Research Report

# The Future of Robo-Advice: Tailor-Made Decision Support for Investors

ROBO-ADVICE HAS THE POTENTIAL TO DISRUPT THE MARKET FOR FINANCIAL ADVICE. ALGORITHMS ALREADY DELIVER LOW-COST, AUTOMATIC, AND STANDARDIZED INVESTMENT GUIDANCE TO CLIENTS FROM ALL WEALTH LEVELS AND ESPECIALLY TO THOSE PREVIOUSLY EXCLUDED FROM PERSONAL FACE-TO-FACE ADVICE. TODAY'S OFFERINGS CONCENTRATE ON CONVENIENCE AND COMPLEXITY REDUCTION, COUPLED WITH PASSIVE INVESTMENTS. THE NEXT STEP WILL ADVANCE ALGORITHMS TO DELIVER TAILOR-MADE DECISION SUPPORT FOR THE GROWING NUMBER OF SELF-DIRECTED INVESTORS. THIS ARTICLE PRESENTS REAL-LIFE EMPIRICAL RESULTS ON THE INTRODUCTION OF A PORTFOLIO OPTIMIZATION TOOL THAT GUIDES BROKERAGE CLIENTS TOWARDS INDIVIDUAL OPTIMAL PORTFOLIOS.

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### Introduction

Robo-advice has been advocated as an answer to both the conflicts of interest inherent in the traditional advisory model (Inderst and Ottaviani, 2009) and the documented underperformance of advised accounts (see, e.g., Hackethal et al., 2012; more recently, Foerster et al., 2015). In the aftermath of the financial crisis, banks and regulators have pushed the standardization and transparency of advisory services. Simultaneously, Internet start-ups have entered the market offering innovative automated investment guidance. These so-called robo-advisors are low-cost online applications that deliver personalized recommendations or discretionary investment management based on self-reported client information. Most importantly, they substantially reduce the stock market entry costs for low net-worth individuals.

### The Evolution of Robo-Advice

Currently, robo-advice concentrates on guiding investors towards sound and low-cost passive investments – blending equity and fixed income instruments. Their often fairly simplistic algorithms are designed to match the consumer's financial and demographic characteristics with fitting asset allocations. Matching algorithms are of course not only prevalent in robo-advice. In 2016, around 70% of UK firms surveyed by the Financial Conduct Authority (FCA) used computer technology for risk profiling and financial planning (see Figure 1). Natural extensions of such technology are tools that provide active investors concrete guidance on how alterations of an existing portfolio improve the risk-return profile. Celent, a research division of Oliver Wyman, estimated a growth rate of 4.9% (1.4%) for the US self-directed (non-self-directed) retail investor segment in 2015. A growing number of self-directed investors – around 50% in 2015 are considered active – trade at least three trades a month.

Yet, the do-it-yourself mentality of modern investors will not fully eliminate personal advice. In fact, analysts expect a growing demand for hybrid models that offer robo-advice plus access to a variety of advice services tailored to different types of clients. J.D. Power (2016) reports a substantial increase on so-called "validator" clients (from 21% to 25% over the recent past). These are mostly self-directed clients that still appreciate on-demand access to advice mainly to verify their own ideas and views. A new breed of online investment tools could bridge the robo sphere and the human advisor sphere especially for this growing client segment. According to the FCA, today, only 15% of UK advisory firms offer tools that "aid decision-making and transacting" to a significant degree and 46% do not provide any (Figure 1). The stage might therefore be set for the next wave of technological innovation.

In order to investigate the usage of investment tools and their effect on investor decision making, we have conducted a field study together with a German online bank that has launched a portfolio optimization tool for its active investors.

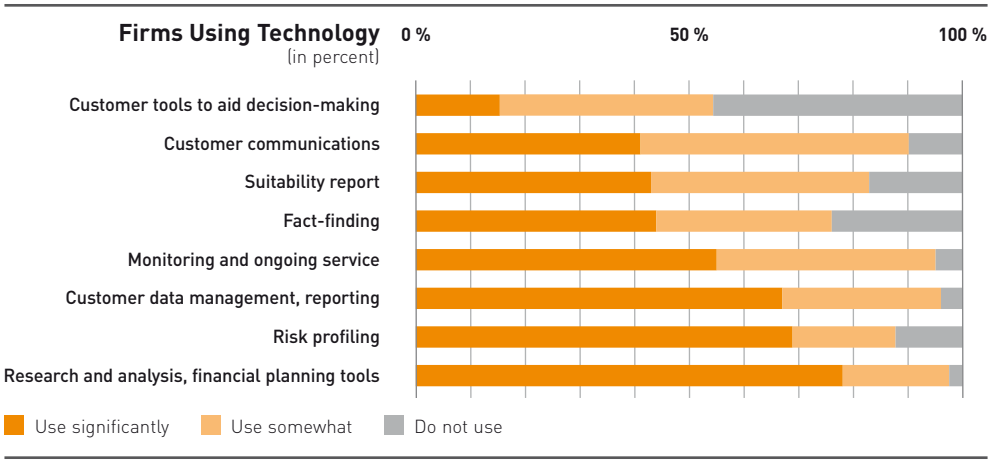


**Figure 1: Use of Technology in the Advice Process (FCA, 2016)**

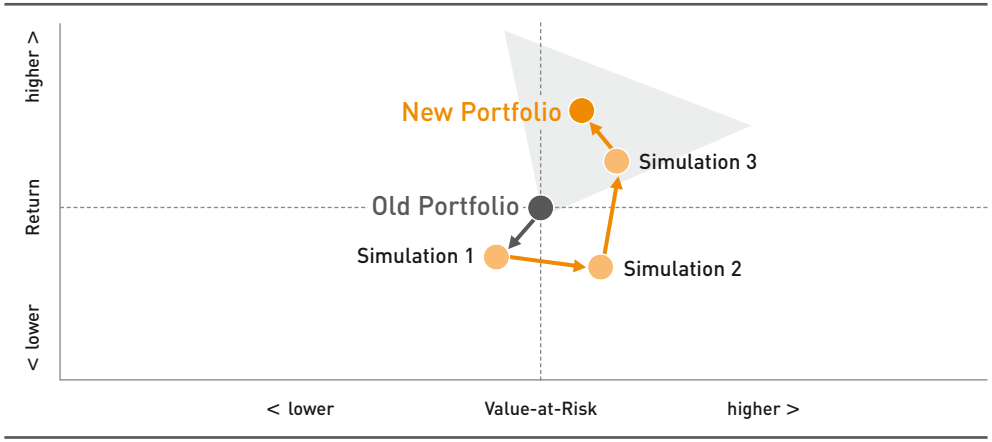


**Figure 2: Illustration of the Portfolio Optimizer's Graphical Output Showing a Simulation User's Fictive Path of Optimization**

### Who Would Benefit?

Self-directed investors tend to overestimate their abilities and the value of their information at hand. Such overconfidence often induces portfolio under-diversification and overtrading (see, e.g., Barber and Odean, 2000). Both investor mistakes can be related to behavioral biases, namely mental accounting and myopic investment (see, e.g., Thaler et al., 1997). Mental accounting limits investors in their ability to aggregate financial decisions. In extreme cases, this would lead to portfolios in which securities are acquired, one at a time, with individual but unrelated trading motives. The benefits of diversification are thereby ignored. Myopic behavior is related to mental accounting in the sense that investors have the impulse to frequently evaluate investments. A combination of both results in the segregation of long investment horizons into separate mental accounts for short, consequent trading periods.

Glaser and Weber (2007) confirm these predictions and find that private investors are unable to state aggregate returns of their portfolio positions and are often un-aware of (trading) cost and consequences of (under-) diversification.

The portfolio optimization tool discussed in this article shows promising features to ameliorate precisely these common biases.

### Description of Investment Tool

We work with a German online bank that offers the full range of retail bank services, such as checking and term accounts, brokerage services as well as consumer and mortgage loans. In 2014, it introduced a portfolio simulation tool that allows its clients to back-test their own and any arbitrary portfolio over a 180-day period based on their current portfolio positions or self-defined security watch lists.

The portfolio optimizer targets insufficient knowledge of aggregate information by providing a simple environment that helps to evaluate investments in the context of the clients' complete portfolios. It serves investors challenged by the trade-off between risk and return of different products by visualizing efficiency gains between simulated portfolios. The optimizer generates a graphical display by plotting a representative dot in a risk-return diagram for each simulated portfolio marking its return on the y-axis and its value-at-risk (VaR) on the x-axis. Figure 2 shows an illustration of the optimizer's output, which appears prominently at the top of the optimizer-page on the brokerage's online platform. Up to four portfolios, i.e., three simulation results plus the actual user portfolio, can be compared on the two dimensional plane. Risk and return values are one-month expectations based on historical data over the last six months. The VaR is provided as a percentage loss and calculated at the 5% level.

### Who Are the Early Adopters?

We count a total of 149,217 simulation runs for the portfolio optimizer over an 17-month period. On average (median), each user conducted 28 (10) simulations and accessed the optimizer on 3.7 (2) different days. The users at the 99$^{th}$ percentile of the simulation-count distribution ran 288 simulations. The bank sent physical invitations letters and invitation E-mails to a total of 72,811 clients from our sample. 4.4% of the clients visited the investment tool in response to the invitation. That portion is comparable to the 5% response rate on an invitation to free advice analyzed by Bhattacharya et al. (2012) who use data from the same brokerage but a different sub-sample of clients.

The probability of using the portfolio optimizer is estimated by a probit regression on client characteristics. It is not surprising that a higher activity on the brokerage's online platform (measured in login days and portfolio turnover) increases the probability of using the optimizer. Considering wealth and income with three categories each, only clients from the highest wealth category (> EUR 100,000 p.a. income) show a higher probability (compared to the lowest category, i.e., < EUR 30,000). Female clients, representing 9.4% (18.3%) of the user group (control group), older clients, and clients from the intermediate income group (EUR 60,000-100,000) are less likely to use the optimizer. The results are in line with expectations since younger, rather male, and more sophisticated – that is wealthier – clients seem to be a plausible audience for technological innovations.

### Does the Tool Have Any Impact on Investor Behavior?

We set up a panel difference-in-differences model on monthly data to produce reliable estimates on the tool's treatment effect. To account for self-selection, we employ a conservative two-stage matching process that identifies valid and balanced treatment and control groups. The first stage generates strata of pre-treatment demographic and account characteristics. The second stage implements a one-to-one nearest neighbor propensity

score matching conducted separately on each stratum.

We estimate the treatment effect on portfolio turnover and the Herfindahl-Hirschman index (HHI) as a measure of portfolio concentration and we find that turnover increases significantly for months in which clients use the portfolio optimizer. Not surprisingly, the effect subsides over in the following months. Moreover, portfolio diversification increases over the subsequent months. We conclude that the tool prompts client actions and ensuing portfolio amendments.

### What Is the Simulation Strategy of Users?

We test for significant changes in key portfolio indicators between the starting portfolio (before the first simulation) and the very last simulation of each client per daily session. Figure 3 illustrates the changes in the key performance indicators. Simulated portfolios get riskier (value-at-risk). At the same time their expected returns improve. The Sharpe ratio, which measures the return-risk trade-off of portfolios, increases substantially throughout the simulations. The HHI, our diversification measure, decreases – indicating a lower portfolio concentration and therefore better diversification. The increase in diversification is likely due to the fact that users tend to swap more single stocks into mutual funds and add new securities as they run additional simulations. Significance tests indicate that all documented changes in portfolio indicators except for return differentials are highly statistically significant. Users thus seem to pursue a simulation strategy that aims for maximizing portfolio efficiency.

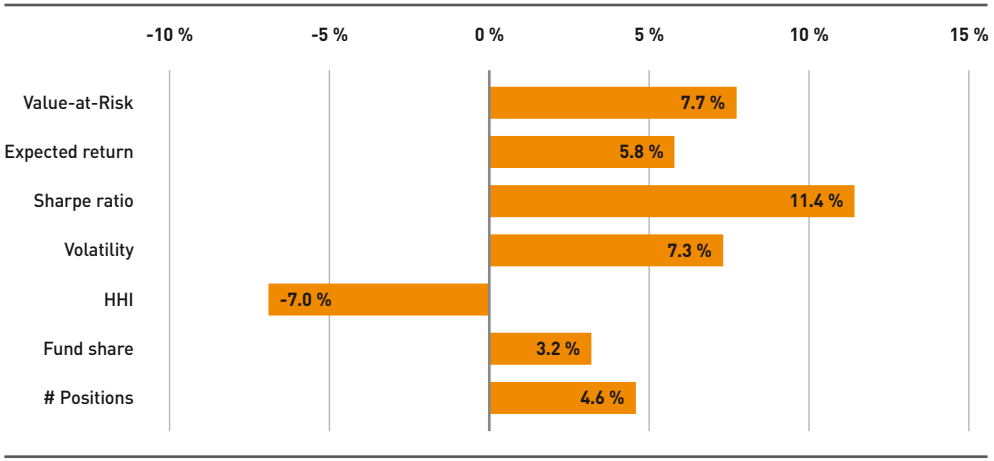


**Figure 3: Percentage Changes of Key Portfolio Indicators on Simulated Portfolios**
(Changes of the daily last simulated portfolio vs. the actual account portfolio; values are relative to the corresponding indicator's actual portfolio sample average)

### Do Users Implement Their Simulations?

We define the simulation implementation as the volume-weighted fraction of simulation positions that were actually traded ex post. We regress the overlap on an indicator for strict Sharpe ratio improvements. The results confirm that clients trade what they simulate and thereby improve the Sharpe ratio of their real portfolio.

### Future Research

In a next step, we will analyze which clients benefit most from online investment guidance for individual portfolio construction. We will also more directly establish a causal relation between usage and improvement through difference-in-differences analyses on user subgroups.

We are still at an early phase of experimenting with this new breed of online investment tools, but our field study indicates that such user-friendly investment tools can guide self-directed investors towards better portfolios without imposing product or risk restrictions.

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