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Fund Savings Plan Choices with and without Robo-Advice

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Abstract

Fund savings plans are a powerful tool to build up savings. Due to low-transaction cost and low minimum contribution rates they are especially suitable for individuals with low wealth. Besides, automatic order execution can counteract a lack of self-control. Setting up a savings plan, however, is non-trivial as the choice of parameters such as contribution rate and fund mix pose potential for mistakes. This paper studies the role of non-individualized defaults and guidance on the choice of savings plan parameters in an unsolicited online setting. For this purpose, we use the natural experiment of introducing an automated investment solution ("robo-advisor") at a large German online bank. Results indicate that robo-advice guidance motivates the choice of better diversified and lower cost funds in savings plans. In contrast, the influence of a default contribution rate is limited to an uplift of very low contribution rates to a new minimum threshold in the robo-advisor.

JEL classification: D14, E43, G11

Keywords: personal finance, defaults, savings plan, ETF

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1. Introduction

The responsibility of making adequate investment and savings decisions is shifting towards the individual. In the domain of retirement savings, this development is driven by the replacement of previously widespread defined benefit type of retirement savings plans by private sector defined contribution plans (Mckenzie and Liersch 2011; Beshears et al. 2015). At the example of U.S. 401(k) retirement savings plans, however, a large body of literature has documented poor decision-making ability in retirement saving. First, retirement saving often fails already at the mere decision of participation in adequate instruments (Benartzi and Thaler 2007). One explanation is bounded rationality and self-control to give up today's consumption for later benefit (Thaler and Benartzi 2004). An underlying cause might be a cognitive bias of underestimating the gains of compound interest (Mckenzie and Liersch 2011). Second, for those who do participate, e.g., through retirement savings plans, inertia leads to low levels of subsequent portfolio rebalancing (Agnew, Balduzzi, and Sundén 2003; Bilias, Georgarakos, and Haliassos 2010). Consistent with the notion of inertia, default enrollment for employer-sponsored retirement savings plans has been found to significantly influence individuals with regards to: (1) increased participation and (2) the passive adoption of default savings parameters (Thaler and Benartzi 2004; Madrian and Shea 2001, 2001; Choi et al. 2002, 2004). In the case of automatic enrollment in these type of plans, default values function as cognitive anchor and, what is more, customers perceive them as advice (Choi et al. 2004).

However, little is known about the savings plan choices of self-directed individual investors outside of the domain of institutionalized retirement savings plans. This is an important field of research for two reasons. First, financial well-being also depends on general precautionary savings, especially as national pension schemes become strained by demographic change. In the European Union (EU), 35.6% of households are unable to cover unexpected financial expenses from their own resources (eurostat 2015a). Retirement savings plans, however, are not suited for general precautionary savings or savings towards large spending as investment in these plans is often not accessible until retirement age. Second, within this context of general savings, self-directed decision-making is of critical meaning as there is a trend towards taking financial decisions online. In 2015, 46% of individuals (age 16-74 years) in the EU used online banking (eurostat 2015b). In the online environment, decisions are regularly taken fully self-directed (FCA 2016). At the same time savings decisions are more difficult as ultra-low interest rates leave a gap in traditional bank products. Both incumbent banks and new financial technology companies offer new online distribution channels for investment products such as automated investment solutions ("robo-advisor").[1] These solutions offer guidance to the investment

[1] Example articles in popular press include: "UK banks set to launch 'robo-advisers'" Financial Times, January 22, 2016; "BlackRock buys 'robo-adviser' to woo millennials" Financial Times, August 26, 2015.

decision process, but no regulated and individualized financial advice (FCA 2015). In other words, while the number of decisions to be made by the individual investor increases in modern financial distribution channels the level of professional help decreases. This development calls for attention as selecting an appropriate contribution rate and a beneficial fund choice within savings plans is not trivial. Literature suggests that individuals benefit from choosing passive instead of active funds (Fama and French 2010; French 2008). However, recent findings by Bhattacharya et al. (2016) show that even among exchange-traded funds (ETFs) a poor fund selection can significantly impair these benefits. As financial education has little long-term effects on better financial decision making (Fernandes, Lynch, and Netemeyer 2014), other measures to help customers choose adequate savings plan parameters are needed. One step towards practical measures is to better understand how individuals choose the contribution rate and fund mix in savings plans.

We address this gap in research by exploring fund savings plan parameter choices of individual investors at a large German online bank. Observed fund savings plans are a type of defined contribution plan with automatic recurring investments in ETFs and/or active mutual funds. It is clearly designed for long-term savings as there is no functionality to set dynamic trading rules (e.g., price limits) except from an automatic annualized percentage-increase in the contribution rate. Since July 2014, the bank additionally offers a robo-advisor tool that provides guidance to the choice of parameters required to set up a savings plan investment.[2] It comprises several anchors and nudges with regards to the choice of fund mix and contribution rate that were not present before its introduction. The robo-advisor tool is the treatment in our natural field experiment.

This paper addresses the following two research questions: (1) Do non-individualized default values influence the savings plan contribution rate choice? (2) Does guidance on fund selection influence the savings plan fund mix choice? Drawing on a large administrative panel dataset of savings plan investors of which part uses an automated investment solution (robo-advisor), this paper extends literature on investor choices and defaults in retirement savings plans (e.g., Benartzi and Thaler 2007) towards new distribution channels and a general savings domain. Specific to our setting are novel types of nudges that are not individualized to each investor and were not available at the time of previous literature on retirement savings plans. Examples are the choice between active and passive funds, defaults in online forms that can be overwritten and interactive lists to explore and custom sort the offered set of funds, e.g., according to fund cost. Lastly, we extend the methodology used in literature on defaults by: (1) controlling for additional investor-specific characteristics, such as wealth and stock

[2] The term "guidance" is used in a regulatory context for a weak – and so far less strictly regulated – form of advice. Since there is no personal advisor present, the investment is in essence made self-directed. Information and software tools provided by the bank do, however "guide" the investor through her decisions. See, e.g., FCA (2016).

market experience, and (2) using a panel setting with repeated observations per individual. There is no systematic limit as to how often individuals in the sample can set up a savings plan. This allows for a more robust identification of the influence of defaults through a within-subject analysis with sufficient estimation power to control for individual fixed effects.

We find that savings plan investors choose the contribution rate as a function of their wealth. Remarkably, the contribution rate choice is not influenced beyond the push to a new minimum contribution rate that is implemented in the robo-advisor. Customers who are financially able to contribute more, still do so, even though the robo-advisor form carries the minimum threshold as default value. In contrast, robo-advice has a significantly positive effect on the fund choice compared to self-directed savings plans in three regards: (1) increased diversification, (2) increased share of passive investment in ETFs by 23.5 percentage-points, and (3) increasing choice of less costly ETFs leading to a reduction in the average total expense ratio of savings plans from 62bps to 37bps. Results of this paper are relevant for bank supervision and for financial institutions designing robo-advisor tools.

2. Related Literature

To the best of our knowledge this paper is the first to analyze the impact of savings defaults in the robo-advice context. It is related to the literature on the effect of defaults for employer-sponsored retirement savings plans. There is a specific relation to the strand of literature that particularly regards the choice of contribution rates in retirement savings plans in the light of enrollment defaults. Thaler and Benartzi (2004) find that offering employees a plan for automatic contribution rate increases on every pay rise has a long-term positive effect on contribution rates. Using overlapping datasets, Choi et al. (2002), Choi et al. (2004), and Madrian and Shea (2001) find that without default enrollment, most employees choose a 401(k) contribution rate equal to the threshold that is matched by the employer. Once enrollment is automatic, most employees save at the default enrollment rate (which in the observed cases is lower). They conclude that employees choose the path of least resistance in their retirement savings. Other reasons for the influence of defaults on an individual's choice might include opt-out costs, procrastination, inattention, or mental anchoring (Bernheim, Fradkin, and Popov 2015). In their empirical settings, however, the default choice is a passive decision, i.e., defaults take effect because employees do not submit their own choice of a contribution rate. The experimental setting of this paper is different as there is no automatic enrollment so that investors need to make an active decision. This comes with the advantage of ruling out opt-out costs and procrastination as explanatory factors for following the default. Our setting narrows down the list of potential default mechanisms to inattention and mental anchoring. Another feature of our setting is the timing of external anchoring.

In our field experiment the anchor is placed during the enrollment process. This distinguishes our setting from the Easy Escalation experiment, e.g., in Beshears et al. (2013). In their setting, savers who already had an employer-sponsored savings plan received a form on which they could tick a box to increase the savings rate to the matching default. The disadvantage of their setting is that customers might be influenced by two strong anchors: their previously chosen contribution rate and the newly proposed contribution rate. Finally, this paper is also related to an older strand of this literature that investigates the anchoring effect of matching threshold (i.e., the maximum savings rate for employer matching) to contribution rates.[3]

There is little normative discussion on welfare effects of defaults and whether default contribution rates should be promoted more from a policy perspective. This is not surprising as the aggregate welfare effect of a default depends on the optimal choice of the default value. A pragmatic approach could thus be to choose defaults in a way that opt-outs are minimized (Thaler and Sunstein 2003). An alternative to making decisions for others (defaults) is to force decisions. Bernheim, Fradkin, and Popov (2015) and Carroll et al. (2009) provide justification that the absence of enrollment defaults or a compulsory active enrollment decision can be favorable. This depends on the individuals' characteristics, including procrastination propensity, time inconsistency of preferences and financial literacy. One way to trigger an active decision is deliberately choosing an extreme default value that poorly matches savers' needs and almost forces individuals to change, e.g., the contribution rate (Choi et al. 2003). In the presence of employer contribution matching, the optimal default might be equal to the matching threshold (Bernheim, Fradkin, and Popov 2015).

There are also limits to when defaults or anchors affect behavior, although evidence is mixed depending on the specific setting. Bronchetti et al. (2013) conduct a field experiment where tax refunds were by default partly paid in the form of bonds instead of cash. Those individuals who had strong pre-existing plans to spend the refund – a group dominated by low-income individuals – did not follow the default. Similarly, Beshears et al. (2015) find that especially those who had low income relative to their peer-group did not react to an anchor constituted by peer-information. In their field experiment, quick enrollment and contribution escalation forms that contained information on peer savings behavior were sent to individuals. In fact, lower-income individuals in each peer group showed less propensity to enroll to savings or increase their contribution rate than the respective control group to which no peer information was shown. In contrast, Beshears et al. (2010) find that low-income individuals are less likely to actively change an enrollment default with extreme contribution rates.

[3] E.g., Papke (1995) analyzes a meta-dataset of employer savings plans with average values for each savings plan.

More evidence that external interventions can influence individuals in their finance-related behavior is provided by the growing literature on reminders in the financial context. Reminder messages can increase savings discipline after a commitment account was opened (e.g., Karlan et al. 2016), unless customers are liquidity constrained (Loibl et al. 2016). In the credit context, investor demand for new loans can be increased by mail marketing (Bertrand et al. 2010), and repayment discipline can be increased by text messages (Karlan, Morten, and Zinman 2015), especially for younger customers (Cadena and Schoar 2011).

3. Experiment setting and sample description

In order to study savings plan decision-making of individual investors, we draw on a sample from a large German online bank. In this chapter, we describe the robo-advisor tool and fund savings plans at this bank. In addition, we provide descriptive statistics of sample investors.

3.1. Fund savings plans

Fund savings plans are an established offer at discount brokers and online banks and also broadly used at the observed bank. The use of savings plans has four main advantages over a lump sum investment. First, convenience and support for customers who lack self-control: Once set-up, fund orders are automatically executed at pre-defined rules (timing, frequency, contribution rate, increase of contribution rate over time). Fund savings plans involve an indefinite commitment and termination requires action. Second, dollar cost averaging: Since the savings plan fixes the contribution rate while the number of shares depends on the market price, more shares are bought when price is low and fewer are bought when price is high. The average purchase cost is thus lower than the simple mean of all transaction prices. Third, transaction cost incentive: Absolute and relative fees per purchase are lower for savings plans. For selected securities, purchase fees are even fully waived. Fourth, lower minimum investment threshold: In a savings plan, fractions of one share can be purchased. Thus, the minimum Euro investment amount is no longer the value of one share of one fund (e.g., EUR 100), but a threshold that is independent of the price of one fund's share (at this bank: EUR 25 per security). Based on these features, a fund savings plan is a tool to make beneficial savings choices: First, behavioral biases such as limited self-control for regular savings can be counteracted. Second, low minimum contribution rates per security allow for investing in several funds and achieving maximum diversification. Third, low contribution rates and low transaction costs enable stock market participation by individuals that have low levels of liquidity, but regular income. Fourth, low transaction costs increase net return of two equal investments in the same funds.

Despite all advantages of savings plans, individuals can still make a number of mistakes: (1) Individuals can choose a contribution rate that is above or below their financial ability. (2) Individuals can choose an unfavorable fund mix. Ideally, selected funds should be (a) passively managed given evidence of active funds underperforming their passive counterparts net of costs (Fama and French 2010) (b) low-cost to maximize return, and (c) well-diversified. Bhattacharya et al. (2016) and Boldin and Cici (2010) find that individuals who invest in ETFs often select expensive and underdiversified ETFs. This paper addresses these potential mistakes.

3.2. Robo-advisor

The robo-advisor tool used for this natural experiment is an automated investment solution that offers a guided process for investments in funds through fund savings plans or fund lump sum investments. Guidance on savings plans is one of the crucial selling propositions of robo-advice and prominently placed in all bank communications, e.g., on the website and in personalized marketing campaigns. Regular personal advice also offered at the observed bank focuses on lump sum purchases. Consequently, investors at the observed bank could not obtain advice on choosing a portfolio for monthly recurring investments of a few hundred Euros before the introduction of robo-advice.

To set-up a savings plan, the robo-advisor requires the investor to make five decisions: (1) contribution rate, (2) intended investment horizon in years, (3) desired risk-level ("low", "medium", "high"), (4) fund type (passive ETFs or actively managed mutual funds or both). Based on these entries, the robo-advisor recommends a diversified asset allocation and a set of corresponding funds. The asset allocation is displayed graphically which has been found to be an information item with significant influence on retirement savings choices towards higher diversification (Bateman et al. 2016). (5) In addition, the investor can choose to change the default fund choice. For this purpose, the robo-advisor provides an interactive list with a broad universe of alternative ETFs and active mutual funds. The investor can, however, not change the recommended asset allocation. Both the default funds and the list of alternative funds cover many of the large asset managers. The default fund is chosen at the discretion of the bank according to several criteria, including low purchase cost, low total expense ratio (TER), high diversification, high Morningstar rating and performance. Purchase cost, TER and past performance of each fund are prominently displayed and the customer can sort the list of alternative funds according to the latter two metrics. In addition, the robo-advisor tool is free of charge. Transaction cost and fees are not different from what self-directed investors at the same bank pay. Based on these features the robo-advisor can be regarded as largely unbiased (Bhattacharya et al. 2012).

The robo-advisor was accessible on the website to every customer. In order to promote the tool, a broad fraction of customers was invited via personalized marketing campaigns to use the tool. While the robo-advisor functionality for lump sum investments was introduced a few weeks before the savings plan functionality, savings plans were specifically mentioned in marketing and even set as the default investment option during part of the sample period. We thus assume that a broad fraction of customers was aware of the robo-advisor and not just those who were specifically searching for it. We apply a matching methodology to control for potential selection biases. Further, we use within-investor comparisons, so it is not necessary for our identification that all customers were aware of the tool.

3.3. Savings plan defaults with and without robo-advice

Choi et al. (2016) find that already small anchors, such as mentioning the maximum possible contribution rate, influence saver's decision making. Which anchors could influence the choice of contribution rates in this sample? Both in the robo-advice and in the self-directed savings plan process the investor needs to enter the desired contribution rate before choosing the securities.[4] In both cases, the contribution rate needs to be entered by typing a number which in the subsequent step determines the number of securities that can be selected/are recommended. In the self-directed form, the information on the EUR 25 minimum threshold (for a savings plan consisting of one security) is displayed right next to the form. Before July 2014, this was the only anchor. After July 2014, the robo-advisor tool introduces three additional anchors: (1) Changed minimum threshold: Setting up a savings plan in the robo-advisor is associated with a minimum threshold of EUR 100. The respective field in the robo-advisor is pre-filled with this number. (2) New restriction: Contribution rate can be increased only in intervals of EUR 25. (3) New anchor: Starting with a contribution rate of EUR 250, the number of asset classes recommended by the robo-advisor increases. Although the robo-advisor is a separate tool with different anchors and restrictions, the order is always concluded in the self-directed order form. Essentially, the robo-advisor populates the self-directed form with the recommendation. Consequently, the choice of new anchor points in the robo-advisor is as good as random since ultimately the "standard" restrictions apply. For example, one portfolio recommended by the robo-advisor for a minimum contribution rate of EUR 100 (EUR 250) consists of 3 (6) funds. Despite this communication in the robo-advisor, the investor could, however, change the contribution rate of the respective portfolio to just EUR 75 (EUR 150) in the last step and would still be able to complete the (robo-advisor) savings plan order. This is possible as long as the new contribution rate meets the general (self-directed) minimum investment amount of EUR 25 per security.

Apart from these defaults and anchors, all features of savings plans described in section 3.2 equally apply to self-directed and robo-advice savings plans. Based on this ultimate freedom of choice we can identify the impact of robo-advisor anchors. We can, however, not fully exclude that some investors note down or manually carry over the recommendation from the robo-advisor tool to the

[4] When using the robo-advisor tool, securities are proposed to the investor or alternatively the investor can choose to select from a list of securities. In the form for self-directed savings plans the investor can either select from a similar list or enter the international security identification number (ISIN) manually.

self-directed form. Such behavior could for example be motivated by the desire to take a break and reconsider the recommendation of the robo-advisor. It would distort results as the respective savings plans would be identified as "self-directed". This is, however, unlikely to be the case in a significant fraction of observations as it would imply additional effort to the investor to copy all parameters, such as international security identification numbers (ISINs) from the robo-advisor tool to the manual order form without any apparent benefit over changing the pre-populated form.

3.4. Sample construction and investor characteristics

To compare investors' choices of savings plan parameters with and without guidance of the robo-advisor, we obtain data from robo-advisor users and non-users. Specifically, we first obtain administrative data from a large fraction of customers who made an investment through the robo-advisor at least once. Second, we draw a random sample of all customers at the bank from 2003 to 2015. Since the bank offers the whole range of standard banking products some customers do not participate in the stock market during the entire sample period. We use all investors that make at least one fund investment since the introduction of the robo-advisor savings plan functionality in July 2014. Individuals below 18 years of age or with negative assets under management are excluded from both samples. In addition, we apply 2 restrictions to ensure that the samples consist of customers who intend to use the savings plan for longer-term investments. First, we delete investors who terminate the savings plan before or at the third execution. Additionally, we delete savings plans for which the initial contribution rate is changed by more than 10% within the first 3 executions. These restrictions are necessary to exclude savings plans that are used for a staggered lump sum investment.[5] Such behavior might be beneficial to some investors due to reduced transaction cost and the dollar cost averaging of savings plans. It could, however, distort observations. Results are robust to the choice of the cut-off (see appendix). Table 1 compares summary statistics on demographic, wealth, and account characteristics of robo-advisor savings plan investors and self-directed savings plan investors. If an investor sets up more than one savings plan after July 2014, the first savings plan is considered. Overall, differences among both groups are economically significant and point towards a selection effect into using the robo-advisor. The groups are least different in terms of gender, marriage, education and monthly logins. Of the treatment group (control group), 83.17% (81.32%) are male, 15.58% (17.83%) have a second account holder which we use as proxy for marriage, 4.02% (6.27%) have an academic title ("Prof." or "Dr."), and a majority of 43.79% (44.06%) have 12 or more logins into the banking system per month. The largest fraction of the treatment group is between 35 and 50 years of age

[5] E.g., instead of a EUR 10,000 lump sum investment, some investors set up a savings plan with a contribution rate of EUR 5,000. After 2 executions, they either terminate the savings plan or reduce contribution rates to a small fraction.

Table 1

Individual savings plan investors (cross-section sample)

The table reports descriptive statistics on demographics, wealth and account characteristics of sample customers. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. If an investor sets up more than one savings plan in the sample period, the first savings plan is considered. Sample size is n=1,046 robo-advice savings plan investors (column 1) and n=3,062 self-directed savings plan investors (column 2). Investors in the treatment group were guided by an automated investment solution ("robo-advisor"). Investors in the control group made a fully self-directed decision. The third column contains the difference in mean between these two groups (percentage points). *AuM* is assets under management, including risky assets and cash. *Monthly Checkacct High-Low* is the monthly average difference between high and low balance on the checking account, *At Least Half Tax Exemption* is an indicator equal to one if a customer allocates at least half of the tax exemption limit to this bank. Reported values are the mean in the three months before robo-advice introduction: February, March, April 2014. *Above Median Prior Non-Robo Trades* is an indicator equal to one if an investor has executed an above-median number of trades.

	Savings plan robo-advice (treatment group)	**Savings plan self-directed** (control group)	
	Mean	Mean	Difference
Customer demographics			
I:Male$_i$	83.17%	81.32%	1.9%
I:Age_Years 18-35$_{i,t}$	33.56%	26.32%	7.2%***
I:Age_Years 35-50$_{i,t}$	39.77%	44.91%	-5.1%***
I:Age_Years 50-65$_{i,t}$	22.18%	23.81%	-1.6%
I:Age_Years 65-$_{i,t}$	4.49%	4.96%	-0.5%
I:AcademicTitle$_i$	4.02%	6.27%	-2.3%***
I:Second Account Holder$_i$	15.58%	17.83%	-2.2%*
Wealth			
I:AuM_Eurok 0-25$_{i,t}$	73.80%	58.07%	15.7%***
I:AuM_Eurok 25-50$_{i,t}$	12.81%	16.36%	-3.6%***
I:AuM_Eurok 50-100$_{i,t}$	7.55%	13.03%	-5.5%***
I:AuM_Eurok 100-150$_{i,t}$	3.54%	5.06%	-1.5%**
I:AuM_Eurok 150-$_{i,t}$	2.29%	7.48%	-5.2%***
I:Monthly Checkacct High-Low 0-1k$_{i,t}$	38.91%	48.89%	-10.0%***
I:Monthly Checkacct High-Low 1k-5k$_{i,t}$	45.22%	35.24%	10.0%***
I:Monthly Checkacct High-Low 5k-10k$_{i,t}$	11.66%	10.45%	1.2%
I:Monthly Checkacct High-Low 10k-$_{i,t}$	4.21%	5.42%	-1.2%
Account activity			
I:At Least Half Tax Exemption$_{i,t}$	32.12%	37.82%	-5.7%***
I:Monthly Logins 0$_{i,t}$	4.97%	6.07%	-1.1%
I:Monthly Logins 1-4$_{i,t}$	21.03%	22.57%	-1.5%
I:Monthly Logins 4-12$_{i,t}$	30.21%	27.30%	2.9%*
I:Monthly Logins 12-$_{i,t}$	43.79%	44.06%	-0.3%
Investment experience			
I:Relationship Length_Years 0-1$_{i,t}$	4.97%	5.39%	-0.4%
I:Relationship Length_Years 1-5$_{i,t}$	26.67%	20.61%	6.1%***
I:Relationship Length_Years 5-9$_{i,t}$	39.48%	31.61%	7.9%***
I:Relationship Length_Years 9-$_{i,t}$	28.87%	42.39%	-13.5%***
I:Above Median Prior Non-Robo Trades$_{i,t}$	33.37%	56.01%	-22.6%***
I:Prior Non-Robo Savings Plan$_{i,t}$	35.47%	62.08%	-26.6%***

(39.77%), has less than EUR 25,000 in assets at this bank (73.80%), has a monthly average difference between high and low balance on the checking account, if existing (potentially serving as proxy for income[6]) of between EUR 1,000 and EUR 5,000 (45.22%), and has been with this bank for 5-9 years (39.48%). The largest fraction of the control group is also between 35 and 50 years of age (44.91%), has less than EUR 25,000 assets under management at this bank (58.07%), between EUR 0 and EUR 1,000 monthly checking account fluctuation (48.89%), but has been with this bank for nine years or more (42.39%). To point out the largest differences, savings plan investors that use the robo-advisor are younger and have lower assets under management, but slightly higher checking account fluctuations. Consistent with younger age, fewer robo-advisor customers have a very long investor relationship of nine years or longer. In addition, a smaller fraction of robo-advisor investors uses at least half of their tax exemption limit at this bank (32.12% vs. 37.82%). One reason could be that more of the robo-advice users have deposits at other banks. Another reason might be that robo-advisor customers only allocated the tax limit needed for their (low) wealth and left the rest unused. Given the high number of monthly logins for both groups, it is in any case likely that most sample customers use this bank for a significant part of their daily banking or brokerage activities. Finally, we measure investment experience in terms of an indicator for above-median number of observed trades. Seru, Shumway, and Stoffman (2010) find that the number of trades is a better proxy for individual experience than the number of years traded. It is noticeable that self-directed investors have significantly higher investment experience. 56.01% of self-directed investors, but only 33.37% of robo-advice investors has executed an above-median number of trades. Besides, 62.08% of self-directed investors, but only 35.47% of robo-advice investors have had a savings plan before. One explanation could, again, be that robo-advisor customers traded at another bank before they opened an account with this bank. One indicator for this would be a high correlation between investor relationship length and number of trades. However, the correlation between these two measures is only 34.4%. It is thus more likely that inexperienced customers use the robo-advisor while experienced customers trade self-directed. This is consistent with Scheurle (2016) who finds that robo-advice increases stock market participation using a related sample. In sum, descriptive statistics suggest that among savings plan investors there is selection of younger, less wealthy and less experienced individuals into robo-advice.

To construct a sample with comparable investors, we perform a nearest-neighbor matching to construct an even sample of robo-advisor and self-directed savings plan investors. Specifically, we use the Coarsened Exact Matching (CEM) method (Iacus, King, and Porro 2012). The method uses regular nearest-neighbor propensity score matching, but restricts the matching to groups with similar characteristics ("buckets") according to the matching variables. The advantage of this approach is that

[6] It needs to be noted that part of sample customers does not have a checking account at this bank. As monthly income is not a focal variable in this analysis, we refrain from dropping such customers. Instead, we set their checking account fluctuation to zero. Besides, it is an assumption that checking account fluctuations come from labor income. Thus, all buckets of EUR 1,000 and above need to be interpreted as marginal effect to either having no checking account, not using the checking account for labor income or having very little labor income.

every matched pair is at large comparable in all characteristics. The disadvantage is that treated observations are dropped if no untreated neighbor is in the same bucket. The sample constructs as follows: First, we use all sample investors who set up at least one savings plan in the robo-advisor tool. Second, as matching group we use all investors who set up at least one fund savings plan since introduction of the robo-advisor savings plan functionality in July 2014, but never make any robo-advisor investment. Third, we match one self-directed nearest neighbor for each investor in the treatment group. Matching is based on all observed characteristics in the three months before robo-advice introduction, i.e., February, March, and April 2014. Demographic matching variables include gender, age, and an indicator for having an academic title. Wealth matching variables include total assets under management and the monthly difference between maximum and minimum checking account balance. If the investor has no checking account, this value is also set to zero. Account activity matching variables include monthly logins and an indicator on whether the investor uses at least half of individual tax exemption amount on interest taxes. Investment experience matching variables include the tenure at the bank, an indicator for prior savings plan usage, and an indicator for above-median number of prior trades. To maximize information content of the experience measure, we regard prior trades across all observed years (up to 2003). All matched self-directed savings plan investors constitute the control group. Sample size is 1,168 individuals each for treatment and control group, respectively. Table 2 reports summary statistics. Through the matching, treatment and control groups in both samples become remarkably similar. Generally, there is a trade-off between creating a matched sample that is larger but more dissimilar between treatment and control group sample and creating a smaller but more homogenous sample. We decide to allow for slight inaccuracy in matching the investors that are at the largest and second-largest end of age, assets-under management, relationship length, and logins. Specifically, we combined buckets for the largest and second-largest feature characteristics of these variables in the first CEM step. This explains slight dissimilarities between the treatment and control group. However, all differences in mean are small and within a range of one to three percent. To achieve further control, we include the matching variables again as control in all regression models.

Table 2

Individual savings plan investors (matched sample)

The table reports descriptive statistics on demographics, wealth and account characteristics of customers who invest in funds through a savings plan between July 2014 and December 2015. Investors who were guided by a robo-advisor for at least one fund investment are the treatment group. All other investors made only fully self-directed decisions and constitute the control group. The control group is restricted through nearest neighbor matching using the Coarsened Exact Matching method (Iacus, King, and Porro 2012). Observations are from a large German online bank sample. Sample size is n=1,168 robo-advice fund savings plan investors (column 1) and n=1,168 self-directed savings plan investors (column 2). The third column contains the difference in mean between these two groups (percentage points). *AuM* is assets under management, including risky assets and cash. *Monthly Checkacct High-Low* is the monthly average difference between high and low balance on the checking account, *At Least Half Tax Exemption* is an indicator equal to one if a customer allocates at least half of the tax exemption limit to this bank. Reported values are the mean in the three months before robo-advice introduction: February, March, April 2014. *Above Median Prior Non-Robo Trades* is an indicator equal to one if an investor has executed an above-median number of trades. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Savings plan robo-advice (treatment group)	**Savings plan self-directed** (control group)	
	Mean	Mean	Difference
Customer demographics			
I:Male$_i$	85.10%	85.10%	0.0%
I:Age_Years 18-35$_{i,t}$	35.02%	35.02%	0.0%
I:Age_Years 35-50$_{i,t}$	41.44%	41.44%	0.0%
I:Age_Years 50-65$_{i,t}$	20.29%	19.95%	-0.2%
I:Age_Years 65-$_{i,t}$	3.25%	3.60%	0.2%
I:AcademicTitle$_i$	3.94%	4.11%	-0.5%
I:Second Account Holder$_i$	15.41%	18.92%	-3.2%**
Wealth			
I:AuM_Eurok 0-25$_{i,t}$	74.57%	74.57%	0.0%
I:AuM_Eurok 25-50$_{i,t}$	12.41%	12.41%	0.0%
I:AuM_Eurok 50-100$_{i,t}$	7.11%	7.11%	0.0%
I:AuM_Eurok 100-150$_{i,t}$	3.34%	2.48%	1.0%
I:AuM_Eurok 150-$_{i,t}$	2.57%	3.42%	-1.0%
I:Monthly Checkacct High-Low 0-1k$_{i,t}$	42.04%	42.21%	-0.2%
I:Monthly Checkacct High-Low 1k-5k$_{i,t}$	43.58%	43.41%	0.2%
I:Monthly Checkacct High-Low 5k-10k$_{i,t}$	10.70%	11.04%	0.0%
I:Monthly Checkacct High-Low 10k-$_{i,t}$	3.68%	3.34%	0.0%
Account activity			
I:At Least Half Tax Exemption$_{i,t}$	33.48%	30.48%	1.4%
I:Monthly Logins 0$_{i,t}$	4.97%	6.42%	-2.2%
I:Monthly Logins 1-4$_{i,t}$	21.92%	21.58%	0.2%
I:Monthly Logins 4-12$_{i,t}$	29.28%	29.45%	1.0%
I:Monthly Logins 12-$_{i,t}$	43.84%	42.55%	1.0%
Investment experience			
I:Relationship Length_Years 0-1$_{i,t}$	4.54%	4.54%	0.0%
I:Relationship Length_Years 1-5$_{i,t}$	25.77%	25.77%	0.0%
I:Relationship Length_Years 5-9$_{i,t}$	37.76%	39.13%	-1.9%
I:Relationship Length_Years 9-$_{i,t}$	31.93%	30.57%	1.9%
I:Above Median Prior Non-Robo Trades$_{i,t}$	36.22%	36.82%	-0.7%
I:Prior Non-Robo Savings Plan$_{i,t}$	43.75%	45.03%	-1.3%

4. Empirical results: savings plan parameter choices

This section provides results on the choice of contribution rate and the fund mix of savings plan investors. First, we present results on contribution rate choice using the matched sample.

4.1. Contribution rate choice

The first research question is whether the contribution rate defaults and anchors in the robo-advisor bias an investor's decision on how much to save. Measuring a bias through defaults requires being able to predict what contribution rate the investor would have chosen without being exposed to the bias. This is a complex endeavor as contribution rate choice could be influenced by observable as well as unobserved characteristics such as family and housing situation as well as planned large expenses. In a first step, we use the matched sample that inherently controls for most observable characteristics. In order to achieve a maximum level of control, we complement results of the matched

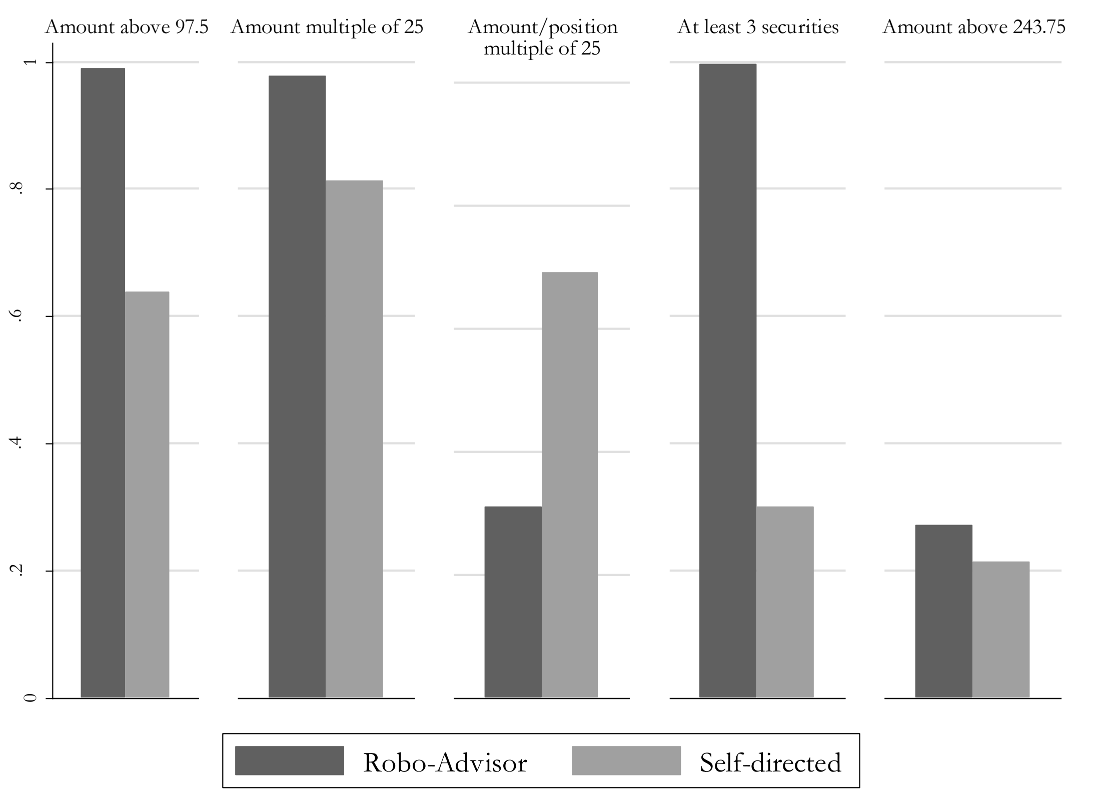

Figure 1: Savings plan parameters
This figure plots the fraction of savings plans with the following parameters: the contribution rate is at least in the EUR 100 bucket (>= EUR 97.50) (column 1), the contribution rate is a multiple of 25 (column 2), the contribution rate per security is a multiple of 25 (column 3), the savings plan comprises at least 3 different securities (column 4), the contribution rate is at least in the EUR 250 bucket (>=247.5). Dark grey bars show the fraction of savings plans set up in the robo-advisor tool and light grey bars show the fraction of savings plans set up self-directed respectively for each parameter. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. Sample size is n=2,336 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor. Matching is performed using the Coarsened Exact Matching method (Iacus, King, and Porro 2012).

sample with a within-subject regression design. For this purpose, we make use of a sub-sample of investors who switch between self-directed and robo-advice savings plans to analyze the influence of robo-advice on the contribution rate choice.

Figure 1 is a summary plot of the most important parameters that might be shaped by the mechanisms of the robo-advisor tool or the properties of the self-directed order form. It is important to note that observed contribution rates are based on executed trades. This means that actual contribution rates might be slightly different from intended contribution rates depending on market liquidity at trade execution. Thus, we define contribution rate buckets with a discrepancy margin of 5%. For example, all trades with observed execution amounts between EUR 97.5–102.50 are attributed to the EUR 100 contribution bucket. Descriptive statistics show that investors do largely follow the additional restrictions on contribution rate and fund choice applied in the robo-advisor tool although

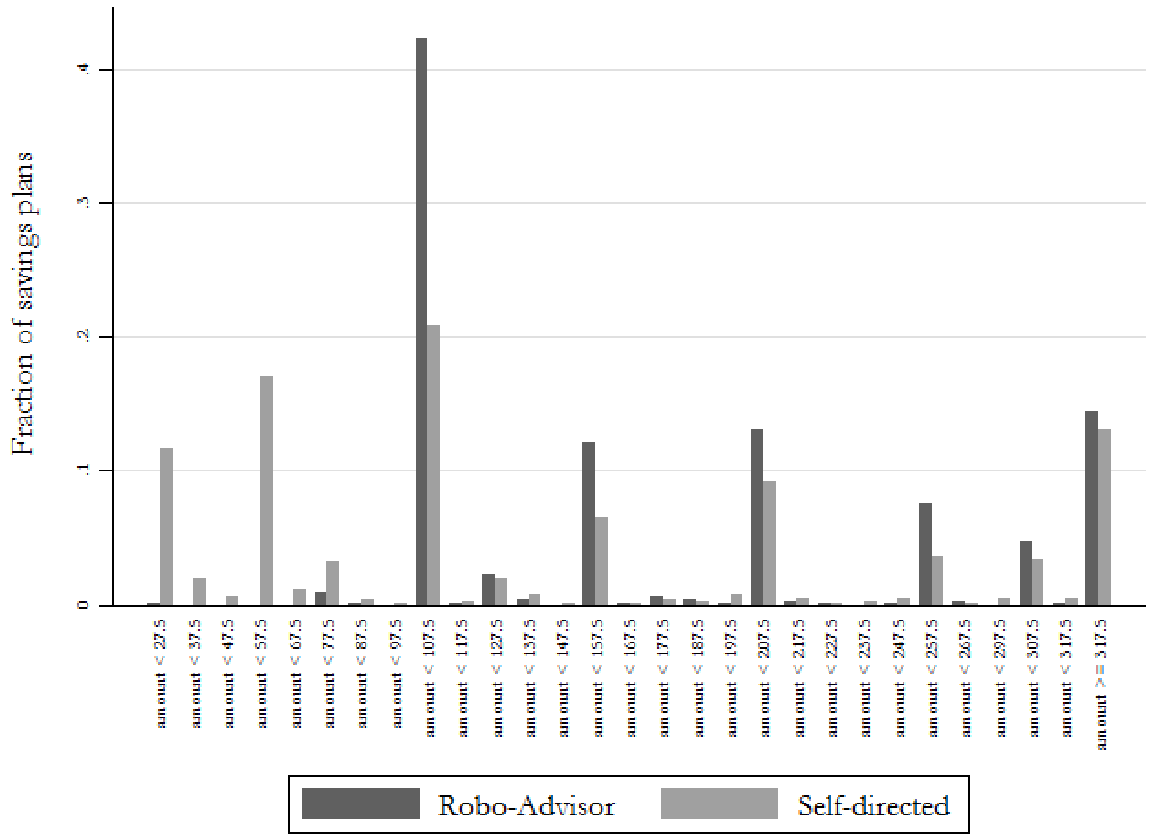

Figure 2: Contribution rates
This figure plots the distribution of contribution rates ("amount") of savings plans. All buckets are mutually exclusive, i.e., do not contain savings plans of smaller buckets. Dark grey bars the fraction of savings plans set up in the robo-advisor tool and light grey bars the fraction of savings plans set up self-directed respectively for each contribution rate bucket. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. Sample size is n=2,336 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor. Matching is performed using the Coarsened Exact Matching method (Iacus, King, and Porro 2012).

they could be changed in the last step of the investment form. Robo-advice savings plans are different to self-directed ones with regards to the following dimensions: (1) Only 63.73% of self-directed savings plans (vs. almost 100% robo-advisor) have a contribution rate that matches or exceeds the minimum contribution rate of the robo-advisor of EUR 100, (2) only 81.21% of self-directed savings plans (vs. 97.65% robo-advisor) have a total contribution rate equal to a multiple of EUR 25, (3) 69.22% of self-directed savings plans (but only 31.04% robo-advisor) have a contribution rate per security of EUR 25, and (4) only 30.12% of self-directed savings plans (vs. almost 100% robo-advisor) comprise 3 or more distinct securities. However, (5) the fraction of savings plans with contribution rates larger than the EUR 250 bucket is similar for self-directed savings plans (21.43%) and robo-advisor savings plans (27.20%).

Do investors follow the defaults? Figure 2 shows a more granular distribution of contribution rates on savings plan level for robo-advisor and self-directed savings plans. There is a pronounced peak in the EUR 100 contribution bucket. Almost half of robo-advisor savings plans (42.20%) belong to this bucket. Interestingly, also the largest fraction of self-directed savings plans has a contribution rate between EUR 97.50 and EUR 107.50, but the fraction is only about one-fifth (20.82%) of all self-directed savings plans. The difference of about 21% percent is almost equal to the fraction of self-directed savings plans with contribution rates below the EUR 100-bucket. At the same time, higher contribution rate buckets have a remarkably similar share of robo-advisor and self-directed savings plans. The EUR 150 bucket has 12.12% robo-advisor vs. 6.55% self-directed savings plans, but the difference becomes smaller with increasing bucket size. This provides evidence that the robo-advisor default of EUR 100 which at the same time is the minimum investment amount does influence contribution rates. The influence, however, is most pronounced for the uplift of very small contribution rates, i.e., through the minimum boundary. There is also an uplift in the EUR 250 bucket for robo-advisor savings plans, but it is much less pronounced. In fact, this uplift appears to be similarly large as the uplift in other buckets that are a multiple of 50, although there is no anchor for such multiples in the robo-advisor.

The graphs are based on the matched sample, i.e., controlling for observable differences between robo-advisor investors and self-directed investors. To achieve a maximum level of control for potential unobserved characteristics, we use a within-subject design to analyze the influence of robo-advice on the contribution rate. For this purpose, a sub-sample of robo-advice users with multiple observations per individual is necessary. We construct a sub-sample that includes all investors that set up at least one robo-advice savings plan and at least one self-directed savings plan since July 2011, i.e., 3 years before the introduction of the robo-advisor savings plan guidance. The sub-sample includes 419 individuals with 1,249 savings plan observations.

Table 3

Users with multiple savings plans (panel sample)

The table reports descriptive statistics on demographics, wealth and account characteristics of one sub-sample at two different points in time. The sub-sample comprises all sample investors who set up at least one robo-advice savings plan and at least one self-directed savings plan between July 2011 and December 2015. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. Sample size is n=419 investors. Column 1 reports observations at the point in time of setting up the first robo-advice savings plan and column 2 at the point in time of setting up the first self-directed savings plan after July 2011. The third column contains the difference in mean between these two observations (percentage points). *AuM* is assets under management, including risky assets and cash. *Monthly Checkacct High-Low* is the monthly average difference between high and low balance on the checking account, *At Least Half Tax Exemption* is an indicator equal to one if a customer allocates at least half of the tax exemption limit to this bank. *Above Median Prior Non-Robo Trades* is an indicator equal to one if an investor has executed an above-median number of trades. Reported values are observed one month before the respective savings plan. *Prior Savings Plan* is an indicator and takes into account all savings plans in the customer relationship (up to January 2003). *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Savings plan robo-advice (treatment group)	**Savings plan self-directed** (control group)	
	Mean	Mean	Difference
Customer demographics			
I:Male$_i$	87.35%	87.35%	0.0%
I:Age_Years 18-35$_{i,t}$	27.92%	32.94%	-5.0%
I:Age_Years 35-50$_{i,t}$	42.96%	40.81%	2.1%
I:Age_Years 50-65$_{i,t}$	25.06%	23.39%	1.7%
I:Age_Years 65-$_{i,t}$	4.06%	2.86%	1.2%
I:AcademicTitle$_i$	6.68%	6.68%	0.0%
I:Second Account Holder$_i$	16.23%	16.23%	0.0%
Wealth			
I:AuM_Eurok 0-25$_{i,t}$	65.39%	70.88%	-5.5%*
I:AuM_Eurok 25-50$_{i,t}$	15.99%	14.32%	1.7%
I:AuM_Eurok 50-100$_{i,t}$	11.46%	8.35%	3.1%
I:AuM_Eurok 100-150$_{i,t}$	3.34%	3.34%	0.0%
I:AuM_Eurok 150-$_{i,t}$	3.82%	3.10%	0.7%
I:Monthly Checkacct High-Low 0-1k$_{i,t}$	41.53%	45.11%	-3.6%
I:Monthly Checkacct High-Low 1k-5k$_{i,t}$	38.90%	37.47%	1.4%
I:Monthly Checkacct High-Low 5k-10k$_{i,t}$	10.98%	10.74%	0.2%
I:Monthly Checkacct High-Low 10k-$_{i,t}$	8.59%	6.68%	1.9%
Account activity			
I:At Least Half Tax Exemption$_{i,t}$	35.80%	26.01%	9.8%***
I:Monthly Logins 0$_{i,t}$	1.19%	2.63%	-1.4%
I:Monthly Logins 1-4$_{i,t}$	10.26%	11.46%	-1.2%
I:Monthly Logins 4-12$_{i,t}$	22.91%	26.01%	-3.1%
I:Monthly Logins 12-$_{i,t}$	65.63%	59.90%	5.7%*
Investment experience			
I:Relationship Length_Years 0-1$_{i,t}$	10.98%	15.51%	-4.5%*
I:Relationship Length_Years 1-5$_{i,t}$	22.67%	27.92%	-5.3%*
I:Relationship Length_Years 5-9$_{i,t}$	30.31%	25.78%	4.5%
I:Relationship Length_Years 9-$_{i,t}$	36.04%	30.79%	5.3%
I:Above Median Prior Non-Robo Trades$_{i,t}$	47.26%	39.86%	7.4%**
I:Prior Non-Robo Savings Plan$_{i,t}$	76.61%	61.34%	15.3%***

Table 4

LPM on choice of default or minimum contribution rates (panel sample)

The table shows marginal effects of the linear probability models. The dependent variable is an indicator set to one if the contribution rate is at the robo-advisor default/minimum, i.e., between EUR 97.50 and EUR 102.50 (column 1), at either the self-directed minimum, i.e., between EUR 24.38 and EUR 25.63 or at the robo-advisor default/minimum (column 2) or at any value below the robo-advisor default/minimum (column 3), The regressions include all self-directed and robo-advisor savings plans between July 2011 and December 2015. All savings plans with at least 3 executions are considered. The sub-sample comprises all sample investors for which at least one savings plan of each type is observed. Robust standard errors clustered by investor are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
Dependent Variable	Robo-Advisor default	Minimum contribution	Robo-advisor default or below
Robo-advice treatment			
I:Robo-advisor$_{i,t}$	0.2189***	0.1728***	-0.042
	(0.0412)	(0.0401)	(0.0350)
Experience			
I: Above Median Prior Non-Robo Trades$_{i,t}$	-0.068	-0.0672	-0.0734
	(0.0760)	(0.0674)	(0.0683)
I: Prior Non-Robo Savings Plan$_{i,t}$	0.03	0.0317	0.0192
	(0.0511)	(0.0528)	(0.0493)
I:Prior Robo Lump Sum Investment$_{i,t}$	-0.1825	-0.1196	-0.143
	(0.1261)	(0.1243)	(0.1178)
I:Prior Robo Savings Plan$_{i,t}$	-0.0076	0.0157	0.0664
	(0.0473)	(0.0492)	(0.0457)
# Observations	1,249	1,249	1,249
Adjusted R^2	0.08	0.04	0.03
Control for robo-advice introduction	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes
Account activity controls	Yes	Yes	Yes
Relationship length controls	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes

Table 3 reports summary statistics at the point in time of the first robo-advice savings plan and at the first self-directed savings plan set up, respectively. In terms of demographics, wealth and account characteristics, the sample is comparable to all robo-advisor savings plan users that constitute the treatment group described in Table 2. Although small, there is some variation in time-varying variables between the two observations in the sub-sample. For example, at the first robo-advice savings plan the smallest wealth group is 5.49% smaller and the fraction of customers with at least half tax exemption is 9.79% larger than at the first self-directed savings plan. In addition, there is variation in the order of observations. 23.39% of observed robo-advisor savings plans were not preceded by any other savings plan of the same investor since introduction of the banking relationship (observed up to January 2003). This variation is the key for identification. Table 4 reports coefficients of a linear probability model on choosing the default contribution rate bucket (EUR 97.50 – 102.50). In addition to all time-varying controls on demographics, wealth and account activity, we include fixed effects and indicators for prior experience with trading, savings plans and robo-advice. In addition, we control for time after introduction of the robo-advisor. The models predict the probability of choosing a contribution rate of about EUR 100 to increase by 21.89% due to robo-advice. The coefficient is highly economically and statistically significant. This result is not surprising given that Figure 2 shows that the largest fraction of robo-advice savings plans has a contribution rate of about EUR 100. As visible in the same graph, one main reason is that EUR 100 is not only the pre-entered default, but also the minimum contribution rate in the robo-advisor. There are two mechanisms of how the minimum limit could affect contribution rates, depending on how customers who planned to invest less set their mental prior: (1) Customers have a relative mental prior, i.e., they plan to invest at the minimum amount, or (2) Customers have an absolute mental prior, i.e., they plan to invest a certain EUR amount. To test these two mechanisms, we run the same within-subject analysis with altered dependent indicators to predict (1) the effect of robo-advice on the probability to set the contribution rate at the minimum amount of robo-advice or self-directed savings plans (column 2) and (2) the effect of robo-advice to invest at the EUR 100 bucket or any value below (column 3). This mechanism influences the identification in a way that a self-directed savings plan observation with contribution rate equal to (1) EUR 25 and (2) any value between EUR 25 and EUR 100 no longer add power to the robo-advice coefficient in the two respective specifications. The coefficient in the second regression is highly significant, but economically smaller than in the first (17.28% increase in probability). The coefficient in the third regression is no longer economically or statistically significant. This set of binary outcome analyses is consistent with the robo-advisor default value not influencing the choice of investors who planned to invest an amount higher than the minimum threshold. The influence of the robo-advisor default contribution rate is only effective through its corresponding function as minimum investment value, i.e., when the investor planned to invest an amount lower than the minimum threshold.

Table 5

Investor characteristics and contribution rate (matched sample)

The table shows coefficients from regressions on the chosen contribution rate for savings plans in Euro. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. All savings plans with at least 3 executions are considered. Sample size is n=2,336 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor. Matching is performed using the Coarsened Exact Matching method (Iacus, King, and Porro 2012). Standard errors clustered by investor are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
Robo-advice treatment				
I:Robo-advisor$_{i,t}$	5.9269	10.7962	7.2819	12.1607
	(20.5609)	(18.7261)	(18.6441)	(19.7326)
Customer demographics				
I:Male$_{i}$		4.9286	22.4702	21.825
		(39.1130)	(40.8830)	(40.8811)
I:Age_Years 35-50$_{i,t}$		27.6925	25.9157	26.5446
		(19.6161)	(25.7854)	(25.7220)
I:Age_Years 50-65$_{i,t}$		9.6615	6.2132	6.2446
		(30.1288)	(31.5070)	(31.5822)
I:Age_Years 65-$_{i,t}$		60.5662	69.1215	70.6202
		(125.0074)	(117.5328)	(117.5479)
I:AcademicTitle$_{i}$		237.3474*	231.7015*	230.5381*
		(131.3239)	(129.1094)	(129.7833)
I:Second Account Holder$_{i}$		-13.1213	-17.7253	-15.9983
		(38.7593)	(40.1278)	(40.5810)
Wealth				
I:AuM_Eurok 25-50$_{i,t}$		-9.6376	12.9904	13.5459
		(28.1412)	(25.6418)	(25.7902)
I:AuM_Eurok 50-100$_{i,t}$		109.2217**	137.8119***	136.096***
		(54.7982)	(53.2747)	(52.4870)
I:AuM_Eurok 100-150$_{i,t}$		171.745	217.546*	214.6757*
		(115.8314)	(119.6817)	(119.7910)
I:AuM_Eurok 150-$_{i,t}$		689.8869***	717.4258***	718.1549***
		(217.0141)	(215.9822)	(216.2935)
I:Monthly Checkacct High-Low 1k-5k$_{i,t}$		7.4099	42.9897	42.1797
		(21.4445)	(29.8067)	(29.8182)
I:Monthly Checkacct High-Low 5k-10k$_{i,t}$		23.419	65.884	64.4845
		(49.2498)	(57.9270)	(58.1510)
I:Monthly Checkacct High-Low 10k-$_{i,t}$		346.9503**	382.4606**	381.4198**
		(167.7022)	(164.6733)	(165.0813)
Experience				
I:Above Median Prior Non-Robo Trades$_{i,t}$			-31.9358	-35.3825
			(33.9595)	(34.7032)
I:Prior Non-Robo Savings Plan$_{i,t}$			-5.0199	-6.8044
			(27.8200)	(27.3482)
I:Prior Robo Lump Sum Investment$_{i,t}$				5.682
				(54.1739)
I:Prior Robo Savings Plan$_{i,t}$				92.5895
				(60.6097)
# observations	3,116	3,116	3,116	3,116
Adj. R^2	0.00	0.08	0.09	0.09
Account activity controls	No	No	Yes	Yes
Relationship length controls	No	No	Yes	Yes

Do individual characteristics predict the chosen contribution rate? Madrian and Shea (2001) find that gender, age and especially income predicts whether investors passively keep a default contribution rate in employer-sponsored savings plans. Table 5 shows coefficients of a set of regressions of observable investor characteristics on the chosen contribution rates. Coefficients on gender and age are not significant. Coefficients on wealth and checking account activity are remarkably economically and statistically significant. Individuals choose a considerably higher contribution rate for their fund savings plan when they have more assets under management or a higher turnover on their checking account. In these regressions, robo-advice has again no significant effect on the contribution rate. This is consistent with Madrian and Shea (2001) who find that higher income employees are considerably less likely to stick to a (low) default value. However, it is unclear from this regression whether an averaging-effect across investors from different wealth bands blurs the true effect. To further test the notion that the robo-advisor default only has a minimum-effect, but no general default-effect, we test whether the predictive marginal contributions for investor assets under management and checking account turnover (see Table 5) are individually sensitive to using the robo-advisor tool. This allows to identify whether investors systematically choose their contribution rate based on their financial ability independent of the influence of robo-advice. Figure 3 plots coefficients

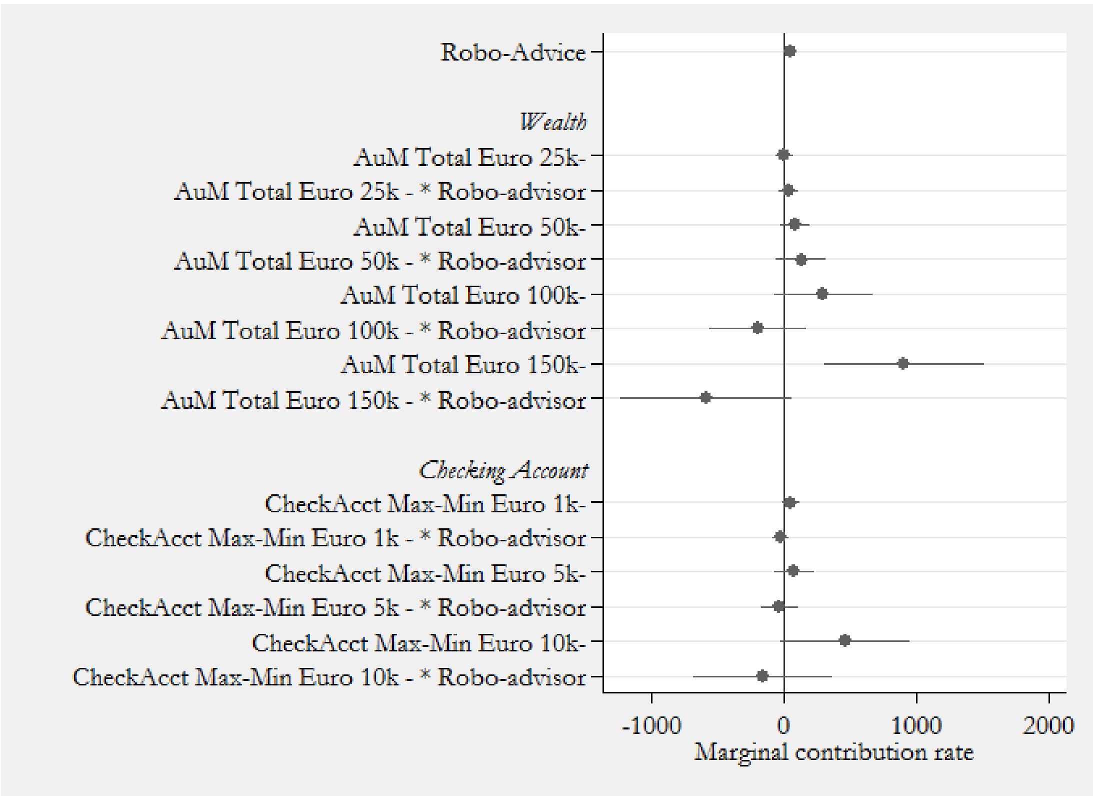

Figure 3: Investor wealth and sensitivity to the robo-advisor default
The figure plots coefficients of an augmented version of the regression in column 4 of Table 5. Interactions of all wealth and checking account turnover variables with an indicator equal to one if the savings plan was set up through the robo-advisor are added. Circles indicate the coefficient point estimates and horizontal bars indicate the 95% confidence intervals.

for wealth and checking account turnover and the respective interactions with robo-advisor usage of an unreported augmented regression. Except for adding interaction terms the regression is equal to the one in column 4 of Table 5. Robo-advisor interaction terms are insignificant for all wealth bands. Results are consistent with Loibl et al. (2016) who find that liquidity conditions and not behavioral or cognitive biases predict (under) saving.

4.2. Fund choice

Given that the impact of contribution rate defaults in the robo-advisor is not significant beyond a raise of contribution rates to the robo-advisor minimum, the question remains whether the fund choice is influenced through robo-advice. In order to elicit the effect of robo-advice on asset allocation and fund choice we compare robo-advice savings plans with self-directed savings plans from our matched sample. In a first step, we base the definition on robo-advice usage of each savings plan. This implies that some of the self-directed savings plans were setup by robo-advice users. Panel A of Table 6 presents statistics on a savings plan level. We compare diversification of self-directed and robo-advisor savings plans using two simple measures of diversification: (a) diversification across number

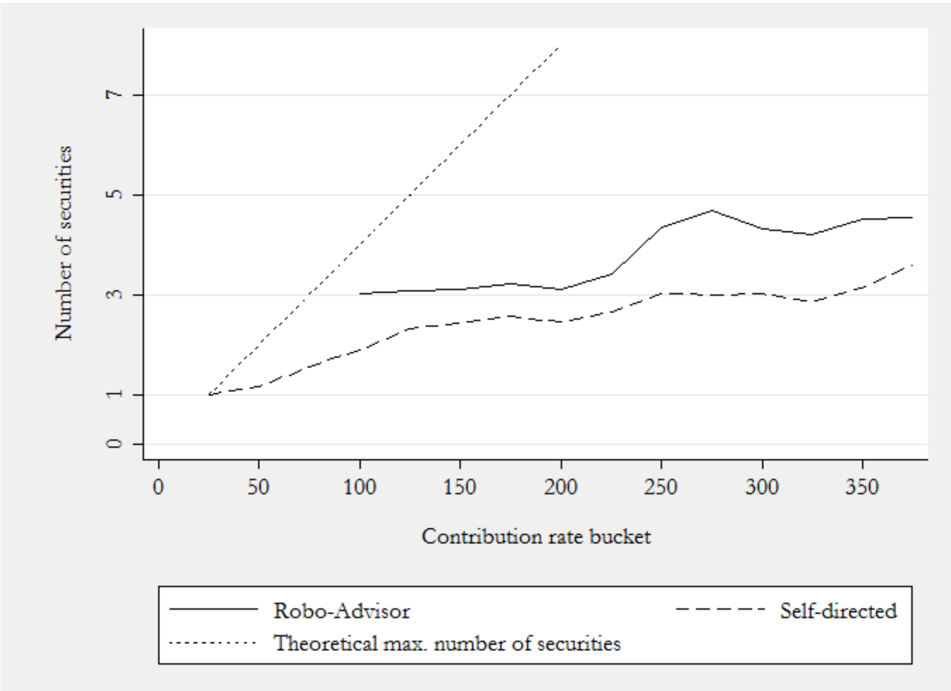

Figure 4: Naïve diversification in savings plans
The figure plots the average number of funds per savings by contribution bucket. The solid line represents robo-advisor savings plans, the dashed line represents self-directed savings plans and the dotted line represents the theoretical maximum number of securities based on the minimum contribution rate of EUR 25 per security at the bank. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. Sample size is n=2,336 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor.

of funds and (b) diversification across number of asset classes based on the field "asset class" in Datastream.

Both measures suggest a significantly better diversification of robo-advice savings plans: (a) The number of funds increases from 2.15 to 3.45 per savings plan and (b) the number of asset classes increases from 1.11 to 2.07 per savings plan through robo-advice. Figure 4 plots the number of securities as a measure of diversification according to the contribution rate, showing that diversification is better in robo-advice independent of the contribution rate. The average number of securities in robo-advice savings plans remains stable at around 3 securities up to the EUR 225 bucket consistent with the default robo-advisor portfolio consisting of three funds. This provides evidence that the increase in diversification can be attributed to investors following the default diversification of the robo-advisor.

What types of funds are chosen? We find that the average TER is low for all types of savings plans, but further decreases by 26 basis points to 37 basis points through robo-advice. Given a fixed performance, lower expenses lead to higher return. Besides, Gil-Bazo and Ruiz-Verdú (2009) identify a negative relation between expenses of mutual funds and their return performance. One explanation for the low expense ratios is a relatively high share of ETFs in all savings plans. 55.92% of self-directed savings plans comprise only ETFs and, despite the higher number of funds per savings plan, even 84.31% of robo-advisor savings plans comprise only ETFs. Panel B further highlights that ETFs are dominant across all savings plan fund choices in the robo-advisor. For statistics in this panel each fund choice is one observation, i.e., a savings plan with three funds makes three observations and one fund can be counted multiple times when chosen in multiple savings plans. Consistent with the notion that robo-advice spurs the choice of ETFs, 86.67% of all savings plan fund choices in the robo-advisor were ETFs. The corresponding number for self-directed savings plans is only 63.14%. This finding is interesting as there is no default towards ETFs in the robo-advisor. Instead, investors can choose between ETFs and actively managed mutual funds by clicking one of two buttons with equal appearance.

A mistake observed to significantly deteriorate performance of ETF investors is selection of high cost ETFs (Boldin and Cici 2010). To test whether savings plan investors in our sample make this mistake, we calculate the fraction of ETFs with below average TER. We calculate the average TER of all purchased funds (robo-advice and self-directed) per fund category (ETF and active mutual fund), Datastream asset class, and month. Panel B of Table 6 reveals that robo-advice users select ETFs that are relatively low-cost as compared to all observed ETF choices. In particular, the fraction of ETFs with below average TER is higher for robo-advice savings plans (83.96%) than for self-directed savings

Table 6

Savings plan characteristics by type of savings plan

The table shows descriptive statistics on fund choice of savings plan investors. Column 1 depicts robo-advice savings plans and column 2 depicts self-directed savings plans. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. Sample size is n=2,336 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor. Matching is performed using the Coarsened Exact Matching method (Iacus, King, and Porro 2012).

	(1)	(2)	
	Savings plan robo-advice	**Savings plan self-directed**	
	Mean	Mean	Difference
Panel A: Savings plans			
Number of funds	3.45	2.15	1.29***
Number of asset classes	2.07	1.11	0.96***
Average TER	0.37%	0.62%	-0.26%***
I:Only passive ETFs	84.31%	55.92%	28.39%***
Obs.	*1,147*	*1,969*	
Panel B: Savings plan fund choices			
Share of ETFs	86.67%	63.14%	23.53%***
Obs.	*3,953*	*4,238*	
ETF choice			
I:Below average TER	83.96%	65.82%	18.14%***
Obs.	*3,416*	*2,370*	
I:Sector fund	0.20%	4.97%	-4.77%***
Obs.	*3,426*	*2,676*	
Panel C: ETF choice mechanism			
I:Minimum TER in choice set	29.71%	17.34%	12.37%***
Obs.	*3,416*	*2,370*	

plans (65.82%). Another mistake by ETF investors is to choose ETFs that focus only on a narrow sector. These ETFs are costly and underperform broadly diversified funds (Bhattacharya et al. 2016).

Given that the fraction of below-average TER funds is larger in robo-advice savings plans we conjecture that the fraction of sector ETFs is also lower. We define such funds based on the investment theme classification of the fund containing the word "sector" and calculate the fraction of sector fund choices with and without robo-advice. Panel B further shows that a lower fraction of funds chosen in robo-advisor savings plans are sector funds that focus on narrow markets. Among self-directed savings plans, 4.97% of all funds in self-directed savings plans have a narrow sector focus. The respective fraction of robo-advice savings plans is only 0.20%. Results for active mutual funds are qualitatively unchanged (see appendix). In sum, these findings suggest that the robo-advisor helps investors setting up savings plans that (1) are better diversified, (2) primarily consist of ETFs, (3) contain low-cost ETFs.

5. Mechanisms of the fund choice

How can the robo-advisor enable investors to make a superior fund choice? One explanation is increased awareness for recurring cost through the robo-advisor. The self-directed order form only shows one-off transaction costs. In contrast, the robo-advisor highlights both one-off transaction costs and TER of each fund very prominently. In addition, the robo-advisor equips the investor with a tool to sort a shortlist of funds according to cost. To explore the conjecture that these design elements increase awareness for recurring cost, we test whether robo-advisor savings plans comprise funds with the lowest available TER. We define an indicator for lowest TER that is restricted to the choice of the robo-advisor, i.e., relative to all other funds of the same type (ETF and active mutual funds) shown in the robo-advisor tool within a given asset class for each month. For self-directed savings plans we define a corresponding measure based on all funds that were bought in self-directed savings plans. Using the sample of matched savings plan investors, we compare the fraction of funds with the lowest TER in robo-advice and self-directed savings plans, respectively. Results are shown in Panel C of Table 6. Compared to self-directed savings plans, a larger fraction of ETFs in robo-advisor savings plans has a TER equal to the respective minimum-TER (29.71% vs. 17.34%). This might indicate that robo-advice investors choose ETFs, and specifically non-sector and low-TER ETFs, because they optimize their choice towards the fund with lowest TER available in the robo-advisor universe. However, the potential size of this TER optimization effect cannot explain the full result. In fact, 90.64% of all lowest cost fund choices (i.e., choices of funds that have a TER equal to the lowest TER available in the robo-advisor universe and the respective category) and 92.02% of lowest cost ETF choices were at the same time the default recommendation in the robo-advisor tool. The respective number for all lowest cost active mutual fund choices amounts to 78.63%. The effect of optimizing for costs is thus largely supported by a favorable default setting in the robo-advisor.

Is there an experience or selection effect? We further analyze the choices of robo-advice users outside of the robo-advisor to explore (1) whether experience with the robo-advisor improves investors' self-directed savings plan choices (experience effect) or (2) whether robo-advice users are investors who make better savings plan choices than non-users (selection effect). For this purpose, we split self-directed savings plans into those set up by investors who used the robo-advisor tool at least once (users) and those who never used the tool (non-users). Furthermore, we distinguish between self-directed savings plans set up by investors who used the robo-advisor tool at least once *before* setting up the respective savings plan (robo-advice experience) and those who did not (no robo-advice experience). In both cases, we compare these self-directed savings plans with all robo-advisor savings plans in the sample of matched investors (see Table A- 7 and Table A- 8 in the appendix). Results show that the self-directed choices of robo-advice users are significantly different from the choices of the same individuals in the robo-advisor tool. For example, the fraction of minimum-TER funds chosen by robo-advice users outside of robo-advice is only 18.08%. This is very close to the fraction of minimum-TER ETFs in all self-directed fund choices (17.34%), but significantly different from the choice of the same individuals in the robo-advisor (29.71%). Similarly, 18.78% of funds chosen in self-directed savings plans by robo-advice users after they have used robo-advice for another savings plan are minimum-TER ETFs. These results show that self-directed savings plans contain significantly fewer funds, are diversified over significantly fewer asset classes and contain more costly funds than robo-advisor savings plans, even if they are set-up by a robo-advice user or a user that has previously set up a robo-advisor savings plan. Only savings plans directly set up in the robo-advisor exhibit superior parameters. These results are consistent with the notion that guidance and cost transparency of the robo-advisor tool itself improves savings outcomes. Neither being affine for tool usage nor prior actual experience with the tool does substantially improve investors' savings plan choices outside when making self-directed choices.

6. Conclusion

Sufficient individual household saving, both for retirement and non-retirement purposes, is a vital component of every individual's financial well-being and a fundamental pillar of stability of the social and financial system. Fund savings plans have a number of advantages for building savings, e.g., counteracting limited self-control by automatic order execution. However, the choice of parameters influences the outcome, e.g., through the cost and diversification of chosen funds. We use administrative data from a large German online bank to study contribution rate and fund choice by individual investors in fund savings plans. Specifically, we explore how external anchors and guidance can influence these decisions, by comparing self-directed individuals with those who use a robo-advisor.

We find that savings plan investors choose the contribution rate as a function of their wealth. Remarkably, the contribution rate choice is not influenced beyond the push to a new minimum contribution rate that is implemented in the robo-advisor. Customers who are financially able to contribute more, still do so, even though the robo-advisor form carries the minimum threshold as default value. In contrast, robo-advice has a significantly positive effect on the fund choice compared to self-directed savings plans in three regards: (1) Increased diversification from 1.11 to 2.07 out of 4 general asset classes, (2) increased choice of passive investment in ETFs by 23.5 percentage-points of savings plan securities, and (3) increasing choice of less costly ETFs leading to a reduction in average TER of savings plans from 62bps to 37bps.

Additional evidence suggests that there are some robo-advice investors who optimize their choice towards the lowest TER funds. Such a TER choice heuristic is motivated in the robo-advisor through increased transparency on TER and a cost sorting function in the robo-advisor compared to the self-directed order form. Both the choice of ETF instead of active mutual funds and the choice of diversified and low cost funds in the robo-advisor are consistent with a TER choice heuristic. However, the bulk of the effect cannot be solely driven by awareness for TERs, but is to a large extent supported by a favorable default setting in the robo-advisor. In fact, 90.64% of all lowest cost fund choices were at the same time the default recommendation in the robo-advisor. These results seem at odds with findings in literature about traditional personal advice biasing the choice towards more costly funds (Foerster et al. 2015; Hoechle et al. 2016) and specifically more costly ETFs (Boldin and Cici 2010). An additional split of self-directed savings plan choices suggests that neither a robo-advisor selection nor a robo-advisor experience effect improves investors' savings plan choices in the way the robo-advisor usage itself does.

Robo-advisors are a new, but fast growing distribution channel of funds. Regulation is weary of benefits through guidance and potential risks through missing individualization. Our findings suggest that in the context of savings plan decisions, the benefits of robo-advice are clearly visible while there is no evidence for systematic biasing effects through a non-individualized default contribution rate.

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Appendix

Table A- 1

LPM on choice of default or minimum contribution rates (robustness on sample selection)

The table shows marginal effects of the linear probability models. The dependent variable is an indicator set to one if the contribution rate is at the robo-advisor default/minimum, i.e., between EUR 97.50 and 102.50 (column 1), at either the self-directed minimum, i.e., between EUR 24.38 and 25.63 or at the robo-advisor default/minimum (column 2) or at any value below the robo-advisor default/minimum (column 3), The regressions include all self-directed and robo-advisor savings plans between July 2011 and December 2015. All savings plans with at least 2 executions are considered. The sub-sample comprises all sample investors for which at least one savings plan of each type is observed. Robust standard errors clustered by investor are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
Dependent Variable	Robo-Advisor Default	Minimum contribution	Robo-advisor default or below
Robo-advice treatment			
I:Robo-advisor$_{i,t}$	0.2244***	0.1711***	-0.0673**
	(0.0366)	(0.0356)	(0.0319)
Experience			
I:Above Median Prior Non-Robo Trades$_{i,t}$	-0.0371	-0.0009	-0.0236
	(0.0654)	(0.0751)	(0.0633)
I:Prior Non-Robo Savings Plan$_{i,t}$	0.0449	0.0614	0.0629
	(0.0438)	(0.0469)	(0.0455)
I:Prior Robo Lump Sum Investment$_{i,t}$	-0.1946*	-0.169	-0.1831*
	(0.1158)	(0.1152)	(0.1069)
I:Prior Robo Savings Plan$_{i,t}$	0.0006	0.0165	0.0391
	(0.0426)	(0.0450)	(0.0421)
# observations	1,551	1,551	1,551
Adj. R^2	0.09	0.04	0.02
Control for robo-advice introduction	Yes	Yes	Yes
Demographics controls	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes
Account activity controls	Yes	Yes	Yes
Relationship length controls	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes

Table A- 2

LPM on choice of default or minimum contribution rates (robustness on sample selection)

The table shows marginal effects of the linear probability models. The dependent variable is an indicator set to one if the contribution rate is at the robo-advisor default/minimum, i.e., between EUR 97.50 and 102.50 (column 1), at either the self-directed minimum, i.e., between EUR 24.38 and 25.63 or at the robo-advisor default/minimum (column 2) or at any value below the robo-advisor default/minimum (column 3), The regressions include all self-directed and robo-advisor savings plans between July 2011 and December 2015. All savings plans with at least 5 executions are considered. The sub-sample comprises all sample investors for which at least one savings plan of each type is observed. Robust standard errors clustered by investor are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
Dependent Variable	Robo-Advisor Default	Minimum contribution	Robo-advisor default or below
Robo-advice treatment			
I:Robo-advisor$_{i,t}$	0.1887***	0.1448***	-0.0813*
	(0.0483)	(0.0481)	(0.0422)
Experience			
I:Above Median Prior Non-Robo Trades$_{i,t}$	-0.0275	-0.0053	0.0197
	(0.0984)	(0.0971)	(0.1031)
I:Prior Non-Robo Savings Plan$_{i,t}$	-0.0081	-0.0018	0.0102
	(0.0553)	(0.0601)	(0.0578)
I:Prior Robo Lump Sum Investment$_{i,t}$	-0.2313	-0.1716	-0.2135
	(0.1490)	(0.1385)	(0.1461)
I:Prior Robo Savings Plan$_{i,t}$	-0.0087	0.0206	0.0401
	(0.0564)	(0.0627)	(0.0532)
# observations	877	877	877
Adj. R^2	0.07	0.03	0.03
Control for robo-advice introduction	Yes	Yes	Yes
Demographics controls	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes
Account activity controls	Yes	Yes	Yes
Relationship length controls	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes

Table A- 3

Investor characteristics and contribution rate (robustness with cross-section sample)

The table shows coefficients from regressions on the chosen contribution rate for savings plans in EUR. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. All savings plans with at least 3 executions are considered. If an investor sets up more than one savings plan in the sample period, the first savings plan is considered. Sample size is n=3,062 self-directed savings plan investors (column 1) and n=1,046 robo-advice savings plan investors (column 2). Investors in the treatment group were guided by an automated investment solution ("robo-advisor"). Investors in the control group made a fully self-directed decision. Robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
Robo-advice treatment				
I:Robo-advisor$_{i,t}$	-70.3699***	-16.0012	-17.3798	-31.6829*
	(19.2604)	(15.1249)	(15.1916)	(19.1258)
Customer demographics				
I:Male$_{i}$		13.2859	24.1028	37.8794
		(23.6020)	(22.0480)	(23.7197)
I:Age_Years 35-50$_{i,t}$		19.2145	20.5301	50.6911*
		(20.2985)	(20.3729)	(26.2352)
I:Age_Years 50-65$_{i,t}$		3.8788	7.0224	38.5112
		(23.6232)	(24.2237)	(25.3008)
I:Age_Years 65-$_{i,t}$		8.8149	11.0540	45.2773
		(69.0988)	(69.2254)	(67.5890)
I:AcademicTitle$_{i}$		120.3847*	114.6896	105.7695
		(72.2772)	(70.7640)	(71.2722)
I:Second Account Holder$_{i}$		-11.2500	-16.4226	-18.3710
		(30.3906)	(30.6273)	(30.6236)
Wealth				
I:AuM_Eurok 25-50$_{i,t}$		60.5159*	75.3676**	94.1744***
		(36.1070)	(37.1249)	(35.8245)
I:AuM_Eurok 50-100$_{i,t}$		119.4011***	138.9130***	167.1567***
		(33.9963)	(35.2216)	(34.3606)
I:AuM_Eurok 100-150$_{i,t}$		240.3070***	270.3467***	295.3056***
		(74.7797)	(75.4438)	(76.8275)
I:AuM_Eurok 150-$_{i,t}$		657.4165***	680.2436***	717.5475***
		(129.4095)	(128.2950)	(134.1435)
I:Monthly Checkacct High-Low 1k-5k$_{i,t}$		-11.6616	19.0376	6.0916
		(19.9527)	(25.0217)	(26.2506)
I:Monthly Checkacct High-Low 5k-10k$_{i,t}$		44.8362	76.3307*	70.6537
		(39.2947)	(44.6332)	(46.3528)
I:Monthly Checkacct High-Low 10k-$_{i,t}$		324.6855**	354.4105**	341.5442**
		(147.8811)	(146.3444)	(139.8447)
Experience				
I: Above Median Prior Non-Robo Trades$_{i,t}$				-102.4192**
				(46.5437)
I: Prior Non-Robo Savings Plan$_{i,t}$				12.4428
				(32.0319)
# observations	4,108	4,108	4,108	4,108
Adj. R^2	0.00	0.06	0.06	0.06
Account activity control	No	No	Yes	Yes
Relationship length control	No	No	No	Yes

Table A- 4

Investor characteristics and contribution rate (robustness with matched sample)

The table shows coefficients from regressions on the chosen contribution rate for savings plans in Euro. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. All savings plans with at least 2 executions are considered. Sample size is n=2,628 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor. Matching is performed using the Coarsened Exact Matching method (Iacus, King, and Porro 2012). Standard errors clustered by investor are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
Robo-advice treatment				
I:Robo-advisor$_{i,t}$	-7.3898	1.2664	-3.9063	-0.2937
	(19.9419)	(16.6534)	(17.2809)	(18.1013)
Customer demographics				
I:Male$_i$		25.0717	36.7859	35.7848
		(35.7040)	(37.2300)	(37.1649)
I:Age_Years 35-50$_{i,t}$		23.3905	17.1888	17.848
		(16.7126)	(21.0427)	(20.9483)
I:Age_Years 50-65$_{i,t}$		11.5564	2.6954	2.9468
		(29.9544)	(32.4235)	(32.5482)
I:Age_Years 65-$_{i,t}$		-18.9962	-14.6505	-12.6618
		(113.3449)	(108.2052)	(108.1708)
I:AcademicTitle$_i$		225.342*	220.5712*	219.3465*
		(122.6628)	(121.0521)	(121.6953)
I:Second Account Holder$_i$		37.2772	37.6818	38.6449
		(43.7767)	(44.8790)	(45.0000)
Wealth				
I:AuM_Eurok 25-50$_{i,t}$		28.6926	37.6728	37.7178
		(22.7174)	(23.1014)	(23.1142)
I:AuM_Eurok 50-100$_{i,t}$		161.2596***	172.8945***	171.4969***
		(53.2961)	(53.5131)	(53.1004)
I:AuM_Eurok 100-150$_{i,t}$		205.0282*	226.7799*	223.3968*
		(111.7614)	(117.2331)	(117.4304)
I:AuM_Eurok 150-$_{i,t}$		851.1693***	860.0374***	860.3427***
		(244.2846)	(241.9629)	(242.3251)
I:Monthly Checkacct High-Low 1k-5k$_{i,t}$		5.3495	35.4423	34.1598
		(18.7844)	(24.6306)	(24.5922)
I:Monthly Checkacct High-Low 5k-10k$_{i,t}$		22.5463	54.7212	53.2223
		(53.6796)	(59.8335)	(60.0189)
I:Monthly Checkacct High-Low 10k-$_{i,t}$		242.2858**	270.6366**	271.2268**
		(116.5678)	(114.3851)	(114.4681)
Experience				
I:Above Median Prior Non-Robo Trades$_{i,t}$			-14.4645	-17.0705
			(27.1823)	(27.7666)
I:Prior Non-Robo Savings Plan$_{i,t}$			-9.8882	-11.7191
			(20.5935)	(19.9158)
I:Prior Robo Lump Sum Investment$_{i,t}$				22.1895
				(51.0329)
I:Prior Robo Savings Plan$_{i,t}$				81.5127
				(51.6188)
# observations	3,610	3,610	3,610	3,610
Adj. R^2	0.00	0.11	0.11	0.11
Account activity controls	No	No	Yes	Yes
Relationship length controls	No	No	Yes	Yes

Table A- 5

Investor characteristics and contribution rate (robustness with matched sample)

The table shows coefficients from regressions on the chosen contribution rate for savings plans in EUR. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. All savings plans with at least 5 executions are considered. Sample size is n=1,886 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor. Matching is performed using the Coarsened Exact Matching method (Iacus, King, and Porro 2012). Standard errors clustered by investor are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
Robo-advice treatment				
I:Robo-advisor$_{i,t}$	-1.1387	3.2936	-1.4578	3.6952
	(18.6476)	(17.5538)	(18.3313)	(18.2993)
Customer demographics				
I:Male$_{i}$		46.1769***	63.2767***	62.836***
		(16.8905)	(20.0407)	(19.9873)
I:Age_Years 35-50$_{i,t}$		-0.7677	-1.4908	-0.4426
		(18.0256)	(21.7555)	(21.5208)
I:Age_Years 50-65$_{i,t}$		21.8623	13.8173	14.4725
		(32.7286)	(31.6043)	(32.0545)
I:Age_Years 65-$_{i,t}$		-111.3611**	-110.5101**	-109.3319**
		(52.5803)	(49.7143)	(49.5145)
I:AcademicTitle$_{i}$		114.8475	119.5078	118.5112
		(99.9085)	(99.2299)	(100.0537)
I:Second Account Holder$_{i}$		39.9765	41.5836	42.4758
		(35.7753)	(36.4731)	(36.7210)
Wealth				
I:AuM_Eurok 25-50$_{i,t}$		26.1538	44.2011*	43.9212*
		(24.9337)	(23.4928)	(23.6653)
I:AuM_Eurok 50-100$_{i,t}$		110.8705**	137.0381***	135.2886***
		(50.9857)	(50.1389)	(50.2602)
I:AuM_Eurok 100-150$_{i,t}$		372.7635**	411.7928**	408.508**
		(161.3995)	(164.9222)	(165.6096)
I:AuM_Eurok 150-$_{i,t}$		545.6958***	569.9183***	571.0996***
		(164.6798)	(171.5606)	(171.5664)
I:Monthly Checkacct High-Low 1k-5k$_{i,t}$		-32.767	-11.5881	-12.3622
		(21.7347)	(22.1738)	(22.1186)
I:Monthly Checkacct High-Low 5k-10k$_{i,t}$		-33.3946	-9.4494	-10.4815
		(39.7518)	(41.2372)	(41.0353)
I:Monthly Checkacct High-Low 10k-$_{i,t}$		180.8522*	197.8509**	196.0999**
		(95.8808)	(95.9546)	(96.2185)
Experience				
I:Above Median Prior Non-Robo Trades$_{i,t}$			-53.8241	-56.6629*
			(32.9781)	(34.1074)
I:Prior Non-Robo Savings Plan$_{i,t}$			-16.34	-18.7292
			(28.6180)	(27.5359)
I:Prior Robo Lump Sum Investment$_{i,t}$				-17.6608
				(54.6609)
I:Prior Robo Savings Plan$_{i,t}$				82.1985
				(62.2965)
# observations	2,357	2,357	2,357	2,357
Adj. R^2	0.00	0.08	0.08	0.08
Account activity controls	No	No	Yes	Yes
Relationship length controls	No	No	No	Yes

Table A- 6

Savings plan characteristics by type of savings plan (Active mutual funds)

The table shows descriptive statistics on fund choice of savings plan investors. Column 1 depicts robo-advice savings plans and column 2 depicts self-directed savings plans. Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. Sample size is n=2,336 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor. Matching is performed using the Coarsened Exact Matching method (Iacus, King, and Porro 2012).

	(1)	(2)	(3)
	Savings plan robo-advice	**Savings plan self-directed**	
	Mean	Mean	Difference
Panel A: Savings Plans			
Number of funds	3.45	2.15	1.29***
Number of asset classes	2.07	1.11	0.96***
Average TER	0.37%	0.62%	-0.26%***
I:Only passive ETFs	84.31%	55.92%	28.39%***
Obs.	*1,147*	*1,969*	
Panel B: Savings Plan Fund Choices			
Share of ETFs	86.67%	63.14%	23.53%***
Obs.	*3,953*	*4,238*	
ETF choice			
I:Below average TER	83.96%	65.82%	18.14%***
Obs.	*3,416*	*2,370*	
I:Sector fund	0.20%	4.97%	-4.77%***
Obs.	*3,426*	*2,676*	
Active mutual fund choice			
I:Below average TER	65.46%	74.01%	-8.55%***
Obs.	*527*	*1,516*	
I:Sector fund	6.07%	16.13%	-10.06%***
Obs.	*527*	*1,562*	
Panel C: ETF choice mechanism			
I:Minimum TER in choice set	29.71%	17.34%	12.37%***
Obs.	*3,416*	*2,370*	

Table A- 7

Savings plan characteristics by type of savings plan (differentiation by robo-advice users)

The table shows descriptive statistics on fund choice of savings plan investors. Column 1 depicts robo-advice savings plans. Columns 2a and 2b split self-directed savings plans into those set up by investors who used the robo-advisor tool at least once (column 2a) and those who never used the tool (column 2b). Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. Sample size is n=2,336 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor. Matching is performed using the Coarsened Exact Matching method (Iacus, King, and Porro 2012).

	(1)	(2a)		(2b)	
	Savings plan robo-advice	**Savings plan self-directed (robo-advice users)**	**Difference (1) -(2a)**	**Savings plan self-directed (non robo-advice users)**	**Difference (1) -(2b)**
	Mean	Mean		Mean	
Panel A: Savings Plans					
Number of funds	3.45	2.64	0.81***	2.03	1.42***
Number of asset classes	2.07	1.21	0.86***	1.08	0.98***
Average TER	0.37%	0.68%	-0.31%***	0.60%	-0.24%***
I:Only passive ETFs	84.31%	49.02%	35.28%***	57.73%	26.58%***
Obs.	*1,147*	*410*		*1,559*	
Panel B: Savings Plan Fund Choices					
Share of ETFs	86.67%	56.06%	30.61%***	65.57%	21.10%***
Obs.	*3,953*	*1,081*		*3,157*	
ETF choice					
I:Below average TER	83.96%	65.77%	18.19%***	65.84%	18.12%***
Obs.	*3,416*	*520*		*1,850*	
I:Sector fund	0.20%	6.77%	-6.56%***	4.44%	-4.24%***
Obs.	*3,426*	*606*		*2,070*	
Active mutual fund choice					
I:Below average TER	65.46%	72.34%	-6.88%***	74.76%	-9.30%***
Obs.	*527*	*470*		*1,046*	
I:Sector fund	6.07%	16.00%	-9.93%***	16.19%	-10.12%***
Obs.	*527*	*475*		*1,087*	
Panel C: ETF choice mechanism					
I:Minimum TER in choice set	29.71%	18.08%	11.64%***	17.14%	12.58%***
Obs.	*3,416*	*520*		*1,850*	

Table A- 8

Savings plan characteristics by type of savings plan (differentiation by robo-advice experience)

The table shows descriptive statistics on fund choice of savings plan investors. Column 1 depicts robo-advice savings plans. Columns 2a and 2b split self-directed savings plans into those set up by investors who used the robo-advisor tool before setting up their self-directed savings plan (column 2a) and those who did not (column 2b). Observations are from a large German online bank sample where a robo-advisor tool with savings plan functionality was observed between July 2014 and December 2015. Sample size is n=2,336 fund savings plan investors with half being investors who used the robo-advisor at least once and the other half being a control group of matched nearest neighbor investors who set up a savings plan, but never invested through the robo-advisor. Matching is performed using the Coarsened Exact Matching method (Iacus, King, and Porro 2012).

	(1)	(2a)		(2b)	
	Savings plan robo-advice	**Savings plan self-directed (robo-advice experience)**	**Difference (1) -(2a)**	**Savings plan self-directed (no robo-advice experience)**	**Difference (1) -(2b)**
	Mean	Mean	Mean	Mean	Mean
Panel A: Savings Plans					
Number of funds	3.45	2.34	1.11***	2.13	1.31***
Number of asset classes	2.07	1.21	0.86***	1.09	0.97***
Average TER	0.37%	0.62%	-0.25%***	0.62%	-0.26%***
I:Only passive ETFs	84.31%	53.37%	30.94%***	56.19%	28.11%***
Obs.	*1,147*	*193*		*1,776*	
Panel B: Savings Plan Fund Choices					
Share of ETFs	86.67%	59.65%	27.02%***	63.56%	23.11%***
Obs.	*3,953*	*451*		*3,787*	
ETF choice					
I:Below average TER	83.96%	68.98%	14.98%***	65.46%	18.50%***
Obs.	*3,416*	*245*		*2,125*	
I:Sector fund	0.20%	3.35%	-3.14%***	5.15%	-4.95%***
Obs.	*3,426*	*269*		*2,407*	
Active mutual fund choice					
I:Below average TER	65.46%	71.82%	-6.36%***	74.31%	-8.84%***
Obs.	*527*	*181*		*1,335*	
I:Sector fund	6.07%	20.88%	-14.81%***	15.51%	-9.44%***
Obs.	*527*	*182*		*1,380*	
Panel C: ETF choice mechanism					
I:Minimum TER in choice set	29.71%	18.78%	10.94%***	17.18%	12.54%***
Obs.	*3,416*	*245*		*2,125*	