Algorithmic vs. Human Portfolio Choice

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Abstract

Robo-advisors that provide investment advice online on the basis of risk profiling questionnaires have recently made a breakthrough in the investment management industry. The validity and reliability 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 users and lets them choose their risk exposure after having received this recommendation. Comprehensive information about savers' characteristics allow us to investigate how the robo-advisor's algorithm maps questionnaire's answers into recommendations and to what extent users follow or deviate from the recommendation. The results provide evidence that risk profiles recommended by the robo-advisor are qualitatively aligned with financial portfolio theory. Although a variety of information is used by the algorithm, the recommendation is heavily based on answers about financial risk

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taking. A large majority of users follow the recommendation and as a result are also strongly influenced by their declared propensity to take financial risk. Factors influencing the recommendation like age, financial wealth and short-term liquidity needs are downplayed by savers. Factors not exploited by the algorithm like saving's goals or professional occupation impact investors' portfolio choice. Gender, although not taken into account by the algorithm, still influences savers' choice after controlling for a wealth of potential confoundings.

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

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1. Introduction

Financial advising is one of the sophisticated services that has been recently disrupted by digital innovations. Traditionally, experts in financial management have relied on meeting and getting to know their users in person in order to give financial advice and provide tailored investment portfolios. The provision of financial advice via personal relationships is now challenged by robo-advisors as they provide the service in a disintermediated and automated fashion (D'Acunto et al. 2019). Appeared in 2008 in the United States during the financial crisis (Narayanan, 2016), robo-advisors use online platforms to compose and manage client portfolios without the need of a traditional financial advisor (Abraham *et al.*, 2019). By simplifying access to financial markets, they have successfully onboarded millions of customers and the number of robo-advisors has increased, notably following the global Covid-19 pandemic (Gan *et al.*, 2021).

Like traditional advisors, robo-advisors typically define investment strategies according to risk profiles and investment goals. However, unlike traditional advisors who can formulate these profiles using multiple methods, such as familiarizing themselves with their client namely by speaking to them directly, robo-advisors rely almost exclusively on the use of self-administered financial risk assessment questionnaires. These questionnaires aim at identifying investment goals and risk attitudes. They ask users about their project, investment horizon, and other objective questions such as age and income. In addition, they also include subjective questions on risk preferences. For example, they ask users how they would react to a loss on an investment or what their tolerance is for losses. Then, robo-advisors use an algorithm to generate a risk profile score. This score determines the ratios of assets invested in stocks, bonds or other less risky financial vehicles (Abraham *et al.*, 2019). Although financial risk assessment questionnaires have been made mandatory by regulation in most developed countries, there is still an ongoing debate about how accurate they are in determining meaningful risk profiles for users.

Several articles provide evidence which suggests that questionnaires in and of themselves may be insufficient to provide accurate risk profiling scores. Rice (2005) examined 131 questionnaires from investment firms and advisors in the US and found that the use of questionnaires to determine investor risk profiles is of limited reliability with the variation in risky assets in investor portfolios in the range of 5 to 15 percent, leaving most variations in answers unexplained. Similarly, Foerster *et al*. (2014) performed a standard regression analysis on questionnaire items using 190 000 Canadian brokerage accounts that took into account risk tolerance (as indicated by answers to simple hypothetical questions), investor time horizon, financial knowledge, income, net worth, age, gender and occupation. They found that the financial risk tolerance questionnaire could only explain 13 percent of variations in the share of risky assets in investor portfolios. However, when the influence of the adviser was taken into account, the share of variation in risky assets that could be explained rose to 31.6 percent. Finally, Lucarelli (2015) found that self-assessment questionnaires are low in reliability and that misclassifications resulting from questionnaires vary from 36 to 65 percent. The results from the literature pose a challenge for robo-advisors as they are greatly dependent on these types of questionnaires to determine the risk profile of investors. The validity of risk profiling questionnaires is extremely important because investment decisions depend on investors' preferences for risk and return. Inaccuracy may lead to inappropriate financial advice and unbalanced trade-offs between risk and return.

Inappropriate financial advice has also been the object of much attention in the literature and in public policy circle, as it may lead to excessive delegation of decision-rights, leading to ill-informed portfolio choices given the psychological and socio-economic profiles of clients (Mullainathan *et al*., 2012). Excessive risks may be taken when clients' willingness to engage their financial resources in risky investments is low or when their needs of liquidity in periods of economic downturns is high, which may happen exactly when their financial assets, if invested in risky investments, are likely to be decreased in value. In contrast, excessive prudence may lead to lower risk premia and in turn lower financial returns, which, in the context of long-term savings such as, e.g. retirement savings, may have a tremendous negative impact to compounded final return. Financial regulators address this question in the new MiFID II regulation (ESMA, 2022), which entered into force in 2018. The regulation strengthens investor protection notably via the improvement of the functioning of financial markets to make them more efficient, resilient and transparent so that financial advice is well-understood by clients. As human financial advisors have little incentive to report whether their proposal was not accepted by clients, it is hard to observe with certainty that the accuracy of financial advice in in-person meetings' data. Yet, studying whether or not financial advice is accepted or modified by clients is of primary importance, as from a theoretical perspective, it gives a unique insight on whether individuals' experience an intrinsic value of decision-rights (Bartling *et al.*, 2014). In the case of portfolio choice, valuing intrinsically decision-rights implies that delegating the choice of portfolio is costly. Although largely unapplied to the question of financial intermediation, this recent literature complements the above-mentioned and now long-standing literature on financial questionnaires as, in addition to studying whether financial advisors identify the preferences of clients, it allows to investigate the extent to which individuals agree with the delegation of the portfolio choice to a robo-advisor. Studying empirically this question is of up-most importance given that the results from the literature are sparse and mixed. Previous researches suggest that individuals experience algorithm aversion (Dietvorst *et al.*, 2015, Filiz *et al.*, 2022) and others suggest that there is, in the context of financial decisions, no aversion (Germann and Merkle, 2022; Holzmeister *et al*., 2022) or little aversion if participants in an experiment can opt-out from the algorithm‘s recommendation (Dietvorst *et al.*, 2018).

This paper relies on a unique data set which allows us to contribute to these two literatures. The company for which we have a comprehensive data set over the period 2015 to 2019, is the leading robo-advisor in France, with over 21,000 customers and 300 million euros under management at the end of the period. Profiling scores are based on a questionnaire common to all users which includes questions about demographics and family characteristics (sex, number of children, age), wealth and income ranges, home ownership, nature of the project, investment horizon, liquidity needs, risk and loss tolerance, and financial knowledge. The dataset includes all answers from the questionnaire as well as the algorithm's recommendations and users' profile choices. Our analysis allows us to identify the factors behind recommended risk profile scores, thus providing a clean test of the role of questionnaires and an empirical test of how the robo-advisor generates personalized financial advice (Capponi *et al*., 2022). In addition, it documents the factors that lead clients to delegate to the algorithm their portfolio choice as well as the factors that lead them to deviate from the recommendation they receive, thus expressing their intrinsic value of choice. The original contribution of this paper is to document the factors that lead users to opt-out from the algorithmic recommendation by choosing a riskier or safer risk profile. Another unique and important feature of our dataset is that it allows us to study characteristics (such as gender, investment project, etc.) which are known by clients – as they release this information for the contract – and observable by the econometrician but that are not used by the algorithm to formulate the recommendation. This additional information sheds light on the impact of characteristics which may impact the choice of a risk profile, but which did not play a role in the formulation of the recommendation.

The results provide evidence that risk profiles recommended by the robo-advisor are qualitatively aligned with financial portfolio theory. Although a variety of information is used by the algorithm, the recommendation is heavily based on answers about financial risk taking. A large majority of users follow the recommendation and as a result are also strongly influenced by their declared propensity to take financial risk. Factors influencing the recommendation like age, financial wealth or short-term liquidity needs are downplayed by savers. Factors like saving's goals or professional occupation impact investors' portfolio choice are not exploited by the algorithm. Savers' sex, although not taken into account by the algorithm, still influences their choice after controlling for a wealth of potential confoundings.

Section 2 reviews the methodology and Section 3 the data. Section 4 studies the determinants of the recommendation formulated by the robo-advisor algorithm and it further reports their impact on the choices of risk profiles that are made by users. Section 5 studies the impact of users' characteristics not used by the algorithm. Section 6 concludes.

2. Methodology

The paper relies on a comprehensive dataset of the leading robo-advisor operating in France. It includes 17,347 contracts from August 28, 2015 to February 20, 2020, excluding the contracts past this date as they may be impacted by the Covid 19 pandemic. The dataset includes information about contracts, information about users, their answers to the questionnaire, algorithm's risk profile recommendations and, finally, the risk profile chosen by users.

2.1. Questionnaire

To open an account with the robo-advisor, customers have to visit the company's website and fill out a questionnaire. The questionnaire, administered in French, collects a rich information set about customers with the aim of determining their risk profile. The first part of the questionnaire deals with customers' goals and current situation. It starts by asking potential customers their investment goal is and provides the following mutually exclusive options: increase savings, prepare a major purchase, bequeath an inheritance, plan their retirement, save in the event of hard times, prepare a real estate investment, finance their children's studies or open an account for their child. The next set of items requests customers to state how much money they would like to deposit into their investment account, the amount they would like to transfer each month, their birth date, fiscal residence, how many children they have, their annual household income, if they own their own place, how much they pay for their mortgage if they have one, the value of their property assets, their wealth, how much they can save each month and the length of their investment horizon (See Appendix A for the phrasing of the questions). The second part of the questionnaire deals with customers' risk/loss aversion, financial knowledge and liquidity needs; the phrasing of these questions is reported in Section 4.

2.2. Risk profiles

Following the completion of the questionnaire, the robo-advisor computes a weighted score based on users' answers and generates an investment profile recommendation that is a risk profile ranging from 1 to 10. The final portfolio is composed of three types of investment vehicles: money market funds, bond exchange traded funds (hereafter ETFs) and stock ETFs. Each risk profile has a different proportion of the three types ranging from the least risky to the riskiest. 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 the least risky portfolio composed exclusively of money market assets which is the less risky asset class. From profile 1 to 6, the proportion of bond exchange traded funds (hereafter ETFs) increases 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.

2.3 Recommendation

Upon the completion of the questionnaire, potential customers are presented with an investment policy statement with the recommended risk profile generated by the algorithm. If they are satisfied with the recommendation, they directly go through the subscription process. If they are not satisfied, they may change it to a higher or a lower risk profile. A change that is not substantial i.e. that leads to a plus one (+1) or minus one (-1) variation from the recommended profile is automatically granted by the interface. If the requested change is equal or greater to a plus two (+2) variation from the recommended profile, the company's staff contacts the customer to review the requested change and ensure that the implications of the additional risk taken by the customer is well-understood.

3. Data

3.1. Descriptive Statistics

The analysis is performed at the contract level and on 17,367 contracts: 16,107 contracts (92.85 percent) belong to users who subscribed only to one contract and 1240 contracts (7.15 percent) belong to users who subscribed to more than one contract. As all users subscribing to a new contract have to fill out the questionnaire again, users with several contracts may change some of their answers to the questionnaire and they may have varying risk profiles.

78 percent of users are men and 22 percent are women. 96.5 percent live in France and 90 percent are born in France. The largest sectors of employment include computer science (17 percent), banking/finance/insurance (12 percent), public administration (8 percent), and consulting (7 percent). Users' ages range from 0 (contracts open on behalf of children) to 89 years old, with a mean age of 36 years old and median age of 32. 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, for a United States-based sample using the 2015 National Financial Capability Study among 1,393 individuals, out of which 214 used a robo-advisor.

The mean risk profile recommended by the robo-advisor is 6.30. The first quartile is 5.00, the median is 6.00 and the third quartile is 8.00. Overall, 69.8 percent of users followed the recommendation, which suggest that a large proportion of them are comfortable with receiving advice from a robo-advisor, in line with the results of Holzmeister *et al.* (2022). Among the 30.2 percent who did not, 59.1 percent chose a safer profile and 40.9 percent a riskier one.4 On average, users who deviated from the recommended profile chose to raise or lower the recommended level by approximately one notch (+0.94 for users who went up and -0.97 who went down). Figure 1 reports the heat map of the recommended and chosen profiles. The graphic shows that changes to go up and down are more likely to happen at the extremity of the spectrum and that in the middle point of the spectrum, changes are more likely to be an increase in the chosen risk profile.

[4] Users who declared a project goal as "save money to get through tough times" could not choose a risk profile greater than 3.

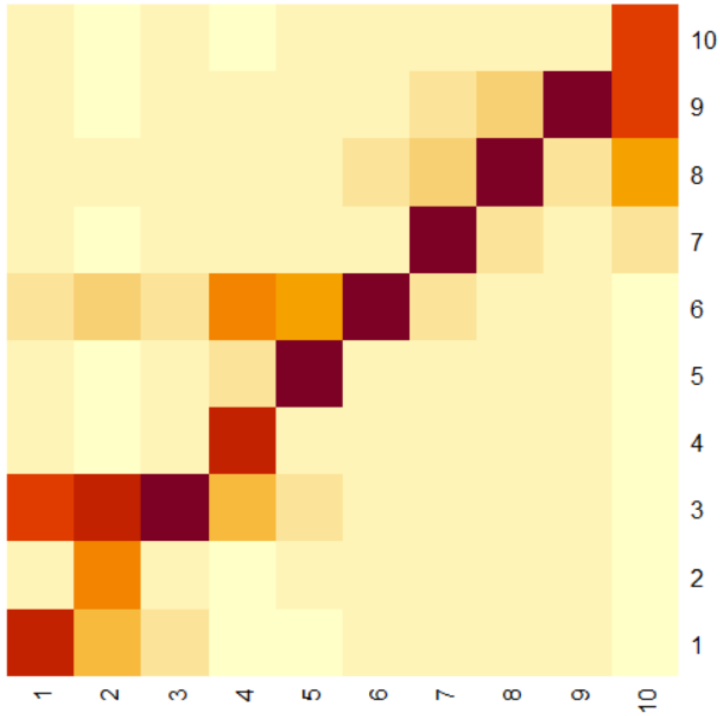

Figure 1 Heat map of recommended (x-axis) and chosen risk profiles (y-axis)

3.2. Econometric strategy

The empirical strategy first aims at studying how the robo-advisor's algorithm weighs the various information provided by the user to recommend a risk profile. The analysis is performed using Ordinary Least Squares (hereafter, OLS) regressions that are reported in Table I. The first results' column reports the impacts of users' characteristics used by the algorithm on the robo-advisor profile recommendation. The second results' column reports the impacts of users' characteristics used by the algorithm on the users' risk profile choice. In this column, the outcome variable is the risk profile used to determine their portfolio. These two models report the impacts of users' characteristics used by the algorithm both on the recommendation made by the algorithm and on the choice made by the users after receiving the recommendation.

Table II further deepens the analysis by comparing the robo-advisor's regression that is first results' column in Table I with that of the users' regression that is reported in the second results' column in Table

I, allowing us to identify which users' characteristics are associated with a deviation from the algorithm's recommendation. This allows us to compare recommendations with users' actual profiles, explain both variables by the same set of users' characteristics and test whether the coefficients of the two OLS regressions are significantly different.

The econometric strategy then uses Logistic regressions to study the impacts of users' characteristics used by the algorithm on the likelihood of users choosing a higher or a lower risk profile than the one recommended by the robo-advisor. The first results' column reports the determinants of the likelihood to switch to a higher profile. The second results' column reports the determinants of the likelihood to switch to a lower profile. Note that when studying changes up, those who had been given a recommended profile of "10" were excluded as they could not choose a higher profile even if they wanted to. Conversely, when studying changes down, those who had been given a recommended profile of "1" were excluded as they could not choose a lower profile even if they wanted to.

The analysis of the determinants of the chosen risk profiles is completed by reporting the impact of a broader set of variables which include users' characteristics that are not used, yet potentially exploitable, by the algorithm. Thus, Table IV extends the analysis displayed in Table I. The inclusion of this broader set of variables allows us to identify the characteristics that impact the choice of risk profiles and that are not used by the algorithm.

4. Determinants of algorithmically-recommended and humanly-chosen risk profiles

The results allow us to identify the extent to which each item affects the algorithm's recommendation of a risk profile as well as the users' choice of a risk profile. The relative explanatory power of each questionnaire item is compared in order to assess its importance both in generating the algorithm's recommendation as well as its role in determining users' choice. For each item, the literature is presented and then followed by the results from Table I, II, III and IV.

4.1. Investment horizon

The widely held view in literature on the impact of investment horizon on portfolio choices is that as investment horizon increases, a larger share of the portfolio should be devoted to risky assets (e.g. Samuelson, 1969; Merton, 1969; Bodie *et al.*, 1992; and Barberis, 2000).

An investor's horizon is measured in the questionnaire with the question: "How long would you like to invest your money? (in years)". The mean horizon declared by users is 10.33 years with a minimum of 2 years and a maximum of 30 years. The first quartile is 5 years, the median is 10 years and the third quartile is 12 years. Horizon has a highly significant effect (at the 0.1% threshold) on risk profiling both for the robo-advisor and for users. In accordance with theory, longer horizons lead to higher recommended and chosen risk profiles. Increasing investor's declared horizon by 10 years makes the algorithm proposing a risk profile 0.44 higher, as reported in Table I. The coefficient in users' regression is not significantly different from the one in the algorithm regression, in Table II, suggesting that the recommendation is commonly followed. As documented by the logistic regressions, a longer horizon increases the probability of investors raising their risk profile compared to the algorithm's recommendation, but only by a negligible margin, in Table III. The overall result holds when considering a broader range of variables in Table IV.

Result *Higher horizon is associated with a recommendation of a higher risk profile, which is accepted by users.*

4.2. Age

Age should be accounted for because of life cycle factors, irrespective of investment horizon. Age is expected to be negatively related to a portfolio's risky share because of a drop of income after retirement, ageing-related health issues, and, possibly increasing risk aversion with age (Bakshi and Chen, 1994). Ameriks and Zeldes (2004) and Agnew *et al*. (2003) find results that are consistent with the life cycle explanation, in that the decision to own stocks is negatively correlated with age. To the contrary, Shum and Faig (2006) and Balloch *et al*. (2014) find a positive relationship.

To test the relationship, seven age dummies were created, ranging from 0-19 years old to more than 70 years old. Once other determinants are controlled for, the algorithm recommends older users lower risk profiles, as reported in Table I, but only by a limited margin. The oldest group is recommended a risk profile higher by 0.34 points than the younger one. The results from the choice of risk profile, reported in the second results' column in Table I, show that users select a risk profile regardless of their age once other determinants are controlled for. This discrepancy between the algorithm recommendation and users' choice leads to a statistically significant difference of the comparison in Table II. This result seems to be more pronounced for the lower aged brackets as the logistic regressions report that the likelihood to switch to a higher profile is slightly increased in the younger age brackets. In addition, the likelihood to switch to a lower risk profile is slightly decreased in the middle-aged age brackets but these effects are limited in magnitude, as reported in Table III.

Result *Older savers are commended lower risk profile while actual choices do not depend on age.*

4.3. Children

Although theoretical analyses between portfolio choice and the presence of children are scarce, the hypothesis that children give higher incentives to set long term goals and invest in higher risk profiles may be formulated. On the other hand, parents may take less financial risks to preserve family's standard of living (Love, 2010).

Table I reports that recommended risk profiles are significantly lower the more children users have. The algorithm reduces the recommended risk profile by approximately 0.1 point for every additional child. Likewise, users with children prefer taking less financial risks than users without children. The comparison in Table II of the algorithm recommendation to the users' choice shows no significant difference, suggesting that the marginal effect of users' choice is negligible. This is true except for users with three or more children, who tend to increase their risk profile by 0.17 points on average compared to the one recommended by the algorithm. Consistent with this result, having children leads to a non-significant likelihood to change risk profile scores, except for users in families with three or more which is consistent with the result displayed in Table II.

Result *The algorithm recommendation to lower the risk profile as the number of children increases is partially accepted by users, as they follow it with one child but tend to disregard it when with two or more children.*

4.4. Income and financial wealth

Financial advisors typically recommend individuals with high incomes and financial wealth to invest a greater proportion of their savings in risky assets, as they can withstand greater financial shocks. On the empirical side, studies show that high-income/wealth users do invest disproportionately more in equity markets than other groups (e.g. Van Rooij *et al*., 2011; Conlin *et al*. 2015; Arrondel *et al*., 2010).

The robot-advisor conforms to this guidance. Higher income or financial wealth users are being recommended higher risk profiles, as reported in Table I. Higher income users follow the recommendation, as shown in Table II, in which, the absence of statistically significant difference between the algorithm recommendation and the users' choice is visible. Table II reports that users with higher financial wealth deviate from the recommendation in that they chose risk profiles that are statistically lower than the ones recommended by the algorithm. Table III shows that compared to users belonging to the lowest wealth ranges, the likelihood to increase the risk profile is decreased and the likelihood to lower the risk profile is increased. The algorithm recommendation to increase the risk profile of users with higher financial wealth is not followed.

Result *The algorithm recommendation to increase the risk profile is followed by users with high incomes but not by users with high financial wealth.*

4.5. Property assets and home-ownership

The literature finds mixed results regarding the relationship between homeownership and financial risk taking. Most empirical studies find that home-ownership is associated with investment in risky assets (Cardak and Wilkins, 2009; Iwaisako, 2009). This is consistent with financial advisors' common recommendation of purchasing a home before investing large amounts of funds in financial markets. 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 with the purchasing of a home represents a consumption commitment, which tends to make a household more risk averse (Grossman and Laroque, 1990; Chetty and Szeidl, 2007).

In line with common financial advice, the robo-advisor recommends home-owners and property asset holders higher risk profiles. The robo-advisor recommends home-owners a 0.39 point higher risk profile than the one that is recommended to renters. Table II shows that owning a home is associated with a decrease in the risk profile that is chosen by users compared to the one that is recommended by the robo-advisor.

Table I reports that having property assets that are worth 100,000 euros or more leads to an increase in the recommended risk profile. Table II helps to further report that the recommendation of the robo-advisor to increase the risk profile the higher the value of the property asset is accepted by users, as users' coefficients associated with their property's value are not statistically different from the robot-advisor's coefficients. The logistic regressions reported in Table III are globally consistent with those results. Further, the addition of other variables reported in Table IV does not change the results reported in Table I.

Result *The algorithm recommendation to increase the risk profile when owning a home and when a higher value of property assets is followed by users.*

4.6. Risk/Loss aversion

Risk and loss aversion are considered key preferences when formulating an investment proposal. Users' risk/loss aversion is assessed through two questions:

Risk Q1. If you invest 10,000 euros over 5 years, what ratio of potential gain / potential loss would you be prepared to bear?

- Potential gain of 5,000 euros / Potential loss of 2,000 euros
- Potential gain of 2,000 euros / Potential loss of 1,000 euros
- Potential gain of 1,000 euros / Potential loss of 400 euros
- Potential gain of 500 euros with no loss of money

The options range from, “Potential gain of 5,000 euros / Potential loss of 2,000 euros” which is a high loss tolerance or low loss aversion attitude to, “Potential gain of 500 euros with no loss of money” which is a no loss tolerance or high loss aversion attitude.

Risk Q2. Over a period of 10 years, you are looking for an investment:

- 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 greater than 15%

The options range from, “With an expected final gain of 20% but with a risk of loss of 5%” which is a low loss tolerance or high loss aversion attitude to, “With an expected final gain of 70% but with a risk of loss greater than 15%” which is a high loss tolerance or low loss aversion attitude.

Two additional questions measure users’ attitudes towards risk and loss. Risk Q3 is a self-assessment of one’s ability to hold their position in bearish markets and Risk Q4 helps document whether the users have previously experienced financial losses.

Risk Q3. Your investment loses 10% of its value in 3 months. What do you do?

- 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
- I do not know

The options range from, “I reinvest to profit from this opportunity,” which is a high loss tolerance or low loss aversion attitude to, “I sell everything,” which is a low loss tolerance or high loss aversion attitude.

Risk Q4. Have you ever suffered losses on your financial investments?

- No I have never suffered losses on my financial investments
- Yes, 10 percent maximum
- Yes, 20 percent maximum
- Yes, over 20 percent

The options range from, “No I have never suffered losses on my financial investments,” which documents the absence of loss experience to “Yes, over 20 percent,” which documents a is a low loss tolerance or high loss aversion attitude.

Reporting being risk/loss averse or that one may panic and sell everything in the presence of losses should lead to a decrease in the risk profile recommendation. The implication in terms of recommendation of the fourth question – Risk Q4 – related to past experience of financial loss is less straightforward. Users who previously have encountered financial losses have first-hand experience to apprehend financials risks. On the other hand, such users might choose safer risk profiles since, as the saying goes, “once bitten, twice shy”.

Let us investigate those questions. In Q1, 45.1 percent of users reported preferring a potential gain of 5,000 euros / potential loss of 2,000 euros, 32.8 percent a potential gain of 2,000 euros / potential loss of 1,000 euros, 16.4 percent a potential gain of 1,000 euros / potential loss of 400 euros, and 5.7 percent a potential gain of 500 euros with no loss of money.

The robo-advisor does not change its recommendation when a user prefers a ratio +1,000/-400 compared to +500/0 (the two coefficients are not significantly different). Its recommendation significantly increases when a client chooses a ratio of +2000/-1000 or +5000/-2000 (+0.125 and +0.309 respectively). Interestingly, users risk profile choices are much more sensitive to Q1’s answer than the robo-advisor is. A small increase in the self-assessed ability to accept risk and losses, even at its first incrementation, is associated to a significant increase in the chosen risk profile. Their selected risk profile increases by 0.487, 0.791 and 1.188 when they report preferring a ratio of +1,000/-400, +2000/-1000, or +5000/-2000 respectively compared to selecting a ratio of +500/0. Table II reports that the difference between the robo-advisor recommendation and the users’ choice is statistically significant. Thus, responses to these questions are very informative of users’ willingness to take risk and potentially accept the incurrence of losses as they inflate the robo-advisor recommendation. Logistic regressions reported in Table III depict a similar picture.

Users are significantly more likely to increase their risk profile proposed by the robo-advisor and less likely to decrease it, as reported in Table III.

Result *The algorithm recommendation to increase the risk profile when declaring being prepared to bear a potential gain / potential loss ratio (expressed in euro amounts) is accepted and amplified by the users.*

In question Q2, 13.4 percent chose an expected gain of 20% with a risk of loss of 5%, 24.1 percent a couple 30/10, 34.6 percent a couple 50/15 and 28.0 percent a couple 70/15+. Compared to the safest choice, all risk profile's coefficients are positive and highly significant, both for the algorithm and for users. Users' answers have a disproportionate impact on the robo-advisor's recommendation. Table I helps report that the recommended risk profile increases by 2.365 for the choice 30/10, 3.825 for the choice 50/15 and up to and 4.018 for the riskiest choice 70/15+. The effect on users' risk profile is weaker but still important, i.e. 1.867, 3.455 and 3.805 for the options 30/10, 50/15 and 70/15+ respectively. Table II shows that the decrease between the robo-advisor's recommendation and the users' profile is statistically significant. Consistent with Table II, Table III reports that users are less likely to increase the risk profile recommendation when answering the ratios 30/10 and 50/15. Similarly, users are more likely to decrease the risk profile recommendation when answering the ratios 30/10, 50/15 and 70/15+.

Result *The risk profile recommended by the algorithm is strongly increasing with the declaration of being prepared to bear a potential gain / potential loss ratio (expressed in percentages of final expected gain and loss). The recommendation is slightly attenuated by users.*

Regarding Q3, 21.1 percent would reinvest to profit from the opportunity; 68.9 percent would stay patient and not panic; 4.5 percent would sell a part to limit their losses; 0.6 percent would sell all their assets whereas 4.9 percent do not know. In regressions, the answers 'sell all' and 'sell part' are grouped due to the limited proportion of users who declared preferring selling all their assets. Compared to selling, the algorithm lowers the risk profile by 0.194 points when users do not know, and increases it by 0.133 and 0.378 points when they answer they would stay patient or reinvest respectively. This item has an equivalent directional effect on risk profiles chosen by users as the difference between the coefficients are not significantly different from zero in Table II.

Result *The algorithm recommendations following the self-assessed preferences after experiencing a loss are followed by users. In particular, the recommendation to increase the risk profile when declaring being willing to reinvest after experiencing losses is accepted by users.*

In question Q4, 45.2 percent answered they have never suffered financial losses; 26.6 reported losses up to 10%, 11.5 percent up to 20% and 17.3 percent more than 20%. Compared to not having incurred losses, reporting previous losses of 10%, 20% or more than 20% makes the algorithm recommend a higher recommended risk profiles by 0.131, 0.255 and 0.399 points respectively. All coefficients are significant at the 0.1% threshold. Users follow the recommendation and choose a higher risk profile when they experienced losses, as reported in Table I, but tend to somewhat dampen the relation between the two, as reported in Table II. Table II confirms this result, as the logistic regressions indicate that users are more likely to decrease their risk profile score and less likely to increase their profile score when having experienced losses compared to the robot recommendations. Overall, these results indicate that having experienced prior losses make users more willing to take financial risks.

Result *Having experienced prior losses leads to a recommendation for a higher risk profile and users tend to follow the recommendation.*

To sum up, there is a strong and significant impact of risk/loss tolerance, as measured by the four questions, to algorithm's recommendations and risk profiles chosen by users. This finding is consistent with an abundant literature which puts forth risk/loss aversion as a main driver of risk taking in financial markets (e.g. Dimmock and Kouwenberg, 2010). The question presenting the trade-off between expected return and probability of a loss has the strongest influence by far.

4.7. Liquidity needs

To benefit from reliable and sustained returns in financial markets necessitates a long enough investment period during which investors navigate through short and medium term volatility without needing liquidity. To the contrary, liquidity-constrained savers take the risk of selling their assets at the worst moment. Therefore, accounting for liquidity needs is an important factor to be considered when recommending a risk profile. In the questionnaire, liquidity needs are assessed through two questions:

Liquidity Q1. Could you need half of your placement before the end of your chosen investment term?

- Certainly not
- Probably not
- Probably
- Very probably

The options range from "certainly not," which indicate a low probability of liquidity needs to "very probably," which indicate a high probability of liquidity needs.

Liquidity Q2. Could you need all the savings invested in [Name of the company] within 2 years?

- Certainly not
- Probably not
- Probably
- Very probably

The options also range from "certainly not," which indicate a low probability of liquidity needs to "very probably," which indicate a high probability of liquidity needs.

Regarding the first question, 1.7% of users would need half of their placement before the end of their chosen term very probably, 12.6% probably, 58.6% probably not and 27.2% certainly not. As for the second question, 1.8% of users would need all their saving before two years very probably, 7.1% probably, 47.9% probably not and 43.2% certainly not. As very few users answer 'very probably' in the two questions, this option is grouped with 'probably' in the econometric analysis.

Compared to the answers "very probably" and "probably", users answering "probably not" and "certainly not" are recommended a risk profile 0.444 and 0.575 higher in Q1, respectively, and 1.039 and 1.427 higher in Q2, respectively, as reported in Tables I. While riskier assets are recommended when users do not express foreseeable liquidity needs, the recommendation is partly disregarded by users, as users choose risk profiles that are respectively, 0.349 and 0.442 higher in Q1 and 0.896 and 1.197 in Q2. Table

II confirms that this decrease is statistically significant. The likelihoods of deviating upward or downward from the recommendation are consistent with the OLS result (see Table III).

Result *Having a low probability of a need for liquidity leads to a recommendation for a higher risk profile and users follow partially the recommendation by accepting the recommended increase but at a level that is lower than the recommendation.*

4.8. Financial knowledge

The literature documents a positive relationship between financial knowledge and proxies of participation in the stock market. Financially literate investors have a greater tendency to participate in the stock market (van Rooij *et al*., 2011, Balloch *et al.*, 2014). Guiso *et al*. (2003) show that education has a positive and significant effect on equity ownership in a series of European countries, even after controlling for differences in age, income and wealth among investors. Campbell (2006) finds a similar result with data from the U.S. Previous research also identifies a positive relationship between financial knowledge and high wealth (Behrman *et al.,* 2012; van Rooij *et al.,* 2012; Jappelli and Padula, 2013).

On the regulatory side, MIFID 2 regulation acknowledges that investors have different levels of financial knowledge, and as a consequence, they should be given different levels of protection. Accordingly, advisers must collect customer information relating to their knowledge about the products and markets with reference to the investment proposal.

To do so, a subsequent part of the questionnaire asks users three True/False questions that are meant to assess their financial knowledge and experience:

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

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

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

For each question, the possible answers are “True” and “False”. The correct answers are respectively “True”, “False” and “True”. After completing each item, users benefit from a feedback with some explanations about why their answer was wrong or right. Correctly tagging Q1, Q2, and Q3 raises the recommendation by 0.180, 0.204 and 0.099 respectively, compared to misclassifying. All coefficients are significant at the 0.01% level. Hence, a user with a 100% score for the three questions is recommended a risk profile that is 0.483 higher. The coefficients of the dummies “I do not know” are not significant, meaning that the robot treats incorrect selection and absence of selection the same way. Table II reports that users’ coefficients are not significantly different from algorithm’s coefficients, except for Q3, for which risk profiles selected by users do not depend on the item being correctly or incorrectly classified.

Result *Having financial knowledge leads to recommended higher risk profile and users follow the recommendation.*

5. Influence of out-of-algorithm users’ characteristics

The robo-advisor does not use all of users’ characteristics to formulate a recommendation. Yet, although unused, these characteristics – which are observable by the econometrician –may influence their risk profile choice. Subsection 5.1 reports the analyses related to the extra information that is available by the robo-advisor at the time of recommendation, and as such, that could potentially contribute to the risk profile recommendation. Subsection 5.2. reports the analyses of the extra information that is not collected by the robo-advisor during the questionnaire phase but afterwards, once users have agreed upon an investment plan and started the subscription phase. This information may still contain valuable information about users’ propensity to take financial risks that is not captured by questionnaire’s variables.

All further analyses rely on information drawn from Table IV in Appendix B which compares OLS regressions of risk profiles chosen by users based on users’ characteristics used by the algorithm with a broader set of variables including users characteristics that are not used by the algorithm, and for some, potentially exploitable by the algorithm.

5.1. Pre-recommendation information

This information is provided by users when they fill out the online questionnaire.

5.1.1. Project's type

Users are asked in the questionnaire to state what their main objectives for saving are. Possible saving goals include 1) growing one's saving, 2) preparing an important purchase, 3) passing on one's wealth, 4) planning for retirement, 5) saving in case of hardship, 6) preparing a real estate project, 7) funding one's childrens' studies and 8) opening a child's account. Partisans of goal-based investing argue that project's type should be taken into account in investment plan proposals (Shefrin and Statman, 2000). Such goal-based approaches may have tremendous implications in terms of investment behavior, as investors decide first how to split their wealth among the different investment goals (Garnano and Rossi, 2022). Then, each investment goal is treated separately and a specific portfolio decision problem is solved (Brunel, 2011). Pan and Statman (2012) further suggest that savers' risk aversion differ across their saving projects.

The algorithm does not use the question about projects for its recommendation, with the exception of recommending automatically the minimal risk profile to users who chose item 5 (the project "saving in case of hardship") – this item is excluded from the econometric analysis. Compared to the baseline answer 'growing one's saving', three out of five items have a strongly significant impact on risk profile: saving for an "important purchase", a "real estate project", or "retirement" lowers their risk profile by -0.29, -0.32 and -0.18 compared to merely saving. Project types therefore impact chosen risk profiles, even after controlling for many meaningful covariates like age, family situation or horizon. This suggests that the settings of goals is associated with a decrease in the willingness to be exposed to risk.

Result *Compared to 'growing one's saving', 'planning an important purchase', a 'real estate' project, or a 'retirement' project leads to a lowering of the risk profile.*

5.2. Saving capacity

Saving abilities i.e. how much users' are able to save at the end of the month may signal information about users' financial capacity in a way that is not perfectly correlated with reported income, financial wealth and property assets. Table IV shows that users who can save more than 2000 euros have a propensity to increase their risk profile.

Result *Users with a large saving ability have a propensity to increase their risk profile.*

5.3. Post recommendation information

This information is provided by users after the recommendation has been made, when they fill in the information that is required for the contract.

5.3.1. Professional category

As education level and financial knowledge may not be fully captured by the questionnaire, professional categories may be informative of users' propensity to choose a higher risk profile. In addition, MiFID II regulations place a greater weight on professional experience in its effort to further account for sources of differences in knowledge across non-professional investors.

Compared to workers, the results show that being a manager, a CEO or a student is not associated with deviation from the algorithm recommendation. However, being an employee, an independent or in the "inactive/other situations" category is associated with a significant propensity to decrease the recommended risk profile by -0.11, -0.11 and -0.3 respectively.

Result *Being in the employee, an independent or in the "inactive/other situations" professional category is associated with a significant propensity to decrease the recommended risk profile.*

5.3.2. Type of saving account

The algorithm does not distinguish between the two types of saving account that users can choose. The first one, called "assurance vie," is a life insurance that is an investment vehicle in which savers are offered a menu of mutual funds. Its main benefit lies in its favorable tax regime. Taxes on accrued gains are significantly reduced after eight years of holding. In addition, subscribers may freely bequeath their capital with total exemption of inheritance tax up to a ceiling. The second type of account is a regular securities account, called "compte titre ordinaire" (CTO), which does not offer tax advantages but gives access to a much broader set of mutual funds and allows the trading of derivative products. Since those additional trading possibilities are not useful in investment accounts where management is fully delegated to the robot-advisor, only 897 users have selected a regular securities account in our dataset compared to 16,038 holders of a life insurance account. Still, the choice of a regular securities account may signal more sophisticated, experienced or knowledgeable investors.

In accordance with this hypothesis, regular securities account holders are found to choose a risk profile that is 0.16 higher than their counterparts.

Result *Compared to users who chose account types which entail fiscal advantages, holders of regular securities accounts have a propensity to choose a higher risk profile.*

5.3.3. Gender

Although subject to heated debates (as illustrated in e.g. Filippin and Crosetto, 2016), an abundant literature seems to document a possible link between gender and risk attitude, as reported in a meta-analysis of 150 studies that finds that women are found to be consistently more risk-averse then men in various contexts (Byrnes *et al.*, 1999). Differences in risk tolerance across genders may be particularly visible in financial decision-making. Sunden and Surette (1998) and Agnew *et al.* (2003) find that household holdings of risky assets are significantly lower for women in retirement savings plans. Barber and Odean (2001) exploit account data from a large discount brokerage and document that women hold on average less risky positions than men within their common stock portfolios

In line with the literature, a small yet significant gender effect is detected. Women choose a risk profile that is 0.05 smaller than the one chosen by men. The weakness of the effect may be explained by at least two reasons. First, it is obtained after controlling by a broad set of covariates including questions about risk aversion, financial literacy, income, and so on. Second, it is possible that a number of accounts, although held by a man or a woman, may have been opened by or in the presence of the partner or spouse.

Result *Compared to men, women have a propensity, although limited in significance and magnitude, to decrease the recommended risk profile.*

5.3.4. Marital status

Marital status could also affect risk profile choices. Barber and Odean (2001) show that the tendency to trade excessively is stronger for single than for married traders. Agnew *et al*. (2003) show that stock allocation in retirement accounts is higher among married investors than among investors who are single. Grable (2000) shows that married individuals are more risk tolerant in a sample of faculty and staff members working at a large university. Bertocchi *et al*. (2011) find that married individuals have a higher propensity to invest in risky assets than single ones.

After controlling for a broad set of covariates, being in a couple (either married or in a common-law relationship) has no significant effect on risk profile choices compared to being single and widowed.

Result *Compared to singles and windows, being in a couple does not impact risk profile choices.*

6. Conclusion

This paper relies on an original and comprehensive data set that allows the study of the accuracy of a robo-advisor's recommendations of a risk profile in a setting in which the robo-advisor's recommendation may be accepted or modified, leading to an increase or a decrease of a user's exposure to risk. This paper may thus analyze the impacts of the various factors that are associated in 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 that risk profiling questionnaires and scoring imply. Having a better understanding of the potential causes for risk profile modifications may help robo-advisories whose services are dependent on providing accurate risk profiling scores.

The main results are threefold. First of all, 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, horizon, financial knowledge, previous experience with financial markets and financial ease. Second, algorithm's recommendations are predominantly accepted by users. 69% of savers follow the recommendation. 12 % of the clients raises the recommendation and 17 % lower it. This result is consistent with a predominant absence of algorithm aversion by savers and underlines the key importance of conceiving a well-designed algorithm from the start. Third, when users reject the algorithm recommendation by choosing a different risk profile, the results document how users proceed and identify the variables that are predictive of changes in risk profiles. For instance, variables that are related to the ability to bear risk i.e. 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 to consider risk profile choices right after the questionnaire, which allows to foreclose all the changes that could be indistinguishably caused by changes in users' situation or in the economic environment. This strength is naturally also a limitation as it limits the scope of the study to only looking at risk profile changes exiting the questionnaire. In order to address this limitation, further research is required to study risk profile modifications, which, ultimately, should be considered over the lifetime of a contract.

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Appendix A. Questionnaire questions and possible responses

Question:

What is your project?

Potential answers:

- 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

Question:

How much money would you like to invest in [Name of the company] to start?

Answer entered in euros

Question:

How much money would you like to invest in [Name of the company] every month?

Answer entered in euros

Question:

How long would you like to invest your money for?

Answer entered in years

Question:

What is your date of birth?

Answer entered in day/month/year format

Question:

Are you a fiscal resident of France?

Potential Answers:

- Yes
- No

Question:

Do you have dependent children?

Potential Answers:

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

Question:

What is the annual revenue of your household?

Potential Answers:

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

Question:

Are you the owner of your main residence?

Potential Answers:

- Yes
- No

Question:

What is the value of your property assets?

Answer entered in euros

Question:

What is the estimated value of your financial assets?

Answer entered in euros

Question:

How much money can you put aside at the end of the month?

Answer entered in euros

Question:

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

- Yes
- No

Note: The second part of the questionnaire deals with risk/loss aversion, need of liquidity and financial literacy. The phrasing of the question is directly reported in Section 4.

Appendix B. Econometric results

Table I. OLS regression of the robo-advisor profile recommendation and users' risk profile choice, based on users' characteristics used by the algorithm

	Robo-advisor					Users				
Variables	Estimates	St. Err.	T-St.	P-value	Sign.	Estimates	St. Err.	T-St.	P-value	Sign.
Intercept	-0.034	0.093	-0.365	0.000	***	-0.235	0.118	-1.998	0.046	*
Horizon	0.044	0.001	32.08	0.000	***	0.046	0.002	26.87	0.000	***
Age 0 to 19	*ref.*					*ref.*				
Age 20 to 29	-0.144	0.043	-3.341	0.000	***	0.036	0.053	1.667	0.505	
Age 30 to 39	-0.140	0.036	-3.838	0.000	***	0.043	0.045	0.961	0.336	
Age 40 to 49	-0.241	0.034	-6.975	0.000	***	-0.030	0.042	-0.720	0.471	
Age 50 to 59	-0.265	0.041	-6.474	0.000	***	-0.057	0.051	-1.122	0.262	
Age 60 to 69	-0.321	0.047	-6.842	0.000	***	-0.095	0.058	-1.647	0.099	.
Age 70 +	-0.346	0.060	-5.728	0.000	***	-0.251	0.075	-3.343	0.000	***
Childless	*ref.*					*ref.*				
One child	-0.116	0.025	-4.632	0.000	***	-0.093	0.031	-2.974	0.003	**
Two children	-0.237	0.027	-8.737	0.000	***	-0.161	0.034	-4.740	0.000	***
Three + children	-0.306	0.038	-7.970	0.000	***	-0.132	0.047	-2.774	0.005	**
Annual income < 25k	*ref.*					*ref.*				
Annual income 25k to 50k	0.211	0.029	7.184	0.000	***	0.205	0.037	5.584	0.000	***
Annual income 50k to 100k	0.345	0.031	10.95	0.000	***	0.317	0.039	8.053	0.000	***
Annual income 100k to 150k	0.462	0.039	11.86	0.000	***	0.429	0.049	8.838	0.000	***
Annual income > 150k	0.536	0.046	11.682	0.000	***	0.393	0.057	6.881	0.000	***
Financial wealth < 10k	*ref.*					*ref.*				
Financial wealth 10k to 50k	0.539	0.025	20.959	0.000	***	0.273	0.032	8.469	0.000	***
Financial wealth 50k to 100k	0.744	0.030	25.023	0.000	***	0.331	0.037	8.904	0.000	***
Financial wealth 100k to 500k	0.857	0.031	27.733	0.000	***	0.358	0.039	9.258	0.000	***

Financial wealth 500k to 1000k	0.874	0.054	16.277	0.000	***	0.352	0.066	5.300	0.000	***
Financial wealth > 1000k	0.743	0.081	9.209	0.000	***	0.272	0.100	2.709	0.007	**
Home owner	0.393	0.028	14.192	0.000	***	0.256	0.034	7.401	0.000	***
No property assets	*ref.*					*ref.*				
Property assets up to 10k	0.036	0.053	0.689	0.491		0.051	0.067	0.766	0.443	
Property assets 10 to 50k	0.052	0.039	1.332	0.191		0.067	0.049	1.434	0.151	
Property assets 50 to 100k	0.096	0.039	2.486	0.183		0.114	0.048	2.353	0.018	*
Property assets 100 to 250k	0.210	0.032	6.545	0.000	***	0.152	0.040	3.806	0.000	***
Property assets 250 to 1000k	0.270	0.044	6.007	0.000	***	0.301	0.056	5.390	0.000	***
Property assets > 1000k	0.238	0.068	3.470	0.000	***	0.103	0.085	1.213	0.225	
Risk Q1 500/0	*ref.*					*ref.*				
Risk Q1 1000/400	0.034	0.041	0.2147	0.805		0.487	0.054	9.098	0.000	***
Risk Q1 2000/1000	0.125	0.042	2.992	0.002	**	0.791	0.054	14.691	0.000	***
Risk Q1 5000/2000	0.309	0.042	7.307	0.000	***	1.188	0.054	21.784	0.000	***
Risk Q2 20/5	*ref.*					*ref.*				
Risk Q2 30/10	2.365	0.030	78.356	0.000	***	1.867	0.038	48.738	0.000	***
Risk Q2 50/15	3.826	0.031	122.730	0.000	***	3.455	0.039	87.370	0.000	***
Risk Q2 70/15+	4.018	0.032	123.995	0.000	***	3.805	0.041	92.689	0.000	***
Risk Q3 Sell all or partially	*ref.*					*ref.*				
Risk Q3 I do not know	-0.194	0.052	-3.745	0.000	***	-0.258	0.066	-3.936	0.000	***
Risk Q3 Stay patient	0.133	0.038	3.542	0.000	***	0.066	0.047	1.401	0.161	
Risk Q3 Reinvest	0.378	0.041	9.138	0.000	***	0.401	0.052	7.729	0.000	***
Risk Q4 Never experienced loss	*ref.*					*ref.*				
Risk Q4 Loss up to 10 percent	0.131	0.021	6.323	0.000	***	0.101	0.026	3.905	0.000	***
Risk Q4 Loss up to 20 percent	0.255	0.028	9.004	0.000	***	0.178	0.035	5.038	0.000	***

Risk Q4 Loss > 20 percent	0.399	0.025	15.762	0.000	***	0.274	0.031	8.724	0.000	***
Liquidity Q1 Probably or very probably	*ref.*					*ref.*				
Liquidity Q1 Probably not	0.444	0.028	15.919	0.000	***	0.349	0.035	9.921	0.000	***
Liquidity Q1 Certainly not	0.575	0.033	17.131	0.000	***	0.442	0.042	10.516	0.000	***
Liquidity Q2 Probably or very probably	*ref.*					*ref.*				
Liquidity Q2 Probably not	1.039	0.035	30.059	0.000	***	0.896	0.044	20.304	0.000	***
Liquidity Q2 Certainly not	1.427	0.038	37.373	0.000	***	1.197	0.048	24.715	0.000	***
Knowledge Q1 Wrong answer	*ref.*					*ref.*				
Knowledge Q1 Does not know	0.095	0.072	1.326	0.185		0.037	0.090	0.411	0.681	
Knowledge Q1 Correct answer	0.180	0.055	3.286	0.001	***	0.183	0.068	2.679	0.007	**
Knowledge Q2 Wrong answer	*ref.*					*ref.*				
Knowledge Q2 Does not know	0.022	0.045	0.499	0.618		0.101	0.056	1.806	0.071	.
Knowledge Q2 Correct answer	0.203	0.044	4.636	0.000	***	0.180	0.055	3.292	0.000	***
Knowledge Q3 Wrong answer	*ref.*					*ref.*				
Knowledge Q3 Does not know	0.011	0.038	0.290	0.771		-0.000	0.047	-0.005	0.996	
Knowledge Q3 Correct Answer	0.099	0.018	5.548	0.000	***	0.022	0.022	1.007	0.314	

Significance levels: *: 5%, **: 1%, ***: 0.1%. Reading: users declaring an income greater than 150,000 euros are recommended a risk profiles 0.536 point higher than the ones for those whose income is less than 25,000 euros. Risk profiles actually selected by the first group is 0.393 point higher than the ones chosen by the reference group. The regression contains the full set of users' caracteristics used by the algorithm to recommend a risk profile.

Table II. Comparison of robo-advisor's and users' OLS regressions

Variables	Robo-advisor coefficients	Users' minus robo-advisor coefficients	Z	P-value	Significance of the difference
Horizon	0.044	0.002	0.897	0.369	
Age 0 to 19	*ref.*				
Age 20 to 29	-0.144	0.180	2.624	0.008	**
Age 30 to 39	-0.140	0.183	3.152	0.002	**
Age 40 to 49	-0.241	0.209	3.803	0.000	***
Age 50 to 59	-0.264	0.206	3.165	0.001	**
Age 60 to 69	-0.320	0.223	2.987	0.003	
Age 70 +	-0.347	0.098	-1.027	0.304	
Childless	*ref.*				
One child	-0.116	-0.023	0.572	0.567	
Two children	-0.237	0.063	1.759	0.078	
Three + children	-0.306	0.175	2.868	0.004	**
Annual income < 25k	*ref.*				
Annual income 25 to 50k	0.211	-0.006	-0.128	0.898	
Annual income 50 to 100k	0.345	-0.028	-0.555	0.579	
Annual income 100 to 150k	0.462	-0.031	-0.506	0.612	
Annual income > 150k	0.535	-0.141	-1.918	0.055	.
Financial wealth < 10k	*ref.*				
Financial wealth 10 to 50k	0.539	-0.265	6.434	0.000	***
Financial wealth 50k to 100k	0.744	-0.412	-8.651	0.000	***
Financial wealth 100k to 500k	0.857	-0.500	-10.094	0.000	***
Financial wealth 500k to 1000k	0.873	-0.522	-6.100	0.000	***
Financial wealth > 1000k	0.743	-0.471	-3.660	0.000	***
Home owner	0.393	-0.137	-3.086	0.002	**
No property assets	*ref.*				
Property Assets 0 to 10k	0.037	0.014	0.170	0.865	
Property Assets 10k to 50k	0.052	0.017	0.284	0.776	
Property Assets 50k to 100k	0.094	0.019	0.314	0.753	

Property Assets 100k to 250k	0.210	-0.058	-1.125	0.260	
Property Assets 250k to 1000k	0.271	0.030	-0.417	0.677	
Property Assets > 1000k	0.233	-0.130	-1.195	0.232	
Risk Q1 500/0	*ref.*				
Risk Q1 1000/400	0.010	0.477	7.034	0.000	***
Risk Q1 2000/1000	0.124	0.667	9.797	0.000	***
Risk Q1 5000/2000	0.308	0.880	12.758	0.000	***
Risk Q2 20/5	*ref.*				
Risk Q2 30/10	2.365	-0.497	-10.199	0.000	***
Risk Q2 50/15	3.825	-0.371	-7.358	0.000	***
Risk Q2 70/15+	4.018	-0.213	-4.081	0.000	***
Risk Q3 Sell all or partially	*ref.*				
Risk Q3 I do not know	-0.193	-0.065	-0.770	0.441	
Risk Q3 Stay patient	0.134	-0.068	-1.115	0.264	
Risk Q3 Reinvest	0.378	0.023	0.348	0.728	
Risk Q4 Never experienced loss	*ref.*				
Risk Q4 Loss up to 10 percent	0.131	-0.030	-0.908	0.364	
Risk Q4 Loss up to 20 percent	0.256	-0.078	-1.719	0.085	.
Risk Q4 Loss > 20 percent	0.399	-0.124	-3.075	0.002	**
Liquidity Q1 Probably or very probably	*ref.*				
Liquidity Q1 Probably not	0.443	-0.095	-2.114	0.034	*
Liquidity Q1 Certainly not	0.575	-0.132	-2.455	0.014	**
Liquidity Q2 Probably or very probably	*ref.*				
Liquidity Q2 Probably not	1.040	-0.145	-2.581	0.009	**
Liquidity Q2 Certainly not	1.427	-0.230	-3.727	0.000	***
Knowledge Q1 Wrong answer	*ref.*				
Knowledge Q1 Does not know	0.096	-0.058	0.504	0.613	
Knowledge Q1 Correct answer	0.180	-0.003	0.036	0.970	
Knowledge Q2 Wrong answer	*ref.*				
Knowledge Q2 Does not know	0.023	0.078	1.087	0.276	
Knowledge Q2 Correct answer	0.204	-0.024	-0.340	0.733	

Knowledge Q3 Wrong answer	*ref.*				
Knowledge Q3 Does not know	0.010	-0.011	-0.176	0.860	
Knowledge Q3 Correct answer	0.099	-0.077	-2.682	0.007	**

Significance levels: *: 5%, **: 1%, ***: 0.1%.

Table III. Logit regressions – Likelihood of users choosing a higher or a lower risk profile than the one recommended by the robo-advisor, based on users' characteristics used by the algorithm.

	Switch to a higher profile				Switch to a lower profile			
Variables	Aver. Marg. Eff.	St. Err.	P-value	Sign.	Aver. Marg. Eff.	St. Err.	P-value	Sign.
Horizon	0.0021	0.0004	0.0000	***	0.0001	0.0005	0.8006	
Age 0 to 19	*ref.*				*ref.*			
Age 20 to 29	0.0367	0.0136	0.0068	**	-0.0181	0.0155	0.2429	
Age 30 to 39	0.0269	0.0121	0.0262	*	-0.0067	0.0124	0.5868	
Age 40 to 49	0.0135	0.0117	0.2496		-0.0263	0.0116	0.0242	*
Age 50 to 59	0.0056	0.0143	0.6959		-0.0399	0.0138	0.0039	**
Age 60 to 69	-0.0053	0.0174	0.7605		-0.0288	0.0156	0.0664	.
Age 70 +	-0.0638	0.0280	0.7605		-0.0254	0.0195	0.1918	
Childless	*ref.*				*ref.*			
One child	-0.0102	0.0082	0.2157		-0.0049	0.0087	0.5716	
Two children	0.0014	0.0083	0.8694		-0.0344	0.0096	0.0005	***
Three + children	-0.0109	0.0087	0.2084		-0.0483	0.0136	0.0004	***
Annual income < 25k	*ref.*				*ref.*			
Annual income 25 to 50k	-0.0097	0.0081	0.2349		-0.0001	0.0115	0.9942	
Annual income 50 to 100k	-0.0132	0.0089	0.1399		0.0057	0.0120	0.6357	
Annual income 100 to 150k	-0.0293	0.0121	0.0157	*	0.0049	0.0143	0.7344	
Annual income > 150k	-0.0281	0.0148	0.0573	.	0.0311	0.0161	0.0544	.
Financial wealth < 10k	*ref.*				*ref.*			
Financial wealth 10 to 50k	-0.0303	0.0069	0.0000	***	0.1417	0.0188	0.0000	***
Financial wealth 50 to 100k	-0.0591	0.0087	0.0000	***	0.1230	0.0125	0.0000	***
Financial wealth 100 to 500k	-0.0475	0.0091	0.0000	***	0.1478	0.0127	0.0000	***
Financial wealth 500 to 1000k	-0.0335	0.0190	0.0774	.	0.1417	0.0188	0.0000	***

Financial wealth > 1000k	-0.0697	0.0322	0.0305	*	0.1357	0.0275	0.0000	***
Home-owner	-0.0138	0.0085	0.1041		0.0562	0.0102	0.0000	***
No property asset	*ref.*				*ref.*			
Property assets up to 10k	-0.0655	0.0174	0.0002	***	-0.0675	0.0237	0.0044	**
Property assets 10 to 50k	-0.0154	0.0114	0.1774		0.0007	0.0140	0.9629	
Property assets 50 to 100k	-0.0159	0.0117	0.1719		-0.0255	0.0143	0.0757	.
Property assets 100 to 250k	-0.0304	0.0098	0.0019	**	-0.0017	0.0117	0.8817	
Property assets 250 to 1000k	-0.0278	0.0152	0.0680	.	-0.0339	0.0159	0.0330	*
Property assets > 1000k	-0.0538	0.0280	0.0550	.	-0.0153	0.0226	0.4973	
Risk Q1 500/0	*ref.*				*ref.*			
Risk Q1 1000/400 *risqueQ2_2*	0.1530	0.0221	0. 0000	***	-0.1768	0.0134	0.0000	***
Risk Q1 2000/1000 *risqueQ2_3*	0.1682	0.0221	0. 0000	***	-0.2578	0.0137	0.0000	***
Risk Q1 5000/2000 *risqueQ2_4*	0.2080	0.0220	0.0000	***	-0.3458	0.0141	0.0000	***
Risk Q2 20/5 *risqueQ3_1*	*ref.*				*ref.*			
Risk Q2 30/10 *risqueQ3_2*	-0.2127	0.0133	0.0000	***	0.1455	0.0117	0.0000	***
Risk Q2 50/15 *risqueQ3_3*	-0.0557	0.0093	0.0000	***	0.1293	0.0126	0.0000	***
Risk Q2 70/15+ *risqueQ3_4*	0.0054	0.0093	0.5637		0.1121	0.0130	0.0000	***
Risk Q3 Sell all or partially	*ref.*				*ref.*			
Risk Q3 I do not know risqueQ4_3	-0.0245	0.0179	0.1717		0.0338	0.0191	0.0761	.
Risk Q3 Stay patient risqueQ4_4	-0.0110	0.0124	0.3776		0.0198	0.0139	0.1554	
Risk Q3 Reinvest risqueQ4_5	0.0203	0.0131	0.1218		0.0107	0.0153	0.4851	
Risk Q4 Never experienced loss	*ref.*				*ref.*			
Risk Q4 Loss up to 10 percent	-0.0126	0.0065	0.0528	.	0.0143	0.0075	0.0552	.
Risk Q4 Loss up to 20 percent	-0.0070	0.0089	0.24287		0.0251	0.0098	0.0107	*

Risk Q4 Loss > 20 percent	0.0161	0.0073	0.0280	*	0.0405	0.0088	0.0000	***
Liquidity Q1 Probably or very probably	*ref.*				*ref.*			
Liquidity Q1 Probably not	-0.0136	0.0084	0.1079		0.0050	0.0106	0.6373	
Liquidity Q1 Certainly not	-0.0048	0.0101	0.6321		0.0020	0.0124	0.8737	
Liquidity Q2 Probably or very probably	*ref.*				*ref.*			
Liquidity Q2 Probably not	-0.0297	0.0103	0.0038	**	0.0063	0.0135	0.6415	
Liquidity Q2 Certainly not	-0.0408	0.0113	0.0003	***	0.0398	0.0146	0.0062	*
Knowledge Q1 Wrong answer	*ref.*				*ref.*			
Knowledge Q1 Does not know	-0.0330	0.0252	0.1912		0.0502	0.0320	0.1162	
Knowledge Q1 Correct answer	0.0222	0.0178	0.2113		0.0689	0.0251	0.0061	*
Knowledge Q2 Wrong answer	*ref.*				*ref.*			
Knowledge Q2 Does not know	0.0133	0.0142	0.3488		-0.0017	0.0185	0.9280	
Knowledge Q2 Correct answer	0.0228	0.0137	0.0967	.	0.0501	0.0179	0.0051	*
Knowledge Q3 Wrong answer	*ref.*				*ref.*			
Knowledge Q3 Does not know	-0.0006	0.0124	0.9613		-0.0089	0.0149	0.5518	
Knowledge Q3 Correct answer	-0.0028	0.0055	0.6129		0.0409	0.0066	0.0000	***

Significance levels: *: 5%, **: 1%, ***: 0.1%.

Table IV. OLS regressions of risk profiles chosen by users based on users' characteristics used by the algorithm (2nd column, same as 3rd column in Table 1) and a broader set of variables including users characteristics not used but potentially exploitable by the algorithm (third column)

	Users' choice based on characteristics used by the algorithm					Users' choice based on characteristics known by the robo-advisor				
Variables	Estimates	St. Err.	T-St.	P-value	Sign.	Estimates	St. Err.	T-St.	P-value	Sign.
Intercept	-0.235	0.118	-1.998	0.046	*	-0.002	0.144	-0.015	0.988	
Horizon	0.046	0.002	26.87	0.000	***	0.047	0.002	25.98	0.000	***
Age 0 to 19	*ref.*					*ref.*				
Age 20 to 29	0.036	0.053	1.667	0.505		-0.034	0.074	-0.046	0.963	
Age 30 to 39	0.043	0.045	0.961	0.336		0.009	0.079	0.124	0.901	
Age 40 to 49	-0.030	0.042	-0.720	0.471		-0.052	0.079	-0.656	0.512	
Age 50 to 59	-0.057	0.051	-1.122	0.262		-0.036	0.084	-1.427	0.670	
Age 60 to 69	-0.095	0.058	-1.647	0.099	.	-0.060	0.092	-0.651	0.515	
Age 70 +	-0.251	0.075	-3.343	0.000	***	-0.234	0.107	-2.190	0.029	*
Childless	*ref.*					*ref.*				
One child	-0.093	0.031	-2.974	0.003	**	-0.086	0.034	-2.545	0.011	**
Two children	-0.161	0.034	-4.740	0.000	***	-0.151	0.037	-4.092	0.000	***
Three + children	-0.132	0.047	-2.774	0.005	**	-0.110	0.050	-2.196	0.028	**
Annual income < 25k	*ref.*					*ref.*				
Annual income 25k to 50k	0.205	0.037	5.584	0.000	***	0.184	0.040	4.607	0.000	***
Annual income 50k to 100k	0.317	0.039	8.053	0.000	***	0.277	0.045	6.155	0.000	***
Annual income 100k to 150k	0.429	0.049	8.838	0.000	***	0.374	0.055	6.860	0.000	***
Annual income > 150k	0.393	0.057	6.881	0.000	***	0.321	0.063	5.117	0.000	***
Financial wealth < 10k	*ref.*					*ref.*				
Financial wealth 10k to 50k	0.273	0.032	8.469	0.000	***	0.2767	0.032	8.297	0.000	***
Financial wealth 50k to 100k	0.331	0.037	8.904	0.000	***	0.321	0.037	8.606	0.000	***
Financial wealth 100k to 500k	0.358	0.039	9.258	0.000	***	0.337	0.039	8.679	0.000	***

Financial wealth 500k to 1000k	0.352	0.066	5.300	0.000	***	0.317	0.067	4.737	0.000	***
Financial wealth > 1000k	0.272	0.100	2.709	0.007	**	0.228	0.100	2.271	0.023	**
Home owner	0.256	0.034	7.401	0.000	***	0.248	0.034	7.155	0.000	***
No property assets	*ref.*					*ref.*				
Property assets up to 10k	0.051	0.067	0.766	0.443		0.055	0.067	0.824	0.409	
Property assets 10 to 50k	0.067	0.049	1.434	0.151		0.067	0.049	1.377	0.168	
Property assets 50 to 100k	0.114	0.048	2.353	0.018	*	0.112	0.048	2.306	0.021	*
Property assets 100 to 250k	0.152	0.040	3.806	0.000	***	0.152	0.040	3.818	0.000	***
Property assets 250 to 1000k	0.301	0.056	5.390	0.000	***	0.290	0.056	5.192	0.000	***
Property assets > 1000k	0.103	0.085	1.213	0.225		0.094	0.085	1.107	0.268	
Risk Q1 500/0	*ref.*					*ref.*				
Risk Q1 1000/400	0.487	0.054	9.098	0.000	***	0.477	0.054	8.898	0.000	***
Risk Q1 2000/1000	0.791	0.054	14.691	0.000	***	0.785	0.054	14.559	0.000	***
Risk Q1 5000/2000	1.188	0.054	21.784	0.000	***	1.199	0.055	21.765	0.000	***
Risk Q2 20/5	*ref.*					*ref.*				
Risk Q2 30/10	1.867	0.038	48.738	0.000	***	1.848	0.038	48.192	0.000	***
Risk Q2 50/15	3.455	0.039	87.370	0.000	***	3.427	0.040	86.467	0.000	***
Risk Q2 70/15+	3.805	0.041	92.689	0.000	***	3.756	0.042	90.303	0.000	***
Risk Q3 Sell all or partially	*ref.*					*ref.*				
Risk Q3 I do not know	-0.258	0.066	-3.936	0.000	***	-0.244	0.065	-3.739	0.000	***
Risk Q3 Stay patient	0.066	0.047	1.401	0.161		0.061	0.047	1.298	0.194	
Risk Q3 Reinvest	0.401	0.052	7.729	0.000	***	0.340	0.052	7.518	0.000	***
Risk Q4 Never experienced loss	*ref.*					*ref.*				
Risk Q4 Loss up to 10 percent	0.101	0.026	3.905	0.000	***	0.096	0.026	3.710	0.000	***
Risk Q4 Loss up to 20 percent	0.178	0.035	5.038	0.000	***	0.170	0.035	4.782	0.000	***

Risk Q4 Loss > 20 percent	0.274	0.031	8.724	0.000	***	0.257	0.031	8.097	0.000	***
Liquidity Q1 Probably or very probably	*ref.*					*ref.*				
Liquidity Q1 Probably not	0.349	0.035	9.921	0.000	***	0.341	0.035	9.712	0.000	***
Liquidity Q1 Certainly not	0.442	0.042	10.516	0.000	***	0.431	0.042	10.257	0.000	***
Liquidity Q2 Probably or very probably	*ref.*					*ref.*				
Liquidity Q2 Probably not	0.896	0.044	20.304	0.000	***	0.862	0.044	19.526	0.000	***
Liquidity Q2 Certainly not	1.197	0.048	24.715	0.000	***	1.169	0.048	24.099	0.000	***
Knowledge Q1 Wrong answer	*ref.*					*ref.*				
Knowledge Q1 Does not know	0.037	0.090	0.411	0.681		0.048	0.090	0.535	0.592	
Knowledge Q1 Correct answer	0.183	0.068	2.679	0.007	**	0.181	0.068	2.651	0.008	**
Knowledge Q2 Wrong answer	*ref.*					*ref.*				
Knowledge Q2 Does not know	0.101	0.056	1.806	0.071	.	0.103	0.056	1.831	0.067	.
Knowledge Q2 Correct answer	0.180	0.055	3.292	0.000	***	0.168	0.055	3.072	0.002	***
Knowledge Q3 Wrong answer	*ref.*					*ref.*				
Knowledge Q3 Does not know	-0.000	0.047	-0.005	0.996		-0.004	0.047	-0.083	0.934	
Knowledge Q3 Correct Answer	0.022	0.022	1.007	0.314		0.023	0.022	1.065	0.287	
Project type Saving						*ref.*				
Project type Important purchase						-0.286	0.066	-4.325	0.000	***
Project type Childrens' studies						0.015	0.084	0.179	0.858	

Project type Real estate		-0.317	0.044	-7.181	0.000	***
Project type Retirement		-0.183	0.038	-4.851	0.000	***
Project type Inheritance		-0.008	0.070	-0.122	0.903	
Saving capacity < 500		*ref.*				
Saving capacity 500-1000		0.005	0.026	0.194	0.846	
Saving capacity 1000-2000		0.050	0.034	1.463	0.143	
Saving capacity > 2000		0.103	0.032	3.249	0.001	**
Prof. category Worker		*ref.*				
Prof. category Manager		-0.059	0.049	-1.213	0.225	
Prof. category CEO		-0.143	0.093	-1.534	0.125	
Prof. category Student		-0.075	0.069	-1.099	0.252	
Prof. category Employee		-0.114	0.053	-2.159	0.031	*
Prof. category Inactive/other		-0.302	0.112	-2.973	0.003	**
Prof. category Independant		-0.115	0.054	-2.123	0.034	*
Securities account (CTO)		0.167	0.045	3.673	0.000	***
Female subscriber		-0.050	0.026	-1.964	0.050	*
In couple		0.016	0.027	0.597	0.551	

Significance levels: *: 5%, **: 1%, ***: 0.1%.