Working Paper 112-2021 | **June 2021**

Robo-Advising for Small Investors: Evidence from Employee Savings Plans

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Abstract

We study the introduction of robo-advising on a large representative sample of Employees Saving Plans. The robo-advisor proposes a portfolio allocation and alerts investors if their allocation gets too far from the target, while investors remain free to follow or ignore the advices. We find that relative to self-managing, accessing the robo-service increases the amount of money invested in the plan, and the exposure to equity. Investors also experience higher risk-adjusted returns, and this is mostly driven by a change in their rebalancing behaviors that keeps them closer to the target. These effects are stronger for investors with smaller portfolios, lower returns and stock market participation, suggesting that automated advice can promote financial inclusion. Our results also highlight the importance of human-robo interactions for influencing investors' portfolio decisions and possibly as a first step towards improved financial capability.

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

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

Acknowledgement

**We are grateful to Francesco D'Acunto, Francesco D'Amuri, Laurent Bach, Jean-Philippe Bianquis, Pascal Blanqué, Ulrich Hege, Fathi Jerfel, Sophie Moinas, Mehrshad Motahari, Sébastien Pouget, Sofia Ramos, Alberto Rossi, Patrick Tissot-Favre, and Wanyi Wang for very useful comments, to Xavier Collot, Corinne Laboureix, Olivier Melennec, Fabien Thevenot for insightful explanations on the institutional setting and to Arnaud Delavoet, Marc-Antoine Hubert, Anthony Lapeyre and Mohamed Youssef for help in the data gathering process. Milo Bianchi acknowledges funding from LTI@Unito, TSE Sustainable Finance Center and ANR (ANR-17-EURE-0010 grant). The data used to carry out this study come from the processing of record keeping and account keeping of AMUNDI ESR employee and pension savings accounts. These data have been analyzed anonymously for scientific, statistical or historical research purposes. We have no material interest that relates to the research described in the paper.*

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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, a growing interest has emerged both in academia and in the industry for automated financial advisors, often called robo-advisors. A key open question is whether automated advice can reduce transaction costs and agency conflicts, and improve investors' financial decisions. This is particularly relevant for investors with lower financial capabilities, who have been traditionally excluded from wealth management services and are those who in principle may have more to benefit from robo-advising (D'Hondt, De Winne, Ghysels and Raymond (2020)).

On the positive side, one may notice that robots have low operating costs, which allows reaching a broader set of investors (Bianchi and Brière (2021)), and they tend to adopt transparent and verifiable procedures, which may limit the extent of biased advice (Philippon (2019*b*)). At the same time, as for many new financial services, robo-advisors may in practice fail to benefit less sophisticated investors, who may be more reluctant to adopt the new technology (Hackethal, Haliassos and Jappelli (2012), Collins (2012), Foster and Rosenzweig (2010)), or may end up misusing it (Campbell (2006)). The empirical question is whether robo-advising can be helpful to investors and, even if so, whether it tempers or exacerbates existing inequalities (Philippon (2019*a*), Abraham, Schmukler and Tessada (2019)).

A second important dimension concerns the dynamics of human-robo interaction in the context of financial services. Building trust is key for financial services, and at the same time mistrust in algorithms seems particularly severe in this context (Bianchi and Brière (2021)). In addition, investors may value a trusting relationship with their advisor even beyond financial performance (Gennaioli, Shleifer and Vishny (2015), Rossi and Utkus (2019*a*)). Human-robo interactions are important when investors decide on whether to accept the robo-service and possibly change their portfolio allocations. They are also important over time, when they may be induced to pay attention to their portfolios even if not used to do so, or when they may be advised to rebalance their portfolio in a given direction even if tempted to do otherwise. Studying these interactions can also shed light on whether investors perceive the robo-service as a complement or a substitute to their own attention and reasoning.

[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 (2020) on misguided beliefs; and Beshears, Choi, Laibson and Madrian (2018) for a review.

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. Some distinctive features of our setting make it particularly useful for our purposes. First, the service under study 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 ignore the advice. This makes it different from the more common robo-advisors that automate portfolio investment and rebalancing, and this allows us to focus on human-robo interactions. As mentioned, these interactions are particularly interesting beyond the time of the robo subscription, showing for example how reliance on the robo-service evolves as investors experience market shocks or as new investment opportunities arise.

In addition, some interesting features come from the investment under study. First, our data cover a representative sample of the French population employed in the private sector. A large proportion of our investors have small portfolios and little experience in the stock market, which makes this sample particularly useful to explore whether robo-advisors can promote financial inclusion.[2] Second, in these plans, employees allocate part of their salaries between a menu of funds proposed by the employer. While relative to stock picking this should minimize issues of underdiversification, as we will see significant heterogeneities in investors' performance are driven by rebalancing behaviors. Third, due to various lock-in rules, these investments have a long-term perspective, which is relatively uncommon in the context of robo-advising (Hammond, Mitchell and Utkus (2016)). Under-participation in retirement plans is a common concern in many developed countries (Poterba (2014), Benartzi and Thaler (2013)), and policy makers debate on whether robo-advisors can help in this respect (OECD (2017)). We show how the robo-service can impact participation to the plan and to the stock market.

The robo-advisor under study was introduced by the asset manager in August 2017. The robo starts by eliciting information on the client's characteristics, builds the client's profile, and proposes a portfolio allocation. If the client accepts the proposal, the robo implements the allocation. A key feature of the robo is that, over time, it also sends email alerts if the current portfolio allocation ends up being too far from the target allocation. The robo suggests to connect to the platform and rebalance the portfolio towards the target, while the ultimate decision has to be taken directly by the investor. As we will see, observing investors' reactions to those alerts, and more generally their behaviors over time, is key to understand how the robo may impact investors' trading and realized returns. Uncovering changes in rebalancing behaviors, and their effects on performance, is an important,

[2] The median value of our portfolios is about 3300 euros, and more than half of them has no equity funds.

and novel, contribution of our study.

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. Absent the robo, employees self-manage their portfolios and have no access to a dedicated advice. We have access to account level data covering the period between September 2016 and 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 which are self-managed and contracts which 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 (who we call robo curious). We obtain detailed information about investors' activities on the platform, both in terms of trading and in terms of digital footprints; moreover, we can exploit the exact knowledge of the algorithm behind the robo, observe the score, the suggested allocations and the alerts the robo may be sending over time; finally, we can construct the returns and various measures of risk of these portfolios.

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, as we briefly outline. 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. In our baseline analysis, we take individuals who have not been exposed to the robo-service as control group. We also 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 can 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 can exploit the knowledge of the functioning of the robo and the various discontinuities in the algorithm in a regression discontinuity design. Fourth, since the decision to take-up the robo may be influenced by interactions occurring at the workplace, we can use the fraction of employees adopting the robo in a given firm as a shifter 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.

We start our analysis by looking at what determines robo adoption and more generally, trust in the robo-service. We find that, apart from gender, observable characteristics have little explanatory power for the take-up decision. At the same time, investors with smaller portfolios are more likely to assign a larger proportion of their assets to the robo, while wealthier investors are more likely to acquire information about the robo without eventually subscribing to the service.

Moreover, for robo curious and robo takers, we can investigate whether the probability of subscribing to the robo depends on the distance between the allocation recommended by the robo and the allocation currently held by the investor. We find that the relation is positive: the further away is the recommendation of the robo, the larger is the probability that the investor accepts it. 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)). We also show that this effect is stronger when the robo proposes riskier allocations.

We then investigate how investors' behaviors change after having taken up the robo in a standard diff-in-diff setting in which we control for individual and time fixed effects. We analyze trading behaviors, and show that robo takers increase their trading activities after the subscription of the robo and, importantly, they also increase their investment in the company's saving plan. These differences in trading activities are associated to a change in risk exposure. We find that, after subscription, robo takers increase their equity share by 8.6%, which corresponds to a 55% increase relative to the average equity share of 15.7%. This is achieved by reducing the weight to bonds and to money market funds and by increasing the weight to balanced and equity funds.

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

We exploit the fact that the robo sends email alerts to investors if their current allocation gets too far away from the target allocation. We ask whether these alerts are effective in inducing investors to rebalance their portfolio and stay closer to the target. These rebalancing behaviors can have important impacts on investors' performance (Bianchi (2018)). Moreover, they shed light on whether investors trust the robo recommendation not only at the time of the subscription but also over time. Exploiting the knowledge of the algorithm governing the alerts, we can construct potential alerts not only for robo takers but also for robo curious (those individuals who have completed the robo survey but have not subscribed to the service), for whom we identify the alerts that the robo would have sent had they taken the robo. We then show, in a standard diff-in-diff specification, that the reception of the robo alert reduces the distance between current and target equity exposure by 7.2%, corresponding to a 62% reduction relative to the average distance of 11.6%.

We also investigate whether these changes in investment strategies are associated to different portfolio returns. We show that robo takers experience an increase of annual returns by 5.4% per year (net of management fees), which is a 80% increase relative to the average return of 6.7%. Part of this effect is due to an increase in risk exposure. Controlling for various measures of portfolio risk, we find that the robo treatment is associated to an increase between 3% and 4% in yearly returns. Together with the increased investment in the saving plan mentioned above, and considering that the management fees associated to the robo are much smaller, these results suggest that the robo can have a significant impact on investors' wealth accumulation in the long run.

Moreover, we investigate the determinants of the increase in returns and distinguish a static effect occurring at the time of the subscription (say, as the investor is moving closer to the efficient frontier) to a dynamic effect associated to the way in which investors rebalance their portfolios over time. We show that the static effect accounts for about 2/5 of the increase in returns, the most important part comes from a change in portfolio dynamics.

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

The importance of these results can be appreciated also in light of recent evidence showing that wealthier individuals earn persistently higher returns, either as they bear larger systematic risk (Bach, Calvet and Sodini

(2020)) or as they are better informed and more sophisticated (Fagereng, Guiso, Malacrino and Pistaferri (2020)). These contributions show that heterogeneity of returns is key for explaining the long-run patterns of wealth accumulation and inequality. Under this perspective, it is remarkable that having access to automated advice can at least partly limit these general patterns.

This paper contributes to a growing literature on the effects of robo-advising on portfolio choices (see D'Acunto and Rossi (2020) and Bianchi and Brière (2021) for overviews). D'Acunto, Prabhala and Rossi (2019) study a portfolio optimizer by an Indian brokerage house and show that the robo has a beneficial impact on less diversified investors as it increases the number of stocks they hold, reduces volatility, and improves market-adjusted performance, but not on diversified investors. Rossi and Utkus (2019*b*) show that robo takers increase investors' exposure to low-cost indexed mutual funds, improve diversification and risk-adjusted performance. Similar findings are reported by Braeuer, Hackethal and Scheurle (2017) and Loos, Previtero, Scheurle and Hackethal (2020) from a German bank; Reher and Sun (2016), instead, find little impacts on mutual fund holders by a specialized robo-advisor U.S. provider. As stressed a key distinctive feature in our analysis is the focus on the dynamic interactions between the robo and the investors, for example upon reception of the alerts, which allows us to show how those interactions impact investors' behaviors and ultimately their portfolio dynamics and returns.

Another 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 (2020), 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. An important difference is that the robo studied by Reher and Sokolinski (2020) directly manages investors' portfolios, while 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 need not 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.

Our paper also 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). We share with this literature the interest on investors' trust when using a new financial service; our specific focus is on the human–robot interaction, which allows investigating how trust can be built and how changes in behaviors can be induced over time.

2 Data

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

These plans are managed by a large French asset manager. While traditionally employees received no advice on these portfolio choices, the asset manager has introduced a robo-advisor service in August 2017. The robo starts by eliciting information on the client's characteristics, and specifically on her risk-aversion (both through quantitative and qualitative questions), financial knowledge and experience (both objective and self-assessed), age and investment horizon. Based on these questions, the robo builds the client's profile (say, prudent, dynamic,..) and proposes a portfolio allocation. The client can visually compare the proposed allocation with her current one both in terms of macro categories (proportion of equity, bonds, money market funds, ...) and of specific funds. If the client accepts the proposal, the robo implements the allocation. If the client rejects, the service is terminated. Over time, the robo also sends email alerts if current portfolio allocation ends up being too far from 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 713 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 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, for individuals who take the robo, we can observe the score they are given by the robo, the associated profile and suggested allocation, and the alerts the robo may be sending over time to propose new allocations. We provide more details about those variables as we proceed with our analysis below.

Our sample 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. 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). 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.[3] Summary statistics of the variables used in the analysis are reported in Table 1.

[3]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).

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) investors' trading activities and portfolio allocations, and ii) 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.[4]

In column 1, we observe that the probability of subscribing to the robo is negatively related to being female and it is positively related to the amount of variable remuneration, though this effect is small in magnitude. It is also negatively related to the past returns, though again the effect is very small.[5] 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 relative to the optimal one (as evaluated by the robo) can be seen as a key component of the value added of the robo. In addition, it has often been argued that human advisors tend to be accommodating when clients express a preferred investment strategy and

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

[5]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.

have no incentive to recommend allocations which are too different from investors' prior, even when this is detrimental to investors' performance (Mullainathan et al. (2012)). It is thus interesting to check whether robo-advisors are better able to induce allocations which are very different from investors' current allocations.

In order to investigate this question, we can exploit the fact that some investors are robo curious: they complete the preliminary survey needed to access the service and observe the robo recommendation but eventually decide not to take up the robo. For robo curious and robo takers, we can define a measure of distance as the absolute value of the difference in the equity share between the allocation proposed by the robo and the allocation already implemented by the individual.[6]

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 under-served 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.

[6] 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 Activities and Investment

We first 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:

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

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.[7]

We report our results in Table 3. 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. In column 2, we focus on portfolio rebalancing implemented by the robo beyond the subscription date, and observe that a significant increase also in these activities (explained in more details below). In column 3, we observe no significant increase in trading activities directly implemented by the investor.

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

3.3 Risk Taking

We now consider whether the robo adoption is associated to changes in the composition of investors' portfolio. As shown in Table 1, the main 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

[7] Alternatively, one can consider regressions at the individual level 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.

funds and the equity parts of balanced funds, over the total value of the portfolio.

Table 4 reports our evidence at the saving vehicle level as in Equation (2). 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

$$y_{j,t} = \alpha + \beta D_j + \gamma_1 (S_j - c) + \gamma_2 D_j (S_j - c) + H^{'}_{j,t} \delta_1 + H^{'}_{j,t} D_j \delta_2 + \varepsilon_{j,t}. \quad (3)$$

where $y_{j,t}$ is the equity share of individual i in contract j at time t. In equation (3) 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

$$y_{j,t} = \alpha + \beta S_j + H^{'}_{j,t} \gamma + \varepsilon_{j,t}, \quad (4)$$

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 (3). In column 1 of Table 5, 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.[8] 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 4. These estimates indicate that the effect of taking up the robo is larger than simply that of being assigned above a given threshold, other features of the robo are also important to induce investors to take up more risk. This can be seen also in Figure 3, which plots the coefficients of a regression on the robo-treatment interacted with time dummies, 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.

3.4 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. If

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

after having connected, the investor decides to make the adjustment, this is automatically 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 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 x.[9] Accordingly, we construct a dummy *Alert* that is equal to one if the distance is above x, and to zero otherwise. On average, in our sample, investors receive an alert in 7.7% of the months after the subscription. 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 robo treatment and the reception of the alert, in a standard diff-in-diff specification as in Equation (2) in which the robo treatment is interacted with the dummy *Alert.*

In table 6, We consider the impact of alerts on rebalancing behaviors. In column 1-3, the dependent variable is the change in the distance between the actual and the target equity share between $t+1$ and $t-1$, where t is the first month at which the distance between those allocations exceeds the alert threshold. In column 1, we observe that robo takers, who actually receive the alert, decrease their distance by 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 2 and 3, we restrict to robo takers and we compare the effect of our alert with another alert which investors receive if they have

[9]The threshold 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. The exact value of the threshold is confidential.

not completed the profiling survey as requested by the regulator (MIF). We observe that the effect of the MIF alert is small 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 x threshold in a standard RDD. We restrict to clients within a distance of 0.1 from the threshold (for comparison, the standard deviation of the distance is 0.75).[10] In column 4, 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.

3.5 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 (2), using realized returns as dependent variable. Throughout this analysis, we use returns net of management fees, which we estimate directly from the liquidation value of the various funds. Results are presented in Table 7.

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. Finally, in column 5, we consider the portfolio's alpha, computed from the CAPM using again as benchmark the returns of all the portfolios in our sample. We observe that the robo treatment is associated to an increase also in the portfolio's alpha of about 2% (the average alpha in our sample is -2%).[11]

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

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

[11] As robustness check, we also consider returns by omitting the employer's stock from our computations. Results are reported in the Online Appendix, the estimated effects are slightly smaller, but overall consistent with the ones in Table 8.

average horizon (17 years). An increase in yearly returns by 5.4% would be associated to an increase in final wealth by about 23,500 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. These estimates are crude and should be interpreted with care, also given that we are considering returns realized over a relatively short period of time. Still, they suggest that the robo can have a significant impact on investors' wealth accumulation in the long run.

3.5.1 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 suboptimal portfolio allocations, since for example they hold biased views about the expected returns and risk, or because they choose allocations at the interior of the efficient frontier. Second, investors 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 change their risk exposure over time by wrongly timing 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 the beginning of 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 $R_1(t) =_s \omega_1(s,t)R(s,t)$, where $R(s,t)$ are the returns of asset s at time t, and the counterfactual returns without the robo are $R_0(t) =_s \omega_0(s,t)R(s,t)$. 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. One way would be to estimate the counterfactual returns the investor would have experienced had she changed her allocation as proposed by the robo at time t^* without changing her rebalancing behaviors at time $t > t^*$. These returns are however not observable, and rebalancing behaviors may vary considerably across clients. Our effects can however be estimated as follows.

Let us define the counterfactual weights $\omega_0^{'}(s,t) = \omega_0(s,t) + (\omega_1(s,t^*) - \omega_0(s,t^*))$, constructed such that $\omega_0^{'}(s,t^*) = \omega_1(s,t^*)$ and $\omega_0^{'}(s,t)$ is parallel to $\omega_0(s,t)$ at $t \geq t^*$. These weights isolate the portfolio change induced at the time of the robo subscription, $\omega_1(s,t^*) - \omega_0(s,t^*)$, while keeping the subsequent portfolio dynamics as fixed (by construction, $\omega_0^{'}(s,t^*)$ has the same dynamics as $\omega_0(s,t)$). The associated counterfactual returns are given by $R_0^{'}(t) =_s \omega_0^{'}(s,t)R(s,t)$, and the static effect is defined as

$$S(t) = R_0^{'}(t) - R_0(t).$$

While $\omega_0(s,t)$ and so $R_0^{'}(t)$ are not observable, we can write

$$R_0^{'}(t) - R_0(t) =_s (\omega_1(s,t^*) - \omega_0(s,t^*))R(s,t),$$

which depends only on the difference $\omega_1(s,t^*) - \omega_0(s,t^*)$. It follows that the static effect can be computed as

$$S(t) = C_1(t) - C_0(t), \tag{5}$$

where $C_1(t) =_s \omega_1(s,t^*)R(s,t)$ is the counterfactual return the investor would have experienced had she kept her portfolio weights constant at the level implemented by the robo at time t^*, and $C_0(t) =_s \omega_0(s,t^*)R(s,t)$ is the counterfactual return the investor would have experienced had she kept her portfolio weights constant at the level observed just before t^*. Both counterfactual returns can be computed with our data. Accordingly, the dynamic effect can be computed as

$$D(t) = R_1(t) - R_0(t) - (C_1(t) - C_0(t)). \tag{6}$$

In column 1 of Table 8, we report our estimates of the static effect according to Equation (5) by considering the same diff-in-diff specification as in Equation (2) with $C_1(t) - C_0(t)$ as dependent variable. For robo takers, we use the portfolio weights observed at the time of the robo subscription; for investors who do not take 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% of the total increase in returns, the remaining 3.4% is driven by the dynamic effect (the total effect, estimated in column 1 of Table 7, is 5.4%). In columns 2-3, we repeat the same decompositions controlling for various measures of risk, and find similar estimates.

An alternative way to estimate our effects can be implemented without introducing counterfactual returns $R_0^{'}(t)$ but rather by exploiting our knowledge of the robo algorithm. We know that, in our sample period, the robo's recommendations are essentially intended to induce constant portfolio weights.[12] Notice that these are intended allocations since the robo does not directly control investors' rebalancing. Hence, if the robo keeps

[12] 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.

the investor's current allocation $\omega_0(s, t^*)$ unchanged and just changes her rebalancing behavior according to constant weights, the investor would experience returns $C_0(t)$. The *intended* dynamic effect can be computed as

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

and the corresponding static effect can be computed as the residual

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

In column 4 of Table 8, we report our estimates of the static effect according to Equation (8). In this specification, the static effect accounts for about 2.3% of the total increase in returns, the remaining 3.1% is driven by the dynamic effect. In columns 5-6, we repeat the same decompositions controlling for various measures of risk, and again find similar estimates.

Overall, these figures show that a key determinant of the increase in returns we observe in our setting is given by what we have called a dynamic effect, which is associated to the way in which investors rebalance their portfolios over time.

4 Financial Inclusion

An important open question is whether robo-services can promote financial inclusion thanks to the ability to serve customers with smaller portfolios. We explore this question by considering whether our main effects of increased risk taking and increased risk-adjusted returns are heterogeneous depending on ex-ante investors' characteristics. We focus on two measures of investors' capability. First, we look at the value of his portfolio, which we take as a proxy 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.[13]

We report our results in Table 9. 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

[13]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%.

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.

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

5 Conclusion

We have found that having access to a robo-advisor induces investors 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 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.

These results leave many questions open for future research. For example: what are the mechanisms whereby the robo can induce investors to take more risk and to change their rebalancing behaviors? What are the long term consequences of the robo adoption? Our analysis highlights the role of human-robo 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. In this way, rather than reducing investors' attention and awareness, the robo-service can be seen as a tool to promote financial education. We believe this aspect is foundational 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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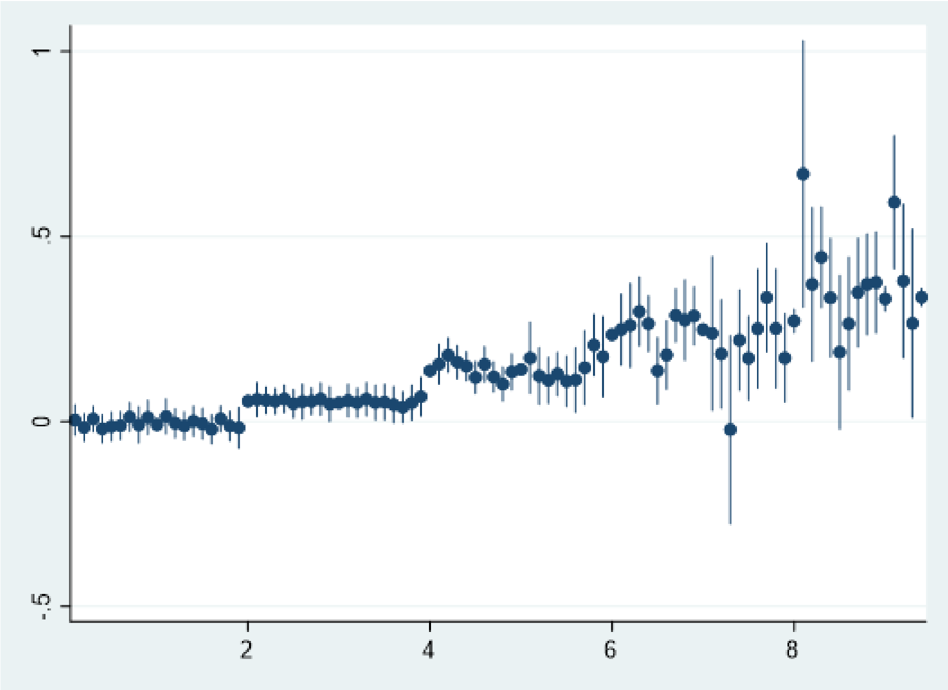
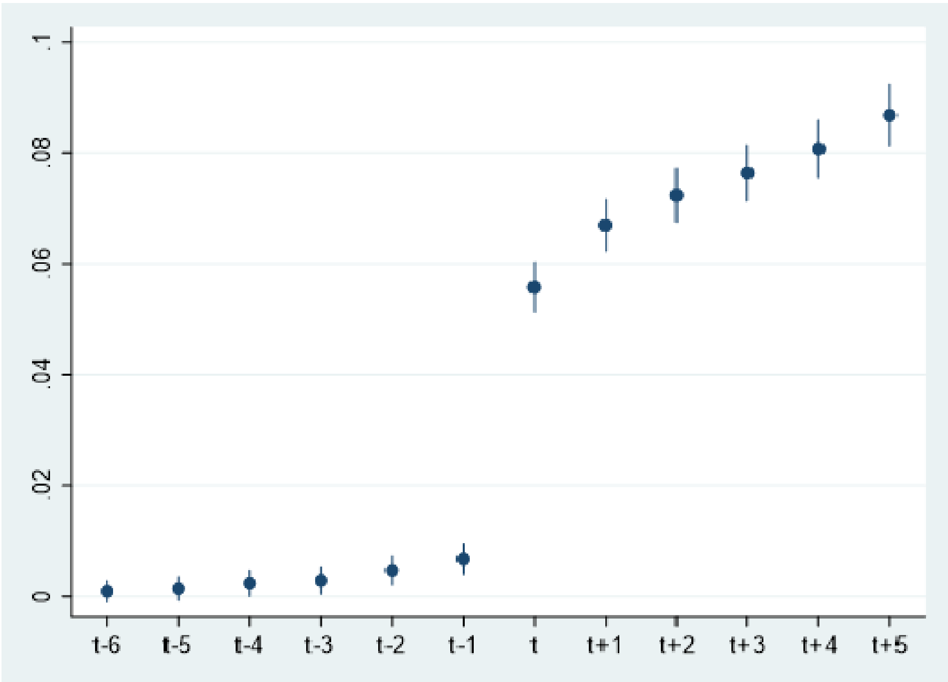
6 Figures and Tables

Figure 1: 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 2: 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: 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 C: 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 D: Performances					
Ann. return	-0.11	0.06	0.33	0.24	1,409,556
Volatility	0.00	0.10	0.30	0.19	1,409,556

NOTE: This table reports descriptive statistics of our variables.

Table 2: Robo Take-Up

	(1)	(2)	(3)	(4)
Dep. Variable	Taker	Share	Taker	
Age	6.63e-05	0.000199	0.00271***	0.00274***
	(0.000107)	(0.000509)	(0.000678)	(0.000644)
Female	-0.00473**	-0.0200***	-0.0238*	-0.0239*
	(0.00203)	(0.00576)	(0.0140)	(0.0145)
Account value (ln)	0.00102	-0.0327***	-0.0198***	-0.0206***
	(0.00186)	(0.00382)	(0.00481)	(0.00518)
Equity share	0.0124	-0.0924**	-0.117***	0.0183
	(0.00807)	(0.0425)	(0.0279)	(0.0459)
Variable remuneration	2.94e-06***	-3.51e-06	-6.43e-06**	-8.12e-06**
	(9.76e-07)	(2.47e-06)	(3.15e-06)	(3.26e-06)
Returns	-0.114	-2.139***	-0.271	-0.177
	(0.0697)	(0.415)	(0.751)	(0.681)
Robo equity distance			0.152***	
			(0.0493)	
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: 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 4: 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 5: 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 6: Alerts and Rebalancing

	(1)	(2)	(3)	(4)
Dep. Variable	Change in Distance Actual - Target Equity			Distance
Robo treated*after*alert	-0.0725***			
	(0.00241)			
Robo treated*after	-0.00428*			
	(0.00242)			
Alert	0.0403***	-0.0261***		
	(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	190,242	83,758	71,888	4,326
R-squared	0.041	0.028	0.010	0.081
Number of Clusters	31,130	31,123	13,282	13,016

NOTE: This table reports the results of OLS regressions. In columns 1-3, the dependent variable is the change in the distance between the actual and the target equity share between t+1 and t-1, where t is first the month at which the distance between those allocations exceeds the alert threshold. In columns 1, the sample is restricted to robo takers and robo curious. Alert is a dummy equal to one if the distance between the actual and the target allocation is above the alert threshold, and to zero otherwise. In column 2-4, 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 4, 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 1-3 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 7: Returns

	(1)	(2)	(3)	(4)	(5)
Dep. Variable			Annual return		alpha
Robo treated*after	0.0539***	0.0518***	0.0306***	0.0423***	0.0197***
	(0.00160)	(0.00163)	(0.00117)	(0.00150)	(0.00178)
Equity share		0.0282***			
		(0.00254)			
Volatility			1.171***		
			(0.0249)		
Beta				0.0299***	
				(0.00268)	
Observations	1,362,797	1,362,797	1,362,797	776,564	776,564
R-squared	0.104	0.104	0.479	0.190	0.028
Number of Clusters	70,656	70,656	70,656	62,136	62,136

NOTE: This table reports the results of OLS regressions. In columns 1-4, the dependent variable is the annual returns at the saving vehicle level. In column 5, the dependent variable is the portfolio alpha, computed from the CAPM using as benchmark the returns of the funds across all investors. 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 8: Returns: Static vs. Dynamic Effect

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Static Effect (1)			Static Effect (2)		
Robo treated*after	0.0200***	0.0105***	0.0217***	0.0232***	0.0101***	0.0202***
	(0.00107)	(0.00101)	(0.00125)	(0.000952)	(0.00103)	(0.000962)
Volatility		0.479***			0.660***	
		(0.0518)			(0.0552)	
Beta			0.00428			0.00302
			(0.00354)			(0.00242)
Observations	1,362,797	1,362,797	776,564	1,362,797	1,362,797	776,564
R-squared	0.014	0.151	0.020	0.019	0.309	0.032
Number of Clusters	70,656	70,656	62,136	70,656	70,656	62,136

NOTE: This table reports the results of OLS regressions. In columns 1-3, the dependent variable is the static effect on annual returns, computed according to equation (7). In column 4-6, the dependent variable is the static effect on annual returns, computed according to equation (10). 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: Heterogenous Impacts

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable		Equity Exposure			Annual return	
Robotreat*after*assets<q25	0.133***			0.0472***		
	(0.00348)			(0.00153)		
Robotreat*after*assets(q25,q50)	0.0789***			0.0226***		
	(0.00407)			(0.00185)		
Robotreat*after*assets(q50,q75)	0.0557***			0.0252***		
	(0.00492)			(0.00215)		
Robotreat*after*assets>=q75	0.0270***			0.0144***		
	(0.00600)			(0.00270)		
Robotreat*after*rem<q25		0.0557***			0.0384***	
		(0.00751)			(0.00261)	
Robotreat*after*rem(q25,q50)		0.127***			0.0457***	
		(0.00316)			(0.00147)	
Robotreat*after*rem(q50,q75)		0.0620***			0.0153***	
		(0.00439)			(0.00204)	
Robotreat*after*rem>=q75		0.0480***			0.0141***	
		(0.00485)			(0.00225)	
Robotreat*after*risk<q25			0.195***			
			(0.00301)			
Robotreat*after*risk(q25,q50)			0.137***			
			(0.00440)			
Robotreat*after*risk(q50,q75)			0.0996***			
			(0.00341)			
Robotreat*after*risk>=q75			-0.0560***			
			(0.00502)			
Robotreat*after*return<q25						0.0578***
						(0.00148)
Robotreat*after*return(q25,q50)						0.0535***
						(0.00132)
Robotreat*after*return(q50,q75)						0.0168***
						(0.00197)
Robotreat*after*return>=q75						-0.0512***
						(0.00372)
Volatility				1.172***	1.171***	1.171***
				(0.0248)	(0.0249)	(0.0249)
Observations	1,450,851	1,450,851	1,450,851	1,365,421	1,365,421	1,365,421
R-squared	0.082	0.080	0.144	0.479	0.479	0.481
Number of Clusters	34,398	34,398	34,398	34,241	34,241	34,241

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

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Amundi
ASSET MANAGEMENT

Working Paper
June 2021

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