Robo-advisers and Investor Behavior*

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Abstract

In recent years, the rise of robo-advisers has provided a new, potentially more cost-effective approach for offering financial advice. Using unique data from a large German retail bank, we investigate the effects of robo-advisers on clients' portfolios. We find that after joining a robo-advising service, clients increase financial risk-taking, hold more diversified portfolios with a larger fraction of index funds, exhibit lower home bias and trend chasing, and increase their (buy) turnover. These effects are generally stronger for former self-directed investors than investors who have previously worked with a human financial advisor. We find that investors also learn from the robo-advisory tool, as evidenced by an improvement in portfolio efficiency in the non-robo advised part of their portfolio. Our research offers a deeper understanding of the trade-offs associated with using robo-advisers.

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Many households rely on financial advisors for investment guidance.[1] Despite the widespread use of financial advice, academic research has raised concerns about the cost and quality of this service. In recent years, a technology-based form of advice, commonly referred to as robo-advice, has emerged as an alternative and possibly more cost-effective way of guiding clients. In 2015, the top four US robo-advisers managed over $76 billion in funds, with a year-on-year growth rate of 116%.

Although its popularity is growing, little is known about how robo-advice impacts clients' portfolios and whether it actually offers substantive benefits compared to traditional in-person advice. Using data on German households, we investigate the effect of robo-advisers on key aspects of clients' portfolio choices. Does robo-advice promote financial risk-taking? Does it mitigate well-known investment biases? Does this type of advice generate positive spill-over effects to other, non-robo-advised accounts?

While (human) financial advisors have the potential to strongly influence their clients' financial risk-taking (Foerster et al., 2017a), the effect of robo-advice on risk-taking is more ambiguous. By providing low-cost access to passive equity investments (e.g., ETFs), robo-advisers could reduce the cost of participating in the stock market and, more generally, the costs of holding equity. However, the lack of a human advisor could limit clients' level of trust in the financial markets and reduce participation and share of risky assets (Guiso, Sapienza and Zingales, 2008). Moreover, without a human advisor clients could not overcome the anxiety associated with holding risky investments (Gennaioli, Shleifer and Vishny, 2015). Consistent with this hypothesis, Foerster et al (2017b) find that a reduction in the supply of financial advisors, due to a regulatory change in Canada, reduces stock market participation and the share of risky assets held by investors.

Financial advisors' clients seem to share many of the behavioral biases already documented in do-it-yourself investors' portfolios: high turnover, under-diversification, home

[1] In the US alone, more than 50% of mutual funds are sold through financial advisors (ICI, 2013). In other countries, financial advice is even more pervasive. For instance, in Canada, 80% of retail assets are invested through financial advisors (CSA, 2012); for Germany, this percentage is estimated at around 75% (Hackethal et. al. 2011).

bias, return-chasing and investing in actively managed and/or expensive funds. Linnainmaa, Melzer and Previtero (2017) document that advisors' own biases—as recorded in their personal portfolios and trades—are likely to generate similar biases in their clients' portfolios. Robo-advisers may be able to reduce client biases by proposing cost-effective, passive and well-diversified investments. Moreover, robo-advice is fully automated, leaving no room for the potential biases that human advisors can pass on to their clients. Contrary to this positive view, academic research has documented how the switch to online brokerage and retirement accounts in the early 2000s increased the frequency of trading and deteriorated performance in both types of accounts (Barber and Odean, 2002; Choi, Laibson and Metrick, 2002). Analogously, robo-advisers could encourage higher turnover, eroding some of the benefits associated with robo-advice.

We use data from a large German retail bank that started offering a robo-advice service in 2014. Three distinctive features of the data make them particularly suitable for addressing our research questions: i) roughly 40 percent of the robo-advised clients had existing accounts at the bank, allowing us to investigate investment behaviors before and after joining the robo-advice service; ii) we can observe the behaviors of bank clients that did not join the robo-advice service (i.e. clients working with human advisors or making their own investment decisions); and iii) we have information on the marketing campaigns that quasi-randomly targeted existing bank clients to advertise the robo-adviser.

We observe the investment behaviors of the 11,145 clients that have joined the robo-adviser since its launch in April 2014 until October 2017. Of these individuals, 4,488 (or 40.3%) were existing clients and the remaining 6,657 (or 59.7%) were new clients. For each existing bank client, we have a full history of all transactions and holdings over his/her relationship with the bank. Since existing clients' average tenure with the bank is approximately nine years, we are able to observe changes in their portfolios *after* joining the robo-advisor. Moreover, we can estimate the effects of robo-advice by using client fixed effects to control for non-time varying unobserved heterogeneity at the client level. As in any fixed effect analysis, changes in unobserved investor characteristics are a potential concern. For instance, an investor's risk appetite may change, encouraging him or her to join a robo-advice service. Although this is a legitimate concern, we use marketing campaign data to document whether the effects of robo-advice are indeed stronger for those clients that joined the service at their own timing compared to those that joined after having been prompted by the bank.

We find that after joining a robo-advising service, clients increase financial risk-taking, hold more diversified portfolios with a larger fraction of index funds, exhibit lower home bias and increase their (buy) turnover. These effects are generally stronger for former self-directed investors than investors who have previously worked with a human financial advisor.

The effects of switching to a robo-adviser are both economically and statistically significant. In estimations with both time and investor fixed effects, using the robo-adviser increases the share of risky assets by 9.5 percentage points (pp) or by 21.3% compared to the unconditional mean of robo-advised clients before joining (44.6%). To better gauge the magnitude of this effect, we can consider that being a woman reduces the share of risky assets by 4.7 percentage points (pp), while five additional years of tenure with the bank increases risky assets by 1.8 pp. Overall, joining a robo-advice service has a positive effect on portfolio diversification and efficiency.

A major concern in all these before-after analyses is that investors could change over time along some unobservable dimensions. To address this endogeneity concern, we run two additional analyses using information about the bank's staggered marketing campaigns to advertise the robo-adviser. Taken altogether, the evidence from marketing campaigns seems to suggest that the effects of robo-advisers are at least as strong for those clients that choose to join the robo-adviser shortly after being randomly contacted by the bank and, hence, less likely to have exactly timed their switch.

We can implement these methodologies primarily because our data comes from a large retail bank that also offers a robo-adviser service. In contrast, data from independent robo-advisers would not typically include information on clients' prior investments, the investments of those who don't sign up for the service, or clients' additional investments outside of their robo-advised accounts. While studying a robo-adviser associated with a bank strengthens our data, it could also limit our ability to generalize our results to independent robo-advisers. Comparing the behaviors of new and existing bank clients joining the robo-advice service to gauge a sense of the potential selection bias in our setting could limit this downside and determine the generalizability of our results to independent robo-advisers.

The paper is organized as follows. Section 1 describes our methodologies and research design. Section 2 gives details of the robo-advice offer, describes our data, gives some descriptive statistics, and describes the variables used to estimate investor behavior. In section 3 we present our results. Section 4 describes future extensions. Section 5 concludes the paper.

1 Methodologies and research design

Estimating the *causal* effect of financial advice on clients' choices is a challenging task for an econometrician. Because clients ultimately self-select into receiving advice, the researchers need to establish the right counterfactual for client behaviors in the absence of advice. We face similar challenges in our investigation of the effects of robo-advisers on their clients' portfolios. Because exogenous or random variations in access to or the supply of advice are rare[2], the use of archival data could be potentially problematic for establishing causality. In principle, the use of a randomized controlled trial (RCT) could solve these identification challenges. Nonetheless, conducting such a field experiment could also be challenging, as we would need not only to randomize access to robo-advice, but also to observe the investment choices of the members of the control group. Moreover, if the field experiment is conducted on a small convenience sample, potential external validity issues could arise.

[2]For a more extensive treatment on the challenges of identifying the causal effects of financial advice, refer to Chalmers and Reuter (2015). In that study, the authors use time-series variation in access to brokers to identify the counterfactual portfolios in the retirement plans of Oregon State employees. Analogously, Foerster et al. (2017b) use a regulatory change that exogenously limited the supply of investment advisors in Canada. The regulation in question was implemented in 2004 in every Canadian province with the exception of Quebec, which implemented a similar regulation three years later. This set-up allows the authors to use a difference-in-differences approach, with investors in Quebec as the control group.

Investors that join a robo-advice service could be—and probably are—substantially different from investors that do not join. A naïve comparison of joiners and non-joiners could then be biased if important factors that may determine the demand for robo-advice are omitted. As a first attempt to identify the effects of robo-advisers on clients' investment decisions, we compare the investment behaviors of bank clients before and after they join the robo service. In practice, we run the following panel regressions:

$$y_{i,t} = \alpha + \beta post_t + \boldsymbol{\theta X}_{i,t} + \tau_t + \delta_i + u_{i,t} \tag{1}$$

All regressions are estimated from 24 months before a client signs up for robo-advice to up to 42 months afterward (for the first cohort, which joined in May 2014). $y_{i,t}$ is our outcome variable of interest measured at the monthly level (e.g., share of risky assets). $\mathbf{X}_{i,t}$ is a vector of non time-varying and time-varying investor-specific controls (e.g., age and gender or checking account balance and number of monthly logins). $Post_t$ is an indicator variable equal to one in the months after the client has joined the robo-advice service. It represents our variable of interest, meant to capture differences in investment behaviors after a client signs up for robo-advice. We include time fixed effects, τ_t, to account for shocks that affect all investors in the same time period. In some specifications, we also include investor fixed effects, δ_i, to account for unobserved and non time-varying heterogeneity at the client level. The standard errors are double-clustered at the investor and at the month level to adjust for heteroskedasticity and serial and cross-sectional correlations in the error term.

By comparing the behaviors of the same investors before and after they join the robo-advice service, we obtain preliminary estimates of the effects of robo-advisers on investment decisions. In particular, the use of investor fixed effects could allow us to control for unobservable non time-varying characteristics at the investor level. Nonetheless, our estimates could still be biased if, for example, investors change their attitudes or beliefs when signing-up for robo-advice. Analogously, we cannot rule out reverse-causality in these specifications.

In other words, investors might join the robo-advice service precisely because they have changed their preferences (or beliefs).

To account for these possibilities, we run two tests that incorporate additional information on the marketing campaigns that the bank conducted between 2014 and 2017 to advertise the robo-advice service. Clients were randomly assigned to campaigns and, hence, contacted at different points in time. The exogenous timing of the campaigns could be helpful in ruling out potential changes at the client level at the moment when clients sign up for the robo-advice service. We interact the $post_t$ variable with an indicator variable equal to one if a client was targeted in the marketing campaign before she joined. The underlying assumption is that clients that sign up without being contacted by the bank are more likely to choose endogenously when to join and, hence, more likely to have experienced relevant changes around the time they sign up. If the robo-adviser's effects are stronger for these clients, then client-driven changes, rather than any changes caused by the robo-adviser, are more likely to be responsible.

We then limit our analyses to the sample of clients in the marketing campaigns and track how quickly clients joined after being contacted by the bank. More specifically, we interact the $post_t$ variable with an indicator variable equal to one if a client signed up in the 30-day period after receiving the marketing materials from the bank. Given the exogenous timing of the campaign, the underlying assumption is that clients that join soon after receiving the bank communication are less likely to have another endogenous motive to switch to a robo-adviser. If the robo-adviser's effects on these clients are similar to the effects on clients joining after 30 days have passed, we can infer that at least some of the changes associated with joining a robo-adviser are more likely to be causal and cannot be ascribed entirely to client-driven changes.

2 Data description

2.1 The robo-adviser

We obtain data from an online bank, the subsidiary of one of the largest German retail banks. This online bank is a full-service bank that offers brokerage services, banking products (e.g., checking and saving accounts, credit cards), mortgages, and financial advice. In May 2014, the bank also introduced a robo-advice service.

The robo-adviser generates recommendations using a three-step process: i) investment planning; ii) fund selection; and iii) execution. See Figure A.1 for a disguised example of the robo-adviser. In the first step, the client provides four inputs: frequency of deposits (recurring savings vs. lump sum investment), amount invested, acceptable level of risk and investment horizon. Based on these inputs, the robo-adviser creates a recommended asset allocation. The share of risky assets generally increases with the desired risk level, the investment amount and horizon. When the investment amount increases, the robo-adviser also adds commodities and real estate to the asset allocation. See Tables A.1 to A.5 for a more detailed description of proposed asset allocations by level of risk, investment amount and investment horizon.

In the second step, the client can choose between ETFs, actively managed funds or a mix of the two. In this step, there is no default selection and the customer is forced to make an active choice. After selecting one of these three options, the robo-adviser recommends a default selection of products per asset class. The client can accept or change this default selection. For each of the proposed products, the client can easily see the management expense ratio, the Morningstar rating, the performance over the past 12 months and 5 years, and the non-recurring trading costs (i.e., exchange fees and front end-loads). The robo-adviser ranks the proposed investment solutions by expense ratio, from lowest to highest. Therefore, affiliated funds from the parent bank or from any other issuers do not receive any special treatment.

In the last execution step, the client enrolls into the robo-advice service and, if he or she is not already a client of the bank, becomes one, either via an online process or a more traditional process using signed paper documents.

2.2 Descriptive statistics: Client demographics and investment accounts

We have obtained data on a large sample of three different types of bank clients: i) all 11,145 clients that have used the robo-adviser; ii) a sample of bank clients that have signed up to work with a human advisor; iii) a sample of 105,463 self-directed clients that have investment accounts. Our robo-advice account data cover the period from May 2014, when the robo-adviser was launched, to October 2017. For all clients, we have demographic and investment data throughout their relationship with the bank, going as far back as January 2003.[3]

In Table 1, we report summary statistics for these three different types of clients over our entire time period (2003-2017). We label clients that joined the robo-advice service at any point in time as robo-advised, even though they may still have other investment accounts with the bank (either overseen by human advisors or self-directed). Clients that worked with a human advisor at any point in time but never signed up to receive robo-advice are considered human-advised. Finally, we refer to clients that joined neither the robo-advice nor the human advice services as self-directed. In this table, we look at client demographics, bank account activity, investment portfolio and a selected sample of outcome variables that we have already computed.

In our sample the average age ranges from 48.6 to 57.6 years, while the fraction of female investors is between 15.2% and 24.9%. Robo-advised investors are demographically similar to self-directed clients, while human-advised investors tend to be older and are more likely to be male. Based on these characteristics, our sample of investors is comparable with the

[3] Overall, we have an unbalanced—yet free of survivorship bias—panel as some clients start and terminate their relationship with the bank during our sample period.

one used in Barber and Odean (2001). We compute the length of clients' relationships with the bank using the date of the first account opened. We observe long-standing relationships in all three client groups, ranging from an average of 9.5 years for robo-advised clients to an average of 13.2 years for human-advised clients). Wealth is measured for each street in Germany, using a categorical variable that ranges from one to nine (highest wealth level). A specialized data provider constructs this variable using several factors, such as house type and size, dominant car brands, rent per square meter, and unemployment rate. We do not observe substantial differences in the wealth level between the three groups.

Our account activity data shows that human-advised investors have on average twice the net cash of self-directed investors (EUR 3,480 vs. 1,692), with robo-advised clients falling in between (EUR 2,701). We compute the net cash as the combined balance on any savings and checking accounts (less the outstanding client debt). Net cash amplitude is the difference between the monthly maximum and minimum in net cash. This measure varies from EUR 3,493 for human-advised clients to EUR 1,597 for self-directed clients. The values observed in our sample seem to suggest that, at this bank, many clients use the checking account as their primary account.

Investors log in to their account quite frequently, from 5.8 (self-directed) to 8.9 days per month (human-advised). Sicherman et al. (2016) report an average of 85 logins into 401(k) accounts over a 2 year period from 2007-2008. Gargano and Rossi (2016) find that investors log in to their brokerage accounts on 17% of all days, or 5.1 days per month. In our sample, the number of logins is naturally higher compared to Sicherman et al. (2016) since our investors have multiple accounts with the bank. To provide a baseline for the login activity associated with basic bank services, we analyze a sample of clients without investment accounts and we find that their average number of logins per month is equal to 4.3 days.

Looking at the investment accounts, self-directed clients and robo-advised clients invest significantly less than human-advised clients (EUR 30,883 and EUR 35,718 vs. 85,704). Self-directed investors have the highest share of individual stocks (52.7%) while have a higher share invested in single stocks while robo-advised clients have the lowest (26.5%). Robo-advised and human-advised clients implement on average 2.4 or 2.5 trades per month, while self-directed investors 1.7 trades.

2.3 Descriptive statistics: Investor behaviors

In the last part of Table 1 we introduce dependent variables related to investor behaviors. We measure risk-taking using stock market participation (extensive margin) and the share of risky assets (intensive margin). We calculate the share of risky assets as the sum of investments in single stocks and equity funds and half of the value invested in balanced funds, divided by total financial wealth in the investment account. We calculate purchase-, sale-, and portfolio-turnover following Barber and Odean (2001).

We measure portfolio under-diversification using the Herfindahl-Hirschman Index (HHI), a commonly accepted and simple measure of diversification (Dorn, Huberman, and Sengmueller 2008; Ivkovic, Sialm, and Weisbenner 2008). Given that this index is calculated by summing the squared portfolio weights of all securities, it follows that the lower the HHI, the lower the under-diversification (hence, the better the diversification). We follow Dorn, Huberman, and Sengmueller (2008) in assuming that if a security is a fund, the fund consists of fifty equally weighted positions. We plan to compute the level of idiosyncratic risk in investors' portfolios as a second measure of diversification, following Calvet, Campbell, and Sodini (2007). We calculate the home bias as the fraction of equity invested in German companies or funds. Passive share is the fraction of index funds in the investment portfolio.

Given that all the variables in Table 1 are computed over our entire sample period, any difference in the outcome variables between client groups could reflect both selection effects and the effects of the robo-adviser. To overcome this limitation, we compute in Table 2 summary statistics for self-directed, human-advised, and robo-advised investors prior to the introduction of the robo-adviser in the two-year period between 2012 and 2013. Therefore, we can interpret differences across client groups in this table as reflecting potential selection effects. We introduce summary statistics associated with the effects of the robo-adviser in Table 3.

Overall, this table indicates that customers who join the robo-advice service are more likely to be younger and have a shorter relationship with the bank. Before joining, they invest less and hold fewer equity investments; their portfolios are less diversified and have a smaller fraction of assets invested in index funds. All of these results are based on descriptive statistics and need to be confirmed using multivariate analyses.

3 Results from before-after analyses

3.1 Before-after analyses: Full sample

In this section we report results from the before-after methodology described previously. Table 3 provides descriptive statistics for robo-advised clients before and after they join the robo-advice service. After joining the service, the average number of logins per month increases by 72.6%, from 26.6 to 45.9. Analogously, the value of the investment portfolio increases by 75.4%, from EUR 41,917 to 73,509. The share invested in funds also increases, from 53.4% to 61.3% of the overall investment account value. The number of trades more than doubles, from 1.7 to 3.7 trades per month. In terms of our outcome variables, we find an increase in the share of risky assets and portfolio turnover. Under-diversification and the home bias in the portfolio decrease, while the fraction of index funds increases by a factor of more than three.

To estimate the effects of the robo-adviser in a multi-variate setting, we run a series of regressions following the methodology presented in *Equation (1).* In Table 4, we introduce the results for the share of risky assets. In column 1, we include only investor and account controls. In columns 2 and 3, we add time fixed effects alone and together with investor fixed effects, respectively. The effects of switching to a robo-adviser are both economically and statistically significant. In the estimation with both time and investor fixed effects, using the robo-adviser increases the share of risky assets by 9.5 percentage points (pp) or by 21.3% compared to the unconditional mean of robo-advised clients before joining (44.6%). To better gauge the magnitude of this effect, we can consider that being a woman reduces the share of risky assets by 4.8 percentage points (pp), while five additional years of tenure with the bank increases risky assets by 1.85%. In this and all the following analyses, the errors are double-clustered at the investor and month level.

In Table 5, we introduce estimates associated with investor behavior and behavioral biases: under-diversification (in columns 1 and 2), home bias (columns 3 and 4) and share of passive investments (columns 5 and 6). Overall, joining a robo-advice service has a positive effect on portfolio diversification and efficiency. After controlling for both time and investor fixed effects, joining the robo-adviser increases diversification and reduces portfolio concentration (the HHI index) by 11.7 pp or by 57.6% compared to the mean value of 20.3%. The robo-adviser reduces also home bias by 10.1 pp, or 28.5% of the mean value (35.4%), and increases the share of passive investments by 20.6 pp, or 171% compared to the mean value of 11.6%.

In Table 6, we present estimates associated with the turnover of the portfolio. In our setting, joining the robo-advice service requires making an investment. Therefore, we exclude from the turnover calculation all the purchases and sales made in the two months after joining to avoid mechanical effects. After joining the robo-advice service, overall portfolio turnover increases by 1.9 pp, or 33.9% compared to the sample mean of 5.6%. Given that the effect on the sell turnover is close to zero (and not even statistically significant), this increase in turnover is entirely explained by an increase in the buy turnover by 3.6 pp or 48% compared to the sample mean before joining.

Overall, our results suggest that, after joining a robo-advice service, investors increase both financial risk-taking and measures of portfolio efficiency, such as the number of investments, geographical diversification and the fraction of index or passive funds. We also find an increase in turnover, driven by buy transactions. We plan to conduct further analyses on the transaction costs associated with these more frequent trades to document if higher turnover offsets some of the potential benefits associated with higher portfolio efficiency.

3.2 Before-after analyses: Formerly self-directed vs. human-advised clients

In order to better understand the potential portfolio efficiency gains associated with joining a robo-adviser, we conduct additional analyses to investigate whether these effects are different for formerly self-directed or human-advised clients switching to robo-advisers. In practice, we interact the variable $post_t$ from *Equation (1)* with an indicator variable $human-advised$ equal to one for formerly human-advised clients. The interaction term will capture the differential effect of robo-adviser for formerly human-advised clients as compared to formerly self-directed ones. We report these results in Table 7. In some cases the interaction term has the opposite sign of the $post_t$ coefficient and statistically significant, suggesting that the effects of the robo-adviser are larger for formerly self-directed clients. For example, the share of risky assets increases by 9.7 pp for formerly self-directed clients, vs. just 5.2 pp (i.e., 9.7-4.5) for formerly human-advised clients. In other words, this effect is almost twice as strong for formerly self-directed clients. Similarly, for formerly human-advised clients the effect on portfolio concentration is only 21.5% (-2.6 pp vs. -12.0) and the effect on passive share is 22.3% (4.7 pp vs. 21.2 pp) compared to the effects for formerly human-advised clients. The effect on home bias for previously human-advised clients is about 40.1% compared to the effect on human-advised clients. For portfolio turnover, the point estimates suggest a stronger effect on human-advised clients. Nonetheless, the difference in the effects for these two categories of investors is not statistically significant. Overall, this evidence suggests that the effect of the robo-adviser could be stronger for formerly self-directed investors.

3.3 Before-after analyses: Endogenous joining and marketing campaigns

A major concern in all the previous before-after analyses is that investors could change over time along some unobservable dimensions (e.g., attitudes to risk). Under this scenario, an investor may decide to start using the robo-adviser precisely *because* he or she wants to try a different trading strategy such as taking on more risk, for instance, or increasing diversification. To address this concern, we run two additional analyses using information about the bank's staggered marketing campaigns to advertise the robo-adviser.

First, we use information on clients that joined the robo-advice service without being in the marketing campaign (or before receiving it). If clients are randomly assigned to staggered campaigns, then we could assume that clients joining without receiving any bank communication should be more likely to endogenously choose when to join the robo-advice service. If so, we would expect larger changes in these clients' investment behaviors after joining if, indeed, changes in preferences are largely driving the decision to join the robo-advice service. In Table 8, we present the results of this estimation, interacting the variable $post_t$ from *Equation (1)* with an indicator variable $marketingcampaign$ equal to one for those clients that joined *after* receiving the bank communication. The interaction term will again capture the differential effect of the robo-adviser for clients that joined after participating in the campaign as compared to clients that joined without (or before) receiving any bank communication. If changes in preferences are largely driving the decision to join the robo-adviser, then we should expect the interaction coefficient to have the opposite sign of the main effect ($post_t$). With the exception of the sell turnover, where both the main and the interaction effects are not statistically significant, for all the other outcomes the interaction term has the same sign as the main effect and is statistically significant. In other words, the effects of the robo-adviser appear to be stronger for those clients that joined after the bank marketing campaign compared to clients that joined without (or before) any communication from the bank.

Second, we limit our analyses to the sample of clients that joined after receiving the bank's communication. We do so to exploit variation in how quickly clients joined the robo-advice service after receiving the marketing materials. Under the assumption that clients were randomly targeted in the different staggered campaigns, clients that join soon after receiving the marketing materials are less likely to be endogenously timing their switch to the robo-adviser.

We present these results in Table 9. In this analysis, we interact the variable $post_t$ from *Equation (1)* with an indicator variable $fastjoiner$ equal to one for those clients that joined within 30 days after receiving the bank communication. The interaction term will again capture the differential effect of the robo-adviser for clients that joined within the first 30 days vs. clients that joined later. Again, if changes in client preferences or beliefs are driving the decision to join the robo-advice service, the we should expect the interaction coefficient to be of the opposite sign of the main effect ($post_t$). With the exception of underdiversification stronger for fast joiners, we find that none of the interaction terms are statistically significant, with many point estimates being either of the wrong sign or non-economically meaningful.

Taken altogether, this evidence from the marketing campaigns seems to suggest that the effects of robo-advisers are at least as strong for those clients that choose to join the robo-adviser shortly after being randomly contacted by the bank and, hence, less likely to have exactly timed their switch. To be clear, we do not claim that these additional analyses completely address the potential endogeneity in the decision to join a robo-advice service. They only provide limited evidence against the notion that the effects observed after joining the robo-adviser are driven largely by changes in clients' preferences or beliefs (that would not be captured by our investor fixed effects).

Given that robo-advisers have existed for a limited time, another legitimate concern is that what we consider to be effects of the robo-adviser could be the result of changes in the macroeconomic conditions (e.g., lower interest rates) or stock market conditions (good returns in our sample period). We plan to use an additional methodology—a difference-in-differences analysis—to try to address these concerns.

3.4 Before-after analyses: Spillover effects

Do robo-advisers generate positive spillover effects in other investment accounts? To investigate investor learning and spillover effects, we rely on the same before-after methodology and the same outcome variables investigated before. The key difference is that we limit our analyses to the *non robo-advised* part of the investment accounts. For example, does risk taking in the *non robo-advised* investments increase after joining the robo-adviser? Investor learning would cause the efficiency of *non robo-advised* accounts to improve and investment biases to decrease, with possible exception of turnover.

We present these results in Table 10. The variable of interest, $post_t$ from *Equation (1)*, will now capture the change in behavior in the *non robo-advised* part of investment accounts. Positive spillover effects should result in coefficient on the $post_t$ indicator variable of the same sign as those previously estimated. With the exception of home bias that increases, we find positive spillover effects for all the other outcome variables. Robo-advised clients increase share of risky assets, diversification, passive share and overall portfolio turnover. However, the effects in the *non robo-advised* part of the investment accounts (Table 10) are much smaller than the effects reported in Tables 4, 5, and 6 for the entire portfolio including the *robo-advised* part. Therefore, we can conclude that our main effects from Tables 4, 5, and 6 are driven by changes in the *robo-advised* part of individual investors' investment accounts.

4 Planned analyses

4.1 Difference-in-differences methodology

A potential concern associated with the before-after analysis is that the time fixed effects might not be able to fully capture the effect of general stock-market or macroeconomic conditions. Robo-advice services have been introduced only in the past few years, and the possibility exists that changes in robo-advised accounts could reflect some external economic trend. We plan to use a difference-in-differences methodology to address this concern.

We first identify among the existing bank clients—either do-it-yourself investors or clients of human advisers—those that joined the robo-adviser. We then match each of these clients with a non-joiner "close" comparable investor from the same investor group based on observable characteristics at the time of switch to the robo-adviser. We define each resulting treated-control pair as a cohort and then stack all cohorts. Finally, we run a generalized difference-in-differences regression specification on this stack of cohorts.

We plan to implement the match using demographic criteria (age and gender) as well as investment account specifics (the dollar value of the client's investment portfolio and its performance over the past 24 months). Specifically, we match with replacement each treated robo investor with the closest non-robo investor, using the Abadie and Imbens (2006) distance metric that weights each dimension by its standard deviation. Both treated and control units must be in the sample for at least two years before and three months after the event to limit changes in composition around the joining date.

In our stacked cohort generalized difference-in-differences analyses, we plan to take the difference in outcome for each treated investor i after joining the robo-advice service (relative to outcomes before the investor joined), and compare it with the difference in outcome for the matched control investor within the same cohort c. In practice, we plan to use the following empirical specification:

$$y_{i,c,t} = \beta(d_{i,c} \times post_{t,c}) + \tau_{t,c} + \delta_{i,c} + u_{i,c,t} \tag{2}$$

As in the previous empirical strategy, all regressions are estimated from 24 months before joining the robo-advice service to up to 20 months afterward. We choose this pre-window period to more accurately test for the parallel trend assumption. The unit-cohort fixed effects $\delta_{i,c}$ ensures that we compare the outcome within the same treated investor before and after the switch to the robo-adviser. The time-cohort fixed effect $\tau_{t,c}$ guarantees that the treated investor is compared only with the matched control investor at each point in time. We use $d_{i,c}$ as a dummy variable to identify treated investors. $Post_{t,c}$ is a dummy variable equal to one if the time period is after the investor signs up for to receive robo-advice. The coefficient β represents the diff-in-diff effect of joining a robo-advice service on the outcome variable relative to a matched counterfactual. The standard errors are double-clustered at the investor and at the month level to adjust for heteroskedasticity and serial and cross-sectional correlations in the error term (Bertrand et al, 2004).

Given that we have monthly data, we plan to determine not only whether the robo-advice service has an overall effect on investors, but also to investigate how the outcome variables evolve over time. This is important for two reasons. First, we can directly check for the parallel trend assumption, to ensure that we are indeed matching treated investors to comparable counterfactuals. Any substantial difference in the pre-trend could make the interpretation of the difference-in-differences results problematic. Second, we can learn if the robo-adviser has an immediate and one-time effect or generates continuous changes over time. We thus also plan to estimate the following equation:

$$y_{i,c,t} = \sum_{k=-24}^{20} \beta_k (d_{i,c} \times \lambda_{t,k,c}) + \tau_{t,c} + \delta_{i,c} + u_{i,c,t} \tag{3}$$

Where $\lambda_{t,k,c}$ is a dummy equal to one if time t is equal to k, and zero otherwise. We plan to cluster the standard errors here at the individual level to control for heteroskedasticity and serial correlation in the error term.

We plan to separately report the results of the difference-in-differences estimates for different groups of investors that join the robo-advice service: former clients of human advisers vs. former self-directed investors. This could provide some useful insights into the effect of robo-advisers on different types of investors.

While this matching strategy tries to come as close as possible to the ideal randomized controlled experiment, we acknowledge that the assignment to control and treatment groups is not, in fact, random. Therefore, this methodology cannot completely address all endogeneity concerns. For example, we can control for pre-trends based on observable characteristics. Nonetheless, there may be other unobserved characteristics that we exclude from the matching procedure that could explain differences in outcome variables after the event.

We plan to partially address this issue by using investors who signed up for robo-advice later in our sample period as a control group for the early participants in the service. Given that the timing of joining may be determined by the random timing of the marketing campaigns, late and early joiners should be closer to each other in terms of unobservable characteristics that could potentially drive both demand for the robo-adviser and outcomes in the periods after the event.

4.2 Field experiment methodology

A randomized controlled trial (RCT) would be the ideal method for estimating the *causal* effects of using a robo-adviser. A key feature of the bank's marketing campaigns could potentially allow us to implement a similar methodology. Between 2014 and 2015, the bank targeted over 106,000 existing clients to advertise the robo-adviser. For each campaign, the bank randomly selected a control group of clients that were left off the campaign. In total there are roughly 7,000 clients that were included in these control groups. This randomization in the access to the marketing campaigns could allow the estimation of two causal effects. First, we can compute the effects of a marketing campaign that promotes robo-advisers on investor behaviors, the *intention to treat* (or ITT) effect. For each outcome of interest (e.g., share of risky assets) we can calculate the following:

$$ITT = y(t) - y(c) \tag{4}$$

Where $y(t)$ is the average outcome in the treatment group of clients included in the marketing campaigns, while $y(c)$ is the average outcome in the control group of the clients that the bank randomly excluded from the campaign. The ITT estimates could provide useful information for understanding the effects of *promoting* robo-advisers. In other words, they can tell us what happens to the average investor chosen to receive marketing materials.

This is different from estimating the causal effect of *using* the robo-adviser on client behavior, or the *treatment on the treated* effect (TOT). We can estimate the TOT as follows:

$$TOT = \frac{y(t) - y(c)}{prob[treated|t] - prob[treated|c]} = \frac{ITT}{prob[treated|t] - prob[treated|c]} \tag{5}$$

In our setting, $prob[treated|t]$ is the average probability of joining the robo-adviser conditional on receiving the marketing materials. Analogously, $prob[treated|c]$ represents the average probability of joining the robo-adviser for clients excluded from the marketing campaign. We plan to more formally estimate the TOT by instrumenting the probability of joining a robo-adviser by the assignment to the marketing campaign. We plan to estimate robo-advisers' impact on investor behavior in a two-stage least squares model:

$$\begin{aligned} \textit{use robo-adviser}_{i,t} &= \alpha_1 + \beta_1 \textit{marketing campaign}_t + \boldsymbol{\theta}_1 \boldsymbol{X}_{i,t} + \tau_{1t} + u_{1i,t} && (6) \\ y_{i,t} &= \alpha_2 + \beta_2 \textit{use } \widehat{\textit{robo-adviser}}_{i,t} + \boldsymbol{\theta}_2 \boldsymbol{X}_{i,t} + \tau_{2t} + u_{2i,t} && (7) \end{aligned}$$

Each regression includes both investor-level controls, $\boldsymbol{X}_{i,t}$, and month fixed effects, τ_{1t} and τ_{2t}. The first stage provides an estimate of each client's predicted probability of using a robo-adviser ($\textit{use } \widehat{\textit{robo-adviser}}_{i,t}$), allowing for variation due to the $\textit{marketing campaign}_t$ instrumental variable. The second stage uses this predicted probability to provide an estimate of the robo-adviser's impact on investor behaviors. The results of the first-stage regression would allow us to establish how powerful the instrument is and whether the marketing campaign increases the probability of joining the robo-advice service. As for the exclusion restriction, the marketing campaigns contain only information about joining the robo-adviser and no additional information about current market conditions. Therefore, we believe that is plausible to assume that our instrument, $\textit{marketing campaign}_t$, would affect our outcomes of interest (e.g., share of risky assets) only by changing the probability of joining the robo-advice service.

5 Conclusion

Assets under management at robo-advisory firms have substantially grown over the past years. Nonetheless, the effects of robo-advisors on investor behavior is largely unexplored. We address this issue using novel data from a large German bank that has introduced a robo-advisory service in 2014.

In estimations with both time and investor fixed effects, we find that the effects of switching to a robo-adviser are both economically and statistically significant. Joining a robo-adviser increases the share of risky assets, the share invested in index funds, and portfolio diversification – as measured by HHI and the home bias. Overall, robo-advisers seem to have a positive effect on portfolio diversification and portfolio efficiency.

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Table 1
Summary Statistics by Client Group (January 2003 - October 2017)

	Self-directed (105,463)		Personal-adviced (4,644)		Robo-adviced (11,145)	
	Mean	SD	Mean	SD	Mean	SD
Demographics						
Female (%)	24.9	43.2	15.2	35.9	20.2	40.2
Age (Years)	49.9	15.5	57.6	12.6	48.6	14.8
Relationship (Months)	135.8	67.1	158.0	67.5	113.9	71.4
Wealth (Microgeo)	6.1	1.9	6.4	1.9	6.0	1.9
Account activity						
Net cash average (EUR)	1,692	8,132	3,480	12,260	2,701	9,948
Net cash amplitude (EUR)	1,597	4,820	3,493	8,017	2,538	6,652
Days per month with login	5.8	6.1	8.9	6.4	8.7	6.7
Number of logins per month	14.6	34.2	24.7	40.7	26.5	56.7
Investment portfolio						
Investment total (EUR)	30,883	112,028	85,704	135,469	35,718	90,560
in stocks (EUR)	16,270	81,252	27,369	66,814	9,457	41,945
in funds (EUR)	10,265	50,401	48,196	88,082	22,345	48,498
Number of trades total (#)	1.7	10.8	2.5	5.0	2.4	3.5
in stocks (#)	0.5	2.2	0.7	2.0	0.4	1.5
in funds (#)	0.1	0.5	0.7	0.9	0.7	1.2
in savings plans (#)	0.5	1.1	0.5	1.1	1.1	1.8
Dependent						
Participation (% of months)	74.0	32.2	87.1	21.0	69.2	33.1
Risky share (%)	46.4	31.2	53.9	23.5	38.5	27.8
Buy turnover (%)	9.3	15.8	7.8	9.1	13.8	17.9
Sell turnover (%)	4.8	10.6	5.8	7.7	4.4	8.1
Portfolio turnover (%)	7.0	12.3	6.8	8.2	9.1	11.4
HHI (%)	32.8	32.4	12.9	15.5	12.0	17.9
Homebias (%)	45.4	37.0	32.1	23.8	24.3	25.8
Passive share (%)	7.9	22.4	11.9	14.2	31.6	35.6

Table 1 provides summary statistics for invidual investors' demographic characteristics, account activity, investment portfolio and our dependent variables, separately for self-directed individual investors, investors having a human financial advisors, and investors using the robo-advisor. Variable descriptions are reported in the text. All the time-invariant variables are measured at the end of 2013. All statistics on time-varying variables are computed on a monthly basis over the period from January 2003 to October 2017.

Table 2
Summary Statistics by Client Group (January 2012 - December 2013)

	Self-directed (87,658)		Personal-adviced (4,373)		Robo-adviced (8,698)	
	Mean	SD	Mean	SD	Mean	SD
Demographics						
Female (%)	24.5	43.0	14.5	35.2	18.8	39.1
Age (Years)	49.7	15.2	57.6	12.4	49.1	14.2
Relationship (Months)	88.9	56.3	100.7	58.7	73.4	56.5
Wealth (Microgeo)	6.1	1.9	6.4	1.9	6.1	1.9
Account activity						
Net cash average (EUR)	1,982	13,977	3,734	11,352	2,666	8,377
Net cash amplitude (EUR)	2,034	5,573	4,309	11,212	3,135	7,048
Days per month with login	6.0	7.0	9.6	7.5	8.5	7.3
Number of logins per month	13.4	26.8	24.9	35.7	19.0	29.1
Investment portfolio						
Investment total (EUR)	36,236	130,626	85,434	126,873	44,954	114,057
in stocks (EUR)	19,242	96,084	28,392	72,574	13,805	53,234
in funds (EUR)	11,662	50,138	44,365	70,489	23,974	56,907
Number of trades total (#)	1.3	5.4	2.5	10.7	1.7	3.4
in stocks (#)	0.4	2.0	0.7	2.1	0.4	1.5
in funds (#)	0.1	0.6	0.8	1.1	0.4	0.7
in savings plans (#)	0.4	1.1	0.4	1.4	0.6	1.4
Dependent						
Participation (% of months)	70.1	42.6	88.2	28.0	58.2	46.9
Risky share (%)	41.1	36.3	53.2	27.8	29.1	31.7
Buy turnover (%)	6.7	16.0	7.4	11.7	7.7	14.6
Sell turnover (%)	4.2	11.4	6.0	9.3	4.0	8.4
Portfolio turnover (%)	5.4	12.7	6.7	9.9	5.8	10.2
HHI (%)	33.8	35.4	12.4	19.4	20.0	28.8
Homebias (%)	46.7	39.6	34.3	27.4	36.9	34.0
Passive share (%)	4.9	17.6	14.6	17.9	9.0	19.3

Table 2 provides summary statistics for invidual investors' demographic characteristics, account activity, investment portfolio and our most important dependent variables, separately for self-directed individual investors, investors having a personal financial advisors at this bank, and investors using the robo-advisor. Variable descriptions are reported in the text. All these time-invariant variables are measured at the end of 2013. All statistics on timevarying variables are computed on a monthly basis over the period from January 2012 to December 2013, before the launch of the robo-adviser.

Table 3
Robo-adviced customers: Before-after summary statistics

	Before			After			Difference (After - Before)	
Variables	Mean	Median	N	Mean	Median	N	Mean	p-value
Account activity								
Net cash average (EUR)	3,618	895	4,488	5,384	1,042	4,488	1,766	.000***
Net cash amplitude (EUR)	3,518	1,695	4,488	3,516	1,655	4,488	-2	.991
Days per month with login	9.7	7.8	4,488	11.5	10.0	4,488	1.8	.000***
Number of logins per month	26.6	12.6	4,488	45.9	18.4	4,488	19.3	.000***
Investment portfolio								
Investment total (EUR)	41,971	12,048	4,488	73,509	29,092	4,488	31,538	.000***
in stocks (EUR)	13,384	1,359	4,488	22,143	2,537	4,488	8,759	.000***
in funds (EUR)	22,397	5,430	4,488	45,055	18,597	4,488	22,658	.000***
Number of trades total (#)	1.7	0.8	4,488	3.7	2.6	4,488	1.9	.000***
in stocks (#)	0.3	0.0	4,488	0.4	0.0	4,488	0.1	.000***
in funds (#)	0.3	0.1	4,488	0.9	0.4	4,488	0.6	.000***
in savings plans (#)	0.8	0.0	4,488	1.9	0.9	4,488	1.1	.000***
Dependent								
Risky share (%)	44.6	43.4	4,486	58.3	59.4	4,488	13.7	.000***
Buy turnover (%)	7.5	3.1	4,488	9.6	5.3	4,488	2.1	.000***
Sell turnover (%)	3.7	1.0	4,488	5.5	1.2	4,488	1.8	.000***
Portfolio turnover (%)	5.6	2.5	4,488	7.5	3.5	4,488	2.0	.000***
HHI (%)	20.3	5.5	4,488	6.7	2.2	4,488	-13.6	.000***
Homebias (%)	35.4	25.0	4,426	22.5	16.6	4,488	-12.9	.000***
Passive share (%)	11.6	0.0	4,426	35.2	27.7	4,488	23.6	.000***

Table 3 provides summary statistics for robo-advice users for the periods before and after they started using the robo-advice service. Investors had to be invested for at least 6 months in the period before using robo-advice and for at least 6 months after using robo-advice for the first time. All variables from the investment portfolio and dependent variables section of this table are calculated conditional on having portfolio holdings in a certain month. This table is based on period between January 2012 and October 2017. Levels of significance are denoted as follows: * if $p<0.10$; ** if $p<0.05$; *** if $p<0.01$.

Table 4
Pre and post analysis: Share of Risky Assets

	Risky Share (mean = 44.6)		
	(1)	(2)	(3)
After Joining Robo-Adviser	9.217***	5.716***	9.541***
	(4.346)	(8.181)	(20.39)
Age	0.0417	0.0428*	
	(1.632)	(1.684)	
Female	-4.548***	-4.753***	
	(-4.681)	(-4.961)	
Wealth	0.392**	0.410**	
	(2.055)	(2.163)	
Relationship (months)	0.0330***	0.0309***	
	(5.283)	(4.573)	
Days per month with login	0.247***	0.284***	0.249***
	(6.020)	(7.289)	(7.796)
Net cash (log)	-1.710***	-2.294***	-0.981***
	(-9.722)	(-22.59)	(-6.379)
Time Fixed Effects	No	Yes	Yes
Investor Fixed Effects	No	No	Yes
N	260,616	260,616	260,616
R-squared	0.085	0.136	0.682

Table 4 reports results from linear regressions of a monthly measure of financial risk-taking (*Risky Share*) of robo-adviced customers between January 2012 and October 2017 onto a dummy set to 1 for the post period (*After Joining Robo-Adviser*), time-invariant customer demographics (*Age, Female*) and time-variant controls (*Logins, Net cash (log)*) without and with time and investor fixed effects. An investor to enter into this regression has to be present for at least 6 months before and after taking robo-advice. For each model, we report the coefficient estimates as well as the corresponding t-values. t-values are based on double-clustered standard errors, robust for correlation across months within same investors and across investors within the same month. All variables are defined in detail in the data section. The constant is omitted. Levels of significance are denoted as follows: * if p<0.10; ** if p<0.05; *** if p<0.01.

Table 5
Pre and post analysis: Under-diversification (HHI), Home Bias, and Passive Share

	HHI (mean = 20.3)		Home Bias (mean = 35.4)		Passive Share (mean = 11.6)	
	(1)	(2)	(3)	(4)	(5)	(6)
After Joining Robo-Adviser	-8.413***	-11.66***	-7.532***	-10.13***	16.67***	20.55***
	(-13.35)	(-26.10)	(-7.290)	(-15.91)	(20.25)	(33.69)
Age	-0.0328		0.0834***		-0.153***	
	(-1.605)		(2.747)		(-5.898)	
Female	-1.868**		-1.866		0.280	
	(-2.294)		(-1.634)		(0.319)	
Wealth	0.397**		0.901***		0.429***	
	(2.576)		(3.925)		(2.609)	
Relationship (months)	-0.0146***		0.00639		-0.0416***	
	(-3.004)		(0.918)		(-7.136)	
Days per month with login	-0.102***	-0.238***	0.0799*	-0.0358	0.0180	0.0722**
	(-2.925)	(-7.927)	(1.793)	(-1.074)	(0.523)	(2.433)
Net cash (log)	0.208***	0.116**	0.197*	0.113*	-0.0804	-0.153**
	(2.623)	(2.124)	(1.781)	(1.906)	(-1.088)	(-2.644)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Investor Fixed Effects	No	Yes	No	Yes	No	Yes
N	260,810	260,810	256,966	256,966	256,966	256,966
R-squared	0.061	0.622	0.047	0.704	0.192	0.695

Table 5 reports results from linear regressions of a monthly measure of portfolio diversification (*HHI*), Home Bias, and Passive Share for robo-advised customers onto a dummy set to 1 for the post period (*After Joining Robo-Adviser*), time-invariant customer demographics (*Age, Female*) and time-variant controls (*Logins, Net cash (log)*) without and with time and investor fixed effects. An investor to enter into this regression has to be present for at least 6 months before and after taking robo-advice. For each model, we report the coefficient estimates as well as the corresponding t-values. t-values are based on double-clustered standard errors, robust for correlation across months within same investors and across investors within the same month. All variables are defined in detail in the data section. The constant is omitted. Levels of significance are denoted as follows: * if $p<0.10$; ** if $p<0.05$; *** if $p<0.01$.

Table 6
Pre and post analysis: Portfolio-, Buy-, and Sell Turnover

	Portfolio Turnover (mean = 5.6)		Buy Turnover (mean = 7.5)		Sell Turnover (mean = 3.7)	
	(1)	(2)	(3)	(4)	(5)	(6)
After Joining Robo-Adviser	0.556	1.950***	1.383**	3.560***	-0.271	0.339
	(1.421)	(4.363)	(2.402)	(6.060)	(-1.005)	(0.853)
Age	0.00412		-0.0126*		0.0209***	
	(0.593)		(-1.653)		(3.145)	
Female	-0.214		-0.302		-0.125	
	(-0.697)		(-0.933)		(-0.418)	
Wealth	0.0349		0.0301		0.0396	
	(0.618)		(0.491)		(0.739)	
Relationship (months)	-0.00406*		-0.0118***		0.00372*	
	(-1.881)		(-4.887)		(1.785)	
Days per month with login	0.361***	0.522***	0.396***	0.587***	0.326***	0.457***
	(19.40)	(24.35)	(20.04)	(23.90)	(18.01)	(22.58)
Net cash (log)	-0.203***	0.137***	-0.213***	0.197***	-0.193***	0.0764***
	(-6.499)	(4.295)	(-6.410)	(4.749)	(-6.321)	(2.876)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Investor Fixed Effects	No	Yes	No	Yes	No	Yes
N	252,318	252,318	252,318	252,318	252,318	252,318
R-squared	0.058	0.333	0.050	0.269	0.046	0.284

Table 6 reports results from linear regressions of a monthly measure of portfolio-, buy-, and sell turnover of robo-advised customers between October 2012 and October 2017 onto a dummy set to 1 for the post period (*After Joining Robo-Adviser*), time-invariant customer demographics (*Age, Female*) and time-variant controls (*Logins, Net cash (log)*) without and with time and investor fixed effects. An investor to enter into this regression has to be present for at least 6 months before and after taking robo-advice. For each model, we report the coefficient estimates as well as the corresponding t-values. t-values are based on double-clustered standard errors, robust for correlation across months within same investors and across investors within the same month. All variables are defined in detail in the data section. The constant is omitted. Levels of significance are denoted as follows: * if p<0.10; ** if p<0.05; *** if p<0.01.

Table 7

Pre and post analysis: Former self-directed vs. human-advised clients

	Risky Share (1)	HHI (2)	Home Bias (3)	Passive Share (4)	Portfolio Turnover (5)	Buy Turnover (6)	Sell Turnover (7)
After Joining Robo-Adviser	9.723***	-12.04***	-10.39***	21.22***	1.558***	3.179***	-0.0632
	(20.90)	(-26.22)	(-15.89)	(37.83)	(4.823)	(6.266)	(-0.268)
After * Human-Advised	-4.501**	9.424***	6.227*	-16.47***	11.68	11.37	12.00
	(-2.407)	(9.481)	(1.978)	(-11.65)	(1.484)	(1.415)	(1.555)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	260,616	260,810	256,966	256,966	252,318	252,318	252,318
R-squared	0.682	0.623	0.704	0.698	0.338	0.272	0.289

Table 7 reports results from linear regressions of a monthly measure of trading behaviors of robo-adviced customers between January 2012 and October 2017 onto a dummy set to 1 for the post period (*After Joining Robo-Adviser*), an interaction of this dummy with a dummy set to 1 for customers having a human financial adviser and time-variant controls (*Logins, Net cash (log)*) with time and investor fixed effects. An investor to enter into this regression has to be present for at least 6 months before and after taking robo-advice. For each model, we report the coefficient estimates as well as the corresponding t-values. t-values are based on double-clustered standard errors, robust for correlation across months within same investors and across investors within the same month. All variables are defined in detail in the data section. Levels of significance are denoted as follows: * if $p<0.10$; ** if $p<0.05$; *** if $p<0.01$.

Table 8
Pre and post analysis: Clients included in marketing campaign vs. not

	Risky Share	HHI	Home Bias	Passive Share	Portfolio Turnover	Buy Turnover	Sell Turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
After Joining Robo-Adviser	7.934***	-8.207***	-7.561***	18.27***	1.666***	2.855***	0.477
	(11.41)	(-15.43)	(-10.09)	(23.81)	(2.654)	(3.942)	(0.802)
After * Campaign	3.469***	-7.445***	-5.537***	4.897***	0.615	1.529**	-0.299
	(3.767)	(-8.959)	(-5.857)	(5.170)	(1.133)	(2.494)	(-0.589)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	260,616	260,810	256,966	256,966	252,318	252,318	252,318
R-squared	0.683	0.626	0.706	0.697	0.333	0.269	0.284

Table 8 reports results from linear regressions of a monthly measure of trading behavior of robo-adviced customers between January 2012 and October 2017 onto a dummy set to 1 for the post period (*After Joining Robo-Adviser*), an interaction of this dummy with a dummy set to 1 if a customer received a marketing campaign beofer joining and time-variant controls (*Logins, Net cash (log)*) with time and investor fixed effects. An investor to enter into this regression has to be present for at least 6 months before and after taking robo-advice. For each model, we report the coefficient estimates as well as the corresponding t-values. t-values are based on double-clustered standard errors, robust for correlation across months within same investors and across investors within the same month. All variables are defined in detail in the data section. Levels of significance are denoted as follows: * if $p<0.10$; ** if $p<0.05$; *** if $p<0.01$.

Table 9
Pre and post analysis: Client joining quickly after campaign vs. not

	Risky Share	HHI	Home Bias	Passive Share	Portfolio Turnvoer	Buy Turnvoer	Sell Turnvoer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
After Joining Robo-Adviser	9.698***	-11.68***	-10.22***	20.55***	2.046***	3.696***	0.397
	(18.36)	(-23.73)	(-14.49)	(30.51)	(4.091)	(5.646)	(0.900)
After * Fast Joiner	1.694	-5.076*	-0.902	2.377	0.252	-0.226	0.731
	(0.972)	(-1.920)	(-0.311)	(0.933)	(0.325)	(-0.228)	(1.077)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	224,823	224,985	221,663	221,663	217,651	217,651	217,651
R-squared	0.691	0.630	0.711	0.702	0.314	0.252	0.268

Table 9 reports results from linear regressions of a monthly measure of trading behavior of robo-adviced customers between January 2012 and October 2017 onto a dummy set to 1 for the post period (*After Joining Robo-Adviser*), an interaction of this dummy with a dummy set to 1 if a customer joins the robo-advice within 30 days after being contacted and time-variant controls (*Logins, Net cash (log)*) with time and investor fixed effects. An investor to enter into this regression has to be present for at least 6 months before and after taking robo-advice and has to be included in a marketing campaign. For each model, we report the coefficient estimates as well as the corresponding t-values. t-values are based on double-clustered standard errors, robust for correlation across months within same investors and across investors within the same month. All variables are defined in detail in the data section. Levels of significance are denoted as follows: * if $p<0.10$; ** if $p<0.05$; *** if $p<0.01$.

Table 10
Pre and post analysis of the non-robo part of the investment portfolio

	Risky Share	HHI	Home Bias	Passive Share	Portfolio Turnvoer	Buy Turnvoer	Sell Turnvoer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
After Joining Robo-Adviser	2.088***	-1.393***	1.044**	1.303***	1.003***	1.224***	0.783***
	(4.635)	(-3.684)	(2.163)	(3.051)	(4.969)	(4.559)	(4.099)
Days per month with login	0.251***	-0.281***	-0.0450	0.0960***	0.527***	0.577***	0.477***
	(7.740)	(-9.619)	(-1.381)	(3.973)	(23.90)	(23.05)	(22.50)
Net cash (log)	-0.883***	0.0741	-0.0489	-0.0402	0.122***	0.155***	0.0893***
	(-5.652)	(1.399)	(-0.849)	(-0.810)	(3.791)	(3.685)	(3.215)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	249,104	249,563	244,849	244,849	249,563	249,563	249,563
R-squared	0.707	0.711	0.760	0.729	0.349	0.290	0.279

Table 10 reports results from linear regressions of a monthly measure of trading behavior calculated using only the non-robo part of robo-adviced customers' investment portfolio (between January 2012 and October 2017) onto a dummy set to 1 for the post period (*After Joining Robo-Adviser*), and time-variant controls (*Logins, Net cash (log)*) with time and investor fixed effects. An investor to enter into this regression has to be present for at least 6 months before and after taking robo-advice. For each model, we report the coefficient estimates as well as the corresponding t-values. t-values are based on double-clustered standard errors, robust for correlation across months within same investors and across investors within the same month. All variables are defined in detail in the data section. Levels of significance are denoted as follows: * if $p<0.10$; ** if $p<0.05$; *** if $p<0.01$.

Appendix

Figure A.1
Disguised Example of Robo-Advice Website

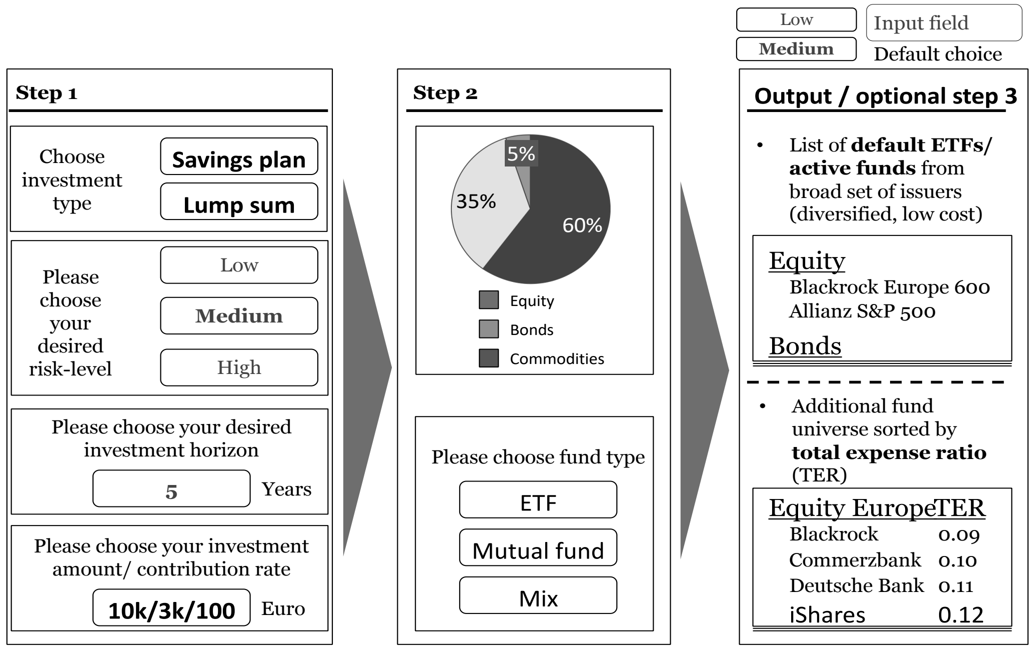

Figure A.1 displays how the robo-adviser generates recommendations using a three-step process: i) investment planning; ii) fund selection; and iii) execution. In the investment planning step, the client provides four inputs: frequency of deposits (recurring savings vs. lump sum investment), acceptable level of risk, investment horizon, and amount invested. Based on these inputs, the robo-adviser creates a recommended asset allocation. In the second step, the client can choose between ETFs, actively managed funds or a mix of the two. In this step, there is no default selection and the customer is forced to make an active choice.

Table A.1
Data collected

Type of data	Description / Variable	Frequency	Availability	Planned availability
Client demo-graphics	Gender Date of birth (measure of age) Microgeographic status (measure of wealth) Account from / till (e.g. checking, saving, etc.) Profession Nationality Zip code	Time invariant	December 2015	July 2017
Time varying customer and account information	Monthly account balances (e.g. checking, saving, etc.) Net cash, average, min, and max Logins (number and distinct days) Historical zip codes Product / contract from / till (e.g. advice) Tax exemption allocated with this bank	Monthly Monthly Monthly Every change Every change Yearly	January 2003 to December 2015	January 2003 to July 2017
Investment account	Position statements Transactions (incl. fees, commissions, limit-order, etc.) Transfers from and to other banks Savings plan details (frequency, valid from, etc.)	Monthly Daily Daily Once	January 2003 to December 2015	January 2003 to July 2017
Marketing Campaigns	Product (e.g. robo-advice, personal advice, other) Date of campaign Channel of campaign (Email, letter, phone) Target group as defined by the bank Treatment group dummy (0 for control) Date reached (email read / phone call) Outcome if applicable	Time invariant	January 2010 to December 2015	January 2010 to July 2017
Securities data	Securities properties provided by the bank Lipper fund database (geographic focus, TER, etc.) Individual security returns from Datastream	Once Yearly Daily	Dec 2015 2011 1999 - 2016	July 2017 Yearly 1999 - 2017

Table A.2

Savings Plan Investment: Recommended Asset Allocation by Risk, Size, and Horizon

	Low				
Investment in EUR (monthly)	100<250		>=250		
Investment horizon in years	<3	>=3	<3	>=3<5	>=5
Fixed income	100	75	100	90	70
Equity	0	25	0	10	30
Commodities	0	0	0	0	0

	Middle				
Investment in EUR (monthly)	100<250		>=250		
Investment horizon in years	<5	>=5	<3	>=3<5	>=5
Fixed income	75	50	90	70	50
Equity	25	50	10	30	40
Commodities	0	0	0	0	10

	High					
Investment in EUR (monthly)	100<250			>=250		
Investment horizon in years	<3	>=3<5	>=5	<3	>=3<5	>=5
Fixed income	75	50	25	70	50	20
Equity	25	50	75	30	40	70
Commodities	0	0	0	0	10	10

Table A.2 displays recommended asset classes for savings-plan investments. Panels A, B, C show how the recommended asset allocation changes with the monthly investment amount in EUR and the investment horizon for *low*, *middle*, and *high* desired risk, respectively.

Table A.3

Lump Sum Investment: Recommended Asset Allocation by Risk, Horizon, and Size

	Low							
Investment horizon in years	<3		>=3<5			>=5		
Investment in EUR thousands	3<50	>=50	3<10	>=10<50	>=50	3<10	>=10<50	>=50
Fixed income	100	90	75	90	85	75	70	60
Equity	0	0	25	10	5	25	30	20
Commodities	0	0	0	0	0	0	0	10
Real Estate	0	10	0	0	10	0	0	10

	Middle								
Investment horizon in years	<3			>=3<5			>=5		
Investment in EUR thousands	3<10	>=10<50	>=50	3<10	>=10<50	>=50	3<10	>=10<50	>=50
Fixed income	75	90	80	75	70	60	50	50	50
Equity	25	10	10	25	30	20	50	40	40
Commodities	0	0	0	0	0	10	0	10	10
Real Estate	0	0	10	0	0	10	0	0	0

	High								
Investment horizon in years	<3			>=3<5			>=5		
Investment in EUR thousands	3<10	>=10<50	>=50	3<10	>=10<50	>=50	3<10	>=10<50	>=50
Fixed income	75	70	60	50	50	50	25	20	20
Equity	25	30	20	50	40	40	75	70	70
Commodities	0	0	10	0	10	10	0	10	10
Real Estate	0	0	10	0	0	0	0	0	0

Table A.3 displays recommended asset classes for lump sum investments. Panels A, B, C show how the recommended asset allocation changes with the investment horizon and the investment amount in EUR thousands for *low*, *middle*, and *high* desired risk, respectively.

Table A.4

Savings Plan Investment: Recommended Products by Risk, Size, and Horizon

	Low				
Investment in EUR (monthly)	100<250		>=250		
Investment horizon in years	<3	>=3	<3	>=3<5	>=5
Fixed income					
Government Europe	75	50	80	60	50
Government Global				10	10
Corporate	25	25	20	20	10
Equity					
Europe		25		10	20
Global					10

	Middle				
Investment in EUR (monthly)	100<250		>=250		
Investment horizon in years	<5	>=5	<3	>=3<5	>=5
Fixed income					
Government Europe	50	25	60	50	30
Government Global		25	10	10	10
Corporate	25		20	10	10
Equity					
Europe	25	50	10	20	25
Global				10	15
Commodities					10

	High					
Investment in EUR (monthly)	100<250			>=250		
Investment horizon in years	<3	>=3<5	>=5	<3	>=3<5	>=5
Fixed income						
Government Europe	50	25	25	50	30	10
Government Global				10	10	
Corporate	25	25		10	10	10
Equity						
Europe	25	50	50	20	25	35
Global			25	10	15	20
Emerging Market						15
Commodities					10	10

Table A.4 displays recommended products for savings-plan investments. Panels A, B, C show how the recommended products change with the monthly investment amount in EUR and the investment horizon for *low*, *middle*, and *high* desired risk, respectively.

Table A.5

Lump Sum Investment: Recommended Products by Risk, Horizon, and Size

	Low							
Investment horizon in years	<3		>=3<5			>=5		
Investment in EUR thousands	3<50	>=50	3<10	>=10<50	>=50	3<10	>=10<50	>=50
Fixed income								
Government Europe	75	65	50	60	60	50	50	30
Government Global		5		10	5		10	10
Government EM								10
Corporate	25	20	25	20	20	25	10	10
Equity								
Europe			25	10	5	25	20	20
Global							10	
Commodities								10
Real Estate		10			10			10

	Middle								
Investment horizon in years	<3			>=3<5			>=5		
Investment in EUR thousands	3<10	>=10<50	>=50	3<10	>=10<50	>=50	3<10	>=10<50	>=50
Fixed income									
Government Europe	50	60	50	50	50	30	25	30	25
Government Global		10	5		10	10		10	10
Government EM			5			10			5
Corporate	25	20	20	25	10	10	25	10	10
Equity									
Europe	25	10	10	25	20	20	50	25	20
Global					10			15	
Emerging Market									10
Germany									10
Commodities						10		10	10
Real Estate			10			10			

	High								
Investment horizon in years	<3			>=3<5			>=5		
Investment in EUR thousands	3<10	>=10<50	>=50	3<10	>=10<50	>=50	3<10	>=10<50	>=50
Fixed income									
Government Europe	50	50	30	25	30	25		10	10
Government Global		10	10		10	10			
Government EM			10			5			
Corporate	25	10	10	25	10	10	25	10	10
Equity									
Europe	25	20	20	50	25	20	50	35	30
Global		10			15		25	20	
Emerging Market						10		15	20
Germany						10			10
USA									10
Commodities									
Commodities			10		10	5		10	5
Precious metals						5			5
Real Estate			10						

Table A.5 displays recommended products for lump sum investments. Panels A, B, C show how recommended products change with the investment horizon and the investment amount in EUR thousands for *low*, *middle*, and *high* desired risk, respectively.