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Augmenting Investment Decisions with Robo-Advice

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Abstract

We study the introduction of robo-advising on a large representative sample of Employee Saving Plans. Differently from many services that fully automate portfolio decisions, our robo-advisor proposes investment and rebalancing strategies, leaving investors free to follow or ignore them. We investigate the resulting human-robot interactions and show that with the robo-service investors increase their attention to the portfolio, their investment in the plan, and their equity exposure. They experience higher risk-adjusted returns, mostly by changing their rebalancing behaviours and staying closer to the target. We discuss how automated advice can promote financial inclusion, and how human-robot interactions can improve financial capability.

Keywords: Robo-Advising, Human-robot Interaction, Financial Inclusion, Portfolio Dynamics, Long-Term Investment

JEL classification: G11, G51, G41, G23, D14

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1 Introduction

Households are increasingly required to take complex financial decisions, and not all of them appear well equipped (Campbell (2006), Lusardi and Mitchell (2014)). While delegating to financial experts may help (Von Gaudecker (2015)), in practice financial advice has its limits. It is costly and, as it has been shown, it does not always serve clients' best interest.[1]

In this context, automated financial advisors, often called robo-advisors, have attracted a growing attention both in academia and in the industry. Robots have low operating costs, which may allow reaching a broader set of investors (Bianchi and Brière (2021)), and they adopt verifiable procedures, which may limit the extent of biased advice (Philippon (2019*b*)). Yet, even if a robot may be devised to reduce transaction costs and agency conflicts, the fundamental aspect is how much investors would be willing to rely on automated recommendations.[2] A second perhaps even more fundamental question is whether the robo-service can be used to complement, rather than to replace, investors' reasoning and actions.[3]

We investigate these issues by exploiting the introduction of a robo-advising service by a major French asset manager in a large set of Employee Saving Plans. 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 sends email alerts if the current portfolio allocation ends up being too far from the target allocation. These alerts suggest to connect to the platform and to rebalance the portfolio towards the target, while the ultimate decision has to be taken directly by the investor.

The key distinctive feature of this service is that it is truly a robo-advisor which gives advice to the investors, both at the time of the subscription and over time, while leaving investors free to follow or to ignore the advice. This makes it different from the

[1]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 (2021) on misguided beliefs. Egan, Matvos and Seru (2019) provide market-wide evidence of financial advisers' misconduct, discuss the associated labor market responses, and suggest that less sophisticated investors may be particularly exposed to repeated misconduct. See also Beshears, Choi, Laibson and Madrian (2018) and Gomes, Haliassos and Ramadorai (2021) for reviews.

[2]Bhattacharya, Hackethal, Kaesler, Loos and Meyer (2012) show that investors who most need advice are least likely to obtain it and that those who obtain the advice hardly follow it, even if the advice was unbiased and improved portfolio efficiency.

[3]See e.g. Siddarth, Acemoglu, Allen, Crawford, Evans, Jordan and Weyl (2021) and Brynjolfsson (2022) for a deeper discussion on AI systems that complement or substitute humans and their far-reaching economic and social effects.

more common robo-advisors (discussed in the literature review) that automate portfolio investment and rebalancing, and this makes it particularly useful for focusing on human-robot interactions both at the time of the subscription and over time.

A recurrent theme of our analysis is that these interactions are key to understand the ultimate effects of the robo on financial outcomes. First, while reliance on algorithms seems particularly delicate in the context of financial services, evidence from other domains suggests that algo-aversion can be partly overcome by letting humans and robots interact.[4] Second, these interactions allow us to study how the reliance on the robo-service evolves over time, say as investors experience market shocks or as new investment opportunities arise. In these instances, investors may be prompted to pay attention to their portfolios even if not used to do so, or they may be advised to rebalance their portfolio in a given direction even if tempted to do otherwise. As we will show, a significant part of our effects are driven by how investors change their behaviors over time, suggesting that the robo can be used to improve investors' decisions, while letting them being the ultimate decision maker.

Another interesting feature of our setting is that a large proportion of our investors have small portfolios and little experience in the stock market. This sample is particularly useful to explore whether robo-advisors can promote financial inclusion. Investors with lower financial capabilities may have in principle the most to gain from robo-advising (D'Hondt, De Winne, Ghysels and Raymond (2020)), but they may also be more reluctant to adopt the new technology (Hackethal, Haliassos and Jappelli (2012), Collins (2012), Foster and Rosenzweig (2010)), or they may end up misusing it (Campbell (2006)). An open empirical question is whether robo-advising tempers or exacerbates existing inequalities (Philippon (2019*a*), Abraham, Schmukler and Tessada (2019)).

The robo-advisor under study was introduced by the asset manager in August 2017. The robo is proposed to employers and, if they accept, employees get a notification on the availability of the service and decide whether or not to subscribe it. Absent the robo, employees self-manage their portfolios and have no access to a dedicated advice. We have access to account level data covering from September 2016 to November 2018, aggregated at the monthly level. Our sample contains all investors who have accepted the robo-service as of November 2018, and for these investors we can observe both contracts

[4] In a forecasting task, Dietvorst, Simmons and Massey (2018) show that participants are more willing to rely on an automated advice when they can even slightly modify the algorithm. Similarly, Burton, Stein and Jensen (2020) present several experimental settings in which algorithm aversion is reduced when giving participants some control over the underlying algorithm. Bianchi and Brière (2021) review some evidence on finance applications.

that are self-managed and contracts that are managed by the robo. In addition, we have extracted random samples of individuals who have not been offered the service (i.e., non-exposed), individuals who have declined the offer without initiating the profiling process (i.e., non-takers), and individuals who have initiated the profiling process without eventually subscribing to the service (whom we call robo curious).

A key challenge for our empirical analysis is that the choice of taking up the robo is voluntary and as such it could be driven by unobserved investors' characteristics that are also related to our outcomes of interest. Our data allow us to address this issue in several ways. First, we employ diff-in-diff specifications in which we compare changes in our outcome of interest associated to the robo take-up to changes in a control group, which in our baseline analysis we define as individuals who have not been exposed to the robo-service. We then consider alternative control groups (i.e. non-takers or curious) so as to isolate the effects of the robo from potentially confounding factors. Second, we exploit the fact that the exposure to the robo depends on an agreement between the employer and the asset manager, and as such it is orthogonal to employee-specific shocks. We then compare exposed to non-exposed individuals in an intention-to-treat specification. Third, we build on our knowledge of the functioning of the robo and on the various discontinuities in the algorithm to implement a regression discontinuity design. Fourth, since the decision to take-up the robo may be influenced by interactions occurring at the workplace, we use the fraction of employees adopting the robo in a given firm as an instrument for the individual propensity to take-up. We provide more details of these alternative specifications, and show the robustness of our findings, as we proceed with the analysis.

Our main findings can be summarized as follows. First, the robo attracts investors who are rather heterogeneous in terms of age, education, wealth; overall, observable investor's characteristics explain little of the take-up decision. Moreover, these investors are even more likely to accept the advice when this differs substantially from their current allocation.[5]

Second, investors who take-up the robo increase their attention to the portfolio, as measured by the amount of time spent on the dedicated company website, and their trading activities. These patterns hold even beyond the time of the robo-subscription.

Third, investors increase the amount they invest in the saving plans, as well as their risk exposure. This is explained not only by a large increase in equity share at the time

[5]This finding can be contrasted with the observation that human advisers tend to gain trust by being accommodating with clients' beliefs and investment strategies (Mullainathan et al. (2012)).

of the subscription, but also by a positive trend after the subscription.

Fourth, the robo-alerts, which by construction are sent after investors experience large shocks to their portfolio, are effective in increasing investors' attention and rebalancing. As a result, investors remain closer to their target equity exposure.

Fifth, investors with the robo experience a substantial increase in returns (net of fees), after controlling for various measures of portfolio risk. Importantly, the main determinant of this increase comes from a change in rebalancing behaviors.

Finally, we show that the increased equity exposure and returns associated to the robo-service are larger for investors with lower financial capabilities, as measured by ex-ante portfolio size (a proxy for financial wealth) and variable remuneration (a proxy for income), and with lower risk exposure and returns at the baseline.

Overall, these findings are encouraging on the possibility to promote human–robot interactions in the field of personal finance. We view our results as contributing to the debate on how automation can impact financial services, and more specifically to a growing literature on the effects of robo-advising on portfolio choices. D'Acunto, Prabhala and Rossi (2019) study an interactive portfolio optimizer offered by an Indian brokerage house and show it has beneficial impacts on less diversified investors, as it induces them to hold a larger number of stocks, but not on diversified investors. D'Acunto et al. (2019), however, do not focus on portfolio dynamics, which is a central feature in our analysis. As we show, the dynamic interactions between the robo and the investors are in our setting key to understand how the robo impacts investors' rebalancing behaviors and performance.[6] These dynamic interactions also distinguish our paper from most other contributions, such as Reher and Sun (2019), Loos, Previtero, Scheurle and Hackethal (2020), Rossi and Utkus (2020), that study automated portfolio managers in which portfolio choices over time are fully delegated to the robo (see D'Acunto and Rossi (2020) and Bianchi and Brière (2021) for overviews).

A second important feature of our study is the focus on investors who have little experience in the stock market and typically no access to financial advising. A similar perspective is taken by Reher and Sokolinski (2021), who exploit the reduction of the account minimum by a major U.S. robo-advisor, and show a significant increase in the share of "middle class" participants, who increase their risky share and their expected returns. While the robo studied by Reher and Sokolinski (2021) directly manages investors' port-

[6]Differently from D'Acunto et al. (2019), in our setting investors do not pick stocks but choose among a menu of funds, which should minimize issues of under-diversification. Rebalancing behaviors may be an equally important source of (under)performance, especially for less sophisticated investors (Bianchi (2018)).

folios, in our setting the robo provides recommendations and investors decide whether or not to follow them. Under this perspective, the difference is important as it shows that improving the participation of small investors does not necessarily mean having them lose controls over their portfolios. In fact, as we emphasize in the concluding remarks, we view investors' active participation as fundamental to promote learning and financial capability and as key when assessing the long-term consequences of the robo-service.

Relatedly, recent contributions show that long-run patterns of wealth accumulation and inequality are strongly driven by the fact that wealthier individuals earn persistently higher returns (Bach, Calvet and Sodini (2020), Fagereng, Guiso, Malacrino and Pistaferri (2020)). Under this perspective, our results suggest that automated advice can at least partly limit these general patterns. They also inform the policy debate on whether robo-advisors can impact participation in long-term saving plans (OECD (2017)).[7]

Finally, our paper relates 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), and our key focus in this respect is on the human-robot interaction.

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

[7] As stressed in Mitchell, Hammond and Utkus (2017), this long-term perspective is relatively uncommon in the context of robo-advising.

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. Importantly, the robo's allocation is built within the funds proposed by the employer; that is, investors have access to exactly the same menu of funds when with and without the robo.[8]

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.[9] 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 the target 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 her account. As of November 2018, around 8,000 companies have access to the offer, that corresponds to 646,884 employees (out of over 1,9 millions employees active in those plans). Out of them, 189,918 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. Out of them, 175,342 individuals ended up not subscribing to the service and we refer to them as robo-curious while the remaining 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 762 different firms. We observe no individual who subscribes to the robo and then terminates the service within our sample period.

In our baseline analysis, our sample includes all the robo-takers and a random sample of 20,000 individuals who 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

[8]The robo is programmed to propose an allocation on the part of the portfolio which is not invested in employer's stock, which may have some specificities (e.g. in terms of matching rule) relative other stocks.

[9]Even if the client accepts the robo's allocation, she is not committed to it in any way, she can change again the allocation right after having taken up the robo.

2018 and are aggregated at the monthly level. We have also extracted a random sample of 20,000 individuals who are exposed but non-takers and a random sample of 20,000 individuals who are curious, which we consider in additional analyses detailed below.

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.[10] We provide more details about those variables as we proceed with our analysis below.

Our sample is 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. The average value of the assets invested in the plan is 7,654 euros, the median is 819 euros. These figures are comparable to those one can find in representative surveys.[11] 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 a brokerage house). 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)

[10] We observe the overall score assigned by the robo, not the single answers provided by the investor on risk aversion, financial literacy, and investment horizon.

[11] 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).

the attention investors pay to their portfolio, ii) their trading activities and portfolio allocations, and iii) their returns and risk.

3.1 Take-Up

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:

$$T_i = \alpha + X_i^{'}\gamma + \mu_f + \varepsilon_i, \tag{1}$$

where T_i is a dummy equal to 1 if individual i working in firm f has taken the robo in period t, X_i is a vector of baseline individual and portfolio characteristics, μ_f are firm fixed effects. Standard errors are clustered at the firm level. For each characteristic X_i we consider the average value observed before August 2017, the date of the first robo introduction. Results are reported in Table 2.[12]

In column 1, we observe that the probability of subscribing to the robo is negatively related to being female and to the past returns, and it is positively related to the amount of variable remuneration, though these effects are small in magnitude.[13] 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, smaller equity exposure and smaller 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 and the one proposed 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

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

[13]We make sure that the proportion of treated individuals correspond to the true population average. In this regression, we include a random sample of 638 takers, 7674 curious and 20,000 exposed not curious so that the proportion of takers is 2.25% and the proportion of curious is 27.11%, which correspond to the true population averages within the group of exposed individuals. The same logic applies to the other regressions in this table.

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.[14]

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, have smaller portfolios and check more frequently their account. 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. In terms of magnitude, one standard deviation increase in the difference in equity shares (equal to 0.27) is associated to a 4.3% increase in the probability to take-up the robo (the average take-up in these specifications is 7%).

Overall, these results point towards an important ability of the robo to reach underserved investors and to change in a substantial way their investment choices. First, while the probability to take-up the robo is hardly affected by observable characteristics (apart from being female), the robo-service appears relatively more important for 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.

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

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. Standard errors are clustered by individual.[15] Unless specified otherwise, our controls include the average equity 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, while we consider alternative specifications in the robustness section.

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, and 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. Our key observation is that, after having taken the robo, investors spend more time on the platform. In column 1, we observe an increase in the number of minutes spent on the platform by 4.6 per month (the average is 6.2); in column 2, we observe an increase in the number of web pages visited per month by 5.8 (the average is 6.5); in column 3, we observe an increase of 0.3 connections per month (the average is 0.8).

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

[15]As we show in the Online Appendix, our results are basically unchanged if we employ double clustering by individual and by time.

report the estimated coefficients $\beta_{-5}, ..., \beta_6$ and the associated 95% confidence intervals. We observe no significant pre-treatment 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 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 column 3.

A related concern is whether the effects persist also beyond the window of the subscription to the service. In column 5, we exclude the two months around the robo subscription and the month of reception of the remuneration, which are generally periods in which investors pay more attention to their portfolio. As intuitive, the estimated effects are smaller in magnitude than the overall effects in column 3, but still significantly different from zero. That is, robo takers display larger levels of attention also beyond even beyond the time of the subscription and the time of reception of the variable remuneration.

In order to check this further, 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 column 6 is for robo treated and column 7 is for non treated (i.e. not exposed and takers before the subscription). 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 (0.8 vs. 0.5 connections). We will get back to investors' increased attention in the next analysis, when describing the effects of the alerts sent by the robo.

Overall, 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, which persists even beyond the time of its subscription.

3.3 Activities and Investment

We now consider trading activities, which 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).

In the next analysis, we consider 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). [16]

We report our results in Table 4. We first consider pure rebalancing activities, in which investors move money across funds without increasing or decreasing their total investment. In column 1, we observe that subscribing to the robo is associated to 0.21 more allocation changes by month, relative to an average of 0.05. The total sum of rebalancing activities includes those implemented by the robo at the time of subscription, those implemented by the robo after the subscription date, and those directly implemented by the investor. In column 2, we focus on portfolio rebalancing implemented by the robo after subscription, and observe that a significant increase also in these activities (explained in more details below). In column 3, we observe no significant increase in rebalancing activities directly implemented by the investor.

The robo take-up is also associated to an increase in the number of personal contributions of 0.005 per month (the average number is 0.03) and to a non-significant decrease in the number of redemptions. The sum of the transactions described in columns 1, 4 and 5 represents the totality of the transactions made in the account.

Interestingly, these patterns translate into an increase in the total amount of money invested in the contract. Robo takers invest 84 euros more per month in their contract,

[16] Alternatively, one can consider regressions at the individual level as in Equation (2) and aggregate over the various contracts an individual may hold (in our sample, we observe on average 2.68 contracts per investor). As we show in the Online Appendix, results at the individual level are qualitatively the same as those at the contract level, indicating very little spillovers across contracts held by the same individual.

while on average monthly net inflows are much smaller (1.7 euros).

3.4 Equity Exposure

We now consider whether the robo adoption is associated to changes in the composition of investors' portfolio. As shown in Table 1, the main types of funds are employer stock (29%), balanced funds (21%), bonds (18%), money market (13%), equity funds (12%). In order have a measure of aggregate risk exposure, we define the equity share as the value of equity, i.e. equity funds and the equity parts of balanced funds, over the total value of the portfolio.

Table 5 reports our evidence at the saving vehicle level as in Equation (4). We observe that the robo subscription is associated to an increase in the equity share by 8.7%. The effect is large, as compared with the average equity share of 18%, 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.

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 algorithm that 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 takes 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

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

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 6, 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.[17] 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

[17]The MSE-optimal bandwidth, computed following Calonico, Cattaneo and Titiunik (2014), is equal to 0.815. Using this bandwidth, we obtain very similar results.

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, showing a large increase in risk exposure at the time of the subscription, but also a positive trend after the subscription.

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). In case of alert, the investor receives an email stating that there is discrepancy between the current and the target allocation, due to the investor's own trading or to a market shock, and she is suggested to connect to the dedicated website to consult her portfolio. The email alert is sent in the month at which the deviation occurs; if the deviation persists an additional email is sent the month after and then alerts stop, even if the deviation persists. Once the investor is connected, the robo proposes to rebalance the portfolio so as to get back to the target allocation and, if the investor accepts, the required adjustment is implemented by the robo.

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, even when investing in funds and not in individual stocks, less sophisticated investors tend to chase trends and as a result their risk exposure displays larger sensitivity to market fluctuations (Bianchi (2018)). Second, investors' reaction to alerts provides (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.

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 τ. Accordingly, we construct a dummy *Alert* that is equal to one if the distance is above τ, and to zero otherwise.[18] On average, in our sample, investors receive an alert in 7.7% of the months after the subscription.[19]

The variable *Alert* 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 reception of the alert depending on whether or not the investor has accepted the robo-service.

We start by checking whether the reception of the alert is associated to an increased attention to the portfolio. In column 1 of Table 7, we observe that indeed upon reception of the alert investors are more likely to connect to the platform; the number of connections increases by 0.23 connections per month, relative to an increase of 0.11 connections associated to the counterfactual alert.[20] In columns 2-6, we consider the associated rebalancing behaviors. In column 2, we consider the probability of rebalancing upon reception of the alert (for robo-takers) or of the counterfactual alert (for robo-curious). The dependent variable is a dummy equal to one if the investor rebalances the portfolio in month t or t+1, where t is the first month at which the distance between the actual and the target allocation exceeds the alert threshold. We observe that robo-takers, who actually receive the alert, are 19% more likely to rebalance their portfolio, as compared to a baseline probability of rebalancing of 11.4% for robo curious.[21] In column 3, the dependent variable is the change in the distance between the actual and the target equity share, and we observe that robo takers decrease their distance by 7.2% 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 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 small

[18]Given our definition of target allocation, *Alert* can only be constructed after the robo adoption (for robo-takers) or its refusal (for robo-curious). The threshold τ is defined in terms of a Synthetic Risk and Reward Indicator (SRRI), a measure of portfolio risk designed by the European Security and Market Authority, and its exact value is confidential.

[19]The standard deviation of *Alert* is 11.3%, showing a significant variation in the number of alerts across investors.

[20]Counterfactual alerts, just like actual alerts, occur after large changes in portfolio weights due to market shocks or active rebalancing, hence it is intuitive that even those alerts are associated to an increased attention.

[21]Karlan, McConnell, Mullainathan and Zinman (2016) show that monthly reminders via SMS increase savings.

and not significant, 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 τ 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).[22] 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 Returns

We consider whether the changes in trading patterns described above are associated to changes in portfolio returns, controlling for various measures of risk. We start with the same specification as in (4), using realized returns as dependent variable. Throughout this analysis, we use returns net of management and fund fees, which we estimate directly from the liquidation value of the various funds. Results are presented in Table 8.

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 6.2%. 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 equity share in the previous period; 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 5% in yearly returns, which is slightly smaller than the baseline estimate but still very large.

These estimates are crude and should be interpreted with care, also given that we are considering realized returns over a relatively short period of time. In order to further investigate their robustness, we consider how much of the effects on realized returns is driven by a change in exposure to standard risk factors. We consider a 5-factors model including 3 equity factors (Fama-French's market, size, value) and 2 fixed-income factors (Barclays' U.S. and Global Bond Index), as in Reher and Sokolinski (2021). We regress

[22] Using the MSE-optimal bandwidth (equal to 0.118) gives very similar results.

each fund's excess return over the U.S. risk-free rate to calculate the beta exposures of each fund. We define $R_t(x)$ as the time-varying expected return of each risky fund x (i.e., equity, balanced, bond, employer stock funds), in excess of the U.S. risk-free rate, which we compute as the cross product of the fund's beta $\beta^f(x)$ and the realized returns of the corresponding factor R_t^f,

$$R_t(x) = \sum\nolimits_f \beta^f(x) R_t^f.$$

For money market funds, we set these returns equal to the U.S. risk-free rate.[23] We can then compute the expected return of each portfolio based on each fund's portfolio weight.

We report our results in columns 5 and 6 of Table 8. We observe that subscribing to the robo is associated to an increase in expected returns by about 2.3% per year. This effect can be compared to an average expected return of 8.4% in our sample. Controlling for the past equity share, the estimated increase in expected returns is equal to about 2% per year.

To have a rough measure of the euro value of these extra returns, consider an investor with average investment in the plan (36,000 euros) and average horizon (17 years). An increase in yearly returns by 5.4% would be associated to an increase in final wealth by about 52,000 euros. Considering instead an increase in expected yearly returns by 2.3%, the associated increase in final wealth would be about 17,000 euros. 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.

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

Static vs. Dynamic Effects

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 portfolio dynamics after the subscription. As shown above, after subscribing to the robo, investors' portfolios change in two dimensions. First, at the time of the subscription, they move from their current allocation to the one proposed by the robo. We call this a static effect, which can positively impact returns to the extent that investors hold sub-optimal portfolio allocations (e.g. they wrongly estimate expected returns and risk or they choose allocations outside the efficient frontier).

[23] See the Online Appendix for more details and alternative specifications.

Second, investors may change the way in which they rebalance their portfolio over time, which we call a dynamic effect. The resulting impact on returns can be positive if for example investors tend to wrongly time the market. We investigate how the two effects contribute to the observed changes in portfolio returns.

Consider an investor who takes up the robo at time t^* and let us define $\omega_1(s,t)$ as the observed portfolio weight on asset s at time $t \geq t^*$ and $\omega_0(s,t)$ as the counterfactual weight on asset s the investor would have had without the robo. The associated portfolio returns at time t are $R_1(t) = \sum_s \omega_1(s,t-1)R(s,t)$, where $R(s,t)$ are the returns of asset s at time t, and the counterfactual returns without the robo are $R_0(t) = \sum_s \omega_0(s,t-1)R(s,t)$. According to the above estimates, the total effect $R_1(t) - R_0(t)$ is around 5.4% in yearly returns, and we wish to decompose this effect into a static and a dynamic effect. In general, this exercise in challenging since we cannot directly observe the returns the investor would have experienced had she taken the robo at time t^* without changing her rebalancing behaviors at time $t > t^*$. Moreover, these rebalancing behaviors (say, passive, contrarian, or trend chasing) may vary considerably across clients and over time.

In our setting, however, we can exploit the knowledge of the robo algorithm. In our sample period, the robo's recommendations are essentially intended to induce constant portfolio weights.[24] Suppose that the robo were to keep the investor's current allocation unchanged and just change rebalancing behavior according to constant weights. The investor would then experience returns $C_0(t+1) = \sum_s \omega_0(s,t^*)R(s,t+1)$, where $\omega_0(s,t^*)$ are the portfolio weights observed just before the robo take-up at t^*,

$$\omega_0(s,t^*) = \frac{\omega_0(s,t^*-1)R(s,t)}{\sum_z \omega_0(z,t^*-1)R(z,t)}.$$

In this case, the robo would only have a dynamic effect, which can be computed as

$$D(t) = C_0(t) - R_0(t). \tag{7}$$

The static effect, due to the fact that the robo is also changing the investor's allocation at t^*, can be then computed as the residual

$$S(t) = R_1(t) - R_0(t) - (C_0(t) - R_0(t)). \tag{8}$$

We report our corresponding estimates in Table 9. In column 1, we estimate the

[24] This would not be true over a longer time period, on which the robo would change the suggested allocations according to the investor's life-cycle.

static effect according to Equation (8) by considering the same diff-in-diff specification as in Equation (4) with $R_1(t) - C_0(t)$ as dependent variable. For robo takers, we use the portfolio weights observed at the time of the robo subscription; for investors who have not been exposed to the robo, we use the portfolio weights observed at the time of the first reception of the variable remuneration.

We observe that the static effect accounts for 2.3% of the total increase in returns, the remaining 3.1% is driven by the dynamic effect (the total effect, estimated in column 1 of Table 8, is 5.4%). In columns 2-4, we repeat the same decomposition controlling for various measures of risk, and find similar estimates in relative terms.

In columns 5-6 of Table 9, we repeat the same analysis considering instead expected returns (as in columns 5-6 of Table 8). We observe that the static effect accounts for about 1.2% of the increase in expected returns, the remaining 1.1% is driven by the dynamic effect (the total effect, estimated in column 5 of Table 8, is 2.3%). Similar results appear when we control for the equity share.

Overall, these figures show that a key determinant of the increase in returns we observe is given by a dynamic effect associated to the way in which investors rebalance their portfolios over time. According to our estimates, a change in rebalancing behaviors is associated to increase of about 200bps per year (in terms of realized returns, controlling for risk) and of about 100bps (in terms of expected returns). It may be useful to put these estimates in perspective with other estimates of rebalancing premia. Comparing portfolio rebalancing with constant weights to a buy-and-hold strategy, Maeso and Martellini (2020) find an annualized rebalancing premium of 100bp in the U.S. stock market, controlling for several risk factors. Similarly, for a diversified portfolio composed only of stocks and bonds, Ang, Brandt and Denison (2014) estimate a rebalancing premium of 0.14 in terms of average returns over realized volatility. As average volatility in our setting is around 10%, this would correspond to a premium of 140bp. These estimates confirm the general message that changing rebalancing behaviors can be a key determinant of portfolio performance.[25]

[25] Evidence along those lines also appears in the mutual fund industry, where according to Berk and Van Binsbergen (2015) half of the value added can be attributed to improved diversification and half to market timing.

4 Effects on Small Investors

An important open question is whether robo-services can have particularly significant effects on 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 for 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 for investors' income. In addition, we consider investors' equity share and returns. For each of these characteristics, we classify investors into quartiles based on the average values observed before August 2017, the date of the first robo introduction.[26]

We report our results in Table 10. In column 1-3, the dependent variable is the equity share. 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 share by 13.3%, those in the last quartile increase their equity share 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 share is exposure for investors with lower equity share at the baseline, and again the effect of the robo is decreasing monotonically with baseline equity exposure.

In columns 4-6, we look at the effect on returns while controlling 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.

While the robo-recommendations are also based on investors' horizon, these patterns are distinct from the impacts of the robo depending on investor's age. Adding the interaction between the robo treatment and investor's age, the effects are slightly stronger for middle-aged investors, while the above results remain unchanged.

Notice also that these effects do not imply that the robo is recommending larger equity exposure, say, to smaller investors. Looking at the correlation between individual

[26] The quartiles in terms of portfolio size are respectively equal to 2176, 10393, and 37010 euros. In terms of variable remuneration, they are equal to 0, 591, and 2369 euros. In terms of monthly returns, they are equal to -0.01%, 0.31%, and 1.39%. In terms of equity share, they are equal to 0, 5.44%, and 22.75%.

characteristics and the risk score assigned by the robo, we observe that the robo tends to recommend larger equity exposure to investors who are younger, male, richer (in terms of portfolio value and variable remuneration) and with larger equity exposure 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 are limited in the sense they they only concern a subset of the investor's overall financial wealth. Yet, they confirm the view that the robo-service can be an important instrument towards financial inclusion (Reher and Sokolinski (2021), D'Hondt et al. (2020)).

5 Self-Selection

The decision to take-up the robo-service is voluntary and it can be driven by possibly unobservable characteristics that may also affect our outcome variables. In our previous analysis, we have addressed this issue by exploiting discontinuities in the robo algorithm or by controlling for time-invariant individual-specific characteristics in a standard diff-in-diff specification. In the latter case, a possible concern is that individual-specific shocks may simultaneously drive the robo subscription and a change in trading behaviors. In this section, we report a series of tests which aim at addressing this concern.

To simplify the exposition, all tables in this section have the same structure, which replicates our main results based on diff-in-diff specifications. In column 1, we consider the effect on attention (as in column 3 of Table 3); in column 2, we consider trading activities (as in column 1 of Table 4); in column 3, we consider net inflows (as in column 6 of Table 4); in column 4, we consider equity exposure (as in column 1 of Table 5); in column 5, we consider returns (as in column 1 of Table 8); in column 6, we consider the static change in returns (as in column 1 of Table 9).[27]

[27]We follow the same structure also for the tables in the Online Appendix in which we present additional robustness checks.

5.1 Varying the Control Group

Our first test investigates the robustness of our findings when we vary the control group. In the baseline analysis, we have compared robo-takers to observationally similar individuals who have not been offered the service, so as to minimize biases deriving from individual-level selection. We now investigate the robustness of our findings when comparing robo-takers to individuals who have been offered the service and did not express interest in the robo or to robo curious. In the first case, we condition on the exposure to the robo, and isolate the effect of taking up the service as opposed to not expressing interest. In the second case, we condition on the fact that the individual has expressed some interest in the robo, and compare the effect of the take-up relative to observing the robo's profiling and recommendation without subscribing to the service.

We report our results in Table 11, in which the control group are those exposed to the robo, and in Table 12, in which the control group are the robo curious. In both tables, results are remarkably similar to our baseline estimates. This is important since it shows that the exact specification of the control group is not a key driver of our results, our estimates are mainly driven by changes in behaviors within the group of robo-takers (as opposed to between groups). Moreover, while robo curious could in principle replicate the robo's recommendation without subscribing, these results suggest that our estimated effect are associated to the adoption of the robo-service, not just to the observation of the robo recommendation.

5.2 Intention to Treat

As a second test, we estimate the effects of being offered the robo-service (as opposed to subscribing to the service) relative to not being exposed to the service. The fact of being offered the robo depends on the choice of the asset manger and the employer, not of the employee, and as such it is likely orthogonal to employee-specific shocks. In Table 13, we observe that our results are qualitatively unchanged.[28]

This is remarkable since these estimates are associated to the mere effect of having been offered access to the robo-service, as opposed to the potentially endogenous take-up decision. As expected, magnitudes are significantly smaller than in our baseline estimates. This is consistent with the fact that robo takers are a small fraction of those who are exposed. In these regressions, the proportion of takers in the sample is 1.32% while in the

[28]Notice that in this table variable $After$ is defined for all households from the set of time dummies.

baseline regressions takers were about 42% of the sample.[29] Importantly, these results suggest that those who do not take the robo display similar behaviors as those who have not been exposed.

5.3 Instrumenting Take-up

As third robustness check, we look for shifters to the propensity to take-up the service which are unlikely to be driven by individual-specific shocks. Interactions on the workplace may be an important determinant of take-up, which can be partly driven by peer effects, or by some word of mouth learning about the service. In fact, we observe an important variation in the take-up decisions across firms. In the 762 firms with at least one taker, the average take-up is 2.5% and the standard deviation is 8.1% with take-up ranging from 0.1% in the 5th percentile to 6.1% in the 95th percentile.

As intuitive, firms with low take-up may be different from firms with high take-up. As we show in the Online Appendix, the fraction of treated individuals is positively associated to employees' average age, assets in the plans, and variable remuneration. At the same time, the validity of the instrument does *not* require that firms' characteristics are orthogonal to take-up rates, nor that we abstract from firm-specific shocks that may also affect take-up rates. Rather, we require that these firm-level shocks are uncorrelated to shocks which are specific to the *individual* employee. Accordingly, we instrument the individual robo take-up at time t by the fraction of employees in the same firm that have adopted the robo at time t.

We report our results in Table 14. We observe that indeed the instrument is a strong predictor of the propensity to take-up. The estimated effects are once again very much in line with the baseline results. In fact, the estimated impact on personal contributions, equity exposure and realized returns are slightly larger than the corresponding OLS.

6 Conclusion

We have found that having access to a robo-advisor induces investors to pay more attention to their portfolios, to increase their investment and exposure to equity, 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

[29] As in Table 2, we make sure that the proportion of treated individuals correspond to the true proportion in the sample of exposed individuals. In this regression, we include a random sample of 638 takers, 7674 curious, 20,000 exposed not curious, and 20,000 not exposed.

in a way that keeps 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.

Our analysis highlights the role of human-robot interactions (e.g. through the alerts) and more generally the importance of having investors being the ultimate decision makers on their portfolios as opposed to fully delegating to the robo. Potentially, this aspect is key to promote investors' learning on how to manage their portfolios and to improve their financial capabilities.[30] In this way, rather than reducing investors' attention and awareness, the robo-service would become a tool to promote financial education, which we believe is a key aspect when assessing the long-run consequences of robo-advising. We view our analysis as a first step in a promising direction, further work is certainly needed.

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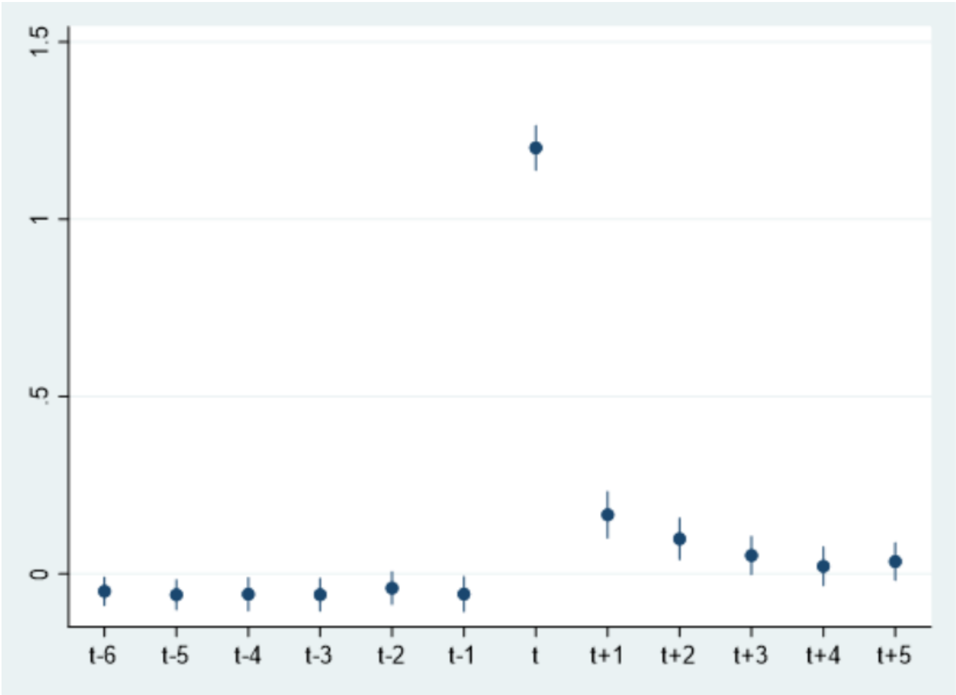
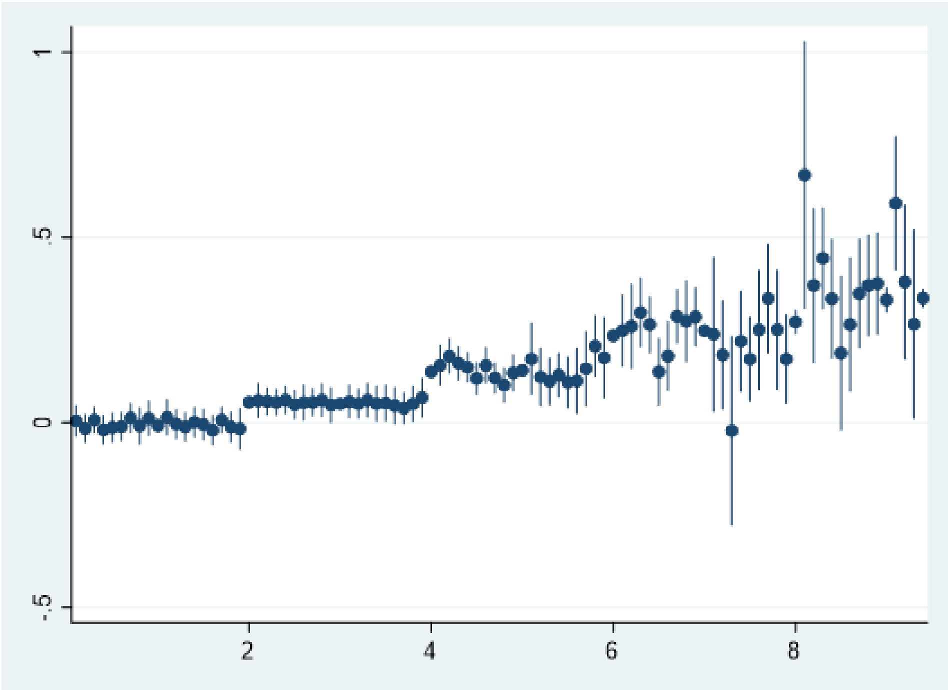
7 Figures and Tables

Figure 1: Investors' Attention: Dynamics



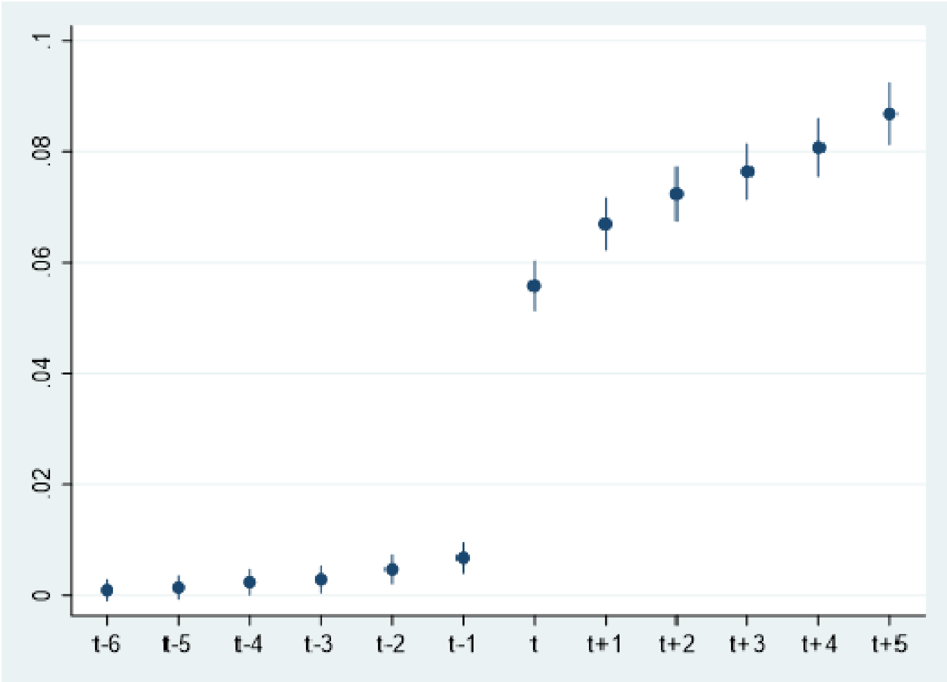
NOTE: This figure displays how the changes in the number of connections to the platform differ between robo takers and non-takers, before and after the robo subscription. T-5/T-1 correspond to months before the treatment, T/T+5 correspond to months after the treatment. The points correspond to the estimated 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.

Table 1: Descriptive Statistics

Variable	p5	mean	p95	sd	N
Panel A: Individual characteristics					
Age	29.00	48.48	67.00	11.72	2,263,612
Female	0.00	0.31	1.00	0.46	2,255,803
Saving plan value	0.00	7,654	36,569	27,065	2,263,612
Total account value	48.73	36,140	148,381	74,763	2,263,612
Yearly variable remuneration	0.00	2,199	9,415	3,568	2,263,612
Nb of saving vehicles	1.00	4.43	11.00	3.44	2,263,612
Panel B: Attention					
Number of connections per month	0.00	0.85	4.00	3.13	2,263,612
Number of web pages viewed per month	0.00	6.51	35.00	23.29	2,263,612
Number of min spent on website per month	0.00	6.17	34.42	28.28	2,263,612
Panel C: Asset allocation					
Weight in diversified equity funds	0.00	0.12	0.80	0.26	1,547,647
Weight in balanced funds	0.00	0.21	1.00	0.34	1,547,647
Weight in employer stock funds	0.00	0.29	1.00	0.43	1,547,647
Weight in bond funds	0.00	0.18	1.00	0.32	1,547,647
Weight in money market funds	0.00	0.13	1.00	0.30	1,547,647
Equity share	0.00	0.18	0.84	0.28	1,547,647
Panel D: Transactions					
Number of asset allocation changes	0.00	0.04	0.00	0.23	2,263,612
Number of asset allocation changes (robo)	0.00	0.01	0.00	0.10	2,263,612
Number of asset allocation changes (free)	0.00	0.01	0.00	0.13	2,263,612
Number of personal contributions	0.00	0.04	0.00	0.21	2,263,612
Number of redemptions	0.00	0.01	0.00	0.10	2,263,612
Net monthly inflow (Euros)	0.00	1.71	107.50	1,966	2,263,612
Panel E: Performances					
Annual return	-0.11	0.06	0.33	0.24	1,409,556
Volatility	0.00	0.10	0.30	0.19	1,409,556
Annual expected return	0.00	0.08	0.27	0.10	1,407,530

NOTE: This table reports descriptive statistics of our variables. Saving plan value refers to the single saving contract, Total account value is the aggregate across all contracts held by the same investor.

Table 2: Robo Take-Up

	(1)	(2)	(3)	(4)
Dep. Variable	Taker	Share	Taker	
Age	6.56e-05	0.000194	0.00269***	0.00272***
	(0.000107)	(0.000509)	(0.000668)	(0.000635)
Female	-0.00444**	-0.0204***	-0.0251*	-0.0251*
	(0.00209)	(0.00561)	(0.0142)	(0.0147)
Account value (ln)	0.000860	-0.0325***	-0.0187***	-0.0197***
	(0.00186)	(0.00378)	(0.00480)	(0.00519)
Equity share	0.0116	-0.0912**	-0.112***	0.0230
	(0.00812)	(0.0434)	(0.0279)	(0.0457)
Variable remuneration	2.80e-06***	-3.47e-06	-6.37e-06**	-8.06e-06**
	(9.91e-07)	(2.46e-06)	(3.11e-06)	(3.23e-06)
Returns	-0.126*	-2.132***	-0.196	-0.106
	(0.0711)	(0.420)	(0.753)	(0.680)
Connections	0.00184	-0.00126	-0.00465***	-0.00429***
	(0.00112)	(0.00176)	(0.00155)	(0.00140)
Robo equity distance			0.154***	
			(0.0494)	
Robo equity change				0.160***
				(0.0400)
Sample	Takers + Exposed	Takers	Takers+Curious	
Mean Dep. Var.	0.02	0.74	0.07	0.07
Observations	27,616	13,676	7,746	7,746
R-squared	0.003	0.046	0.014	0.018
Number of Clusters	1,966	713	591	591

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 columns 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). All regressions include firm 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)	(7)
Dep. Variable	Minutes	Pages	Number of connections				
Robo treated*after	4.594***	5.781***	0.296***	0.223***	0.112***		
	(0.146)	(0.119)	(0.0169)	(0.0156)	(0.0163)		
Remun.t-3 to t-1						0.191***	0.131***
						(0.0476)	(0.00879)
Remun.t						0.767***	0.511***
						(0.0573)	(0.0167)
Remun.t+1 to t+3						0.0311	0.0245**
						(0.0264)	(0.0103)
Sample	All			No rem	No Rem Sub	Treated	Non-treated
Observations	782,421	782,421	782,421	637,074	627,286	71,288	682,839
R-squared	0.027	0.050	0.029	0.013	0.012	0.031	0.022
Number of Clusters	34,441	34,441	34,441	33,019	33,018	13,098	34,409

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 3-7, the dependent variable is the number of connections per month. In column 4, we exclude the month before and the month at which the individual has received the variable remuneration. In column 5, the sample excludes the two months around the robo subscription and the month of the reception of the remuneration. In columns 6-7, 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 6, the sample is restricted to robo treated; in column 7, the sample is restricted to non- treated investors. All regressions include individual and time fixed effects. Controls include the average equity 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 4: Trading Activities

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Changes	Robo(>t)	Individual	Contributions	Redemptions	Net inflows
Robo treated*after	0.214***	0.0402***	0.000116	0.00550***	-0.000623	83.77***
	(0.00141)	(0.000682)	(0.000990)	(0.00113)	(0.000523)	(7.598)
Observations	1,567,958	1,567,958	1,567,958	1,567,958	1,567,958	1,567,958
R-squared	0.057	0.027	0.001	0.058	0.006	0.015
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 equity 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 5: Risk Taking

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Equity Sh.	Equity	Balanced	Employer	Bond	Money
Robo treated*after	0.0866***	0.0272***	0.228***	0.00234***	-0.155***	-0.0916***
	(0.00220)	(0.00183)	(0.00318)	(0.000721)	(0.00292)	(0.00250)
Observations	1,450,851	1,450,851	1,450,851	1,450,851	1,450,851	1,450,851
R-squared	0.069	0.010	0.199	0.005	0.118	0.058
N. of Clusters	34,398	34,398	34,398	34,398	34,398	34,398

NOTE: This table reports the results of OLS regressions at the saving account level. In column 1, the dependent variable is the equity 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. All regressions include individual and time fixed effects. Controls include the average equity 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: 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)
Horizon2	-0.00137***	-0.00138***	-0.00149***	0.000337	0.000390
	(0.000209)	(0.000192)	(0.000223)	(0.000486)	(0.000262)
Horizon3	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)
Sample		Robo		Non-Robo	Robo
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 equity 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: Alerts and Rebalancing

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Connections	Rebalancer	Change in Distance Actual - Target Equity			Distance
Robo treated*Alert	0.121***	0.190***	-0.0725***			
	(0.0338)	(0.00689)	(0.00241)			
Robo treated	0.700***	0.0155***	-0.00428*			
	(0.0502)	(0.00180)	(0.00242)			
Alert	0.115**	0.114***	0.0403***	-0.0261***		
	(0.0570)	(0.00448)	(0.00165)	(0.00178)		
Alert MIF					-0.00661	
					(0.00448)	
I(distance>cutoff)						-0.0127**
						(0.00619)
Distance (SRRI)						0.465***
						(0.0572)
Distance*I(dist>cutoff)						-0.427***
						(0.101)
Sample		Robo takers+curious			Robo takers	
Observations	173,392	190,242	190,242	83,758	71,888	4,326
R-squared	0.036	0.235	0.041	0.028	0.010	0.081
Number of Clusters	31,130	31,123	31,123	13,282	13,016	

NOTE: This table reports the results of OLS regressions. In column 1, the dependent variable is the number of connections per month. In column 2, the dependent variable is a dummy equal to one if the investor rebalances the portfolio in month t or t+1, where t is the first month at which the distance between the actual and the target allocation exceeds the alert threshold. In columns 3-5, the dependent variable is the change in the distance between the actual and the target equity share between t+1 and t-1. 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. For robo-takers, the target allocation is the one proposed by the robo; for robo-curious, it is the one held at the time of the completion of the robo survey. 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 8: Returns

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable		Realized Return			Expected Return	
Robo treated*after	0.0539***	0.0518***	0.0306***	0.0423***	0.0235***	0.0197***
	(0.00160)	(0.00163)	(0.00117)	(0.00150)	(0.000418)	(0.000413)
Equity share		0.0282***				0.0508***
		(0.00254)				(0.000990)
Volatility			1.171***			
			(0.0249)			
Beta				0.0299***		
				(0.00268)		
Observations	1,362,797	1,362,797	1,362,797	776,564	1,360,033	1,360,033
R-squared	0.104	0.104	0.479	0.190	0.199	0.205
Number of Clusters	34,241	34,241	34,241	32,485	70,565	70,565

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 columns 5-6, the dependent variable is the expected annual returns at the saving vehicle level. 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 9: Returns: Static vs. Dynamic Effect

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Static (Realized)				Static (Expected)	
Robo treated*after	0.0232***	0.0229***	0.0101***	0.0202***	0.0121***	0.00864***
	(0.000952)	(0.000947)	(0.00103)	(0.000962)	(0.000285)	(0.000271)
Equity share		0.00443***				0.0465***
		(0.000969)				(0.000769)
Volatility			0.660***			
			(0.0552)			
Beta				0.00302		
				(0.00242)		
Observations	1,362,797	1,362,797	1,362,797	776,564	1,360,033	1,360,033
R-squared	0.019	0.151	0.309	0.032	0.244	0.251
Number of Clusters	70,656	70,656	70,656	62,136	70,565	70,565

NOTE: This table reports the results of OLS regressions aimed at decomposing the total change in returns associated to the robo-service between a static effect occurring at the time of the subscription and a dynamic effect associated to different portfolio dynamics after the subscription. For robo-takers, define t* as the date of robo-subscription and, for non-exposed, as the date of first reception of the variable remuneration. In columns 1-4, the dependent variable is the static effect on annual returns, computed according to equation (8), which is the difference between the returns the investor has experienced after t* and those she would have experienced had she kept her portfolio weights constant at the level observed just before t*. In columns 5-6, the dependent variable is the same static effect, computed instead on expected returns. 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 10: 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$\geq q75$	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$\geq$ 75		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 $\geq q75$			-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$\geq q75$						-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	34,398	34,398	34,398	34,241	34,241	34,241

NOTE: 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.

Table 11: Control Group: Exposed

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Connections	Trading	Inflows	Equity	Returns	Static
Robo treated*after	0.261***	0.216***	75.72***	0.0854***	0.0396***	0.00915***
	(0.0155)	(0.00140)	(7.494)	(0.00220)	(0.00126)	(0.000592)
Observations	797,443	1,477,329	1,477,329	1,415,310	1,333,971	1,333,971
R-squared	0.022	0.070	0.018	0.069	0.135	0.020
Number of Clusters	34,448	34,448	34,397	34,310	34,310	34,476

NOTE: This table reports the results of OLS regressions in which the control group are exposed individuals who did not take the robo. In column 1, the dependent variable is the number of connections per month; in column 2, the dependent variable is the number of allocation changes per month; in column 3, the dependent variable is the net monthly inflow in euros; in column 4, the dependent variable is the equity share; in columns 5, the dependents variable is the annual return; In column 6, the dependent variable is the static effect as defined in equation (7). 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: Control Group: Curious

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Connections	Trading	Inflows	Equity	Returns	Static
Robo treated*after	0.266***	0.210***	73.25***	0.0754***	0.0563***	0.0128***
	(0.0152)	(0.00138)	(7.359)	(0.00222)	(0.00124)	(0.000579)
Observations	815,775	1,650,285	1,650,285	1,595,684	1,487,612	1,487,612
R-squared	0.025	0.056	0.022	0.059	0.179	0.033
Number of Clusters	34,524	34,524	34,517	34,483	34,483	34,574

NOTE: This table reports the results of OLS regressions in which the control group are individuals who expressed interest but did not take the robo (robo curious). In column 1, the dependent variable is the number of connections per month; in column 2, the dependent variable is the number of allocation changes per month; in column 3, the dependent variable is the net monthly inflow in euros; in column 4, the dependent variable is the equity share; in columns 5, the dependents variable is the annual return; In column 6, the dependent variable is the static effect as defined in equation (7). 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 13: Intention to Treat

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Connections	Trading	Inflows	Equity	Returns	Static
Robo exposed*after	0.0420***	-0.00371***	4.729	0.00720***	0.0103***	0.0153***
	(0.0104)	(0.000601)	(6.795)	(0.000468)	(0.00188)	(0.00150)
Observations	1,103,174	1,957,338	1,831,557	1,743,852	1,743,852	1,743,852
R-squared	0.024	0.014	0.006	0.101	0.433	0.016
Number of Clusters	48,043	48,043	47,958	47,717	47,717	48,079

NOTE: This table reports the results of OLS regressions in which the treatment are individuals who have been proposed the robo service and the control are individuals who have not been exposed. In column 1, the dependent variable is the number of connections per month; in column 2, the dependent variable is the number of allocation changes per month; in column 3, the dependent variable is the net monthly inflow in euros; in column 4, the dependent variable is the equity share; in columns 5, the dependents variable is the annual return; In column 6, the dependent variable is the static effect as defined in equation (7). 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 14: IV Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Connections	Trading	Inflows	Equity	Returns	Static
Robo treated*after	0.135***	0.146***	234.9***	0.118***	0.0683***	0.0514***
	(0.0344)	(0.00562)	(25.08)	(0.00449)	(0.00572)	(0.00379)
	First Stage: Robo Treated					
Fraction of treated employees	13.131***	7.699***	7.699***	7.637***	7.392***	7.392***
	(1.2902)	(0.8995)	(0.8995)	(0.9135)	(0.8457)	(0.8457)
F-Stat (first stage)	103.57	73.26	73.26	69.9	76.4	76.4
Observations	780,112	1,554,438	1,554,438	1,450,851	1,362,797	1,362,797
R-squared (within)	0.028	0.053	0.015	0.063	0.104	0.011
Number of Clusters	334,431	34,431	34,398	34,241	34,241	34,441

NOTE: This table reports the results of 2SLS regressions in which the probability to adopt the robo service is instrumented by the fraction of employees in the same firm who have taken-up the robo. In column 1, the dependent variable is the number of connections per month; in column 2, the dependent variable is the number of allocation changes per month; in column 3, the dependent variable is the net monthly inflow in euros; in column 4, the dependent variable is the equity share; in columns 5, the dependents variable is the annual return; In column 6, the dependent variable is the static effect as defined in equation (7). 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.

8 Online Appendix

Table 15: Individual Level

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Connections	Trading	Inflows	Equity	Returns	Static
Robo treated*after	0.296***	0.263***	129.1***	0.0729***	0.0197***	0.00983***
	(0.0169)	(0.00230)	(15.66)	(0.00179)	(0.00147)	(0.000689)
Observations	782,234	782,234	782,234	777,832	740,462	740,462
R-squared	0.029	0.074	0.026	0.080	0.153	0.033
Number of Clusters	34,441	34,441	34,441	34,408	34,285	34,285

Note: This table reports the results of OLS regressions at the individual level, aggregating over all contracts held by the same individual. In column 1, the dependent variable is the number of connections per month; in column 2, the dependent variable is the number of allocation changes per month; in column 3, the dependent variable is the net monthly inflow in euros; in column 4, the dependent variable is the equity share; in columns 5, the dependents variable is the annual return; In column 6, the dependent variable is the static effect as defined in equation (7). 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 16: Cluster by Individual and Time

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Connections	Trading	Inflows	Equity	Returns	Static
Robo treated*after	0.296***	0.213***	85.64***	0.0866***	0.0539***	0.0200***
	(0.0828)	(0.0401)	(24.10)	(0.00386)	(0.00905)	(0.00436)
Observations	780,080	1,554,304	1,554,304	1,450,261	1,361,023	1,361,023
R-squared	0.595	0.330	0.073	0.932	0.568	0.577
Number of Clusters	34,400/26	34,400/26	34,353/26	34,175/26	34,175/26	34,410/26

NOTE: This table reports the results of OLS regressions in which standard errors are clustered both by individual and by time (double clustering). In column 1, the dependent variable is the number of connections per month; in column 2, the dependent variable is the number of allocation changes per month; in column 3, the dependent variable is the net monthly inflow in euros; in column 4, the dependent variable is the equity share; in columns 5, the dependents variable is the annual return; In column 6, the dependent variable is the static effect as defined in equation (7). 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 are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 17: Fraction of Takers and Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Age	Female	Assets	Equity	Returns	Connect.	Remuner.
Fraction of treated employees	3.123**	-0.0264	1.289***	-0.0531	-0.00285	0.189	2,706***
	(1.417)	(0.0585)	(0.395)	(0.0485)	(0.00195)	(0.361)	(564.6)
Sample	Firms with at least one taker						
Observations	762	762	732	732	722	736	744
R-squared	0.006	0.000	0.014	0.002	0.003	0.000	0.030

NOTE: This table reports the results of OLS regressions. All dependent variables are defined as the firm-level average before the first robo introduction (August 2017) while the fraction of treated employees is the firm-level average after the firm's exposure to the robo. The sample includes all firms with at least one robo-taker. In column 1, the dependent variable is the average age of the employees; in column 2, the average gender ratio; in column 3, the average portfolio value (in log); in column 4, the average equity share; in column 5, the average portfolio returns; in column 6, the average number of connections; in column 7, the average value of the variable remuneration. Standard errors are in parenthesis. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Expected Returns

As mentioned, expected returns in Section 3.6 are based on a 5-factors model. We consider the classic Fama-French 3 factors (market, size, value), taken from Ken French's library, and 2 fixed income factors: Barclays Global Bond Index Unhedged and Barclays U.S. Bond Index Unhedged, both in USD, taken from Bloomberg. We consider returns net of the U.S. risk-free rate, computed as the one-month Treasury yield (also taken from Ken French's library). We regress each fund's excess return (with a minimum of 10 observations per fund) to calculate the beta exposure of each fund over our sample period.

In the main text, we have defined time-varying expected returns, consistent with our purposes of highlighting the possibility of a static and a dynamic effect. Accordingly, we have multiplied the beta of each fund by the corresponding realized return of each factor. Alternatively, one may have assumed that expected returns are constant, and compute the expected returns of each factor based on historical averages. One would define $\overline{R}(x)$ as the (constant) expected return of each risky fund x, computed as the cross product of the fund's beta $\beta^f(x)$ and the historical returns of the corresponding factor $\overline{R}^f$,

$$\overline{R}(x) = \sum\nolimits_f \beta^f(x)\overline{R}^f.$$

In order to compute historical averages, the earliest date at which our fixed-income factors are available is January 1990. We can then compute the $\overline{R}^f$ as the average return between 1990 and 2018, the end of our sample. Alternatively, as in Reher and Sokolinski (2021), we can consider the post financial crisis period and start our time series in 2010. In the fist case, we would obtain that the robo treatment is associated to an increase in expected returns of 27bps, while in the second case the associated increase would be equal to 46bps. Both results are significantly different from zero at the 1% level.

Important Information

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