}	-0.302
	(0.000)	(0.000)	(0.687)	(0.000)	(0.000)	(0.334)
c.Income	6.230^{***}	7.046^{***}	5.050^{***}	6.338^{***}	7.141^{***}	5.480^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
c.RE.Wlth	0.244^{***}	0.301^{***}	0.172^{**}	0.219^{***}	0.272^{***}	0.163^{**}
	(0.000)	(0.002)	(0.049)	(0.000)	(0.000)	(0.040)
c.RE.Dbt	-0.222^{***}	-0.227^{**}	-0.241^{**}	-0.205^{***}	-0.192^{**}	-0.220^{**}
	(0.002)	(0.017)	(0.019)	(0.000)	(0.030)	(0.016)
c.Food Expnd.	-0.442	-0.473	-0.137	-0.821^{**}	-0.924	-0.709
	(0.442)	(0.553)	(0.862)	(0.020)	(0.182)	(0.228)
c.Safe Inc.	6.035^{***}	6.794^{**}	4.783^{*}	4.576^{***}	5.693^{***}	3.383^{**}
	(0.001)	(0.010)	(0.063)	(0.000)	(0.000)	(0.044)
c.RiskTol.Prov.	-12.088^{***}	-12.296^{***}	-12.480^{***}	-13.009^{***}	-12.391^{***}	-13.670^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
c.RiskTol.	4.476^{***}	3.796^{***}	5.329^{***}	4.806^{***}	3.956^{***}	5.714^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
c.Inv.Exp.<1yr	-1.791^{**}	-2.872^{**}	-0.352	-2.007^{***}	-3.714^{***}	-0.183
	(0.033)	(0.016)	(0.756)	(0.000)	(0.000)	(0.768)
c.Inv.Exp.>3yrs	1.206	-0.264	3.285^{***}	1.402^{**}	-0.363	3.289^{***}
	(0.146)	(0.814)	(0.005)	(0.024)	(0.576)	(0.000)
c.Age>=35<50	-5.653^{***}	-3.724^{***}	-7.589^{***}	-4.649^{***}	-2.375^{***}	-7.080^{***}
	(0.000)	(0.007)	(0.000)	(0.000)	(0.006)	(0.000)
c.Age>=50<65	-14.113^{***}	-8.998^{***}	-19.603^{***}	-13.823^{***}	-8.720^{***}	-19.278^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
c.Age>=65	-20.142^{***}	-11.811^{***}	-29.443^{***}	-15.870^{***}	-7.356^{***}	-24.971^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
c.Male	0.720	1.170	0.159	0.241	0.923	-0.487
	(0.274)	(0.182)	(0.870)	(0.886)	(0.206)	(0.558)

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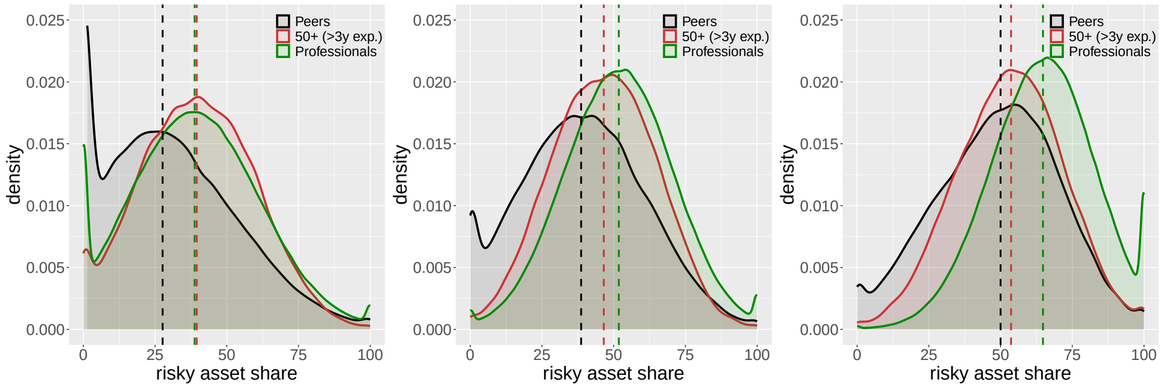
Table A.3 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)
c.Married	−0.805	−0.118	−1.647	−0.954	−0.199	−1.761***
	(0.290)	(0.912)	(0.120)	(0.142)	(0.934)	(0.004)
c.Kids	−0.466*	−0.805**	−0.156	−0.490**	−0.675**	−0.292
	(0.059)	(0.016)	(0.654)	(0.010)	(0.040)	(0.342)
c.Prof.Train.	−1.092	−1.745	−0.675	−1.728***	−1.772**	−1.681**
	(0.242)	(0.173)	(0.611)	(0.004)	(0.040)	(0.032)
c.ALevels	−0.239	−1.192	0.498	−0.468	−1.187	0.301
	(0.808)	(0.350)	(0.731)	(0.426)	(0.376)	(0.786)
c.College	0.958	0.567	1.185	−0.166	−0.409	0.094
	(0.329)	(0.680)	(0.384)	(0.768)	(0.606)	(0.978)
c.Retired	−2.838	−5.020*	0.059	−6.261***	−7.894***	−4.516***
	(0.228)	(0.097)	(0.987)	(0.000)	(0.000)	(0.000)
c.Self Empl.	−1.676	−0.750	−2.838	−0.610	1.615	−2.988**
	(0.181)	(0.653)	(0.120)	(0.648)	(0.208)	(0.012)

Notes: For Bayesian hierarchical Tobit, we compute marginal effects for each advisor a at each draw of advisor a's reaction function β_a for 1000 randomly selected client profiles. We average the obtained marginal effects over the advisors and compute corresponding p-values. Finally, we compute the overall average of marginal effects over the iterations and report these in the table. In columns (5) and (6), we perform the described procedure for lay and professional advisors separately.

2 Distribution of Advice: Further Sensitivity Analysis

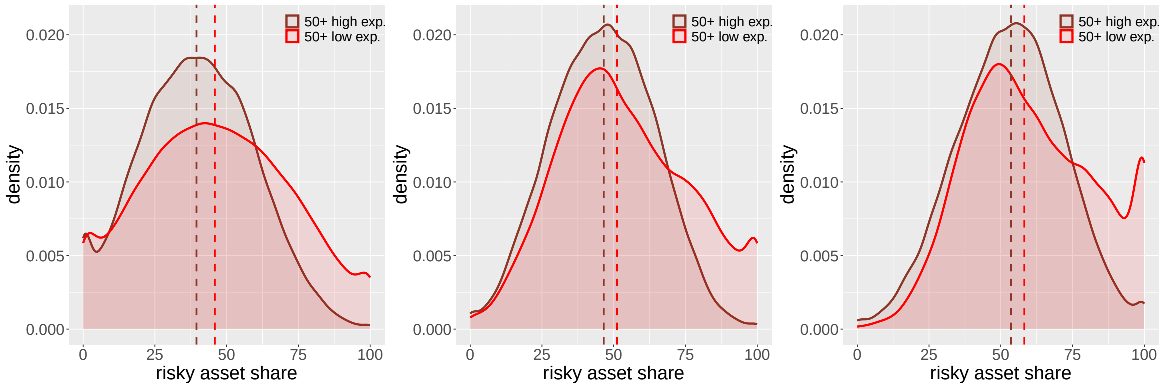
Figure A.1
Distributions of predicted risky asset share recommendations for Young Low Earner by 50+ group with investment experience > 3 years



(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Peers are selected among laymen based on age (35 years and younger), income ($\leq$ € 25,000), and education (no college degree). 50+ group is selected among laymen based on age (50 years and older), income ($\geq$ € 62,500), education (college degree), and experience (> 3 years). Professionals are all of the professional advisors.

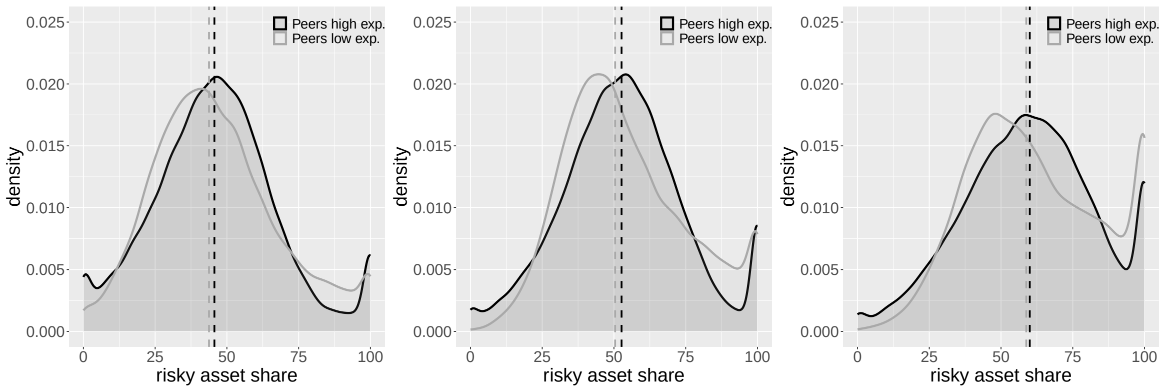
Figure A.2
Distributions of predicted risky asset share recommendations for Young Low Earner by 50+ group based on investment experience



(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: 50+ group is selected among laymen based on age (50 years and older), income ($\geq$ € 62, 500), and education (college degree). 50+ group is then divided into two sub-groups, with low ($\leq$ 3) and high (> 3 years) investment experience.

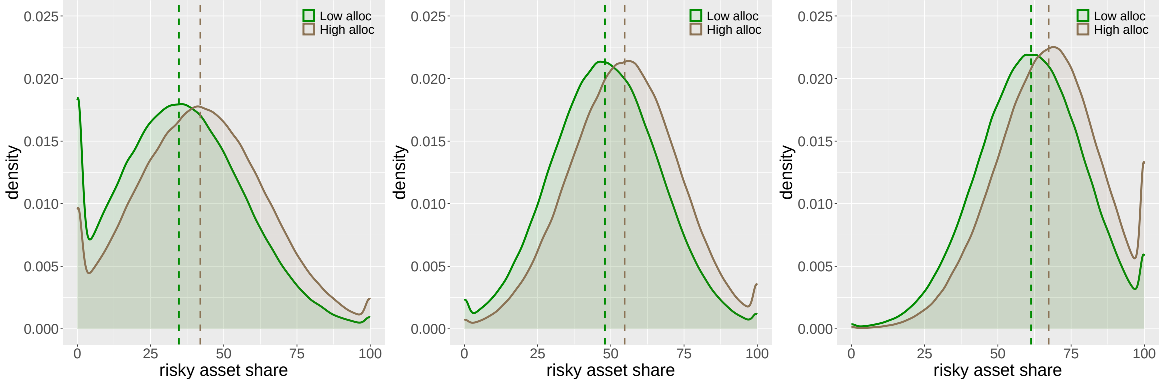
Figure A.3
Distributions of predicted risky asset share recommendations for Wealthy 50-65 by peers based on experience



(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Peers are selected among laymen based on age (between 50 and 65 years), income ($\geq$ € 62, 500), and education (college degree). Peers are then divided into two sub-groups, with low ($\leq$ 3) and high (> 3 years) investment experience.

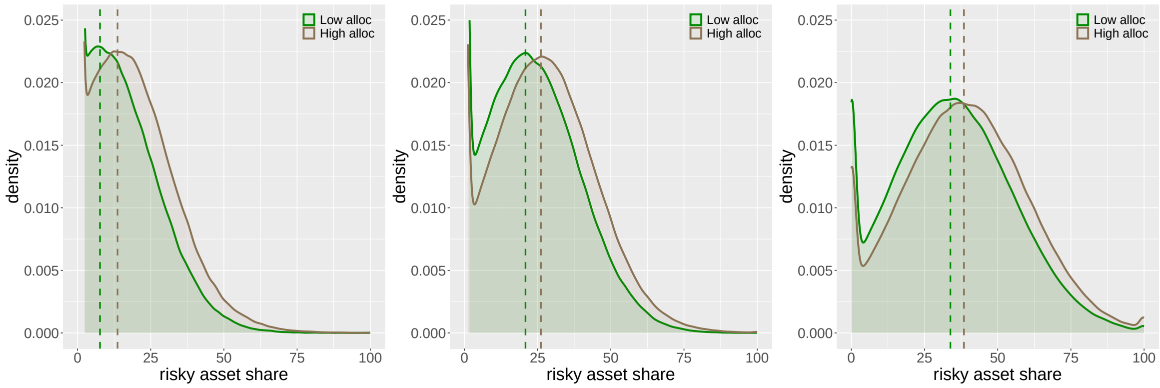
Figure A.4
Distributions of predicted risky asset share recommendations for Young Low Earner by professionals based on advisors' own risky share allocation



(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Professional advisors are divided into two sub-groups, with low and high own risky asset share allocation. Advisors' own allocation is defined as low (high), when advisors' own private risky asset share lies in the range from 0 to 49% (50 to 100%).

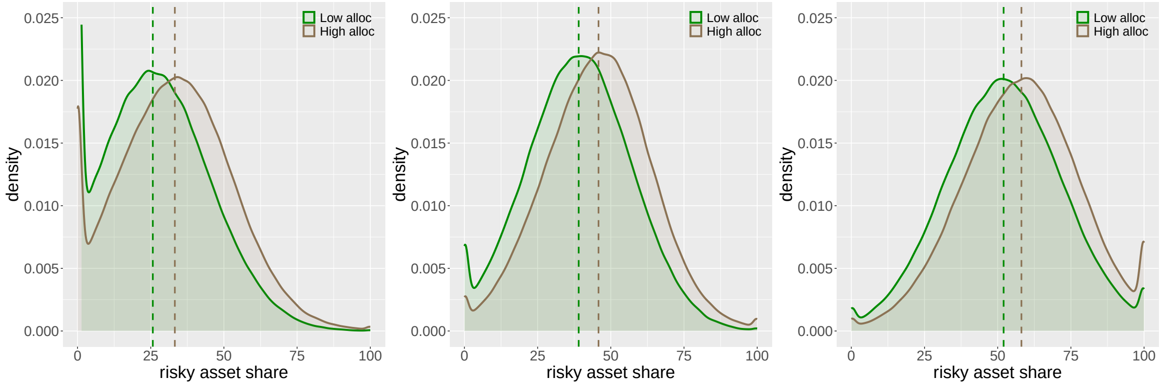
Figure A.5
Distributions of predicted risky asset share recommendations for Wealthy Retiree by professionals based on advisors' own risky share allocation



(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Professional advisors are divided into two sub-groups, with low and high own risky asset share allocation. Advisors' own allocation is defined as low (high), when advisors' own private risky asset share lies in the range from 0 to 49% (50 to 100%).

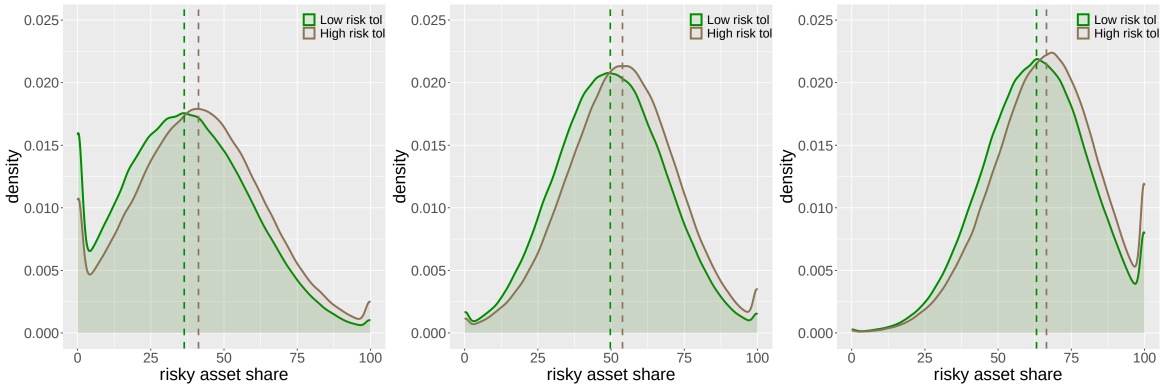
Figure A.6
Distributions of predicted risky asset share recommendations for Wealthy 50-65 by professionals based on advisors' own risky share allocation



(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Professional advisors are divided into two sub-groups, with low and high own risky asset share allocation. Advisors' own allocation is defined as low (high), when advisors' own private risky asset share lies in the range from 0 to 49% (50 to 100%).

Figure A.7
Distributions of predicted risky asset share recommendations for Young Low Earner by professionals based on advisors' risk tolerance

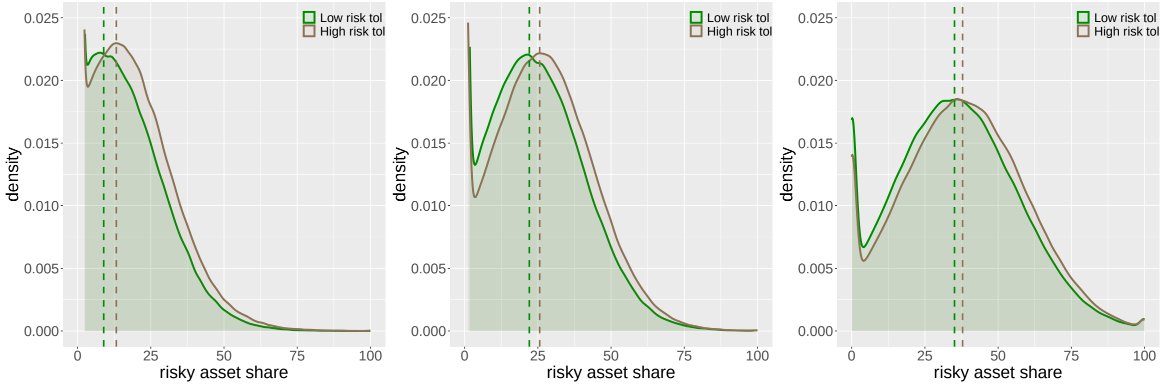


(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Professional advisors are divided into two sub-groups, with low and high risk tolerance. Advisors' risk tolerance is defined as low (high) when the score from the bomb-game lies in the range from 1 to 49 (from 50 to 100).

Figure A.8

Distributions of predicted risky asset share recommendations for Wealthy Retiree by professionals based on advisors' risk tolerance

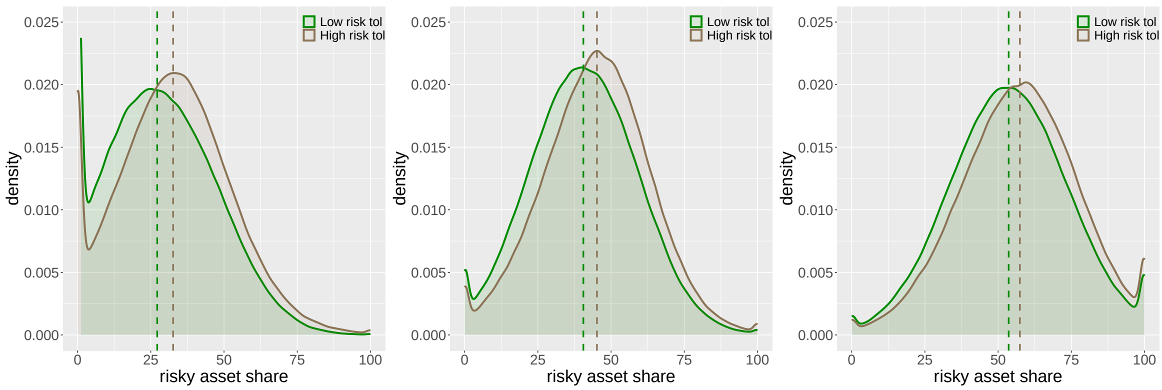


(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Professional advisors are divided into two sub-groups, with low and high risk tolerance. Advisors' risk tolerance is defined as low (high) when the score from the bomb-game lies in the range from 1 to 49 (from 50 to 100).

Figure A.9

Distributions of predicted risky asset share recommendations for Wealthy 50-65 by professionals based on advisors' risk tolerance



(a) Low risk tol (b) Medium risk tol (c) High risk tol

Notes: Professional advisors are divided into two sub-groups, with low and high risk tolerance. Advisors' risk tolerance is defined as low (high) when the score from the bomb-game lies in the range from 1 to 49 (from 50 to 100).

Table A.4
Summary statistics of heterogeneity of professional advice for Young Low Earner based on advisors' characteristics

		advisors' allocation		advisors' risk tol	
		low	high	low	high
low risk tol	min	0	0	0	0
	1Q	19.81	26.77	21.28	26.19
	Median	34.67	42.00	36.42	41.29
	Mean	35.38	42.41	37.14	41.71
	3Q	49.68	57.27	51.87	56.44
	max	100	100	100	100
	sd	21.16	21.92	21.53	21.98
	IQR	29.87	30.50	30.58	30.25
medium risk tol	min	0	0	0	0
	1Q	35.45	42.02	37.01	41.23
	Median	47.98	54.71	49.74	53.90
	Mean	48.03	54.59	49.83	53.77
	3Q	60.57	67.19	62.58	66.42
	max	100	100	100	100
	sd	18.53	18.54	18.66	18.78
	IQR	25.12	25.17	25.57	25.19
high risk tol	min	0	0	0	0
	1Q	49.06	55.14	50.70	54.20
	Median	61.35	67.33	63.10	66.51
	Mean	61.09	66.82	62.82	65.94
	3Q	73.47	79.11	75.27	78.39
	max	100	100	100	100
	sd	17.84	17.47	17.84	17.74
	IQR	24.40	23.97	24.56	24.19

Notes: Advisors' own allocation is defined as low (high), when advisors' own private risky asset share lies in the range from 0 to 49% (50 to 100%). Advisors' risk tolerance is defined as low (high) when the score from the bomb-game lies in the range from 1 to 49 (from 50 to 100).

Table A.5
Summary statistics of heterogeneity of professional advice for Wealthy Retiree based on advisors' characteristics

		advisors' allocation		advisors' risk tol	
		low	high	low	high
low risk tol	Min	0	0	0	0
	1Q	0.00	1.62	0.00	1.34
	Median	7.67	13.67	8.92	13.23
	Mean	11.57	16.02	12.62	15.63
	3Q	19.51	25.53	21.14	24.98
	Max	100	100	100	100
	sd	12.92	14.83	13.64	14.62
	IQR	19.51	23.91	21.14	23.65
medium risk tol	min	0	0	0	0
	1Q	8.72	13.89	9.91	13.34
	Median	20.86	26.12	22.09	25.62
	Mean	21.96	26.76	23.21	26.23
	3Q	32.95	38.26	34.40	37.71
	Max	100	100	100	100
	sd	16.18	17.15	16.66	17.02
	IQR	24.24	24.37	24.49	24.37
high risk tol	min	0	0	0	0
	1Q	19.54	23.90	20.68	23.29
	Median	33.84	38.48	35.10	37.86
	Mean	34.51	38.87	35.80	38.23
	3Q	48.29	53.15	49.73	52.52
	Max	100	100	100	100
	sd	20.47	21.04	20.81	20.94
	IQR	28.75	29.25	29.04	29.23

Notes: Advisors' own allocation is defined as low (high), when advisors' own private risky asset share lies in the range from 0 to 49% (50 to 100%). Advisors' risk tolerance is defined as low (high) when the score from the bomb-game lies in the range from 1 to 49 (from 50 to 100).

Table A.6
Summary statistics of heterogeneity of professional advice for Wealthy 50-65 based on advisors' characteristics

		advisors' allocation		advisors' risk tol	
		low	high	low	high
low risk tol	Min	0	0	0	0
	1Q	12.70	19.73	13.85	19.54
	Median	25.72	33.24	27.19	32.62
	Mean	26.63	33.48	28.19	32.96
	3Q	38.75	46.35	41.04	45.46
	max	100	100	100	100
	sd	17.99	19.01	18.53	18.95
	IQR	26.05	26.62	27.19	25.91
low risk tol	Min	0	0	0	0
	1Q	26.77	33.39	28.11	32.87
	Median	39.03	45.80	40.54	45.18
	Mean	39.02	45.55	40.69	44.86
	3Q	51.14	57.69	53.06	57.00
	Max	100	100	100	100
	sd	17.89	18.08	18.16	18.17
	IQR	24.37	24.29	24.95	24.13
low risk tol	Min	0	0	0	0
	1Q	38.60	44.59	40.07	43.81
	Median	52.02	58.10	53.60	57.43
	Mean	52.04	57.80	53.65	57.05
	3Q	65.50	71.34	67.20	70.68
	Max	100.00	100.00	100.00	100.00
	sd	19.83	19.70	19.96	19.82
	IQR	26.91	26.75	27.13	26.87

Notes: Advisors' own allocation is defined as low (high), when advisors' own private risky asset share lies in the range from 0 to 49% (50 to 100%). Advisors' risk tolerance is defined as low (high) when the score from the bomb-game lies in the range from 1 to 49 (from 50 to 100).

Table A.7
Bayesian Hierarchical Tobit - Ex-post analysis of advisor effects
The table reports ex-post analysis of advisor effects in Bayesian hierarchical Tobit. We compute individual posterior means of predicted recommendations for an average client and regress these on advisor characteristics.

	estimate	p-value
const	23.753	0.013
‘a.Prof.Adv.=1‘	−3.569	0.001
a.Age	0.131	0.002
a.Male	1.683	0.171
a.College	−0.857	0.381
a.Income	0.439	0.621
a.RE.Wlth	−0.079	0.395
a.Fin.Wlth	−0.245	0.554
a.Curr.Alloc	2.202	0.000
a.Ret.Exp.10yrs	0.057	0.030
a.Ret.Exp.1yr	0.040	0.133
a.RiskTol.	0.046	0.016
a.Patience	−0.142	0.529

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