Robo-Advising for Small Investors*

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Abstract

We study the effects of robo-advising on investors' attention, trading, and performance on a large set of Employees Saving Plans covering a representative sample of French employees. We find that relative to self-managing, accessing the robo services is associated to an increase in the time investors spend to follow their portfolios and to an increase in trading activities. After having taken up the robo, investors are willing to increase their investment, bear more risk, and to rebalance their portfolio in a way to keep their allocation closer to the target. They also experience higher risk-adjusted returns. These effects tend to be stronger for investors with smaller portfolios, who are less likely to have access to traditional advice. Our results shed light on the dynamics of investors' trust towards the robo service and suggest that automated advice can promote financial inclusion.

Keywords: Robo-Advising, Financial Inclusion, Long-Term Investment, Limited Attention.

JEL codes: G11; G51; G41; G23; D14

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1 Introduction

Households are increasingly required to take complex financial decisions in various domains, ranging from asset accumulation, mortgages, investment and pension plans (Greenwood and Scharfstein (2013); Guiso and Sodini (2013)). Taking efficient decisions requires sophisticated tools, and not all households appear well equipped. It is now established that a significant fraction of households makes poor financial decisions (Campbell (2006)). At the same time, many of them lack a good understanding of basic principles describing financial products or financial markets (Lusardi and Mitchell (2014)). These behaviors can have important consequences in terms of investors' welfare and of market efficiency, and at a broader level in terms of economic growth and inequality (Lusardi, Michaud and Mitchell (2017); Bianchi (2018); Bach, Calvet and Sodini (2020)).

Resorting to financial experts could be a natural response for households who lack the knowledge to take effective decisions. Von Gaudecker (2015), for example, shows that poor financial literacy is associated to poor portfolio performance, but the effect fades away for those relying on professional advice. In practice, the argument has its limits. First, financial advice is costly, only those with enough wealth may afford it or find it profitable. Second, advisors need themselves to have the skills to offer services that are suited to the clients' requirements. Third, the advisor should have the incentives to act in the client's best interest. Accumulated evidence shows this need not be the case, which results in distorted advises and even poorer investors' performance (see e.g. Mullainathan, Noeth and Schoar (2012), Foà, Gambacorta, Guiso and Mistrulli (2019) on distorted incentives and Foerster, Linnainmaa, Melzer and Previtero (2017), Linnainmaa, Melzer and Previtero (2020) on misguided beliefs; and Beshears, Choi, Laibson and Madrian (2018) for a review).

This begs the question of whether new forms of financial advice can be designed so as to reduce transaction costs, agency conflicts, and provide customized recommendations in time of need. Even in such ideal case, a second issue is whether investors rationally choose to delegate and to follow the advises, possibly even when they would be tempted to do otherwise. This is key also for designing interventions aimed at improving investors' welfare (Inderst and Ottaviani (2012)).

We investigate these issues by exploiting the introduction of a robo advising service by a major French asset manager. We have access to account level data on a large set of employee savings plans, covering a representative sample of the French population employed in the private sector. In these plans, employees allocate part of their salaries between a menu of funds proposed by the employer, they can increase their investment and rebalance their portfolio over time as they wish. These investments are subject to various lock-in rules, so they tend to have a relatively long horizon.

While traditionally employees received no advice on these portfolio choices, the asset manager has introduced a robo-advisor service in August 2017. The robo starts by eliciting information on the client's characteristics, builds the client's profile, and proposes a portfolio allocation. If the client accepts the proposal, the robo implements the allocation. Over time, the robo also sends email alerts if the current portfolio allocation ends up being too far from the target allocation.

Our data cover the period between September 2016 and November 2018 and are aggregated at the monthly level. We obtain detailed information about investors' activities on the platform, both in terms of trading and in terms of digital footprints; moreover, we can exploit the exact knowledge of the algorithm behind the robo, observe the score, the suggested allocations and the alerts the robo may be sending over time; finally, we can construct the returns and various measures of risk of these portfolios.

We structure our analysis around two main questions. First, we investigate whether the robo changes the attention that investors pay to their portfolio. We aim at providing evidence relating in particular to recent theories of rational inattention and of behavioral inattention (see e.g. Veldkamp (2011) and Gabaix (2019) for overviews). Moreover, and more broadly, we shed light on whether in our setting automation tends to substitute or complement human reasonings and actions.

Our second key question is whether subscribing to the robo changes trading activities and impacts investors' performance in a significant way. Several arguments have been put forward whereby robots could help. Robots have low operating costs and so they allow reaching investors who have been traditionally excluded from wealth management services. Robots may limit the extent of biased investment advises by adopting transparent and verifiable procedures. Their enhanced accountability may increase investors' trust (Philippon (2019)). Finally, robots may use information about the characteristics and the behaviors of the client in way to gain a fine understanding of his preferences and needs, which may also reduce the impact of clients' behavioral biases (Braeuer, Hackethal and Scheurle (2017), D'Acunto, Prabhala and Rossi (2019)).

We start our analysis by looking at the determinants of robo adoption and more generally of how much investors trust the robo service. We find that, as intuitive, young and more attentive investors are more likely to take the robo. Interestingly, the probability of taking up the robo is negatively related to the size of the investors' portfolio. The reason may be related the robo fee structure, which is proportional to the value of the assets under management, and it suggests that indeed the robo is able to reach less wealthy investors. Moreover, investors with smaller portfolios are more likely to assign a larger fraction of their assets to the robo.

Conversely, wealthier investors are more likely to acquire information about the robo (what we call robo curious) without eventually subscribing to the service. Moreover, for robo curious and robo takers, we can investigate whether the probability of subscribing to the robo depends on the distance between the allocation recommended by the robo and the allocation currently held by the investors. We find that the relation is positive: the further away is the recommendation of the robo relative to the current allocation, the larger is the probability that the investor subscribes to the robo. This finding can be contrasted with the observation that human advisers tend to gain trust from their clients by being accommodating with clients' beliefs and suggested investment strategies (Mullainathan et al. (2012)). We also show that this effect is stronger when the robo proposes riskier allocations. Moreover, investors who are younger, female, those who have larger risk exposure and lower past returns as well as less attentive investors are more likely to accept a larger increase in their risk exposure.

In terms of investors' attention, we focus on the amount of time each investor spends on the dedicated company website (number and duration of connections, number of pages visited). We show that, while as intuitive the robo tends to attract more attentive investors, investors' attention increases even more after the robo subscription. For example, robo-takers increase the number of minutes spent on the platform by 4.7 per month, which can be compared to the average of 3.8. The effect persists even if we exclude the dates of subscription of the robo, and it is particularly strong around the dates of reception of the variable remuneration.

We also investigate whether investors' attention is related to past returns (Sicherman, Loewenstein, Seppi and Utkus (2016)). In a rational inattention setting, Alvarez, Guiso and Lippi (2012) show that investors who have more volatile portfolios should value information more and observe their portfolio more frequently (see also Huang and Liu (2007)). On the other hand, behavioral models incorporating loss or information aversion suggest that investors may be reluctant to check their portfolios when the risk of bad news is larger, i.e. when returns are low and volatility is high (see Pagel (2018) and Andries and Haddad (2020)). Our results tend to support the second view. Our investors pay more attention to their portfolios when returns are large and volatility is low. Interestingly, this tendency is even stronger after having subscribed to the robo.

We then analyze how increased attention translates into different trading behaviors. In a rational inattention setting, Abel, Eberly and Panageas (2013) show that if transaction costs have a small fixed component, an observation of the portfolio should always be associated to a transaction and it should occur at constant intervals of time independent on the state. This could be contrasted with more behavioral theories in which, irrespective of the shape of transaction costs, investors may observe and trade more frequently in particular states, e.g. when they experience large shocks to their returns (Grinblatt and Keloharju (2001)), and they may observe their portfolio without making any trade (see e.g. Epstein and Schneider (2010) and Bianchi and Tallon (2019) on ambiguity aversion). We observe that, even though transaction costs have essentially no fixed component in our setting, over 60% of the connections to the platform are not associated to any trading activity. This is the case both for robo takers and for non-takers, which is again more in line with behavioral theories of inattention.

We also show that robo takers increase their trading activities after the subscription of the robo and, importantly, they also increase their voluntary contributions to the company's saving plan. These differences in trading activities are associated to a change in risk exposure. We find that, after subscription, robo takers increase their equity share by 8.6%, which corresponds to a 55% increase relative to the average equity share of 15.7%. This is achieved by reducing the weight to bonds and to money market funds and by increasing the weight to balanced and equity funds.

In order to shed further light on the change in risk exposure, we exploit some discontinuities associated to the robo algorithm. Based on the answers to the survey, the robo builds a score for each investor and assigns the investor into an interval. The equity exposure proposed by the robo is a step function: it is constant within the interval, and it increases for higher intervals. We obtain the score assigned to each individual, and the associated allocation rule, and we investigate the effect of being assigned just above or below a given threshold in a classic regression discontinuity design. We find that being assigned just above a threshold increases the equity share by 5%. The effect is significant, but lower than the one estimated above. An interpretation is that, on top of the effect of the algorithm, other aspects of the service proposed by the robo induce investors to take more risk. In fact, we observe a large increase in risk exposure at the time of the subscription, but also a positive trend after the subscription. This motivates us to further explore whether the robo affects rebalancing behaviors over time.

We exploit a specific feature of the robo that sends email alerts to investors if their current allocation gets too far away from the target allocation. We ask whether these alerts are effective in inducing investors to rebalance their portfolio and stay closer to the target. These rebalancing behaviors can have important impacts on investors' performance (Bianchi (2018)). Moreover, they shed light on whether investors trust the robo recommendation not only at the time of the subscription but also over time. Exploiting the knowledge of the algorithm governing the alerts, we can construct potential alerts not only for robo takers but also for robo curious (those individuals who have completed the robo survey but have not subscribed to the service), for whom we identify the alerts that the robo would have sent had they taken the robo. We then show, in a standard diff-in-diff specification, that the reception of the robo alert reduces the distance between current and target equity exposure by 4.8%, corresponding to a 41% reduction relative to the average distance of 11.6%.

We also investigate whether these changes in investment strategies are associated to different portfolio returns. We show that robo takers experience an increase of annual returns by 5.4% per year, which is a 80% increase relative to the average return of 6.7%. Part of this effect is due to an increase in risk exposure. Controlling for various measures of portfolio risk, however, we find that the robo treatment is associated to an increase between 3% and 4% in yearly returns. Together with the increased investment in the saving plan mentioned above, and considering that the management fees associated to the robo are much smaller, these results suggest that the robo can have a significant impact on investors' wealth accumulation in the long run. Moreover, the increase in returns is only partly driven by the allocation change occurring at the time of the robo subscription. An important part of this increase comes from a change in rebalancing behaviors over time, as emphasized above.

Finally, we explore whether the robo service can promote financial inclusion by affecting investors with lower financial capabilities. We show that our main effects are heterogeneous depending on ex-ante investors' characteristics, and in particular on portfolio size (a proxy of financial wealth), on the value of the variable remuneration (a proxy for income) as well as on risk exposure and returns at the baseline. In particular, the increase in equity exposure associated to the robo is larger for investors with smaller portfolio, lower remuneration and lower equity exposure at the baseline. Moreover, the increase in returns is also larger for smaller investors and for investors with lower returns at the baseline. These results show that the effects of the robo tend to be particularly important precisely on investors who are less likely to receive traditional advice and to participate to the stock market, thereby confirming the view that having access to automated advice can be an important instrument towards financial inclusion.

This paper contributes to a growing literature on the effects of robo advising on portfolio choices (see D'Acunto and Rossi (2020) for an overview). D'Acunto et al. (2019) study a portfolio optimizer by an Indian brokerage house and show that the robo has a beneficial impact on less diversified investors as it increases the number of stocks they hold, reduces volatility, and improves market-adjusted performance, but not on diversified investors. Rossi and Utkus (2019) show that robo takers increase investors' exposure to low-cost indexed mutual funds, improve diversification and risk-adjusted performance. Similar findings are reported by Braeuer et al. (2017) and Loos, Previtero, Scheurle and Hackethal (2020) from a German bank, and in Reher and Sokolinski (2020), who focus on how the robo improves market participation of middle class investors. Reher and Sun (2016), instead, find little impacts on mutual fund holders by a specialized robo-advisor U.S. provider.

Relative to this literature, a key distinctive feature of our study is the focus on investments in employee saving plans. These data cover a representative sample of the French population working in the private sector, which allows us to focus on investors who have not been covered by typical studies say on clients of an online brokerage firm. We can then focus on investors who have little experience in the stock market and had typically no access to financial advising. Moreover, as mentioned, this investment involves choosing between a pre-determined menu of funds, which relative to stock picking should minimize issues of underdiversification, and it has a long-term perspective, which is relatively uncommon in the context of robo advising (Hammond, Mitchell and Utkus (2016)). Our data also allow to compare, for the same investor, behaviors in contracts managed by the robo relative to self-managed contracts and, in addition, we can track investors over time, thereby uncovering important effects of the robo on dynamic portfolio choices.

From a more general perspective, our paper contributes to the literature on financial innovation and investors' behaviors. Consistently with our findings, recent evidence suggests that new investment products and services can induce investors to increase their participation in the stock market (see e.g. Calvet, Celerier, Sodini and Vallee (2020) and Hong, Lu and Pan (2020)). A key challenge is how new products can be properly understood and used, especially by less sophisticated investors (see e.g. Lerner and Tufano (2011) for a discussion based on historical evidence, and Bianchi and Jehiel (2020) for a theoretical investigation). We share with this literature the focus on investors' trust when using a new financial service, and investigate how trust can be built and how changes in behaviors can be induced over time.

2 Data

The portfolio choices under study concern a large set of employee saving plans. Each year, as part of their compensation, employees receive a sum of money to be allocated across a set of funds offered by the employer. The employer can offer two types of contracts, which differ in the lock-in period: 5-years (*plan d'épargne entreprise*) or until retirement (*plan d'épargne pour la retraite collectif*). Employees can make extra investment in the plan, withdraw money after the lock-in period (or under exceptional circumstances), and freely rebalance their portfolios over time. An individual can simultaneously hold several contracts from past and current employers.

These plans are managed by a large French asset manager. While traditionally employees received no advice on these portfolio choices, the asset manager has introduced a robo-advisor service in August 2017. The robo starts by eliciting information on the client's characteristics, and specifically on her risk-aversion (both through quantitative and qualitative questions), financial knowledge and experience (both objective and self-assessed), age and investment horizon. Based on these questions, the robo builds the client's profile (say, prudent, dynamic,..) and proposes a portfolio allocation. The client can visually compare the proposed allocation with her current one both in terms of macro categories (proportion of equity, bonds, money market funds, ...) and of specific funds. If the client accepts the proposal, the robo implements the allocation. If the client rejects, the service is terminated. Over time, the robo also sends email alerts if current portfolio allocation ends up being too far from proposed allocation. Moreover, over time, the client can submit new answers to the robo and get a new profile and a new proposed allocation.

If the employer subscribes to the robo service, its employees are informed via email and they have the option to accept it on one or more of their saving accounts. The cost of the service is borne by the employee, and it has an employer-specific component and an employee-specific component, which depends on the value of the her account. As of November 2018, around 8,000 companies have access to the offer, that corresponds to over 600,000 employees and around 1.2 millions accounts (out of over 4.5 millions accounts managed by the asset manager). Out of them, about 190,000 individuals have expressed interest in the robo and started the procedure to receive the service by formally signing a "counselling agreement" in at least one of their account; we refer to them as robo-curious. Out of them, 14,576 individuals have subscribed to the robo and we refer to them as robo-takers. This correspond to 17,069 accounts managed by the robo in 712 different firms.

In most of the analysis, our sample includes all the robo-takers and a random sample of 20,000 individuals that are "not-exposed" (i.e. employees of companies which do not have access to the service). We restrict to individuals who have completed at least one transaction in one of their account in our sample period. This gives us a sample of 34,517 individuals and 92,578 contracts. Our data cover the period September 2016 to November 2018 and are aggregated at the monthly level. In some additional analysis (detailed below), we also consider individuals which are exposed but non-takers, as well as robo curious.

We take advantage of several sources of (anonymized) data. First, we have obtained detailed information on the investment choices. We observe the menu of funds offered by the employer, the allocation chosen by the employee, new investments, rebalancing, and withdrawals. In addition, building on the information on returns of the various funds, we have constructed the returns and various measures of risk of these portfolios (as detailed below). Third, we have extracted information about investors' activities on the platform, both in terms of trading and in terms of digital footprints (number of connections, duration, pages visited).

Fourth, for individuals who take the robo, we can observe the score they are given by the robo, the associated profile and suggested allocation, and the alerts the robo may be sending over time to propose new allocations. We provide more details about those variables as we proceed with our analysis below.

Our sample should be considered as representative of the French population of private sector employees. The firms under study are representative of the French population of private firms, and all employees in these firms have access to the saving plans. As mentioned, this allows us to include in our analysis small investors, who tend to be underrepresented in studies focusing on stock market participants (say, from brokerage house). The average value of the assets invested in the plan is 7,654 euros, the median is 819.5 euros. These figures are comparable to those one can find in representative surveys.[1] Summary statistics of the variables used in the analysis are reported in Table 1.

3 Results

We structure our analysis as follows. First, we consider which individual characteristics tend to be associated to the propensity to take the robo, within the sample of employees who have been exposed to the robo. Then, we turn to the effects of robo taking on i) the attention investors pay to their portfolio, ii) their trading activities and portfolio allocations, and iii) their returns and risk.

3.1 Trust

We start by investigating who is more likely to take the robo. We focus on the sample of exposed individuals and consider the following linear probability model:

$$T_{i,f,t} = \alpha + X^{'}_{i,t}\gamma + \mu_f + \mu_t + \varepsilon_{i,f,t}, \tag{1}$$

where $T_{i,f,t}$ is a dummy equal to 1 if individual i working in firm f has taken the robo in period t, $X_{i,t}$ is a vector of individual and portfolio characteristics, μ_f and μ_t are firm and time fixed effects, respectively. Standard errors are clustered at the firm level. Results are reported in Table 2.[2] We restrict to one observation per individual: for robo takers, we include the month of

[1] For example, data on household savings report average financial wealth around 60,000 euros and, for those who have access to employee savings' plans, these plans represent on average around 20% of their financial wealth. Sources: Observatoire de l'Epargne Européenne (http://www.oee.fr/files/faits_saillants_-_2020_t2.pdf) and Autorité des marchés financiers (https://www.amf-france.org/fr/actualites-publications/publications/rapports-etudes-et-analyses/les-actifs-salaries-et-lepargne-salariale).

[2] Probit regressions give similar results, we prefer to report linear regressions given the large number of fixed effects in equation 1.

the subscription; for non-takers, we include one month taken at random.[3]

In column 1, we observe that the probability of subscribing to the robo is negatively related to age, to being female, to the amount invested in the plan and it is positively related to the amount of attention devoted to the portfolio (as measured by the number of past connections to the platform). Investors tend to take the robo for saving vehicles with a shorter horizon (*plan d'épargne entreprise,* which as mentioned is locked-in for 5 years), and in months around the reception of the variable remuneration, an observation we will use below. Past returns and past risk exposure do not seem to have a significant impact.

In column 2, we consider the extensive margin. We restrict to robo takers and use as dependent variable the percentage of assets managed by the robo, relative to the total assets in the investor's portfolio. We observe that investors with smaller portfolios, larger risk exposure and larger past returns tend to delegate a larger fraction of their portfolio to the robo. The same holds for male investors.

A key question is whether the robo can induce significant changes in investors' portfolios and whether recommending large changes impacts the probability that the investor takes up the service. The distance between the investor's current allocation relative to the optimal one (as evaluated by the robo) can be seen as a key component of the value added of the robo. In addition, it has often been argued that human advisors tend to be accommodating when clients express a preferred investment strategy and have no incentive to recommend allocations which are too different from investors' prior, even when this is detrimental to investors' performance (Mullainathan et al. (2012)). It is thus interesting to check whether robo advisors are better able to induce allocations which are very different from investors' current allocations.

In order to investigate this question, we can exploit the fact that some investors are "robo curious": they complete the preliminary survey needed to access the service and observe the robo recommendation but eventually decide not to take up the robo. For robo curious and robo takers, we can define a measure of distance as the absolute value of the difference in the equity share between the allocation proposed by the robo and the allocation already implemented by the individual.[4]

In columns 3 and 4, the dependent variable is a dummy equal to one if the investor is a robo taker, and to zero if the investor is a robo curious. We observe that the probability to take up the robo, conditional on having observed the recommendation, is higher for investors who are older, male,

[3] Results including all observations are very similar, we focus on the restricted sample as it allows to increase the variation in our dependent variable and so possibly statistical power.

[4] If an individual observes several robo recommendations in a given month without subscribing the robo, we consider the latest recommendation in the month.

have smaller portfolios and are more active (i.e., they check more frequently their account and visualize the robo recommendation). In column 3, we observe that the further away is the recommendation of the robo relative to the current allocation, the larger is the probability that the investor subscribes to the robo. Put differently, investors do not seem interested in paying for a service which would induce only a minimal change in their current allocation. In column 4, we instead look at the effect of the difference (not in absolute value) between equity share proposed by the robo and the current equity share, and observe that the riskier is the proposed allocation relative to the current one, the more likely is that the investor takes up the robo.

A key feature of the robo seems to be the ability to induce larger risk taking. To shed further light on this aspect, in column 5, we restrict to robo takers and analyze the determinants of the accepted change in equity exposure (not in absolute value). We observe that investors who are younger, female, those who have larger risk exposure and lower past returns as well as less attentive investors are more likely to accept a larger increase in their risk exposure.

In column 6, we check whether the effects in column 5 are driven by the fact that some type of investors are systematically offered riskier allocations. We restrict to robo curious (i.e. to recommendations which have been visualized but not accepted) and observe that the patterns are different from those in column 5. For example, it is not the case that females or investors with larger risk exposure are always recommended an increase in their risky allocation; rather, as we highlight above, it is that females and investors with larger risk exposure are more likely to accept an increase in their risky allocation.

Overall, these results point towards an important ability of the robo to reach under-served investors and to change in a substantial way their investment choices. First, the robo seems more attractive to investors with smaller portfolio, who may be less likely to have access to external professional advice. Second, and in contrast to typical human advisers, the robo is able to implement allocations which are quite far from investors' current allocations. In particular, investors seem attracted by allocations which are riskier than their current position, an issue we will explore in more details below.

3.2 Attention

We explore the behavioral changes associated to the robo in the following fixed-effects OLS specification:

$$y_{i,t} = \alpha_i + \beta T_{i,t} + X'_{i,t}\gamma + \mu_t + \varepsilon_{i,t}, \tag{2}$$

where α_i and μ_t are individual and time fixed effects, $T_{i,t}$ is a dummy equal to 1 if individual i has taken the robo in period t, and $X_{i,t}$ is a vector of individual and portfolio characteristics. Unless specified otherwise, our controls include the average risky share and the average returns over the past 12 months, the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Our coefficient of interest β measures how, for a given individual i, the outcome $y_{i,t}$ varies with the adoption of the robo, compared to the changes experienced in the control group. In most of this analysis, our control group is defined by a sample of individuals who have not been exposed to the robo.

We first consider the level of attention that investors pay to their portfolios. As mentioned, we have extracted the login activities made on the platform dedicated to the employee saving plan. We observe the number of connections, the number of web pages visited, the number of minutes spent on the platform. We report our results in Table 3. In columns 1,3,5 we consider specifications with no controls and no individual fixed effects; in columns 2,4,6 we consider the specification in Equation (2). Our key observation is that, after having taken the robo, investors spend more time on the platform. In terms of number of connections, for example, we observe an increase of 0.28 connections per month, which is large in relation to the average number of connections of 0.5. Similarly, investors increase the number of minutes spent on the platform by 4.7 per month (relative to an average of 3.8), and they increase the number of web pages visited per month by 5.8 (relative to an average of 4).

In order to check the parallel trend assumption and uncover possible dynamics of those effects, we consider the following regression

$$y_{i,t} = \alpha_i + \sum_{s=-5}^{6} \beta_s \mu_{t+s} T_{i,t} + X_{i,t}^{'} \gamma + \mu_t + \varepsilon_{i,t}, \tag{3}$$

where μ_{t-s} and μ_{t+s} correspond to months before and after the treatment and the other variables are as in (2). In Figure 1, we consider the number of connections per month and report the estimated coefficients $\beta_{-5}, ..., \beta_6$ and the associated 95% confidence intervals. We observe no significant pretreatment differences. We also observe that the effect is largest right after having taken the robo and tends to vanish, at least temporarily, after about three months. The other measures of attention display similar dynamics.

One may question whether the increased attention is associated to the robo subscription or to other events occurring at the same time. A typical event that increases investors' attention is the reception of the remuneration that needs to be allocated across the various funds in the saving plan.

Employees typically receive a communication before the reception and they are asked to choose their allocation in the next month. Indeed, we observe an increase in activities on the platform during the month of reception of the remuneration, and if that corresponds to the month of robo subscription we may confound the two effects. In column 1-3 of Table 4, we exclude the month before and the month at which the individual has received the variable remuneration. We see that our estimates are only slightly smaller than those in Table 3, and still significantly different from zero.

A related concern is whether the effects persist also beyond the window of the subscription to the service. We consider whether robo takers have a different level of attention around the time of the reception of the remuneration, conditional on the fact that this occurs at least two months after the subscription of the robo. We compare the number of connections for robo treated and non robo treated (including individuals who never take the robo and robo takers before subscription) between months $t-3$ and $t+3$, where t corresponds to the reception of the remuneration. The associated regressions are in Table 4, column 4 is for robo treated and column 5 is for non treated. We observe that robo takers are more attentive throughout than non robo takers, and this is true in particular in the month of reception of the remuneration (0.7 vs. 0.3 connections). Finally, in column 6, we look at months excluding the two months around the robo subscription and the month of reception of the remuneration, which are generally periods in which investors pay less attention to their portfolio. Also in those months, robo takers display larger levels of attention, though the difference is lower. These result show that investors do not take the robo as a substitute for their own attention. Rather, the robo is associated to an increased level of attention, even beyond the time of its subscription and the time of reception of the variable remuneration.

In Table 5, we investigate the effects of past returns on attention. As mentioned, this allows to shed some light on alternative theories of investors' attention. According to rational (in)attention, investors should pay more attention to their portfolio when they are more likely to acquire useful information, that is the case when uncertainty is large and so prices are more volatile (Alvarez et al. (2012)). Behavioral theories instead incorporate forms of loss or disappointment aversion and predict that investors may shy away from information when this risks to bring bad news, as such, they may be reluctant to check their portfolios when returns are low and volatility is high (Pagel (2018), Andries and Haddad (2020)).

We start by looking at the effects of market returns. In column 1, we observe that investors tend to pay more attention to their portfolio when market returns are larger. In column 2, we observe that this tendency is even stronger for robo takers, for which the additional effect is almost as big as the baseline effect in column 1. In columns 3 and 4, we look at individual returns, controlling for market returns through time fixed effects. Results are very similar. Investors tend to pay more attention in periods when own returns are larger, and this is even more so for robo takers. We then consider the effect of market volatility. Investors tend to pay more attention to their portfolio when market volatility is lower (column 5, though the estimate is not statistically different from zero), and this is even more so for robo takers (column 6).[5]

These results bring support to behavioral theories suggesting that, rather than for gathering potentially useful information, investors tend to pay attention to their portfolio in order to derive pleasure from observing higher returns, and at the same time they are reluctant to pay attention when losses are more likely. Interestingly, subscribing to the robo tends to exacerbate this tendency.

3.3 Activities

We ask whether the increased level of attention documented above translates into an increase in trading activities. Possible activities include investing extra money in the plan, which can be done freely at any point in time with no cap on the amount invested; withdraw money from the plan, which can be done only after the expiration period or in exceptional circumstances (e.g. death, invalidity, purchase of a house as primary residence, ...); or changing the portfolio composition, i.e. the weights to the various funds offered by the employer. None of these operations is directly subject to fees on the part of the asset manager (robo fees are proportional to the amount held in the plan).

We report our results in Table 6. In column 1, we observe that subscribing to the robo is associated to 0.27 more allocation changes by month, relative to an average of 0.19. In columns 2 and 3, we distinguish changes dictated by the robo from those directly chosen by the investor. As expected, most of the increase in trading activities is directly associated to the robo, but there is a small increase also in the activities chosen by the investor.

The robo is also associated to an increase in personal contributions of 0.006 (the average number is 0.03) and to a decrease in the number of redemptions by 0.0015 (the average number is 0.03). Interestingly, these patterns translate into an increase in the total amount of money invested in the plan. Robo takers invest 132 euros more per month in their plan, while on average monthly net inflows in the plan are negative (−39.3 euros).

An interesting aspect is the relation between attention and trading activities. The average number of trading activities is 0.19 per month, which can be compared to the average number of connections equal to 0.5 per month. That is, in 62% of the cases, a connection is not associated to any trading activity. This ratio is similar (in fact, slightly higher) for robo takers,

[5] The effect of individual volatility, controlling for market volatility, is qualitatively similar but less precisely estimated.

for whom 67% of connections are not associated to any trade (the average number of connections is 1.04 and the average number of trading activities is 0.34 per month). While of course investors can make several operations in each connection, the majority of connections in our sample are not associated to any trading activity. This is in contrast with rational theories of inattention, whereby since transaction costs have no fixed component in our setting, an observation of the portfolio should always be associated to a transaction (Abel et al. (2013)).

3.4 Risk Taking

We now consider whether the robo adoption is associated to changes in the composition of investors' portfolio. As shown in Table 1, the main type of funds are employer stock (34%), balanced funds (20%), bonds (16%), money market (11%), equity funds (9%), guaranteed funds (5%) and blocked cash (2%).

In order to construct an aggregate measure of risk exposure, we classify funds between risky and safe. Among risky funds, we include equity funds, employer stock, balanced and guaranteed funds, while we consider the other funds as safe. We define the risky share as the value of risky funds over the total value of the portfolio. In alternative specifications, we also disaggregate balanced funds and include the equity parts of balanced funds into equity funds.

We start with regressions at the saving vehicle level:

$$y_{j,t} = \alpha_j + \beta T_{j,t} + X_{j,t}^{'}\gamma + \mu_t + \varepsilon_{j,t}, \tag{4}$$

where the treatment $T_{j,t}$ equals 1 if investor i has taken up the robo in saving vehicle j at time t (to simplify notation in what follows we use the subscript j, t instead of i, j, t), α_j are saving vehicle fixed effects, and the rest is as in Equation (2). We also consider regressions at the individual level as in Equation (2), in which we aggregate over the various contracts an individual may hold. As mentioned, each investor can hold several contracts (in our sample, we observe on average 2.68 contracts per investor) and she can subscribe to the robo on one or several contracts. In our sample, 14,576 individuals have taken the robo in at least one contract, and out of the 41,595 contracts held by those individuals, 17,069 contracts are covered by the robo. We can then investigate whether taking a robo in one contract affects the trading activity in a contract held by the same individual but not covered by the robo.

Table 7 reports our evidence at the saving vehicle level. We observe that the robo induces an increase in the risky share by 25.3% in absolute terms. The effect is large, as compared with the average risky share of 70%, and it is mainly driven by an increase in balanced funds by 22.8% and by a decrease in bond funds by 15.5% and in money market funds by 9.2%. We also notice that the robo induces a very minimal change in investors' exposure to the employer stock.

Similarly, in column 7, we consider the equity share, which disaggregates balanced funds according to their proportion of equity funds, and observe that the robo subscription is associated to an increase in the equity share by 8.7% in absolute term, while the average equity share is 15.7%.

In Table 8, we report regressions at the individual level. We observe that magnitudes are very similar to the ones in Table 7. At the individual level, the robo induces an increase in the risky share by 19.1%. Conditional on taking the robo, the saving vehicle managed by the robo represent on average 76% of the overall value of the investor's portfolio, which implies that spillovers are minimal ($25.3 * 0.76 = 19.2$). A similar patter emerges by looking at the various components of the risky share.

In order to better address whether the increased risk taking is driven by the robo, as opposed to confounding factors occurring at the same time of the subscription of the robo, we can exploit our knowledge of the functioning of the robo, and in particular of the algorithm which maps investors' characteristics to the recommended allocation. This recommendation depends on a score that the robo constructs starting from investors' answers and that aggregates various dimensions, in particular investor's attitudes towards risk and experience in financial products. The resulting score is a variable taking values from 1 to 10 (with two decimals); in our sample its average is equal to 3.37 and its standard deviation is equal to 2.54. When an individual is assigned above a given cutoff, conditional on her investment horizon, the robo proposes a larger exposure to risk. Cutoffs are defined at 2, 4, 6 and 8 and, as the score increases, the robo suggests diversified funds with a larger proportion of equity. We are then interested in evaluating how these discontinuities affect investors' equity share.

Consider an individual i who takes up the robo on contract j at time t, denote with S_j the score that the robo has assigned to individual i in contract j, with c the closest discontinuity threshold and with D_j a dummy equal to one if $S_j \geq c$ and to zero otherwise. We can consider a standard regression discontinuity specification as

$$y_{j,t} = \alpha + \beta D_j + \gamma_1 (S_j - c) + \gamma_2 D_j (S_j - c) + H^{'}_{j,t} \delta_1 + H^{'}_{j,t} D_j \delta_2 + \varepsilon_{j,t}. \quad (5)$$

where $y_{j,t}$ is the equity share of individual i in contract j at time t. In equation (5) we allow for different slopes and intercepts on both sides of the cutoff, as captured by the coefficients γ_1, γ_2, we control for the investor's horizon $H_{j,t}$ (in polynomial form) and we allow the horizon to have a different effect depending on the sign of the dummy D_j. Our coefficient of interest is β, which estimates the effect on risk taking of being assigned just below or above the threshold. We consider investors within a distance of 0.5 or of

0.25 from the threshold.

We start by providing descriptive evidence on how the score S_j assigned by the robo impacts investors' equity share, controlling for the investor's horizon $H_{j,t}$. In Figure 2, we plot the estimated β coefficient of the following regression

$$y_{j,t} = \alpha + \beta S_j + H_{j,t}^{'}\gamma + \varepsilon_{j,t}, \tag{6}$$

and the associated 95% confidence intervals. We see that investors' equity share increases with the score, with jumps around the thresholds. We investigate this more formally by estimating equation (5). In column 1 of Table 9, we report consider a bandwidth equal to 1. We show that being assigned just above the threshold induces a 5% increase in the equity share, relative to very similar investors assigned just below the threshold. In column 2, we consider as dependent variable the average equity share between time t and time $t+1$, which may provide a more accurate estimate since if the subscription is at time t, the corresponding allocation sometimes is realized with some delay, at time $t+1$; in column 3, we consider a bandwidth equal to 0.5. We observe in columns 2-3 that our result is basically unchanged. We then perform two placebo tests. In column 4, we consider the average equity share between time t and time $t+1$ in contracts that individual i holds but on which she has not subscribed to the robo. In column 5, we consider as dependent variable the equity share at $t-1$, just before the robo subscription. In both columns, we observe no significant increase in the equity share for individuals just above the thresholds, which supports our interpretation that the effect in columns 1-3 are driven by the robo.

The above analysis shows that being assigned just above a discontinuity threshold induces an increase of 5% in the equity share, relative to an average of 15.7%. It is interesting to compare this figure with the 8.6% increase in the equity share shown in Table 5. These estimates indicate that the effect of taking up the robo is larger than simply that of being assigned above a given threshold, other features of the robo are also important to induce investors to take up more risk. This can be seen also in Figure 3, which plots the coefficients of a regression as in (3) with equity share as dependent variable. We observe a large increase in risk exposure at the time of the subscription, but also a positive trend after the subscription. We will further investigate dynamic behaviors in the next section.

3.5 Rebalancing

An important feature of the robo service is that it sends alerts to investors in case their current allocation is far from the target allocation, as defined at the time of the robo subscription (or of the latest robo profiling). We are interested in investigating how investors respond to those alerts for two reasons. First, we check whether the alerts are effective in inducing investors to rebalance their portfolio so as to stay closer to their target allocation. It has been shown that less sophisticated investors tend to chase trends and as a result their exposure to risk display larger sensitivity to market fluctuations (Bianchi (2018)). Second, investors' reaction to alerts provide (indirect) evidence on whether they trust the robo recommendation not only at the time of the subscription but also after having experienced the service, and in particular after relatively large shocks to their portfolios (either due to market trends or to their own rebalancing).

We organize our analysis in two steps. First, we consider the sample of robo takers and robo curious (i.e., those individuals who have completed the robo survey but have not subscribed to the service). For these investors, we can build the distance between the current allocation and the target allocation. For robo takers, we define the target allocation as the one proposed by the robo and accepted by the investor. For robo curious, we define the target allocation as the one held at the time of completion of the robo survey, which the investor has preferred to the one proposed by the robo. The robo is programmed to send email alerts to investors if the distance between the current and the target allocation exceeds a threshold x.[6] Accordingly, we construct a dummy *Alert* which equal to one if the distance is above x, and to zero otherwise. This variable can be constructed also for robo curious, and it identifies the alerts that the robo would have sent had they taken the robo. We can then measure, for robo takers and robo curious, how the distance between current and target equity exposure varies with the robo treatment and the reception of the alert, in a standard diff-in-diff specification as in (4) in which the robo treatment is interacted with the dummy *Alert*.

In columns 1-5 of Table 10, the dependent variable is the change in the distance between the actual and the target equity share between $t+1$ and $t-1$, where t is first the month at which the distance between those allocations exceeds the alert threshold. In column 1, we observe that robo takers, who actually receive the alert, decrease their distance by 4.8% more than robo curious. The effect is large: conditionally on being alerted, the average distance is 11.6% and the average change in the distance is -2.3%.

In columns 2 and 3, we distinguish between positive and negative deviations from the target equity share, and observe that the effect of the alerts is larger when the current allocation exceeds the target allocation. That is, investors are more likely to follow the robo's recommendation when this prescribes a reduction than when it prescribes an increase in the exposure to equity. Considering the triple-difference specification, we confirm that the difference in the coefficients between columns 2 and 3 is statistically

[6] The threshold is not defined directly in terms of equity share but of a Synthetic Risk and Reward Indicator (SRRI), a measure of portfolio risk designed by the European Security and Market Authority. The exact value of the threshold is confidential.

significant.

In columns 4 and 5, we restrict to robo takers and we compare the effect of our alert with another alert which investors receive if they have not completed the profiling survey as requested by the regulator (MIF). We observe that the effect of the MIF alert is very small, confirming that the robo makes investors' portfolio closer to their target thanks to its specific alert.

Our second step of analysis focuses on robo takers and exploits the discontinuity in the alert around the x threshold in a standard RDD. We restrict to clients within a distance of 0.1 from the threshold (for comparison, the standard deviation of the distance is 0.75). In column 6, we observe that ending up just above the threshold, and thereby receiving the robo alert, induces a 1.27% decreases the distance between the current and the target portfolio allocation in terms of equity share. This confirms the previous findings and shows that the robo alert is indeed effective in making investors rebalance their portfolio so as to bring them closer to their target allocation.

3.6 Performance

We consider whether the changes in trading patterns described above are associated to changes in portfolio performance, which we measure simply by looking at realized returns controlling for various measures of risk. We start with the same specification as in (4), using realized returns as dependent variable. Results are presented in Table 11.

In column 1, we show that the robo treatment is associated to an increase in returns by 5.4% per year. This effect is large, compared to an average return of 6.7%. At the same time, we know from the previous analysis that the robo induces investors to take more risk, so we ask how much of the increase in returns is explained by increased risk. In column 2, we control for the risky share; in column 3, we control for volatility, computed over a rolling window of 12 months; in column 4, we control for the beta of the portfolio, computed by taking as benchmark the returns of all the portfolios in our sample. We observe in these specifications that the robo treatment is associated to an increase between 3% and 4% in yearly returns, which is slightly smaller than the baseline estimate but still very large.[7]

These extra returns can be compared to the fees associated to the subscription of the robo. On average, in our sample, investors pay a management fee equal to 0.01% of the amount invested in the saving plan. For robo takers, the fee is on average equal to 0.05% of the portfolio. These results

[7] We also check whether the increase in performance is driven by the change in exposure to the employer's stock, which may represent a significant fraction of the investor's portfolio and it is typically much more volatile than the other funds. We show that, when omitting the employer's stock, the effect of the robo remains large and, in relative terms, only slightly smaller.

suggest that the robo can have a significant impact on investors' wealth accumulation in the long run.

We investigate the determinants of the increase in returns associated to the robo by distinguishing a static effect occurring at the time of the subscription of the robo from a dynamic effect associated to different rebalancing behaviors. In order to isolate the former, we construct the variable *Return Difference* as the difference between the returns experienced by the investor and the counterfactual returns she would have earned had she kept her portfolio fixed at some initial level. Specifically, for robo takers, *Return Difference* is the difference between actual returns and those she would have experienced had she kept throughout the sample the same portfolio she had just before the subscription of the robo. For an investor who does not take the robo, *Return Difference* uses as counterfactual the returns she would have experienced had she kept the same portfolio as the one held just before the first reception of the variable remuneration. We can then use the specification as in Equation (4) with *Return Difference* as dependent variable.

In column 5 of Table 11, we observe that the static effect of the robo subscription is associated to an increase in returns by 2.3% per year. This number can be interpreted as the extra return the investor would have gained had she changed the portfolio following the robo recommendation and then kept the portfolio constant throughout the sample. The effect is significant but smaller than the total increase by 5.4% estimated in column 1. By construction, the difference between the two estimates is driven by the fact that the robo subscription induces different rebalancing behaviors over time, as highlighted in the previous section. This is also confirmed in Figure 4, where we plot the coefficients of a regression as in (3) with returns adjusted for volatility as dependent variable. We observe that the largest increase in performance occurs a few months after the subscription of the robo.

3.7 Financial Inclusion

An important open question is whether robo services can promote financial inclusion thanks to the ability to serve customers with smaller portfolios. We explore this question by considering whether our main effects of increased risk taking and increased risk-adjusted returns are heterogeneous depending on ex-ante investors' characteristics. We focus on two measures of investors' capability. First, we look at the value of his portfolio, which we take as a proxy of investors' financial wealth. Second, we look at the value of the variable remuneration, which is proportional to the investor's wage and hence can be taken as a proxy of investors' income. In addition, we consider investors' risk exposure and returns. For each these characteristics, we classify investors into quartiles based on the average values observed before August 2017, the date of the first robo introduction.

We report our results in Table 12. In column 1-3, the dependent variable is the equity exposure. In column 1, we observe that the increase in equity exposure associated to the robo is larger for investors with smaller portfolio and in fact it is decreasing monotonically with size. Investors in the first quartile, i.e. those with smaller portfolios, increase equity exposure by 13.3%, those in the last quartile increase their equity exposure by 2.7%. All our estimates across quartiles are statistically different from each other. A similar pattern emerges when we consider quartiles based on the value of the variable remuneration. In column 3, we observe that the increase in equity exposure is larger for investors with lower equity exposure at the baseline, and again the effect of the robo is decreasing monotonically with baseline risk exposure.

In columns 4-6, we look at the effect on returns and control for volatility. In columns 4 and 5, we observe that the increase in returns associated to the robo is larger for investors with smaller portfolio and lower variable remuneration. In column 6, we observe larger increase in returns for investors with lower returns at the baseline.

Overall, these results suggest that the robo is able to induce larger portfolio changes on smaller investors, in terms of income and of wealth; that is, precisely on those who are less likely to receive traditional advice and to participate to the stock market. Moreover, the robo tend to reduce cross-investors differences in returns and risk exposure, as its effects are larger on those with lower returns and lower risk exposure at the baseline. These results confirm the view that the robo service can be an important instrument towards financial inclusion (Reher and Sokolinski (2020)).

4 Conclusion

We have found that having access to a robo-advisor induces investors to pay more attention to their portfolios, to increase their trading activities and their exposure to risk, and it results in higher risk-adjusted returns. We have shown that an important dimension of these effects is dynamic: the robo is able to induce investors to rebalance their portfolio in a way that get them closer to the target allocation. We have also found that these effects are particularly strong for investors with smaller portfolio, who are less likely to be served by traditional advice.

This is a first preliminary exploration and many aspects require further research. For example: what are the mechanisms whereby the robo can induce investors to take more risk? What are the long term consequences of the robo adoption? At a broader level, a key question is also whether investors interact differently with a robo than with a human adviser; our analysis hints at some differences and at some similarities, but further work is certainly needed.

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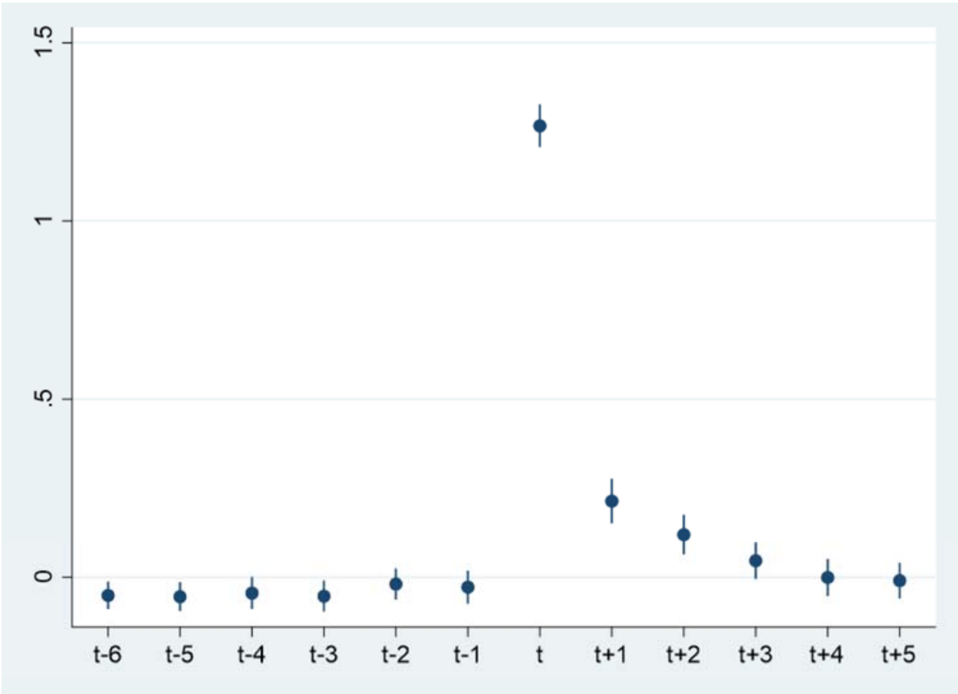
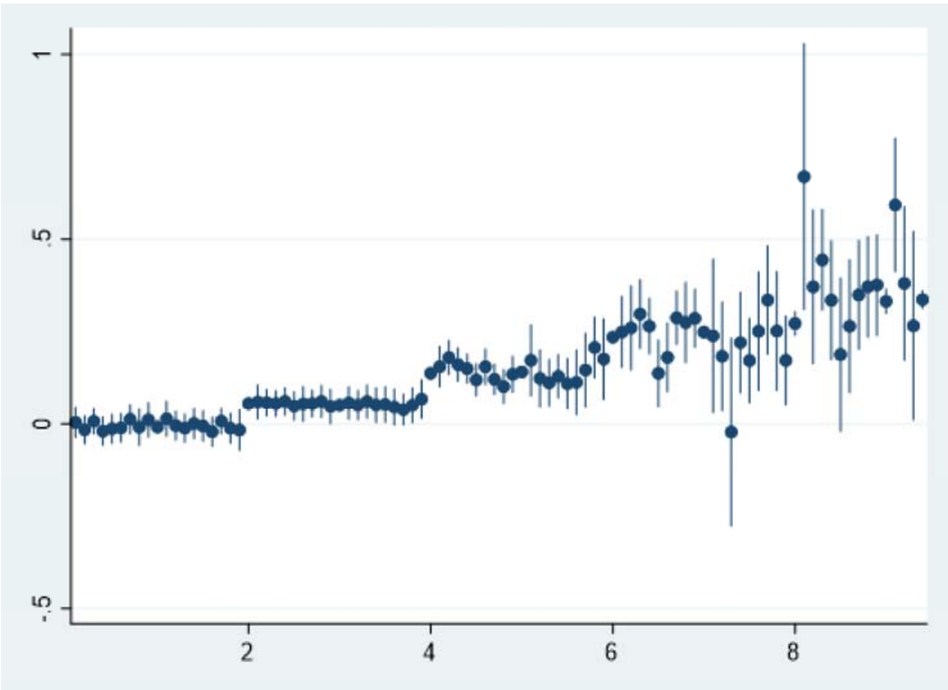
5 Figures and Tables

Figure 1: Investors' Attention: Dynamics



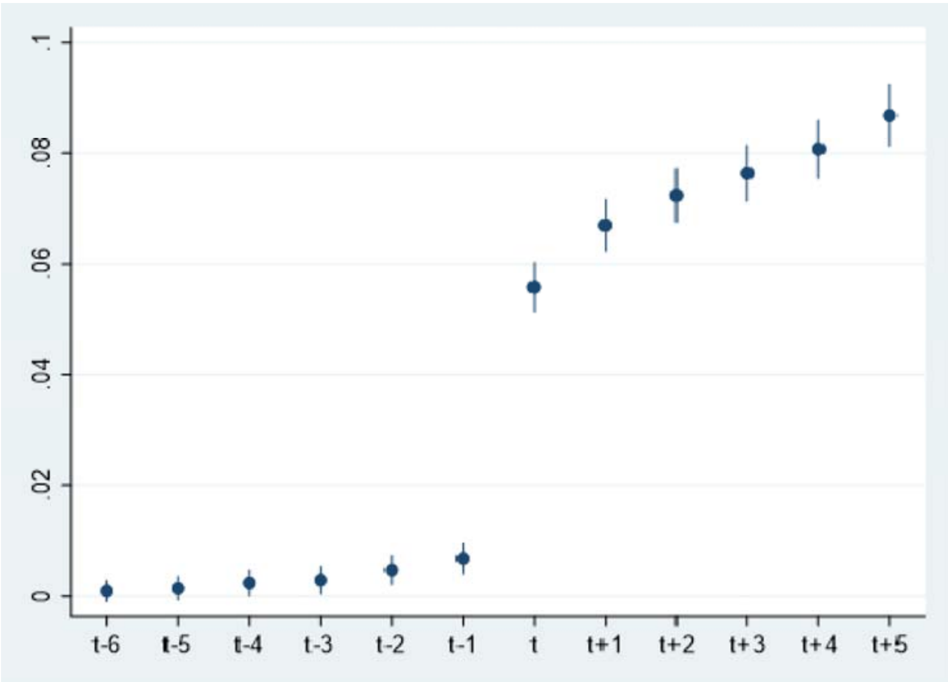
Note: This figure displays how the changes in the number of connections to the platform differ between robo takers and non-takers, before and after the robo subscription. T-5/T-1 correspond to months before the treatment, T/T+5 correspond to months after the treatment. The points correspond to the estimated beta coefficients of equation (3), the bars correspond to 95% confidence intervals.

Figure 2: Investor Score and Equity Share



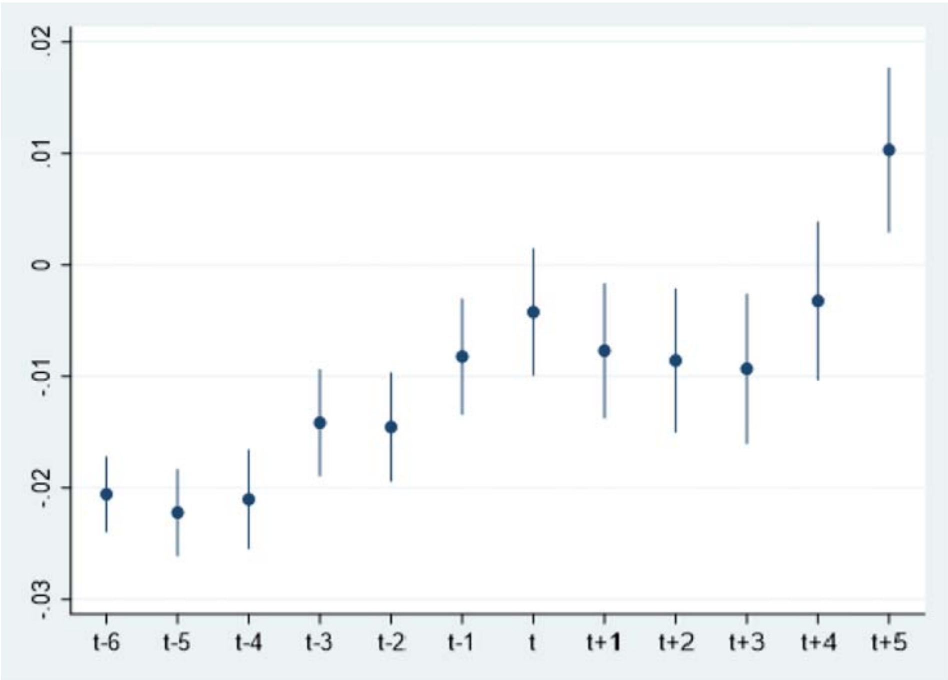
NOTE: This figure plots investors' equity share as a function of the risk score assigned by the robo, controlling for investors' horizon. The points correspond to the estimated beta coefficients of equation (6), the bars correspond to 95% confidence intervals.

Figure 3: Equity Exposure: Dynamics



NOTE: This figure displays how the changes in equity exposure differ between robo takers and non-takers, before and after the robo subscription. T-5/T-1 correspond to months before the treatment, T/T+5 correspond to months after the treatment. The points correspond to the estimated beta coefficients of equation (3), the bars correspond to 95% confidence intervals.

Figure 4: Risk-Adjusted Returns: Dynamics



Note: This figure displays how the changes in returns adjusted for volatility differ between robo takers and non-takers, before and after the robo subscription. T-5/T-1 correspond to months before the treatment, T/T+5 correspond to months after the treatment. The points correspond to the estimated beta coefficients of equation (3), the bars correspond to 95% confidence intervals.

Table 1: Descriptive Statistics

Variable	p5	mean	p95	sd	N
Panel A: Individual characteristics					
Age	29	48.4828	67	11.7225	2,263,612
Female	0	0.3053	1	0.4606	2,255,803
Saving plan value	0	7,654	36,569	27,065	2,263,612
Total account value	48.73	36,140	148,381	74,763	2,263,612
Nb of saving vehicles	1	4.4334	11	3.4352	2,263,612
Nb of LT saving vehicles	0	1.3051	4	1.4359	2,263,612
Nb of ST saving vehicles	1	3.1282	8	2.5580	2,263,612
Panel B: Attention					
Number of connexions per month	0	0.4926	2	2.4692	2,263,612
Number of web pages viewed per month	0	4.0528	24	17.3932	2,263,612
Number of min spent on website per month	0	3.8180	22.3833	21.2251	2,263,612
Panel C: Asset allocation					
Risky share	0	0.7052	1	0.3334	2,173,345
Risky share wo employer stock	0	0.5491	1	0.3651	1,926,082
Equity exposure	0	0.1568	0.5708	0.2020	2,173,345
Weight in diversified equity funds	0	0.0922	0.4584	0.1703	2,173,345
Weight in balanced funds	0	0.2029	0.8612	0.2838	2,173,345
Weight in employer stock funds	0	0.3439	1	0.3901	2,173,345
Weight in guarantee funds	0	0.0483	0.3727	0.1554	2,173,345
Weight in other funds	0	0.0179	0.0852	0.0902	2,173,345
Weight in bond funds	0	0.1616	0.9185	0.2701	2,173,345
Weight in money market funds	0	0.1120	0.7404	0.2373	2,173,345
Weight in blocked cash funds	0	0.0212	0.1196	0.0977	2,173,345
Panel D: Transactions					
Monthly contribution (Euros)	0	266.2853	1103.95	1334.23	2,263,612
Monthly personal contribution (Euros)	0	68.2276	200	631.05	2,263,612
Monthly redemption (Euros)	0	305.5624	4.99	4856.52	2,263,612
Net monthly inflow (Euros)	0	-39.2772	1038.89	5008.97	2,263,612
Net monthly voluntary inflow (Euros)	0	-237.3349	192.17	4887.17	2,263,612
Personal contributions	0	0.1822	1	0.4668	2,263,612
Asset allocation changes	0	0.1939	1	0.5455	2,263,612
Asset allocation changes (robo)	0	0.0278	0	0.1939	2,263,612
Asset allocation changes (life-cycle funds)	0	0.1328	1	0.3627	2,263,612
Asset allocation changes (individual)	0	0.0329	0	0.3441	2,263,612
Number of redemptions	0	0.0322	0	0.2070	2,263,612
Panel E: Performances					
Ann. return	-0.0969	0.0662	0.3177	0.1768	2,040,570
Volatility	0.0005	0.0968	0.2579	0.1311	2,040,570
Ann. return (wo employer stock)	-0.0195	0.0315	0.1226	0.2045	1,580,493
Volatility (wo employer stock)	0	0.0406	0.1290	0.1721	1,580,493
Panel F: Robo interest					
Nb of saving vehicles with robo	0	0.5471	2	0.6971	2,263,612
Nb of LT saving vehicles with robo	0	0.1998	1	0.4004	2,263,612
Nb of ST saving vehicles with robo	0	0.3473	1	0.4767	2,263,612
Robo treated (in a given saving vehicle)	0	0.1811	1	0.3851	2,263,612

NOTE: This table reports descriptive statistics of our variables.

Table 2: Robo Take-Up

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Taker	Share	Taker		Equity Change	
Age	-0.000384***	5.85e-07	0.00309***	0.00359***	-0.00139***	-0.00239***
	(0.000145)	(0.000574)	(0.000469)	(0.000421)	(0.000311)	(0.000381)
Female	-0.0347***	-0.0141**	-0.0348***	-0.0342***	0.0117**	-0.0274***
	(0.00413)	(0.00558)	(0.0109)	(0.0108)	(0.00534)	(0.00569)
Account value (ln)	-0.00582*	-0.0358***	-0.0546***	-0.0579***	0.00122	0.0179***
	(0.00303)	(0.00554)	(0.00434)	(0.00443)	(0.00311)	(0.00325)
Long-term contract	-0.0240**	-0.114***	0.137***	0.143***	0.0124	0.0241
	(0.0106)	(0.0263)	(0.0186)	(0.0154)	(0.00967)	(0.0193)
Past risky share	0.000964	0.0874***	0.0194	0.0625	0.389***	-0.355***
	(0.0364)	(0.0272)	(0.0863)	(0.0838)	(0.0369)	(0.0333)
Variable remuneration	-5.43e-08	-3.29e-07	-2.59e-06	-3.57e-06**	2.71e-06**	2.54e-06*
	(8.65e-07)	(1.62e-06)	(1.62e-06)	(1.72e-06)	(1.23e-06)	(1.45e-06)
Past return	0.0576	0.741***	-0.158	-0.272	-0.625***	1.024***
	(0.223)	(0.232)	(0.434)	(0.409)	(0.239)	(0.302)
Connexions	0.0243***	-0.00121	0.00845***	0.00955***	-0.00604***	-0.00158
	(0.00402)	(0.00104)	(0.00201)	(0.00218)	(0.00208)	(0.00128)
Remuneration in t	0.0828***	0.00530	0.0230*	0.0191	0.0163**	0.0158***
	(0.0152)	(0.0111)	(0.0129)	(0.0127)	(0.00784)	(0.00443)
Remuneration in t-1	0.145***	-0.00798	0.0283*	0.0235	0.0145**	0.0158*
	(0.0409)	(0.00686)	(0.0169)	(0.0150)	(0.00725)	(0.00835)
Robo equity distance			0.119***			
			(0.0239)			
Robo equity change				0.270***		
				(0.0334)		
Robo visualitions			0.0162***	0.0150***	0.00127	0.00976***
			(0.00249)	(0.00233)	(0.00105)	(0.00184)
Sample	Takers + Exposed	Takers	Takers+Curious		Takers	Curious
Observations	116,661	15,702	31,858	31,858	15,702	16,156
R-squared	0.086	0.077	0.046	0.064	0.136	0.158
Number of Clusters	1,823	745	927	927	745	719

NOTE: This table reports the results of OLS regressions. In column 1, the dependent variable is a dummy equal to 1 if the individual has taken up the robo and to zero if the individual has been exposed to the robo and has not taken it. In column 2, the sample is restricted to robo takers and the dependent variable is the fraction of the investor's portfolio managed by the robo. In column 3-4, the dependent variable is a dummy equal to 1 if the individual has taken up the robo and to zero if the individual is robo curious (i.e., has observed the recommendation of the robo and has not accepted it). In columns 5-6, the dependent variable is the change in equity exposure proposed by the robo relative to the current allocation. In column 5, the sample is restricted to robo takers, in column 6, the sample is restricted to robo curious. All regressions include firm and time fixed effects. Standard errors, clustered at the firm level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 3: Investors' Attention

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Connexions		Minutes		Pages	
Robo treated*after	0.277***	0.278***	4.042***	4.717***	5.082***	5.869***
	(0.0205)	(0.0156)	(0.162)	(0.133)	(0.146)	(0.108)
Robo treated	0.761***		5.634***		5.671***	
	(0.0199)		(0.135)		(0.113)	
Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	879,041	782,234	879,041	782,234	879,041	782,234
R-squared	0.048	0.021	0.046	0.029	0.080	0.059
Number of Clusters	34,441	34,441	34,441	34,441	34,441	34,441

NOTE: This table reports the results of OLS regressions. In columns 1-2, the dependent variable is the number of connections per month; in columns 3-4, the dependent variable is the number of minutes spent on the dedicated website per month; in columns 5-6, the dependent variable is the number of webpages visited per month. In columns 2,4,6 regressions include individual, time fixed effects and our set of controls: the average risky share and the average returns over the past 12 months, the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 4: Investors' Attention: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Minutes	Pages		Connexions		
Robo treated*after	3.250***	4.041***	0.205***			0.0842***
	(0.127)	(0.102)	(0.0148)			(0.0154)
Remuneration months t-3 to t-1				0.187***	0.0583***	
				(0.0477)	(0.00625)	
Remuneration month t				0.757***	0.299***	
				(0.0568)	(0.0115)	
Remuneration months t+1 to t+3				0.0313	0.00514	
				(0.0263)	(0.00717)	
Observations	637,029	637,029	637,029	71,285	682,680	627,071
R-squared	0.010	0.023	0.008	0.031	0.012	0.006
Number of Clusters	33,019	33,019	33,019	13,098	34,409	33,018

NOTE: This table reports the results of OLS regressions. In column 1, the dependent variable is the number of minutes spent on the dedicated website per month; in column 2; the dependent variable is the number of webpages visited per month; in columns 3-6, the dependent variable is the number of connections per month. In column 1-3, we exclude the month before and the month at which the individual has received the variable remuneration. In columns 4-5, time t corresponds to the reception of the remuneration, conditional on the fact that this occurs at least two months after the subscription of the robo. In column 4, the sample is restricted to robo treated; in column 5, the sample is restricted to non- treated investors. In column 6, the sample excludes the two months around the robo subscription and the month of the reception of the remuneration. All regressions include individual and time fixed effects. Controls include the average risky share and the average returns over the past 12 months, the account value in the previous month, the value of the yearly variable remuneration. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 5: Investors' Attention and Past Returns

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Number of connexions per month					
Market return	0.0871***	-0.0343***				
	(0.00801)	(0.00239)				
Robo treated*after*market return		0.0810**				
		(0.0319)				
Robo treated*market return		0.399***				
		(0.0204)				
Return			0.0252***	-0.0183***		
			(0.00289)	(0.00146)		
Robo treated*after*return				0.0615***		
				(0.0166)		
Robo treated*return				0.102***		
				(0.00916)		
Market volatility					-0.0322	1.005***
					(0.288)	(0.105)
Robo treated*after*market volatility						-25.86***
						(1.408)
Robo treated*market volatility						-8.076***
						(0.909)
Robo treated*after		0.271***		0.294***		2.011***
		(0.0156)		(0.0157)		(0.0905)
Observations	782,234	782,234	782,234	782,234	650,300	650,300
R-squared	0.016	0.019	0.019	0.022	0.017	0.024
Number of Clusters	34,441	34,441	34,441	34,441	34,104	34,104

NOTE: This table reports the results of OLS regressions. The dependent variable is the number of connections per month. All regressions include individual fixed effects, regressions in columns 3-4 also include time fixed effects. Controls include the average risky share and the average returns over the past 12 months, the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 6: Trading Activities

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Changes	Robo	Individual	Contributions	Redemptions	Net inflows
Robo treated*after	0.272***	0.273***	0.00376**	0.00658***	-0.00157*	131.6***
	(0.00231)	(0.00137)	(0.00154)	(0.00160)	(0.000921)	(16.07)
Observations	782,234	782,234	782,234	782,234	782,421	782,234
R-squared	0.075	0.166	0.002	0.168	0.011	0.026
Number of Clusters	34,441	34,441	34,441	34,441	34,441	34,441

NOTE: This table reports the results of OLS regressions. In column 1, the dependent variable is the number of allocation changes per month; in columns 2-3, the dependent variable is the number of allocation changes induced by the robo and directly chosen by the individual, respectively; in column 4, the dependent variable is the number of personal contributions; in column 5, the dependent variable is the number of redemptions; in column 6, the dependent variable is the net monthly inflow in euros. All regressions include individual and time fixed effects. Controls include the average risky share and the average returns over the past 12 months, the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 7: Risk Taking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Risky Sh.	Equity	Balanced	Employer	Bond	Money	Equity Sh.
Robo treated*after	0.253***	0.0272***	0.228***	0.00234***	-0.155***	-0.0916***	0.0866***
	(0.00338)	(0.00183)	(0.00318)	(0.000721)	(0.00292)	(0.00250)	(0.00220)
Observations	1,450,851	1,450,851	1,450,851	1,450,851	1,450,851	1,450,851	1,450,851
R-squared	0.209	0.010	0.199	0.005	0.118	0.058	0.069
N. of Clusters	72,292	72,292	72,292	72,292	72,292	72,292	72,292

NOTE: This table reports the results of OLS regressions at the saving account level. In column 1, the dependent variable is the risky share; in column 2, it is the portfolio weight in diversified equity funds; in column 3, it is the weight in balanced funds; in column 4, it is the weight in employer stock funds; in column 5, it is the weight in bond funds; in column 6, it is the weight in money market funds; in column 7, it is the equity weight. All regressions include individual and time fixed effects. Controls include the average risky share and the average returns over the past 12 months, the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 8: Risk Taking (individual level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Risky Sh.	Equity	Balanced	Employer	Bond	Money	Equity Sh.
Robo treated*after	0.191***	0.0199***	0.181***	-0.00453***	-0.134***	-0.0505***	0.0729***
	(0.00297)	(0.00142)	(0.00273)	(0.00105)	(0.00267)	(0.00194)	(0.00179)
Observations	777,832	777,832	777,832	777,832	777,832	777,832	777,832
R-squared	0.185	0.013	0.182	0.013	0.117	0.036	0.080
N. of Clusters	34,408	34,408	34,408	34,408	34,408	34,408	34,408

Note: This table reports the results of OLS regressions at the individual level. In column 1, the dependent variable is the risky share; in column 2, it is the portfolio weight in diversified equity funds; in column 3, it is the weight in balanced funds; in column 4, it is the weight in employer stock funds; in column 5, it is the weight in bond funds; in column 6, it is the weight in money market funds; in column 7, it is the equity weight. All regressions include individual and time fixed effects. Controls include the average risky share and the average returns over the past 12 months, the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 9: Risk Taking (RDD)

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Equity Sh.	Average Equity Sh.			Past Equity Sh.
I(score>cutoff)	0.0514***	0.0506***	0.0593*	0.0353	0.00642
	(0.0158)	(0.0145)	(0.0330)	(0.0379)	(0.0197)
Score -cutoff	0.0313	0.0340	-0.0355	0.0739	0.00303
	(0.0417)	(0.0383)	(0.183)	(0.0968)	(0.0521)
Score -cutoff*I(score>cutoff)	-0.128***	-0.136***	-0.159	0.00626	0.00428
	(0.0451)	(0.0414)	(0.191)	(0.104)	(0.0564)
I(score>cutoff)*horizon	0.00546***	0.00587***	0.00554***	-0.00553***	-7.37e-05
	(0.000889)	(0.000817)	(0.00137)	(0.00204)	(0.00111)
Horizon	0.0462***	0.0466***	0.0491***	0.0139**	0.000547
	(0.00248)	(0.00228)	(0.00281)	(0.00590)	(0.00310)
Horizon-sq	-0.00137***	-0.00138***	-0.00149***	0.000337	0.000390
	(0.000209)	(0.000192)	(0.000223)	(0.000486)	(0.000262)
Horizon-cub	4.78e-06	5.30e-06	6.53e-06	-1.90e-05*	-1.20e-05*
	(4.91e-06)	(4.51e-06)	(5.23e-06)	(1.13e-05)	(6.15e-06)
Observations	5,038	5,041	3,944	2,836	5,061
R-squared	0.488	0.540	0.535	0.079	0.398

NOTE: This table reports the results of OLS regressions. In column 1, the dependent variable is the equity share at t, the time of the robo subscription; in columns 2 and 3, the dependent variable is the average equity share between time t and time t+1; in column 4, the dependent variable is average equity share between time t and time t+1 in contracts held by individual i but not managed by the robo; in column 5, the dependent variable is the equity share at time t-1. In column 1,2,4 and 5 we estimate equation (5) with a bandwidth equal to 1; in column 3 we use a bandwidth equal to 0.5. All regressions include time fixed effects. Controls include the average risky share and the average returns over the past 12 months, the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 10: Alerts and Rebalancing

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Change in Distance Actual - Target Equity Share					Distance
Robo treated*after*alert	-0.0489***	-0.0693***	-0.0492***			
	(0.00300)	(0.00544)	(0.00430)			
Robo treated*after	0.0203***	0.0176*	0.0249***			
	(0.00368)	(0.0103)	(0.00482)			
Alert	0.00989***	0.0326***	0.0147***	-0.0346***		
	(0.00239)	(0.00421)	(0.00375)	(0.00182)		
Alert MIF					-0.00731*	
					(0.00408)	
I(distance>cutoff)						-0.0127**
						(0.00527)
Distance (SRRI)						0.474***
						(0.0487)
Distance*I(dist>cutoff)						-0.407***
						(0.0862)
Sample	Robo takers+curious			Robo takers		
		Actual>Target	Actual<Target			
Observations	139,598	59,097	64,204	82,330	70,610	4,326
R-squared	0.031	0.063	0.026	0.039	0.017	0.332
Number of Clusters	25,337	14,386	17,736	15,262	14,979	

NOTE: This table reports the results of OLS regressions. In columns 1-5, the dependent variable is the change in the distance between the actual and the target equity share between t+1 and t-1, where t is first the month at which the distance between those allocations exceeds the alert threshold. In columns 1-3, the sample is restricted to robo takers and robo curious. Alert is a dummy equal to one if the distance between the actual and the target allocation is above the alert threshold, and to zero otherwise. In column 2, the sample is restricted to observations in which the difference between the actual and the target allocation is positive while in column 3 to observations in which the difference is negative. In column 4-6, the sample is restricted to robo takers. Alert MIF is a dummy equal to one if the investor receives an alert as they have not completed the profiling survey requested by the regulator. In column 6, the dependent variable is the distance between the actual and the target equity share, the sample is restricted to observations in which the distance based on SRRI does not exceed 0.1, I(distance>cutoff) is a dummy equal to one if the distance is above the alert threshold, and to zero otherwise. All regressions include time fixed effects, and in columns 1-5 also individual fixed effects. Controls include the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 11: Returns

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable		Annual return			Return Diff	Equity
Robo treated*after	0.0539***	0.0471***	0.0306***	0.0423***	0.0232***	0.0893***
	(0.00160)	(0.00168)	(0.00117)	(0.00150)	(0.000952)	(0.00226)
Average risky share (t-12 - t-1)		0.0775***				
		(0.00614)				
Volatility			1.171***			
			(0.0249)			
Beta				0.0299***		
				(0.00268)		
Robo treated*after*mkt ret t+1						0.00734***
						(0.000904)
Market return t+1						-0.00516***
						(0.000623)
Observations	1,362,797	1,362,797	1,362,797	776,564	1,362,797	1,391,684
R-squared	0.104	0.105	0.479	0.190	0.019	0.071
Number of Clusters	70,656	70,656	70,656	62,136	70,656	72,211

NOTE: This table reports the results of OLS regressions. In columns 1-4, the dependent variable is the annual returns at the saving vehicle level. In column 5, the dependent variable is the difference between the returns experienced by the investor and the counterfactual returns she would have earned had she kept the same portfolio as the one just before the subscription of the robo (for robo takers) or just before the first reception of the variable remuneration (for non-takers). In column 6, the dependent variable is the equity share. Market excess returns is the difference between the average returns of risky assets and the average returns of safe assets at time t+1 in our sample. All regressions include individual and time fixed effects. Controls include the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 12: Heterogenous Impacts

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable		Equity Exposure			Annual return	
Robotreat*after*assets<q25	0.133***			0.0472***		
	(0.00348)			(0.00153)		
Robotreat*after*assets(q25,q50)	0.0789***			0.0226***		
	(0.00407)			(0.00185)		
Robotreat*after*assets(q50,q75)	0.0557***			0.0252***		
	(0.00492)			(0.00215)		
Robotreat*after*assets>=q75	0.0270***			0.0144***		
	(0.00600)			(0.00270)		
Robotreat*after*rem<q25		0.0557***			0.0384***	
		(0.00751)			(0.00261)	
Robotreat*after*rem(q25,q50)		0.127***			0.0457***	
		(0.00316)			(0.00147)	
Robotreat*after*rem(q50,q75)		0.0620***			0.0153***	
		(0.00439)			(0.00204)	
Robotreat*after*rem>=q75		0.0480***			0.0141***	
		(0.00485)			(0.00225)	
Robotreat*after*risk<q25			0.195***			
			(0.00301)			
Robotreat*after*risk(q25,q50)			0.137***			
			(0.00440)			
Robotreat*after*risk(q50,q75)			0.0996***			
			(0.00341)			
Robotreat*after*risk>=q75			-0.0560***			
			(0.00502)			
Robotreat*after*return<q25						0.0578***
						(0.00148)
Robotreat*after*return(q25,q50)						0.0535***
						(0.00132)
Robotreat*after*return(q50,q75)						0.0168***
						(0.00197)
Robotreat*after*return>=q75						-0.0512***
						(0.00372)
Volatility				1.172***	1.171***	1.171***
				(0.0248)	(0.0249)	(0.0249)
Observations	1,450,851	1,450,851	1,450,851	1,365,421	1,365,421	1,365,421
R-squared	0.082	0.080	0.144	0.479	0.479	0.481
Number of Clusters	72,292	72,292	72,292	70,931	70,931	70,931

NOTE: This table reports the results of OLS regressions. In columns 1-3, the dependent variable is the equity share; in columns 4-6, the dependents variable is the annual return. The estimated coefficients refer to the interaction between the robo treatment and investor's quartile based on portfolio size, value of the variable remuneration, equity share, and returns. Quartiles are determined based on the average values observed before the first robo introduction (August 2017). All regressions include individual and time fixed effects. Controls include the account value in the previous month, the value of the yearly variable remuneration, a dummy if the variable remuneration was received in the current month and a dummy if the variable remuneration was received in the past month. Standard errors, clustered at the individual level, are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.