Algorithmic vs. Human Portfolio Choice

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Abstract

Robo-advisors that provide investment advice using risk profiling questionnaires have recently made a breakthrough in the investment management industry. The validity of these questionnaires is crucial as profiling inaccuracies can lead to a mismatch between investment proposals and retail investors' preferences. This paper uses data from a robo-advisor that makes portfolio recommendations to its potential clients and lets them choose their risk exposure after having received this recommendation. We provide evidence that although recommendations by the robo-advisor are qualitatively aligned with portfolio theory, the recommendation is heavily based on answers about financial risk taking. A large majority of clients follow the recommendation and as a result are also strongly influenced by their declared propensity to take financial risks.

Les robo-conseillers qui fournissent des conseils en investissement à l'aide de questionnaires de profilage de risque ont récemment marqué une avancée dans l'industrie de la gestion d'actifs. La

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validité de ces questionnaires est cruciale, car des imprécisions dans le profilage peuvent entraîner un décalage entre les propositions d'investissement et les préférences des investisseurs particuliers. Cet article utilise les données d'un robo-conseiller qui formule des recommandations de portefeuille à ses clients potentiels et leur permet de choisir leur niveau d'exposition au risque après avoir reçu cette recommandation. Nous montrons que, bien que les profils de risque recommandés par le robo-conseiller soient qualitativement cohérents avec la théorie des portefeuilles, la recommandation repose fortement sur les réponses relatives à la prise de risque financier. Une large majorité de clients suivent la recommandation et, par conséquent, sont également fortement influencés par leur propension déclarée à prendre des risques financiers.

Keywords Robo-advisor, Human-algorithm interaction, portfolio choice, behavioral household finance.

JEL D14 G11 G23 G41 G51

Acknowledgment We thank for useful comments François Langot, Olivier L'Haridon, Christophe Hurlin, Sébastien Saurin and participants of the Laboratoire d'Economie d'Orléans seminar, at the Risk forum in Paris, the LFIN Seminar at Louvain-la-neuve, the Investor Emotions & Asset Pricing workshop at Lille, the AFFI (French Finance Association) Conference, the ANR AESOP workshop at the University of Rennes and the Paris IdR PREF workshop on Household Finance held at the Institut Louis Bachelier. We would like to thank the two anonymous referees for their useful comments and suggestions. This research has been conducted within the PREF research initiative under the aegis of the Europlace Institut of Finance, a joint initiative by Yomoni and the University of Orléans, France.

Introduction

Robo-advisors are reshaping the wealth management industry. These automated investment platforms use algorithms to provide portfolio recommendations and manage assets, often with minimal or no human interaction (D'Acunto et al., 2019). Since their emergence in the United States in 2008 during the financial crisis (Narayanan, 2016) and more recently the COVID-19 pandemic (Gan et al., 2021), robo-advisors have grown rapidly. By lowering entry barriers and simplifying access to financial markets, they have attracted millions of clients worldwide. The digitalization of financial services has profoundly transformed financial advice (Philippon, 2019). This shift has important implications for financial intermediation, investor protection, and portfolio efficiency as robo-advisors compose and manage client portfolios without the need of a traditional financial advisor (Abraham et al., 2019).

Unlike traditional advisors, robo-advisors rely almost entirely on self-administered online questionnaires to construct investment recommendations. These questionnaires, now widespread and in many countries required by regulation (e.g., MiFID II in the EU), ask clients to report information related to their socio-economic situation, in particular their financial situation, investment goals, time horizon, and risk preferences. The responses are processed by an algorithm that assigns the client a risk profile, which in turn determines the recommended asset allocation. Although this approach reduces costs and increases scalability, it raises fundamental concerns about accuracy, personalization, and delegation. Prior work has questioned the reliability of these questionnaires. Rice (2005) highlights arbitrariness in scoring, while Foerster et al. (2014) show that questionnaire-based risk profiles explain only 13% of the variance in actual portfolio risk, rising to 31% when advisor influence is included. Lucarelli (2015) documents high misclassification rates, and Boulu-Reshef and Helleringer (2024) identify shortcomings in MiFID II compliance. Misclassified profiles may ultimately lead to inappropriate financial advice (Mullainathan et al., 2012).

This paper investigates how robo-advisors generate risk profile recommendations and how clients respond to them. Using a comprehensive dataset from France's largest robo-advisor, we analyze about 80,000 onboarding experiences between 2015 and 2023. The dataset includes clients' full questionnaire responses, algorithmic recommendations, the final portfolio choices made by clients and additional information not used by the algorithm but that could impact clients in their decisions.

Profiling scores are derived from a standardized questionnaire administered to all users, covering demographics and family characteristics (e.g., sex, age, number of children), wealth and income ranges, home ownership, nature of the investment project, investment horizon, liquidity needs, risk and loss tolerance, and financial knowledge. Every client in the dataset received a recommendation, enabling us to identify the factors driving recommended risk profiles and providing a clean empirical test of how the robo-advisor generates personalized financial advice (Capponi et al., 2022).

Our analysis makes three main contributions. First, we document how the algorithm translates client input via the questionnaire into recommended risk profiles and test the extent to which recommendations align with standard financial theory. Prior research (e.g., Rice, 2005; Foerster et al., 2014; Lucarelli, 2015) has shown that questionnaire-based profiles often explain only a small fraction of the variation in actual portfolio risk. Our setting allows us to observe both the full decision process and the final allocation, offering a cleaner test of questionnaire informativeness and predictive validity.

Second, we examine how clients react to the recommendations. Most clients follow the algorithm, but a significant minority deviates by selecting more conservative or more aggressive portfolios. This behavioral divergence offers rare insight into the intrinsic value clients place on retaining decision rights (Bartling et al., 2014) in the context of financial delegation. Prior research on delegation to algorithms suggests a preference for human advice, particularly after observing algorithmic errors (Dietvorst et al., 2015; Filiz et al., 2022). However, aversion to algorithms can be mitigated by allowing minimal control (Dietvorst et al., 2018) or increasing transparency (Yeomans et al., 2019). Other studies even report preferences for algorithmic judgment in well-defined tasks (Logg et al., 2019; Holzmeister et al., 2023; Germann and Merkle, 2023), that different investors have differentiated use of algorithms in the context (D'Hondt and Roger, 2017; Bianchi and Brière, 2024), and emphasize that the nature of the task (Castelo et al., 2019) and context matters in shaping aversion (Castelo, 2024). Our setting allows us to examine these issues using high-stakes financial choices rather than experiments (Dietvorst et al., 2015, 2018; Filiz et al., 2022).

Third, we exploit a unique feature of the platform: some variables, which are observable to the fintech and the econometrician, are not used by the algorithm. For example, gender and the type of investment project are recorded but not incorporated into the recommendation. In the case of gender, using such information would amount to outright discrimination, which explains its exclusion. This setup allows us to investigate how these characteristics nonetheless influence investors' risk profile choices, and to assess the boundaries of the information set employed by the algorithm.

Section 1 presents the subscription process. Section 2 describes the data. Section 3 studies the determinants of the recommendation formulated by the robo-advisor algorithm and how customers respond to the recommendation. We then conclude.

1. Subscription Process

1.1. Questionnaire

To open an account with the robo-advisor, potential clients begin by visiting the company's website and completing an online questionnaire, administered in French. This questionnaire gathers detailed information about each client's investment objectives, financial situation, and personal characteristics. The goal is to assess the client's risk profile and generate a personalized investment recommendation as part of the onboarding process.

The first set of questions is related to their investment: Investment goal, initial and recurring invested amount, investment horizon and saving capacity. The second set addresses their socio-demographic and economic situation: date of birth, fiscal residency, number of dependent children, income, financial and property wealth, payment of rents or mortgages and homeownership. A third set is related to their risk aversion, liquidity needs, financial knowledge and previous investment experience. The wording of the questions is reported in Appendix A.

1.2. Risk Profiles

Following the completion of the questionnaire, the robo-advisor computes a weighted score based on clients' answers and generates an investment recommendation that is a risk profile ranging from 1 to 10. Each profile relates to a portfolio, from the least risky to the riskiest, invested in three asset classes: money market funds, bond exchange traded funds (ETFs) and stock ETFs. Fees, which range between 0.9% and 1.6%, are calculated on the total amount of the contract and are deducted annually. Table 1 indicates the share of each asset class for every profile.

Table 1. Share in percentage of each asset class by risk profiles

Risk profiles	1	2	3	4	5	6	7	8	9	10
Money market assets	100	80	60	40	20	0	0	0	0	0
Bond ETFs	0	10	20	30	40	50	40	30	20	0
Stock ETFs	0	10	20	30	40	50	60	70	80	100

Profile 1 is composed exclusively of money market assets which is the less risky asset class. The proportion of bond ETFs increases from profile 1 to 6 then decreases from profile 7 to 10. The higher the profile the larger the share of stock ETFs in the portfolio, which is riskier than money market assets and bonds.

1.3. Portfolio Recommendations

Potential customers are then presented with an investment policy statement with the recommended risk profile. If they are satisfied with the recommendation, they directly go through the subscription process. If they are not, they can change it to a higher or a lower risk profile. If the requested change is equal or greater to a plus two (+2) variation from the recommended profile, the company's staff may contact the customer to review the requested change and ensure that the implications of the additional risk taken by the customer is well-understood.

2. Data and econometric strategy

2.1. Descriptive statistics

The analysis of algorithmic recommendations is performed on 136,187 recommendations, including those provided to prospects who filled in the questionnaire but did not subscribe. The analysis of clients' choices is performed on 79,874 contracts, which include 68,953 unique clients between September 2015 and December 2023. 60,556 clients (87.8%) hold only one contract, and 8,397 clients (12.2%) hold two or more contracts. As all clients subscribing to a new contract have to fill out the questionnaire again, clients with several contracts may change some of their answers to the questionnaire and may have varying risk profiles.

70.4 percent of clients are men and 29.6 percent are women. The minimum investment horizon is 2, the median at 10, the mean is 11 and the maximum is 30 years. 56.4% of the clients are homeowners. Clients' ages range from 0 (contracts open on behalf of children) to 120 years old, with a median age of 34 years old and mean age of 36. They have on average 0.75 dependent children. These age statistics are consistent with the ones reported by Todd and Seay (2020) who find that the use of a robo-advisor is associated with being younger.

The mean risk profile recommended by the robo-advisor is 6.47, with the 1st quartile at 5, the median at 7 and the 3rd quartile at 8. Figure 1 reports the proportion of recommended risk profiles.

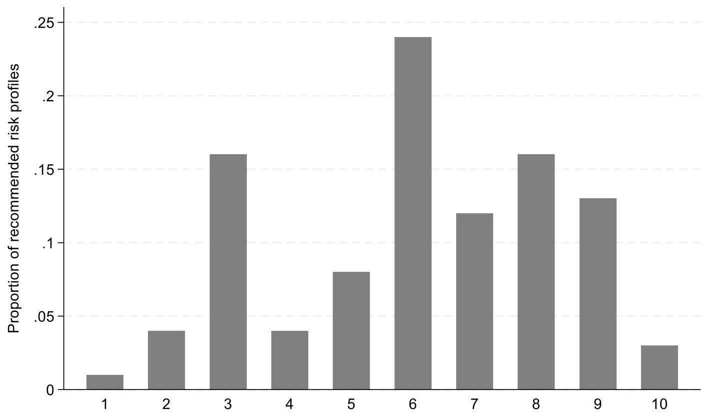

Figure 1. Proportion of recommended risk profiles

64.8% of users follow the recommendation. Of those who do not follow the recommendation, 57.0% choose a more conservative profile and 43.0% a riskier profile. Among those who deviate, the average distance from the recommendation is 2.02: +1.90 for users who move to a riskier profile and –2.14 for users who move to a safer profile.

2.2. Econometric strategy

The econometric strategy relies primarily on the causal test of the impact of questionnaires on portfolio recommendations and final choice of customers. In addition, the collection of additional information that is not used by the algorithm helps further explain the factors associated with the acceptance or modification of the recommendation.

Table A1 uses an ordinary least squares regression to study the determinants of the robo-advisor's recommendation based on most answers from the questionnaire. They are related to the investment horizon, age, number of dependent children, annual income, financial wealth, housing situation (home ownership, property assets, mortgage, rent), risk tolerance, liquidity needs, financial knowledge, and one project type, which is saving in case of hardship.

Table A2 extends the analysis of Table A1 by reporting ordinary least squares regressions of clients' final choices, using an expanded set of variables that include client characteristics that are not in the algorithm's information set.

Table A3 relies on a logistic regression to study clients' characteristics associated with accepting the robo-advisor recommendation using the same information set as in Table A2. This helps to understand the impact of economic, social and behavioral determinants of the choice to comply with the recommendation.

Table A4a and A4b refine the results of Table A3 using a logistic regression to examine the likelihood of clients deviating upward and downward from the recommendation, respectively.

3. Results

3.1. Determinants of Robo-Advisor Risk Profile Recommendations

Table A1 presents the results of an ordinary least square regression estimating how the robo-advisor generates a recommended profile score based on prospective clients' characteristics. The dependent variable is the risk profile score, and the model includes the information from the questionnaire that is used to generate the recommendation. For clarity, the results are reported in terms of their quantitative importance in the recommendation.

3.1.1. Most influential determinants

The most influential determinant is by far Risk Q2, which assesses tolerance for probabilistic loss. The question states: *"Over a period of 10 years, you are looking for an investment: – With an expected final gain of X% but with a risk of loss of Y%"*, with X={20,30,50,70} and Y={5,10,15,>15}. The four possible answers present trade-offs between higher expected returns and higher potential losses over a long horizon. Q2 has a strong impact on the recommendation: those selecting the most conservative scenario (20% gain with 5% loss) are, on average, recommended a profile 3.45 points lower than those choosing the riskiest option (see Table A1). This response leads to a substantial decrease in the risk score. Although the influence of Q2 on the recommendation is qualitatively consistent with both the literature on risk and loss aversion in portfolio allocation and with MiFID regulation, its quantitative impact may be questioned.

The second most influential determinant is declaring "Saving in case of hardship" as investment project. Customers in this situation receive risk profiles that are 2.68 points lower on average. This recommendation is consistent with the literature on lower risk exposure in case of needs of precautionary savings. Guiso et al. (1996) and Fagereng et al. (2017) show that households facing income risk and liquidity need to hold safer portfolios.

Investment horizon is the third most influential predictor. Compared to the reference category of 10 to 14 years, clients with a short investment horizon of 1 to 3 years are assigned risk profiles that are on average 1.57 points lower, indicating that the algorithm does account for the typical recommendation of reducing exposition to financial markets when investment horizons shorten. A broad literature in financial economics validates this view (Samuelson, 1969; Merton, 1969; Bodie et al., 1992; Barberis, 2000).

3.1.2. Determinants with moderate influence

Users' characteristics which produce a moderate influence on the recommendation are financial wealth, property assets, mortgage, annual income, risk preferences in terms of gains and losses, assessment of ability to hold one's positions in bearish markets, previous experience with financial markets, liquidity needs, age and number of dependent children.

With respect to financial wealth, relative to clients with less than €10,000 in financial assets, those with higher financial wealth that are recommended an increase in the risk score between 0.52 and 0.80 points. Interestingly, the coefficient plateaus at around €250,000 and above, suggesting diminishing marginal influence. This recommendation is consistent with a well-established view about the relationship between financial wealth and risk-taking. Financial advisors typically recommend wealthier clients to allocate a greater share of savings to risky assets, given their higher capacity to absorb stocks.

Similarly, homeownership and property assets are associated with a higher recommended risk profile. Homeownership increases the score by 0.28 points, which is consistent with financial advisors' common recommendation of purchasing a home before investing large amounts of funds in financial markets. Compared to clients with no property assets, those with assets exceeding €1 million are assigned risk profiles 0.38 points higher. Although property assets like financial assets act as a buffer against market volatility, the economic literature adds important nuances. Cocco (2005) and Yao and Zhang (2005) show in life-cycle calibrated models of portfolio choice that individuals for whom real estate is a higher fraction of their total wealth invest less in risky assets and in financial markets, after controlling for wealth. In addition, the presence of large adjustment costs in purchasing a home represents a consumption commitment, which tends to make households more risk averse (Grossman and Laroque, 1990; Chetty and Szeidl, 2007).

Clients with mortgages receive higher recommended risk profiles. For instance, those with monthly repayments above €3,000 are advised profiles 0.29 points higher than clients without a mortgage. This positive association is somewhat counterintuitive: one would expect mortgage repayment obligations to reduce disposable income and constrain the ability to smooth consumption in the event of a market downturn.

Annual income is also positively related to the recommended risk profile. Clients with incomes below €25,000 receive a recommended score that is 0.33 points lower than the reference group (those earning between €50,000 and €100,000), while those earning more than €150,000 receive profiles 0.17 points higher.

Risk Q1 assesses preferences for numerical couples of gains and losses. The question states: "*If you invest €10,000 over 5 years, what ratio of potential gain / potential loss would you be prepared to bear? - Potential gain of X euros / Potential loss of Y euros*" with X = {5000, 2000, 1000, 500} and Y = {2000, 1000, 400, 0}. The impact on recommendations is consistent with theoretical expectations: higher risk aversion leads to more conservatively recommended portfolio allocation. For example, clients preferring a gain/loss scenario of €1,000/€400 compared to a scenario of €5,000/€2000 see their profile reduced by 0.39 points. At the same time, it is not entirely clear why Risk Q1 exerts a much lower influence compared to Q2, although the two questions address similar dimensions of risk tolerance. Two possible explanations are that Q1 emphasizes a shorter investment horizon (5 years vs. 10 years for Q2) and that it is framed in terms of absolute gains and losses, which may not adequately capture how investors evaluate risk.

Risk Q3 is a self-assessment of one's ability to hold their position in bearish markets. It states: "*Your investment loses 10% of its value in 3 months. What do you do?*" The five possible answers are "*I reinvest to profit from this opportunity*", "*I stay patient and do not panic*", "*I sell a part to limit my potential losses*", "*I sell everything*" and "*I do not know*". Compared to clients who would remain patient, those who would sell all their assets are recommended profiles 0.27 points lower. Conversely, clients who would reinvest receive profiles 0.27 points higher. Reinvesting or remaining patient reflects an ability to remain composed during market downturns and therefore leads to more risky recommendations.

Risk Q4 helps document whether clients have previously experienced financial losses. It states: "*Have you ever suffered losses on your financial investments?*", with possible answers ranging from none, 10 percent maximum, 20 percent maximum, to over 20 percent. Experience with financial losses leads to higher recommended scores: those reporting losses of more than 20% are assigned profiles 0.49 points higher than clients with no loss experience. The implication of this question for the recommendation is less straightforward. Users who have previously incurred financial losses possess first-hand experience in dealing with investment risk, which may foster greater acceptance of market fluctuations. Conversely, such experience may also reinforce caution, consistent with the notion that prior losses increased sensitivity to risk.

Liquidity needs are assessed through two questions. Liquidity Q1 states: "*Could you need half of your placement before the end of your chosen investment term?*" The options range from "*Certainly not*" to "*Certainly*" Liquidity Q2 states: "*Could you need all the savings invested in [Name of the company] within 2 years?*" The options range from "*Certainly not*" to "*Certainly*".

Liquidity needs are associated with lower recommended risk profiles. For example, those who report needing all their funds within the next two years with certainty receive risk profiles reduced on average by 0.96 points compared to those who answer certainly not. These recommendations are consistent with the literature on precautionary savings and liquidity needs. Liquidity-constrained savers take the risk of selling their assets at the worst moment.

The older the clients, the lower the risk recommended by the algorithm, everything else equal. Relative to clients aged below 17, those over 69 are recommended a risk profile 0.50 points lower. This recommendation is broadly consistent with the literature on age and life-cycle considerations. Risk-taking is expected to decline with age because of reduced post-retirement income, health risks, and potentially greater risk aversion (Bakshi and Chen, 1994).

The number of dependent children negatively affects the recommended risk profile. Relative to childless clients, having one, two, or three or more children reduces the profile by 0.13, 0.26, and 0.34 points, respectively. Although theoretical models linking family size to portfolio choice are scarce, one may hypothesize that parents adopt more conservative positions to protect household living standards (Love, 2010), which is consistent with the recommendation. Alternatively, children could foster longer-term planning and thereby increase the willingness to invest in riskier portfolios.

3.1.3. Determinants with no or weak influence

Savers' characteristics which have weak or no statistical influence on the recommendation are rents and financial knowledge.

High rental expenses slightly reduce the recommended score. Savers paying more than €2,000 in monthly rent are recommended a risk profile lower by 0.07 compared to savers paying less than €1,000. Like mortgage payments, rents reduce disposable income and could limit the household's ability to smooth consumption in the event of adverse market shocks. From this perspective, a somewhat stronger effect on the algorithm's recommendations could have been expected.

Part of the questionnaire asks clients True/False questions that are meant to assess their financial knowledge and experience. Knowledge Q1 states "A high gain prospect implies a high risk of capital loss" (which is right). Knowledge Q2 states "An ETF is a fund in which capital is guaranteed" (which is wrong) and Knowledge Q3 states "By delegating the management of my portfolio to a management company, I renounce making any investment decisions myself on it" (which is true). After completing each question, clients benefit from feedback with some explanations about why their answer was wrong or right. Incorrectly tagging Q1, Q2, and Q3 decreases the recommendation by a small margin. For instance, incorrect answers to Q2 reduce the recommendation by 0.19 points. Although the quiz satisfies the MiFID II regulatory requirement to tailor market exposure to clients' financial knowledge, the formulation of the questions appears primarily designed to provide minimal investor education for prospects.

3.2. Determinants of clients' portfolio choices

Table A2 reports the results of an ordinary least squares regression predicting clients' risk profile choices. The specification includes all variables used by the algorithm as well as an extensive set of additional demographics, financial, and behavioral controls that the algorithm does not use. This approach serves two purposes. First, it examines whether the determinants of human portfolio choice align with those of the algorithmic portfolio recommendation. Second, it evaluates the role of out-of-algorithm variables, assessing whether they exert a significant influence on human decisions.

3.2.1. Influence of in-algorithm clients' characteristics

Overall, the findings from Table A1 are broadly validated by clients. Only a few variations emerge. The variable “Saving in case of hardship” reduces the risk score by 2.67 in Model 1, whereas in Model 2 this effect is slightly less strong as it reduced the risk score by 2.14. By contrast, the effect of “Risk Q1” is amplified: clients opting for less risky gambles display substantially lower risk profiles, with coefficients as large as –0.71 in Model 2 compared to –0.24 in Model 1. These discrepancies, however, remain relatively minor. On the whole human portfolio choices remain closely aligned with algorithmic recommendations, which is line with the fact that 64.8% of users follow the recommendation.

3.2.2. Influence of out-of-algorithm clients’ characteristics

Some of these characteristics are collected during the questionnaire phase, before a recommendation is made. Others are collected during the contracting phase, after the recommendation. A third category of information is market performance at the time of subscription.

Clients’ characteristics that were reported in the questionnaire and not used by the algorithm are investment objectives (other than “Saving in case of hardship” which is used by the algorithm) and saving capacity.

Regarding investment objectives, the questionnaire includes a preliminary question about clients’ project type. Clients may select from the following options: “Grow my savings,” “Prepare a major purchase,” “Bequeath an inheritance,” “Plan my retirement,” “Save in the event of hard times,” “Prepare a real estate investment,” “Finance my children’s studies” and “Open an account for my child.”

All coefficients associated with saving goals are statistically significant, which could be seen as consistent with goal-based investing approaches, where the type of savings project impacts investment preferences (Shefrin and Statman, 2000). Garnano and Rossi (2024), Brunel (2011), and Pan and Statman (2012) highlight that savers' risk attitudes differ depending on the underlying project. However, after taking into account other answers in the questionnaire about liquidity needs, horizon, risk preferences, etc., it is hard to interpret exactly what investment goals capture.

Saving capacity ("How much money can you put aside at the end of the month?") is positively correlated with risk-taking, and while the coefficients are statistically significant, their quantitative impact is weak.

Clients' characteristics that were reported in the contract, thus after the recommendation, and that were not used by the algorithm are clients' profession, gender (derived from the civility in the contract), matrimonial situation and opting for a securities account.

Male clients are significantly more likely to choose higher risk profiles. The quantitative impact is small (+0.098) but still notable given that the regression includes a large set of potential confounding factors and that two thirds of subscribers follow the recommendation of a gender-blind algorithm. This result is consistent with the literature highlighting gender differences in risk attitudes (Byrnes et al., 1999) and in particular in finance (Sunden and Surette, 1998; Agnew et al., 2003).

Marital status has neither a strong nor significant effect contrary to what a few articles suggest (Barber and Odean, 2001, Agnew et al., 2003, Grable, 2000; Bertocchi et al., 2011).

The algorithm does not distinguish between the two types of saving account that users can choose. The first one, called "assurance vie," is a tax-favored saving product in which savers are offered a menu of mutual funds. The second type of account is a regular securities account, called "compte titre ordinaire" (CTO), which gives access to a much broader set of individual stocks and mutual funds. Only a minority of users have selected a regular securities account in our dataset compared to life insurance accounts. Still, the choice of a regular securities account may signal more sophisticated, experienced or knowledgeable investors. Contrary to this hypothesis, holders of regular securities accounts are not found to choose riskier profiles.

3.2.3. Market performance

Market performance is defined as the annual rate of return of a broad stock index (MSCI World). Savers could choose riskier investment in periods of bull markets (Direr and Yayi, 2014). Although statistically significant, recent market performance is not positively associated with choosing higher risk profiles.

3.3. Client Compliance with Robo-Advisor Recommendation

Results in Table A3 present the average marginal effects from a logit regression model in which the dependent variable is whether or not the client followed the investment recommendation provided by the robo-advisor. The aim is to identify categories of savers who are particularly prone to follow the recommendation. The analysis reveals several significant patterns.

3.3.1. Factors associated with higher compliance

The results suggest that age is positively associated with acceptance of the recommendation. Relative to the reference group (30–39 years), younger clients (18–29) are significantly less likely to comply (–1.9 percentage points), while older clients (40 and above) show progressively higher compliance. For example, clients aged 50–59 are 7 percentage points more likely to follow the recommendation, and clients over 69 show the highest compliance (+9.8 percentage points).

Clients with one child or three or more children are more likely to comply, although having two children is not significantly associated with compliance.

Clients with mortgages, especially in the €500–€3000 range, are consistently more likely to comply compared to those without a mortgage.

Among professional categories, workers, CEOs, students, and the self-employed are more likely to follow the recommendation compared to managers (reference group), while employees and inactive individuals show no significant difference.

Single and cohabiting clients are significantly more likely to comply than those in a couple.

3.3.2. Factors associated with lower compliance

Clients with longer investment horizons are less likely to conform to the recommendation although the relationship is somewhat not linear. This last result may be driven by the fact that the recommended risk profile does not increase enough with horizon or that long-term investors are more likely to plan and follow their own preferences.

Financial wealth has a consistently strong and negative association with compliance: clients with larger financial assets (e.g., over €250k) are much less likely to comply with the recommendation.

Homeowners are 2.7 percentage points less likely to comply, possibly reflecting higher financial autonomy or sophistication.

Clients who answer correctly financial knowledge questions are also significantly less likely to comply with the recommendation than clients who answer incorrectly do not know.

Clients with higher monthly saving capacity are less likely to comply, suggesting that financially stronger individuals may feel less need to follow external advice.

Men are significantly less likely to comply than women (–1.4 percentage point).

Market performance at the subscription date is negatively associated with compliance: as market performance improves, clients are slightly less likely to follow the recommendation, suggesting some optimism bias in bullish times.

3.3.3. Factors showing unclear association with compliance

No clear monotonic relationship between income and compliance is observed. Clients earning between 25k and 50k are slightly less likely to comply, while those earning over 150k show a modest increase in compliance.

Risk tolerance shows a complex relationship with compliance. Clients who prefer safer outcomes in risk tolerance questions are significantly less likely to follow the robo-advisor's recommendation. For instance, those selecting a low risk profile in Risk Q1 are 8 to 9 percentage points less likely to comply. Conversely, clients showing greater tolerance for portfolio volatility in Risk Q2 or staying invested in a downturn in Risk Q3 are more likely to follow the recommendation, which suggests that Risk Q2 may indeed be capturing a preference for lower risk.

Likewise, clients who certainly need liquidity before the end of the investment horizon (Liquidity Q1) are slightly less likely to comply, while those who expect liquidity needs in the next two years (Liquidity Q2) are significantly more likely to follow the recommendation.

Compliance varies significantly with the purpose of the investment. Clients saving for retirement or children's studies are more likely to comply, while those investing in real estate purchases are substantially less likely to follow the advice. This could potentially reflect different levels of perceived flexibility or risk tolerance across project types.

Overall, the results point to higher compliance among older, risk-tolerant, financially less educated individuals, and those with specific goals such as retirement. Conversely, financially wealthier clients, investors with long horizons and in couple are more likely to deviate from the robo-advisor's recommendation, potentially because they feel more empowered. These results highlight the importance of tailoring robo-advisory services to client profiles and improving transparency or justification of recommendations for more autonomous clients.

3.4. What variables explain upward and downward deviations from the recommendation?

Results in Table A3 inform about the propensity of various investor groups to abide by the algorithm's recommendation but do not tell in which direction those groups deviate. Tables A4a and A4b report logit regressions estimating the likelihood that clients deviate either upward (selecting a riskier portfolio than recommended) or downward (choosing a safer portfolio). Note that in the analysis of upward moves, investors with a recommended profile of 10 were excluded, as no higher profile was available. Conversely, in the analysis of downward moves, those with a recommended profile of 1 were excluded, as no lower profile was available.

3.4.1. In-algorithm determinants

With respect to investment horizon, compared to the medium-term reference group (10–14 years), shorter horizons reduce the likelihood of upward deviation (–6.0 and –5.9 percentage points for 1–3 years and 4–6 years, respectively) and show either no effect or a small negative effect on downward deviation. By contrast, long horizons are consistently associated with greater willingness to increase risk: clients with horizons over 25 years are +7.6 percentage points more likely to deviate upward and less likely to deviate downward. Those with a horizon of 7–9 years show a distinct pattern, being +2.7 percentage points more likely to deviate downward.

With respect to age, younger clients tend to deviate upward, while older ones are less likely to do so: those aged 18–29 are +2.4 points more likely to increase risk, whereas clients over 69 are –10.6 points less likely. In downward deviations, the youngest group is more likely to deviate downward, and the probability decreases steadily with age.

Having one child slightly reduces the likelihood of upward deviation (–1.2 points), with no further effect for larger families. In contrast, having children lowers the probability of downward deviation, and the effect strengthens with the number of children.

Higher annual income (>€150k) decreases upward deviation (–1.7 points) but does not predict downward deviation. By contrast, financial wealth shows opposite patterns: high-wealth clients are less likely to upgrade risk (–1.6 points) but more likely to deviate downward, with the probability increasing steadily with wealth. Property wealth is similarly linked to conservatism: those with €50k–€1M in assets or home ownership are less likely to deviate upward and more likely to deviate downward. Mortgage holders, however, are less likely to deviate upward, while mortgage levels do not significantly predict downward deviation.

Self-reported attitudes toward risk strongly predict deviations in both directions. Clients rejecting hypothetical losses (Risk Q1) or preferring safe portfolios (Risk Q2) are much less likely to deviate upward (–11 to –15 points) but substantially more likely to deviate downward, with Risk Q1 responses raising downward deviation probabilities by up to +19.6 points. Similarly, Risk Q4 responses predict greater downward deviation. Conversely, clients who say they would reinvest in case of market drops are slightly more likely to upgrade risk (+1.3 points).

Liquidity questions have mixed effects: they do not consistently predict upward deviation, but reporting potential liquidity needs decreases the likelihood of deviating downward.

Literacy is a strong determinant of behavior in both directions. Lower knowledge reduces the propensity to increase risk (–2 to –8 points for incorrect or "don't know" answers) and also reduces downward deviation (–2.4 to –4.3 points). This suggests that financially less knowledgeable clients are more likely to comply with the recommendation rather than deviate either way.

3.4.2. Out-of-algorithm determinants

Compared to the project category "savings", retirement (–5.8 points), children's studies, or inheritance projects (–5.1 points) reduce upward deviations. In contrast, real estate projects increase upward deviations (+4.1 points) but also predict higher downward deviations. Inheritance projects also increase downward deviation.

Higher self-reported saving capacity is positively associated with deviations in both directions: clients with greater saving ability are between +1.7 and +2.7 points more likely to deviate upward and are also more likely to deviate downward.

Compared to managers, workers (–3.0), students (–1.5), and independents (–1.6) are less likely to deviate upward, while workers, CEOs, and independents are also less likely to deviate downward. Other categories show limited effects.

Men are significantly more likely to increase risk (+3.7 points) and less likely to deviate downward (–2.4 points), confirming gender differences in risk attitudes. Marital status does not predict upward deviations but shows some effects on downward deviations: single and cohabiting clients are less likely to deviate downward than those in a couple.

Having a securities account (CTO) does not significantly affect deviations.

Market performance has a small but statistically significant positive effect in both directions: each unit increases the probability of upward deviation by 0.11 points and also increases downward deviation slightly.

The results show some asymmetry. Long horizons, younger age, higher saving capacity, stronger financial literacy, and tolerance for losses increase the likelihood of upward deviations. Conversely, risk aversion, financial and property wealth, conservative projects, and older age drive downward deviations. In both cases, clients with lower knowledge, less clear goals, or liquidity needs are more likely to comply with algorithmic recommendations.

Conclusion

This paper relies on an original and rich data set that allows the study of the determinants of a robo-advisor's portfolio recommendations in a setting in which the advice may be accepted or modified, leading to an increase or a decrease of a client's exposure to risk. It analyzes the impacts of the various factors that are associated with changes in risk profile and documents the direction of the changes as well as their severity. In doing so, the paper sheds light on the challenges of risk profiling questionnaires in their capacity to assess clients' characteristics and preferences while meeting regulatory requirements. Better understanding the potential causes that make clients deviate from risk profile recommendations may help robo-advisories whose services are dependent on designing accurate, comprehensive and valid questionnaires.

The main results are threefold. First, the findings provide evidence that the risk profiling by the algorithm broadly follows commonly accepted financial principles. Recommended risk profile increases with declared propensity to take risk, absence of short-term liquidity needs, longer investment horizon, better financial knowledge, previous experience with financial markets and financial ease. We also show that a small set of variables, especially one question about risk-return arbitrages, have a disproportionate impact on the recommendation.

Second, the algorithm's recommendations are widely accepted by clients, as 64.8% follow the suggested profile, which indicates little evidence of algorithm aversion among clients. Several factors could explain this result. Although the interpretation that clients might genuinely agree with the recommendation cannot be discarded, strong anchoring effects could be at play. Individuals may also display a general tendency to defer to perceived expert prescriptions — even when the expert is an algorithm. It should also be noted that the role of the algorithm is limited to proposing a risk profile and that the asset management remains operated by humans. A broad acceptance of the recommendation also highlights the critical importance of designing a robust algorithm, since any embedded bias is likely to be reflected in investors' portfolio choices.

Third, when clients reject the algorithm recommendation by choosing a different risk profile, the results identify key variables that are predictive of changes in risk profiles. For instance, variable that are related to the ability to bear risk i.e. older age, having children, financial wealth, attitudes towards risk and need of liquidity are associated with the changes in risk profile compared to the recommendation.

A strength of our methodology is that it considers risk profile choices immediately after the questionnaire, thereby excluding changes that could otherwise be indistinguishably driven by shifts in clients' circumstances or the economic environment. However, this strength also constitutes a limitation, as it restricts the analysis to risk profile changes observed at the end of the questionnaire. To address this limitation, further research is needed to examine risk profile adjustments over time.

References

Abraham, F., Schmukler, S. L., Tessada, J., 2019. Robo-advisors: Investing through machines. World Bank Research and Policy Briefs 134881.

Agnew, J., Balduzzi, P., Sunden, A., 2003. Portfolio choice and trading in a large 401(k) plan. American Economic Review 93, 193-215.

Bakshi, G. S., Chen, Z., 1994. Baby boom, population aging, and capital markets. Journal of Business 67, 163-202.

Barber, B. M., Odean, T., 2001. Boys Will Be Boys: Gender, Overconfidence, And Common Stock Investment. Quarterly Journal of Economics, 116, 261-292.

Barberis, N., 2000. Investing for the Long-Run when Returns are Predictable. Journal of Finance 55, 225-64.

Bartling, B., Fehr, E., Herz, H., 2014. The Intrinsic Value of Decision Rights. Econometrica 82, 2005-2039.

Bertocchi, G., Brunetti, M., Torricelli, C., 2011. Marriage and other risky assets: A portfolio approach. Journal of Banking and Finance 35, 2902-2915.

Bianchi, M., Brière, M., 2024. Human-Robot Interactions in Investment Decisions, Management Science, 10.1287/mnsc.2022.03886.

Bodie, Z., Merton, R., Samuelson, W. F., 1992. Labor Supply Flexibility and Portfolio Choice in a Life-Cycle Model. Journal of Economic Dynamics and Control 16, 427-449.

Boulu-Reshef, B., Helleringer G., 2024. Les questionnaires MiFID ne naissent pas tous égaux : stratégies de détection de la vulnérabilité potentielle des investisseurs. In : Normand-Caillère, S., Mauclair S. (Ed.), Vulnérabilité et entreprise, LexisNexis, Paris.

Brunel, J. L. P., 2011. Goal-Based Wealth Management in Practice. The Journal of Wealth Management, 14, 17-26.

Byrnes, J. P., Miller, D. C., Schafer, W. D., 1999. Gender Differences in Risk Taking: A Meta-Analysis. Psychological Bulletin 125, 367-383.

Capponi, A., Ólafsson, S., Zariphopoulou, T., 2022. Personalized Robo-Advising: Enhancing Investment Through Client Interaction. Management Science, 68, 2485-2512.

Castelo, N., Bos, M. W., Lehmann, D. R., 2019. Task-Dependent Algorithm Aversion. Journal of Marketing Research 56, 809-825.

Castelo, N., 2024. Perceived corruption reduces algorithm aversion. Journal of Consumer Psychology 34, 326-333.

Chetty, R., Szeidl, A., 2007. Consumption commitments and risk preferences. The Quarterly Journal of Economics 122, 831-877.

Cocco, J., 2005. Portfolio Choice in the Presence of Housing. The Review of Financial Studies 18, 535-67.

D'Acunto, F., Prabhala, N., Rossi, A. G., 2019. The Promises and Pitfalls of Robo-Advising. The Review of Financial Studies 32, 1983-2020.

D'Hondt, C., Roger, P., 2017. Investor Sentiment and Stock Return Predictability: The Power of Ignorance. Finance 38, 7-37.

Dietvorst, B., Simmons, J., Massey, C., 2015. Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err. Journal of Experimental Psychology: General 144, 114-126.

Dietvorst, B., Simmons, J., Massey, C., 2018. Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. Management Science 64, 983-1476.

Direr, A., Yayi, É., 2014. Les choix de portefeuille des épargnants sur le cycle boursier et le cycle de vie. Économie et Statistiques 472, 125-52.

Fagereng, A., Gottlieb, C., Guiso, L., 2017. Asset Market Participation and Portfolio Choice over the Life-Cycle. The Journal of Finance 72, 705-750.

Filiz, I., Judek, J., Lorenz, M., Spiwoks, M., 2022. Algorithm Aversion as an Obstacle in the Establishment of Robo Advisors. Journal of Risk and Financial Management 15, 353.

Foerster, S., Linnainmaa, J., Melzer, B., Previtero, A., 2014. The costs and benefits of financial advice. 2014 AEA discussing paper in the session of Household Finance.

Gan, L. Y., Khan, M. T. I., Liew, T. W., 2021. Understanding consumer's adoption of financial robo-advisors at the outbreak of the COVID-19 crisis in Malaysia. Financial Planning Review 4, 1-18.

Gargano, A., Rossi, A. G., 2024. Goal Setting and Saving in the FinTech Era. Journal of Finance 79, 1931-1976.

Germann, M., Merkle, C., 2023. Algorithm Aversion in Delegated Investing. Journal of Business Economics 93, 1691-1727.

Grable, J. E., 2000. Financial Risk Tolerance and Additional Factors That Affect Risk Taking in Everyday Money Matters. Journal of Business and Psychology 14, 625-630.

Grossman, S. J., & Laroque, G., 1990. Asset Pricing and Optimal Portfolio Choice in the Presence of Illiquid Durable Consumption Goods. Econometrica 58, 25-51.

Guiso, L., Jappelli, T., Terlizzese, D., 1996. Income Risk, Borrowing Constraints, and Portfolio Choice. The American Economic Review 86, 158-172.

Holzmeister, F., Holmén, M., Kirchler, M., Stefan, M., Wengström, E., 2023. Delegation Decisions in Finance. Management Science 69, 4828-4844.

Love, D. A., 2010. The Effect of Marital Status on Savings and Portfolio Choice. Review of Financial Studies 23, 385-432.

Lucarelli, C., Uberti, P., Brighetti, G., 2015. Misclassifications in financial risk tolerance. Journal of Risk Research 18, 467-482.

Merton, R. C., 1969. Lifetime portfolio selection under uncertainty: The continuous-time case. Review of Economics and Statistics 51, 247-257.

Mullainathan, S. Noeth, M., Schoar, A., 2012. The Market for Financial Advice: An Audit Study. NBER Working Papers 17929, National Bureau of Economic Research, Inc.

Narayanan, A., 2016. As Robo Advisors Go Viral, Where Do Traditional Money Managers Go? Investor's Business Daily. Accessed: March 31, 2022.

Pan, C. H., Statman, M., 2012. Questionnaires of Risk Tolerance, Regret, Overconfidence, and Other Investor Propensities. Journal of Investment Consulting 13, 54-63.

Philippon, T., 2019. The FinTech Opportunity. In: Agnew, J., Mitchell, O. S. (Ed.), The Disruptive Impact of FinTech on Retirement Systems (Oxford, 2019; online edn, Oxford Academic, 24 Oct. 2019).

Rice, D., 2005. Variance in risk tolerance measurement: Toward a uniform solution. Golden Gate University.

Samuelson, P., 1969. Lifetime portfolio selection by dynamic stochastic programming. The Review of Economics and Statistics 51, 239-246.

Shefrin, H., Statman, M., 2000. Behavioral Portfolio Theory. Journal of Financial and Quantitative Analysis 35, 127-151.

Sunden, A. E., Surette, B. J., 1998. Gender Differences in the Allocation of Assets in Retirement Savings Plans. American Economic Review Papers and Proceedings 88, 207-211.

Todd, T. M., Seay, M. C., 2020. Financial attributes, financial behaviors, financial-advisor-use beliefs, and investing characteristics associated with having used a robo-advisor. Financial Planning Review 3, e1104.

Yao, R., Zhang, H. H., 2005. Optimal Consumption and Portfolio Choices with Risky Housing and Borrowing Constraints. Review of Financial Studies 18, 197-239.

Yeomans M, Shah A, Mullainathan S, Kleinberg J., 2019. Making sense of recommendations. Journal of Behavioral Decision Making 32: 403-414.

Appendix A. Questionnaire

Q: What is your project?

- Grow my savings
- Prepare a major purchase
- Bequeath an inheritance
- Plan my retirement
- Save in the event of hard times
- Prepare a real estate investment
- Finance my children's studies
- Open an account for my child

Q: How much money would you like to invest in [Name of the company] to start?
Answer entered in euros

Q: How much money would you like to invest every month?
Answer entered in euros

Q: How long would you like to invest your money for?
Answer entered in years

Q: What is your date of birth?
Answer entered in day/month/year format

Q: Are you a fiscal resident of France?

- Yes
- No

Q: Do you have dependent children?

- None
- One Child
- Two Children
- Three Children or more

Q: What is the annual revenue of your household?

- Less than 25K
- Between 25K and 50K
- Between 50K and 100K
- Between 100K and 150K
- More than 150k

Q: Are you the owner of your main residence?

- Yes
- No

Q: How much do you repay each month for your mortgage?
Answer entered in euros

Q: What is the value of your property assets?

Answer entered in euros

Q: What is the estimated value of your financial assets?
Answer entered in euros

Q: How much can you put aside at the end of the month?
Answer entered in euros

Liquidity Q1: Could you need all the savings held with [Name of the company] within the next two years?

- Certainly not
- Probably not
- Probably
- Certainly

Liquidity Q2: Could you need half of your investment before the end of the selected investment period?

- Certainly not
- Probably not
- Probably
- Certainly

Q: Have you ever invested money in a life insurance contract, securities account or stock savings plan (PEA)?

- Yes
- No

Knowledge Q1: “A high gain prospect implies a high risk of capital loss.”

- True
- False
- I do not know

Knowledge Q2: “An ETF is a fund for which the capital is guaranteed.”

- True
- False
- I do not know

Knowledge Q3: “By delegating the management of my portfolio to a management company, I renounce making any investment decisions myself on it.”

- True
- False
- I do not know

Risk Q4: Have you already endured losses on your financial investments?

- No, I have not endured a loss on my financial investments
- Yes, of 10% maximum
- Yes, of 20% maximum
- Yes, of more than 20%

Risk Q1: What profit/loss ratio are you willing to accept by investing €10,000 over 5 years? There is no right or wrong answer.

- Potential gain of €5,000 / Potential loss of €2,000
- Potential gain of €2,000 / Potential loss of €1,000
- Potential gain of €1,000 / Potential loss of €400
- Potential gain of €500 / Potential loss of €0

Risk Q2: What profit/loss ratio are you willing to accept by investing over 10 years?

- With an expected final gain of 20%, but with a risk of loss of 5%
- With an expected final gain of 30%, but with a risk of loss of 10%
- With an expected final gain of 50%, but with a risk of loss of 15%
- With an expected final gain of 70%, but with a risk of loss above 15%

Risk Q3**:** If your investment loses 10% of its value in 3 months, what do you do?

- I reinvest to benefit from this opportunity
- I wait without panicking
- I sell a portion to limit my potential losses
- I sell everything
- I do not know

Appendix B. Econometric results

Table A1: Determinants of Robo-Advisor Risk Profile Recommendations

OLS Regression Results

Variable	Coefficient	Standard Error	t-statistic
Intercept	7.326***	(0.013)	562.68
Horizon 1 to 3 years	-1.572***	(0.010)	-158.18
Horizon 4 to 6 years	-0.643***	(0.007)	-88.24
Horizon 7 to 9 years	-0.028***	(0.008)	-3.74
Horizon 10 to 14 years	ref	—	—
Horizon 15 to 19 years	0.028**	(0.009)	3.26
Horizon 20 to 25 years	0.054***	(0.008)	6.64
Horizon > 25 years	0.076***	(0.015)	5.24
Age 0 to 17	0.257***	(0.010)	25.14
Age 18 to 29	0.006	(0.007)	0.93
Age 30 to 39	ref	—	—
Age 40 to 49	-0.092***	(0.008)	-11.39
Age 50 to 59	-0.117***	(0.010)	-11.88
Age 60 to 69	-0.119***	(0.013)	-8.99
Age > 69	-0.242***	(0.020)	-12.05
Childless	ref	—	—
One child	-0.133***	(0.007)	-17.76
Two children	-0.258***	(0.008)	-32.74
Three + children	-0.342***	(0.011)	-29.90
Annual income < 25k	-0.334***	(0.009)	-38.38
Annual income 25 to 50k	-0.124***	(0.007)	-18.85
Annual income 50 to 100k	ref	—	—
Annual income 100 to 150k	0.100***	(0.009)	11.31
Annual income > 150k	0.167***	(0.014)	12.33
Financial wealth < 10k	ref	—	—
Financial wealth 10 to 50k	0.516***	(0.007)	73.24
Financial wealth 50 to 100k	0.687***	(0.009)	80.71
Financial wealth 100 to 250k	0.760***	(0.010)	79.20
Financial wealth 250 to 1000k	0.802***	(0.011)	72.63
Financial wealth > 1000k	0.800***	(0.023)	34.70
Homeowner	0.283***	(0.009)	28.33
No property assets	ref	—	—
Property assets < 10k	0.113***	(0.018)	6.41
Property assets 10 to 50k	0.177***	(0.011)	16.68
Property assets 50 to 100k	0.231***	(0.010)	22.38
Property assets 100 to 250k	0.303***	(0.009)	33.28
Property assets 250 to 1000k	0.351***	(0.009)	39.23
Property assets > 1000k	0.376***	(0.021)	18.23
No mortgage	ref	—	—
Mortgage < 500	0.213***	(0.014)	15.18
Mortgage 500 to 1000	0.245***	(0.009)	28.67
Mortgage 1000 to 2000	0.247***	(0.009)	28.64
Mortgage 2000 to 3000	0.242***	(0.015)	16.37
Mortgage > 3000	0.289***	(0.022)	13.33
Rent < 1000	ref	—	—
Rent 1000 to 2000	-0.058***	(0.011)	-5.27
Rent > 2000	-0.072**	(0.026)	-2.79
Risk tolerance Q1 5000/2000	ref	—	—

Risk tolerance Q1 2000/1000	-0.236***	(0.006)	-38.09
Risk tolerance Q1 1000/400	-0.393***	(0.008)	-47.80
Risk tolerance Q1 500/0	-0.241***	(0.012)	-19.99
Risk tolerance Q2 70/15+	ref	—	—
Risk tolerance Q2 50/15	-0.187***	(0.007)	-28.47
Risk tolerance Q2 30/10	-1.385***	(0.008)	-175.80
Risk tolerance Q2 20/5	-3.448***	(0.009)	-382.88
Risk tolerance Q3 Sell all	-0.275***	(0.031)	-8.95
Risk tolerance Q3 Sell partially	-0.186***	(0.013)	-14.37
Risk tolerance Q3 Do not know	-0.375***	(0.010)	-36.29
Risk tolerance Q3 Stay patient	ref	—	—
Risk tolerance Q3 Reinvest	0.272***	(0.006)	43.14
Risk tolerance Q4 Never experienced loss	ref	—	—
Risk tolerance Q4 Loss < 10 percent	0.166***	(0.006)	27.00
Risk tolerance Q4 Loss < 20 percent	0.347***	(0.009)	39.55
Risk tolerance Q4 Loss > 20 percent	0.493***	(0.008)	61.95
Liquidity needs Q1 Certainly not	ref	—	—
Liquidity needs Q1 Probably not	-0.152***	(0.007)	-21.81
Liquidity needs Q1 Probably	-0.578***	(0.009)	-65.74
Liquidity needs Q1 Certainly	-0.693***	(0.018)	-37.62
Liquidity needs Q2 Certainly not	ref	—	ref
Liquidity needs Q2 Probably not	-0.309***	(0.006)	-50.16
Liquidity needs Q2 Probably	-0.928***	(0.011)	-87.99
Liquidity needs Q2 Certainly	-0.961***	(0.018)	-52.59
Knowledge Q1 Wrong answer	-0.137***	(0.014)	-9.66
Knowledge Q1 Do not know	-0.029*	(0.013)	-2.28
Knowledge Q1 Correct answer	ref	—	—
Knowledge Q2 Wrong answer	-0.191***	(0.010)	-19.04
Knowledge Q2 Do not know	-0.125***	(0.006)	-19.30
Knowledge Q2 Correct answer	ref	—	—
Knowledge Q3 Wrong answer	-0.126***	(0.005)	-23.27
Knowledge Q3 Do not know	-0.064***	(0.012)	-5.44
Knowledge Q3 Correct answer	ref	—	—
Project Saving in case of hardship	-2.677***	(0.014)	-190.57

*Notes: *** p<0.01, ** p<0.05, * p<0.1*

Model Statistics:

- Observations: 136,187
- R^2: 0.8426
- Adjusted R^2: 0.8425
- F-statistic: 11,570***
- RMSE: 0.882

Table A2: Client Risk Profile Choice – Including out-of-algorithm variables

OLS Regression with All Available Information

Variable	Coefficient	Standard Error	t-statistic
Intercept	7.749***	(0.034)	225.39
Horizon 1 to 3 years	-1.557***	(0.025)	-62.85
Horizon 4 to 6 years	-0.701***	(0.017)	-42.03

Horizon 7 to 9 years	-0.044**	(0.016)	-2.79
Horizon 10 to 14 years	ref	—	—
Horizon 15 to 19 years	0.133***	(0.018)	7.21
Horizon 20 to 25 years	0.156***	(0.018)	8.84
Horizon > 25 years	0.273***	(0.030)	8.95
Age 0 to 17	0.233***	(0.036)	6.44
Age 18 to 29	0.087***	(0.016)	5.63
Age 30 to 39	ref	—	—
Age 40 to 49	-0.066***	(0.018)	-3.60
Age 50 to 59	-0.116***	(0.023)	-4.98
Age 60 to 69	-0.214***	(0.032)	-6.77
Age > 69	-0.245***	(0.047)	-5.19
Childless	ref	—	—
One child	-0.094***	(0.017)	-5.42
Two children	-0.189***	(0.018)	-10.28
Three + children	-0.196***	(0.026)	-7.55
Annual income < 25k	-0.193***	(0.022)	-8.86
Annual income 25 to 50k	-0.029*	(0.015)	-1.96
Annual income 50 to 100k	ref	—	—
Annual income 100 to 150k	0.041*	(0.018)	2.24
Annual income > 150k	0.033	(0.029)	1.13
Financial wealth < 10k	ref	—	—
Financial wealth 10 to 50k	0.458***	(0.017)	27.14
Financial wealth 50 to 100k	0.522***	(0.020)	26.63
Financial wealth 100 to 250k	0.512***	(0.022)	23.69
Financial wealth 250 to 1000k	0.463***	(0.025)	18.49
Financial wealth > 1000k	0.512***	(0.052)	9.86
Homeowner	0.126***	(0.021)	5.93
No property assets	ref	—	—
Property assets < 10k	0.136***	(0.037)	3.63
Property assets 10 to 50k	0.125***	(0.022)	5.56
Property assets 50 to 100k	0.135***	(0.023)	5.93
Property assets 100 to 250k	0.161***	(0.020)	8.14
Property assets 250 to 1000k	0.201***	(0.020)	10.28
Property assets > 1000k	0.193***	(0.044)	4.39
No mortgage	ref	—	—
Mortgage < 500	0.150***	(0.032)	4.77
Mortgage 500 to 1000	0.213***	(0.019)	11.43
Mortgage 1000 to 2000	0.226***	(0.018)	12.33
Mortgage 2000 to 3000	0.232***	(0.030)	7.64
Mortgage > 3000	0.203***	(0.044)	4.59
No rent	ref	—	—
Rent < 1000	ref	—	—
Rent 1000 to 2000	-0.016	(0.023)	-0.67
Rent > 2000	-0.057	(0.053)	-1.08
Risk tolerance Q1 5000/2000	ref	—	—
Risk tolerance Q1 2000/1000	-0.389***	(0.014)	-28.44
Risk tolerance Q1 1000/400	-0.691***	(0.019)	-37.10
Risk tolerance Q1 500/0	-0.714***	(0.030)	-24.07
Risk tolerance Q2 70/15+	ref	—	—
Risk tolerance Q2 50/15	-0.478***	(0.014)	-33.70
Risk tolerance Q2 30/10	-1.729***	(0.018)	-97.17
Risk tolerance Q2 20/5	-3.326***	(0.022)	-152.96

Risk tolerance Q3 Sell all	-0.346***	(0.085)	-4.08
Risk tolerance Q3 Sell partially	-0.233***	(0.032)	-7.38
Risk tolerance Q3 Do not know	-0.372***	(0.025)	-14.71
Risk tolerance Q3 Stay patient	ref	—	—
Risk tolerance Q3 Reinvest	0.237***	(0.013)	17.65
Risk tolerance Q4 Never experienced loss	ref	—	—
Risk tolerance Q4 Loss < 10 percent	0.110***	(0.013)	8.31
Risk tolerance Q4 Loss < 20 percent	0.231***	(0.018)	12.51
Risk tolerance Q4 Loss > 20 percent	0.275***	(0.017)	16.09
Liquidity needs Q1 Certainly not	ref	—	—
Liquidity needs Q1 Probably not	-0.129***	(0.015)	-8.62
Liquidity needs Q1 Probably	-0.448***	(0.020)	-22.83
Liquidity needs Q1 Certainly	-0.522***	(0.045)	-11.60
Liquidity needs Q2 Certainly not	ref	—	—
Liquidity needs Q2 Probably not	-0.255***	(0.013)	-19.38
Liquidity needs Q2 Probably	-0.799***	(0.025)	-31.69
Liquidity needs Q2 Certainly	-0.815***	(0.047)	-17.22
Knowledge Q1 Wrong answer	-0.173***	(0.037)	-4.75
Knowledge Q1 Do not know	-0.161***	(0.034)	-4.68
Knowledge Q1 Correct answer	ref	—	—
Knowledge Q2 Wrong answer	-0.215***	(0.024)	-9.14
Knowledge Q2 Do not know	-0.181***	(0.015)	-11.85
Knowledge Q2 Correct answer	ref	—	—
Knowledge Q3 Wrong answer	-0.081***	(0.012)	-6.54
Knowledge Q3 Do not know	-0.025	(0.030)	-0.84
Knowledge Q3 Correct answer	ref	—	—
Project Saving in case of hardship	-2.140***	(0.033)	-64.84
Project type Savings	ref	—	—
Project type Important purchase	-0.137***	(0.024)	-5.76
Project type Children's studies	-0.222**	(0.071)	-3.11
Project type Real estate	-0.182***	(0.039)	-4.61
Project type Retirement	-0.181***	(0.021)	-8.51
Project type Inheritance	-0.223***	(0.031)	-7.13
No saving capacity	ref	—	—
Saving capacity < 500	ref	—	—
Saving capacity 500-1000	0.072***	(0.013)	5.42
Saving capacity 1000-2000	0.091***	(0.018)	4.91
Saving capacity > 2000	0.057*	(0.026)	2.23
Prof. category Manager	ref	—	—
Prof. category Worker	-0.110***	(0.021)	-5.18
Prof. category CEO	0.060	(0.048)	1.26
Prof. category Employee	-0.037*	(0.016)	-2.27
Prof. category Student	-0.084**	(0.028)	-2.99
Prof. category Inactive/other	-0.084	(0.046)	-1.82
Prof. category Independent	-0.042*	(0.018)	-2.40
Securities account (CTO)	-0.118	(0.252)	-0.47
Male subscriber	0.098***	(0.012)	8.24
In couple	ref	—	—
Single	-0.021	(0.018)	-1.14
In civil union	0.030	(0.018)	1.66
Separated	-0.051	(0.028)	-1.84
In cohabitation	-0.0004	(0.026)	-0.01
Widowed	-0.055	(0.061)	-0.91

Market performance	0.0016***	(0.0003)	5.20

*Notes: *** p<0.01, ** p<0.05, * p<0.1*

Model Statistics:

- Observations: 79,784
- R^2: 0.618
- Adjusted R^2: 0.617
- F-statistic: 1,517***
- RMSE: 1.472

Table A3: Client Compliance with Robo-Advisor Recommendation

Logit Regression - Average Marginal Effects

Variable	AME	Standard Error	p-value
Horizon 1 to 3 years	0.0593***	(0.0082)	<0.001
Horizon 4 to 6 years	0.0649***	(0.0054)	<0.001
Horizon 7 to 9 years	-0.0462***	(0.0049)	<0.001
Horizon 10 to 14 years	ref	—	—
Horizon 15 to 19 years	-0.0081	(0.0058)	0.160
Horizon 20 to 25 years	-0.0099*	(0.0056)	0.076
Horizon > 25 years	-0.0722***	(0.0093)	<0.001
Age 0 to 17	0.0096	(0.0116)	0.409
Age 18 to 29	-0.0190***	(0.0049)	<0.001
Age 30 to 39	ref	—	—
Age 40 to 49	0.0437***	(0.0059)	<0.001
Age 50 to 59	0.0704***	(0.0075)	<0.001
Age 60 to 69	0.0544***	(0.0101)	<0.001
Age > 69	0.0981***	(0.0154)	<0.001
Childless	ref	—	—
One child	0.0218***	(0.0056)	<0.001
Two children	0.0029	(0.0058)	0.619
Three + children	0.0290***	(0.0083)	<0.001
Annual income < 25k	-0.0040	(0.0070)	0.570
Annual income 25 to 50k	-0.0099**	(0.0046)	0.034
Annual income 50 to 100k	ref	—	—
Annual income 100 to 150k	-0.0052	(0.0057)	0.367
Annual income > 150k	0.0187**	(0.0091)	0.041
Financial wealth < 10k	ref	—	—
Financial wealth 10 to 50k	-0.0463***	(0.0055)	<0.001
Financial wealth 50 to 100k	-0.0501***	(0.0064)	<0.001
Financial wealth 100 to 250k	-0.0755***	(0.0069)	<0.001
Financial wealth 250 to 1000k	-0.0921***	(0.0080)	<0.001
Financial wealth > 1000k	-0.0864***	(0.0163)	<0.001
Homeowner	-0.0269***	(0.0067)	<0.001
No property assets	ref	—	—
Property assets < 10k	-0.0019	(0.0119)	0.875
Property assets 10 to 50k	0.0065	(0.0071)	0.360
Property assets 50 to 100k	0.0063	(0.0072)	0.385
Property assets 100 to 250k	0.0052	(0.0063)	0.408
Property assets 250 to 1000k	0.0085	(0.0062)	0.172

Property assets > 1000k	-0.0014	(0.0139)	0.922
No mortgage	ref	—	—
Mortgage < 500	0.0212**	(0.0102)	0.038
Mortgage 500 to 1000	0.0215***	(0.0060)	<0.001
Mortgage 1000 to 2000	0.0216***	(0.0058)	<0.001
Mortgage 2000 to 3000	0.0289***	(0.0096)	0.003
Mortgage > 3000	0.0167	(0.0139)	0.229
Rent < 1000	ref	—	—
Rent 1000 to 2000	-0.0008	(0.0073)	0.913
Rent > 2000	0.0173	(0.0167)	0.299
Risk tolerance Q1 5000/2000	ref	—	—
Risk tolerance Q1 2000/1000	-0.0370***	(0.0044)	<0.001
Risk tolerance Q1 1000/400	-0.0913***	(0.0060)	<0.001
Risk tolerance Q1 500/0	-0.0828***	(0.0097)	<0.001
Risk tolerance Q2 70/15+	ref	—	—
Risk tolerance Q2 50/15	0.0671***	(0.0044)	<0.001
Risk tolerance Q2 30/10	0.1115***	(0.0057)	<0.001
Risk tolerance Q2 20/5	0.0930***	(0.0070)	<0.001
Risk tolerance Q3 Sell all	0.0344	(0.0290)	0.236
Risk tolerance Q3 Sell partially	0.0107	(0.0103)	0.303
Risk tolerance Q3 Do not know	0.0245***	(0.0085)	0.004
Risk tolerance Q3 Stay patient	ref	—	—
Risk tolerance Q3 Reinvest	0.0004	(0.0042)	0.928
Risk tolerance Q4 Never experienced loss	ref	—	—
Risk tolerance Q4 Loss < 10 percent	-0.0027	(0.0042)	0.526
Risk tolerance Q4 Loss < 20 percent	-0.0128**	(0.0058)	0.027
Risk tolerance Q4 Loss > 20 percent	-0.0099*	(0.0054)	0.066
Liquidity needs Q1 Certainly not	ref	—	—
Liquidity needs Q1 Probably not	0.0060	(0.0047)	0.199
Liquidity needs Q1 Probably	0.0042	(0.0062)	0.505
Liquidity needs Q1 Certainly	-0.0280*	(0.0147)	0.057
Liquidity needs Q2 Certainly not	ref	—	—
Liquidity needs Q2 Probably not	0.0052	(0.0042)	0.213
Liquidity needs Q2 Probably	0.0064	(0.0082)	0.435
Liquidity needs Q2 Certainly	0.0621***	(0.0164)	<0.001
Knowledge Q1 Wrong answer	0.0881***	(0.0131)	<0.001
Knowledge Q1 Do not know	0.1007***	(0.0129)	<0.001
Knowledge Q1 Correct answer	ref	—	—
Knowledge Q2 Wrong answer	0.0631***	(0.0079)	<0.001
Knowledge Q2 Do not know	0.0438***	(0.0050)	<0.001
Knowledge Q2 Correct answer	ref	—	—
Knowledge Q3 Wrong answer	0.0430***	(0.0040)	<0.001
Knowledge Q3 Do not know	0.0559***	(0.0103)	<0.001
Knowledge Q3 Correct answer	ref	—	—
Project Saving in case of hardship	0.0237**	(0.0110)	0.031
Project type Savings	ref	—	—
Project type Important purchase	0.0085	(0.0077)	0.272
Project type Children's studies	0.0587**	(0.0235)	0.013
Project type Real estate	-0.0667***	(0.0123)	<0.001
Project type Retirement	0.0459***	(0.0069)	<0.001
Project type Inheritance	0.0181*	(0.0100)	0.069
Saving capacity < 500	ref	—	—
Saving capacity 500-1000	-0.0283***	(0.0042)	<0.001

Saving capacity 1000-2000	-0.0379***	(0.0057)	<0.001
Saving capacity > 2000	-0.0172**	(0.0080)	0.033
Prof. category Manager	ref	—	—
Prof. category Worker	0.0400***	(0.0070)	<0.001
Prof. category CEO	0.0423***	(0.0155)	0.007
Prof. category Employee	0.0081	(0.0052)	0.119
Prof. category Student	0.0179**	(0.0090)	0.048
Prof. category Inactive/other	-0.0111	(0.0146)	0.448
Prof. category Independent	0.0223***	(0.0056)	<0.001
Securities account (CTO)	-0.0995	(0.0781)	0.203
Male subscriber	-0.0136***	(0.0038)	<0.001
In couple	ref	—	—
Single	0.0319***	(0.0058)	<0.001
In civil union	-0.0034	(0.0057)	0.550
Separated	-0.0053	(0.0089)	0.550
In cohabitation	0.0329***	(0.0081)	<0.001
Widowed	-0.0240	(0.0193)	0.214
Market performance	-0.0015***	(0.0001)	<0.001

*Notes: *** p<0.01, ** p<0.05, * p<0.1*

Model Statistics:

- Observations: 79,784
- Log-likelihood: -50,124.32
- AIC : 100,421.2

Table A4a: Likelihood of Clients Deviating Upward from the Recommendation

Logit Regression - Average Marginal Effects

Variable	AME	Standard Error	p-value
Horizon 1 to 3 years	-0.0604***	(0.0073)	<0.001
Horizon 4 to 6 years	-0.0587***	(0.0048)	<0.001
Horizon 7 to 9 years	0.0176***	(0.0042)	<0.001
Horizon 10 to 14 years	ref	—	—
Horizon 15 to 19 years	0.0236***	(0.0049)	<0.001
Horizon 20 to 25 years	0.0320***	(0.0045)	<0.001
Horizon > 25 years	0.0758***	(0.0072)	<0.001
Age 0 to 17	-0.0088	(0.0096)	0.360
Age 18 to 29	0.0241***	(0.0040)	<0.001
Age 30 to 39	ref	—	—
Age 40 to 49	-0.0313***	(0.0051)	<0.001
Age 50 to 59	-0.0559***	(0.0070)	<0.001
Age 60 to 69	-0.0757***	(0.0100)	<0.001
Age > 69	-0.1061***	(0.0167)	<0.001
Childless	ref	—	—
One child	-0.0124**	(0.0048)	0.010
Two children	0.0008	(0.0051)	0.881
Three + children	-0.0013	(0.0073)	0.858
Annual income < 25k	0.0103	(0.0058)	0.078
Annual income 25 to 50k	0.0077	(0.0039)	0.050
Annual income 50 to 100k	ref	—	—
Annual income 100 to 150k	-0.0006	(0.0050)	0.900
Annual income > 150k	-0.0172*	(0.0083)	0.038

Financial wealth < 10k	ref	—	—
Financial wealth 10 to 50k	0.0045	(0.0044)	0.310
Financial wealth 50 to 100k	-0.0088	(0.0052)	0.091
Financial wealth 100 to 250k	-0.0087	(0.0058)	0.133
Financial wealth 250 to 1000k	-0.0167*	(0.0070)	0.017
Financial wealth > 1000k	0.0157	(0.0151)	0.296
Homeowner	-0.0003	(0.0056)	0.9517
No property assets	ref	—	—
Property assets < 10k	0.0070	(0.0093)	0.451
Property assets 10 to 50k	-0.0093	(0.0058)	0.111
Property assets 50 to 100k	-0.0133*	(0.0060)	0.028
Property assets 100 to 250k	-0.0197***	(0.0053)	<0.001
Property assets 250 to 1000k	-0.0241***	(0.0053)	<0.001
Property assets > 1000k	-0.0152	(0.0135)	0.261
No mortgage	ref	—	—
Mortgage < 500	-0.0284**	(0.0090)	0.002
Mortgage 500 to 1000	-0.0193***	(0.0052)	<0.001
Mortgage 1000 to 2000	-0.0171***	(0.0051)	<0.001
Mortgage 2000 to 3000	-0.0132	(0.0088)	0.131
Mortgage > 3000	-0.0170	(0.0131)	0.196
Rent < 1000	ref	—	—
Rent 1000 to 2000	0.0056	(0.0059)	0.343
Rent > 2000	-0.0129	(0.0143)	0.365
Risk tolerance Q1 5000/2000	ref	—	—
Risk tolerance Q1 2000/1000	-0.0232***	(0.0038)	<0.001
Risk tolerance Q1 1000/400	-0.0381***	(0.0054)	<0.001
Risk tolerance Q1 500/0	-0.1187***	(0.0094)	<0.001
Risk tolerance Q2 70/15+	ref	—	—
Risk tolerance Q2 50/15	-0.1121***	(0.0035)	<0.001
Risk tolerance Q2 30/10	-0.1534***	(0.0049)	<0.001
Risk tolerance Q2 20/5	0.0026	(0.0056)	0.640
Risk tolerance Q3 Sell all	-0.0472	(0.0298)	0.114
Risk tolerance Q3 Sell partially	-0.0124	(0.0091)	0.174
Risk tolerance Q3 Do not know	-0.0083	(0.0074)	0.266
Risk tolerance Q3 Stay patient	ref	—	—
Risk tolerance Q3 Reinvest	0.0131***	(0.0034)	<0.001
Risk tolerance Q4 Never experienced loss	ref	—	—
Risk tolerance Q4 Loss < 10 percent	-0.0157***	(0.0036)	<0.001
Risk tolerance Q4 Loss < 20 percent	-0.0138**	(0.0050)	0.006
Risk tolerance Q4 Loss > 20 percent	-0.0049	(0.0045)	0.274
Liquidity needs Q1 Certainly not	ref	—	—
Liquidity needs Q1 Probably not	-0.0148***	(0.0040)	<0.001
Liquidity needs Q1 Probably	0.0082	(0.0052)	0.112
Liquidity needs Q1 Certainly	0.0117	(0.0126)	0.352
Liquidity needs Q2 Certainly not	ref	—	—
Liquidity needs Q2 Probably not	0.0029	(0.0035)	0.408
Liquidity needs Q2 Probably	0.0325***	(0.0068)	<0.001
Liquidity needs Q2 Certainly	-0.0393**	(0.0146)	0.007
Knowledge Q1 Wrong answer	-0.0556***	(0.0112)	<0.001
Knowledge Q1 Do not know	-0.0772***	(0.0119)	<0.001
Knowledge Q1 Correct answer	ref	—	—
Knowledge Q2 Wrong answer	-0.0395***	(0.0066)	<0.001
Knowledge Q2 Do not know	-0.0402***	(0.0044)	<0.001

Knowledge Q2 Correct answer	ref	—	—
Knowledge Q3 Wrong answer	-0.0182***	(0.0034)	<0.001
Knowledge Q3 Do not know	-0.0259**	(0.0090)	0.004
Knowledge Q3 Correct answer	ref	—	—
Project type Savings	ref	—	—
Project type Important purchase	-0.0173**	(0.0064)	0.007
Project type Children's studies	-0.0750***	(0.0218)	<0.001
Project type Real estate	0.0412***	(0.0098)	<0.001
Project type Retirement	-0.0575***	(0.0061)	<0.001
Project type Inheritance	-0.0513***	(0.0103)	<0.001
Saving capacity < 500	ref	—	—
Saving capacity 500-1000	0.0233***	(0.0035)	<0.001
Saving capacity 1000-2000	0.0273***	(0.0049)	<0.001
Saving capacity > 2000	0.0170*	(0.0070)	0.016
Prof. category Manager	ref	—	—
Prof. category Worker	-0.0300***	(0.0059)	<0.001
Prof. category CEO	-0.0170	(0.0131)	0.192
Prof. category Employee	-0.0033	(0.0044)	0.453
Prof. category Student	-0.0153*	(0.0071)	0.033
Prof. category Inactive/other	-0.0088	(0.0138)	0.527
Prof. category Independent	-0.0160***	(0.0048)	<0.001
Securities account (CTO)	0.0322	(0.0644)	0.616
Male subscriber	0.0370***	(0.0034)	<0.001
In couple	ref	—	—
Single	-0.0079	(0.0050)	0.118
In civil union	0.0070	(0.0049)	0.155
Separated	0.0123	(0.0081)	0.129
In cohabitation	-0.0086	(0.0069)	0.209
Widowed	-0.0056	(0.0211)	0.790
Market performance	0.0011***	(0.0001)	<0.001

*Notes: *** p<0.01, ** p<0.05, * p<0.1*

Model Statistics:

- Observations: 75,419
- Log-likelihood: -35,159.71
- AIC = 70,491.41

Table A4b: Likelihood of Clients Deviating Downward from the Recommendation

Logit Regression - Average Marginal Effects

Variable	AME	Standard Error	p-value
Horizon 1 to 3 years	-0.0063	(0.0064)	0.328
Horizon 4 to 6 years	-0.0125**	(0.0041)	0.002
Horizon 7 to 9 years	0.0267***	(0.0035)	<0.001
Horizon 10 to 14 years	ref	—	—
Horizon 15 to 19 years	-0.0156***	(0.0043)	<0.001
Horizon 20 to 25 years	-0.0225***	(0.0044)	<0.001
Horizon > 25 years	-0.0163*	(0.0078)	0.036
Age 0 to 17	0.0315***	(0.0095)	<0.001
Age 18 to 29	-0.0077*	(0.0039)	0.046
Age 30 to 39	ref	—	—
Age 40 to 49	-0.0169***	(0.0043)	<0.001

Age 50 to 59	-0.0295***	(0.0053)	<0.001
Age 60 to 69	-0.0130	(0.0069)	0.057
Age > 69	-0.0383***	(0.0101)	<0.001
Childless	ref	—	—
One child	-0.0137***	(0.0041)	<0.001
Two children	-0.0122**	(0.0042)	0.004
Three + children	-0.0363***	(0.0061)	<0.001
Annual income < 25k	-0.0101	(0.0055)	0.068
Annual income 25 to 50k	-0.0001	(0.0034)	0.984
Annual income 50 to 100k	ref	—	—
Annual income 100 to 150k	0.0060	(0.0040)	0.136
Annual income > 150k	0.0013	(0.0063)	0.837
Financial wealth < 10k	ref	—	—
Financial wealth 10 to 50k	0.0617***	(0.0052)	<0.001
Financial wealth 50 to 100k	0.0839***	(0.0056)	<0.001
Financial wealth 100 to 250k	0.1078***	(0.0058)	<0.001
Financial wealth 250 to 1000k	0.1241***	(0.0064)	<0.001
Financial wealth > 1000k	0.1105***	(0.0115)	<0.001
Homeowner	0.0360**	(0.0049)	0.026
No property assets	ref	—	—
Property assets < 10k	-0.0145	(0.0103)	0.157
Property assets 10 to 50k	0.0015	(0.0056)	0.783
Property assets 50 to 100k	0.0089	(0.0055)	0.105
Property assets 100 to 250k	0.0210***	(0.0047)	<0.001
Property assets 250 to 1000k	0.0209***	(0.0046)	<0.001
Property assets > 1000k	0.0261**	(0.0093)	0.005
No mortgage	ref	—	—
Mortgage < 500	0.0087	(0.0074)	0.242
Mortgage 500 to 1000	0.0027	(0.0044)	0.534
Mortgage 1000 to 2000	0.0042	(0.0041)	0.315
Mortgage 2000 to 3000	0.0020	(0.0066)	0.758
Mortgage > 3000	0.0108	(0.0094)	0.247
Rent < 1000	ref	—	—
Rent 1000 to 2000	-0.0048	(0.0056)	0.390
Rent > 2000	-0.0133	(0.0122)	0.277
Risk tolerance Q1 5000/2000	ref	—	—
Risk tolerance Q1 2000/1000	0.0563***	(0.0032)	<0.001
Risk tolerance Q1 1000/400	0.1157***	(0.0042)	<0.001
Risk tolerance Q1 500/0	0.1957***	(0.0070)	<0.001
Risk tolerance Q2 70/15+	ref	—	—
Risk tolerance Q2 50/15	0.0493***	(0.0036)	<0.001
Risk tolerance Q2 30/10	0.0284***	(0.0044)	<0.001
Risk tolerance Q2 20/5	-0.1007***	(0.0062)	<0.001
Risk tolerance Q3 Sell all	0.0206	(0.0200)	0.303
Risk tolerance Q3 Sell partially	0.0083	(0.0077)	0.279
Risk tolerance Q3 Do not know	-0.0125	(0.0064)	0.052
Risk tolerance Q3 Stay patient	ref	—	—
Risk tolerance Q3 Reinvest	-0.0064	(0.0033)	0.052
Risk tolerance Q4 Never experienced loss	ref	—	—
Risk tolerance Q4 Loss < 10 percent	0.0151***	(0.0032)	<0.001
Risk tolerance Q4 Loss < 20 percent	0.0267***	(0.0042)	<0.001
Risk tolerance Q4 Loss > 20 percent	0.0329***	(0.0040)	<0.001
Liquidity needs Q1 Certainly not	ref	—	—

Liquidity needs Q1 Probably not	-0.0036	(0.0035)	0.296
Liquidity needs Q1 Probably	-0.0291***	(0.0049)	<0.001
Liquidity needs Q1 Certainly	0.0072	(0.0114)	0.529
Liquidity needs Q2 Certainly not	ref	—	—
Liquidity needs Q2 Probably not	-0.0098**	(0.0031)	0.002
Liquidity needs Q2 Probably	-0.0413***	(0.0069)	<0.001
Liquidity needs Q2 Certainly	-0.0195	(0.0129)	0.130
Knowledge Q1 Wrong answer	-0.0434***	(0.0109)	<0.001
Knowledge Q1 Do not know	-0.0244*	(0.0098)	0.013
Knowledge Q1 Correct answer	ref	—	—
Knowledge Q2 Wrong answer	-0.0323***	(0.0065)	<0.001
Knowledge Q2 Do not know	-0.0056	(0.0037)	0.136
Knowledge Q2 Correct answer	ref	—	—
Knowledge Q3 Wrong answer	-0.0271***	(0.0031)	<0.001
Knowledge Q3 Do not know	-0.0362***	(0.0081)	<0.001
Knowledge Q3 Correct answer	ref	—	—
Project type Savings	ref	—	—
Project type Important purchase	0.0147*	(0.0059)	0.013
Project type Children's studies	0.0063	(0.0163)	0.700
Project type Real estate	0.0295***	(0.0092)	0.001
Project type Retirement	0.0089	(0.0050)	0.073
Project type Inheritance	0.0261***	(0.0064)	<0.001
Saving capacity < 500	ref	—	—
Saving capacity 500-1000	0.0047	(0.0031)	0.132
Saving capacity 1000-2000	0.0136**	(0.0041)	0.001
Saving capacity > 2000	0.0077	(0.0057)	0.179
Prof. category Manager	ref	—	—
Prof. category Worker	-0.0125*	(0.0055)	0.022
Prof. category CEO	-0.0276*	(0.0121)	0.022
Prof. category Employee	-0.0049	(0.0040)	0.225
Prof. category Student	-0.0064	(0.0080)	0.424
Prof. category Inactive/other	0.0121	(0.0100)	0.226
Prof. category Independent	-0.0088*	(0.0042)	0.037
Securities account (CTO)	0.0636	(0.0532)	0.232
Male subscriber	-0.0242***	(0.0028)	<0.001
In couple	—	—	—
Single	-0.0242***	(0.0043)	<0.001
In civil union	0.0001	(0.0041)	0.987
Separated	-0.0040	(0.0063)	0.524
In cohabitation	-0.0239***	(0.0063)	<0.001
Widowed	0.0190	(0.0123)	0.121
Market performance	0.0004***	(0.0001)	<0.001

*Notes: *** p<0.01, ** p<0.05, * p<0.1*

Model Statistics:

- Observations: 79,147
- Log-likelihood: -31,486.32
- AIC : 63,092.67