THE PERFORMANCE AND ASSET ALLOCATION OF GERMAN ROBO-ADVISORS¹

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After a short historical perspective on the emergence of robo-advisors and an overview of how they manage other people's money, we evaluate the performance of five German robo-advisors in the period between May 2015 and December 2018. Performance tests are conducted using Sharpe's (1966) and Jensen's (1968) performance methodologies. We also employ the returns-based style analysis of Sharpe (1992) to determine the exposure of robo-advisors to different non-overlapping asset classes. We report the following findings: First, no robo-advisor was able to beat the benchmark before or after considering fees. Second, robo-advisor performance varies greatly in the sample period even for portfolios that should appeal to clients with similar risk preferences. Third, these performance differences remain unexplained after accounting for the different asset allocations.

Keywords: robo-advisor, robo-advice, FinTech, style analysis

JEL-codes: G11, G21, G23

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1. INTRODUCTION

This article compares actual performances of five German robo-advisors over the May 2015 – December 2018 period, and explains performance differences between them using returns-based style analysis (Sharpe 1992). Returns-based style analysis tries to “reverse-engineer” the actual asset allocation of a portfolio using statistical methods. It must be contrasted with holdings-based style analysis, which tries to determine the investment style by looking at the individual portfolio holdings.

Robo-advisors can be defined as “automated online services that use computer algorithms to provide financial advice and manage customers’ investment portfolios” (Fisch et. al. 2018). The first robo-advisors have been founded in the United States in 2010. Since robo-advisors are a relatively recent phenomenon, the academic literature covering the topic is still very scarce. Lam (2016) and Puhle (2016) describe the evolution, regulation and inner workings of robo-advisors. A more recent source, Fisch et al. (2018), focuses on the historical development and future challenges of robo-advisors and analyzes their impact on retirement planning. We are not aware of any article that analyses the performance and asset allocation of robo-advisors in detail. Backend Benchmarking publishes a quarterly report covering US robo-advisors’ performance (The Robo Report) but this analyzes the performances not in the same detail as we do.

The performance of mutual funds has been analyzed extensively though, starting with the seminal work of Jensen (1968). A more recent analysis focusing on equity managers is Bhargava et al. (2001).

This paper contributes to the literature in two ways. First, we analyze the actual performances of German robo-advisors using descriptive statistics and returns-based style analysis. Second, we document significant performance differences between robo-advisors. The portfolios that we analyze have a similar asset allocation and should hence appeal to people with a similar risk preference. This finding suggests that robo-advisors manage portfolios in different ways and choosing the wrong robo-advisor has a significant negative impact on terminal wealth.

The paper is organized as follows. We introduce robo-advisors in Section 2. Section 3 explains how robo-advisors typically manage clients’ money. In Section 4, we analyze the historical performance of five German robo-advisors in detail. Section 5 concludes the article.

2. WHAT ARE ROBO-ADVISORS?

Richard J. Koreto coined the term “robo-advisor” in an article he wrote for the magazine *Financial Planning*, but his robo bears no resemblance to today’s robo-advisors (Koreto 2002). What do we mean nowadays, when we refer to robo-advisors? Investopedia defines robo-advisors as “an online wealth management service that provides automated, algorithm-based portfolio management advice without the use of human financial planners”. According to Wikipedia, robo-advisors are “a class of financial adviser that provides financial advice or portfolio management online with minimal human intervention.” Both definitions point to three important characteristics of robo-advisors: they provide (i) an automated investment solution, (ii) that is digitally delivered and (iii) uses algorithms to recommend asset allocations to customers.

Robo-advisors are a global phenomenon. The first robo-advisor, Betterment, started in the United States in 2010 and is currently the largest independent robo-advisor with around \$9 billion assets under management (AuM), followed by Wealthfront with \$7 billion AuM. The largest robo-advisors in the United States are those owned by fund managers, brokers or banks though: Vanguard Personal Advisor Services, which was founded in 2015 manages already \$83 billion and Schwab Intelligent Portfolios is the number two robo-advisor with \$19 billion AuM. *Figure 1* shows that robo-advisors – seven years after they first appeared – are still being launched, but nowadays mainly by fund managers, brokers or banks. In late 2017 or early 2018, we expected to see launches from Morgan Stanley, Wells Fargo, and Goldman Sachs. A.T. Kearney estimates the U.S. robo-advisor market to be around to \$2.2 trillion in 2012 (A. T. Kearney 2015).

Europe is the second largest robo-advisor market after North America. The first robo-advisor that was launched in Europe is nutmeg (United Kingdom, 2011). The first German robo-advisor, Quirion, appeared in 2013. Quirion is a subsidiary of the Berlin-based Quirin Bank, a private bank focusing on wealth management. The first independent robo-advisors, Ginmon and Vaamo, appeared

Figure 1. US robo-advisor launch timeline.

Source: Barron's (2017)

Figure 2. German robo-advisor launch timeline with estimated AuM in €million

Source: author’s estimates based on Extra-Magazin (2017), TechFluence (2017) and company press releases.

in 2014. Germany, the focus of this article, is an important market for robo advice not only in Europe but worldwide. According to some sources, in November 2017 there were 31 robo-advisors operating in Germany (TechFluence 2017) with an estimated €1.5 billion AuM.²

Scalable Capital leads the market in Germany with €500 million AuM and 15,000 clients followed by Liquid with €130 million AuM and 400 clients. Because of a minimum investment of €100,000, Liquid focuses on more wealthy individuals and hence has a smaller number of clients. Scalable Capital is also number two in Europe – after UK-based nutmeg (AuM ~ €700 million). Exact AuM numbers are generally hard to come by since there is no mandatory reporting as there is, for example, in the United States (reported in Form ADV documents). Therefore, we need to rely on self-reporting by companies. With more than 30 robo-advisors fighting for clients, only well-established companies are open to AuM- and client number reporting.³ Figure 2 shows the launch timeline and a current estimate of German robo-advisor AuM in €million.

In the Asia/Pacific region, robo-advisors appeared relatively late. We have seen launches only in the last couple of years. Bambu, a leading B2B robo-advisor in Singapore was launched in February 2016 for example. The Asia/Pacific region is a little late because of the relative scarcity of available exchange traded funds (ETF), which are normally used by robo-advisors to implement the portfolios

² Author’s estimate based on data from TechFluence (2017), Extra-Magazin (2017) and company reports.

³ Only Scalable Capital and Liquid have released press releases with detailed information on AuM, client numbers and client characteristics.

they recommend. Besides established banks, there are also a couple of independent robo-advisors that have been launched or are in the process of launching across Asia and the Pacific: Ignition Wealth (Australia), Lingji (China), Chloe (Hong Kong), Theo (Japan), and Smartly and Bambu (Singapore). IDC (2017) estimated in a November 2017 report that AuM in Asia/Pacific will grow to \$500 billion by 2021.

3. HOW DO ROBO-ADVISORS MANAGE CLIENTS' MONEY?

In Germany, there exist currently around 30 robo-advisors (Micobo 2018) and all of them seem to tout their superior investment model. A closer look reveals though that nearly all investment models are firmly rooted in modern portfolio theory (MPT). Hence, one would not expect much performance differences between recommended portfolios for people with similar risk preferences.

Most robo-advisors use portfolio models in the tradition of modern portfolio theory (see e.g. Markowitz 1952 and Sharpe 1964) to manage money for clients. In order to recommend specific portfolios to investors, robo-advisors first need to establish a set of suitable (or in some cases even efficient) portfolios. The robo-advisor then selects one portfolio from this set that is most suitable for the client, e.g. corresponds to their risk preference.

The first step in this procedure is to establish the investment universe, i.e. the set of asset classes in which to invest in. Research shows that asset allocation is one of the most important drivers of portfolio returns (and not e.g. individual security selection), so robo-advisors focus on asset classes and not individual securities. The investment universe of typical robo-advisors consists of domestic and international stocks (both developed and emerging markets), government and corporate bonds (both potentially from developed and emerging markets). Some robo-advisors include more exotic asset classes like treasury inflation-protected securities (TIPS), real estate, commodities or precious metals. The main goal is to have portfolio with exposures to many diverse risk factors. However, one also has to be aware of the implementation problem. The asset classes should be easily investable for example via an ETF. Some asset classes that would offer diversification potential are unfortunately out-of-reach for the typical retail investor, e.g. private equity investments and hedge funds. They have high minimum investment requirements and are hence usually not included in the investment universe. However, there are exceptions. Liquid, the number two robo-advisor in Germany, with a focus on wealthy individuals offers indirect investment in private equity funds. The number and the composition of the investment universe differs from robo-advisor to robo-advisor, but usually between 5 and 15

asset classes are included: Scalable Capital includes 6 major asset classes and Wealthfront includes 11. Each asset class is then mapped to one or more concrete investment assets, e.g. the asset class US Large Cap Equity could be mapped to an iShares S&P 500 ETF.

In the second step, parameters of the multi-variate asset class return distribution are estimated. In a mean-variance framework, one has to estimate means and variances of asset class returns and the correlations between the different asset classes. This input is then fed into an optimizer, which outputs the portfolio with the maximum expected return for a given level of risk. Unfortunately, the optimizer is very sensitive to changes in inputs (especially the means) and the resulting asset class weights are often non-sensible (Michaud 1989). A couple of methods have been proposed to deal with this problem, mainly constrained optimization and the Black/Litterman approach (Black – Litterman 1992). Wealthfront includes minimum and maximum weights for each asset class in the optimization procedure and uses the Black/Litterman model to estimate sensible asset class expected returns, which it updates with internal views regarding the performance of the asset classes.

Not all robo-advisors use the mean-variance framework for the optimization problem selection: Scalable Capital for example uses a mean-Value-at-Risk (VaR) framework. Other robo-advisors are not even employing a formal optimization method but instead construct portfolios using approaches that are more heuristic.

The last step consists of recommending one specific portfolio from the efficient set to a client. To accomplish this, robo-advisors ask clients to fill out risk profile questionnaires and estimates the client's risk preference from the given answers. Once the risk preference has been established, the corresponding portfolio is recommended. In the early days, the set of portfolios was small: Vaamo used 3 portfolios differing only in their weights to the target asset classes and Ginmon used 11 portfolios. Scalable Capital constructs 23 different portfolios ranging from a 2% VaR (1 year, 99%) to 25% VaR.

After establishing the initial portfolio, robo-advisors monitor the portfolio and apply changes to it, when market conditions or the risk preferences of the client change. Even if model inputs do not change, simply by being invested in the markets, the actual asset class weights diverge from the proposed weights over time. These weights are brought back to their recommended levels in a process that is called rebalancing. Rebalancing can be done at specific points in time (e.g. yearly) or done on an event-based basis (e.g. when the divergence between actual and recommended weights is large).

For a more detailed discussion of the mechanics of robo-advisor investing, see Lam (2016), Puhle (2016) or Fisch et al. (2018).

4. HOW ARE ROBO-ADVISORS PERFORMING?

Robo-advisors differ in their investment methodology, described above and tout their uniqueness. In the end, what matters is portfolio performance. Of course, to evaluate robo-advisor offerings one has to take into account several characteristics, e.g. investment methodology, ease-of-use, fees – but surely also performance.

Unfortunately, in the past it was hard or impossible to get reliable portfolio performance figures from robo-advisors. Recently reports have been published containing performance figures from portfolios funded with real money. In Germany, the internet portal BrokerVergleich publishes monthly performance data for 16 robo-advisor portfolios (BrokerVergleich 2018). In the United States, Backend Benchmarking publishes quarterly robo-advisor performance figures (Backend Benchmarking 2019)

We analyze whether robo-advisors can deliver a performance similar to a benchmark performance. Furthermore, we look at differences between individual robo-advisor returns and try to explain them.

4.1. Data

Our data consists of monthly performance figures reported by the German internet portal BrokerVergleich.de (BrokerVergleich 2019). BrokerVergleich.de currently tracks the performance of investment accounts at 16 German robo-advisors, all of which it has funded with real money. Of the 16 accounts, five have been opened in May 2015, three have been added in May 2016, three in May 2017 and a further five in May 2018.

In our current study, we focus on the five portfolios that cover the longest interval, from May 2015 to December 2018. To make the performance figures comparable even for the nonprofessional, BrokerVergleich.de opened accounts for an individual with a moderate risk preference, resulting in each case in a portfolio of roughly 50% equities and 50% fixed income. The equity part of the portfolios is usually internationally invested in developed and emerging market stocks, but the fixed income part mainly in European government and corporate bonds. *Table 1* contains information on the tracked robo-advisor portfolios.

Table 1. Coverage data for robo advisors

	Initialization of coverage	Number of observations
Easyfolio	2015-05	44
Fintego	2015-05	44
Quirion	2015-05	44
SutorBank	2015-05	44
Vaamo	2015-05	44
GINMON	2016-05	32
Scalable Capital	2016-05	32
Whitebox	2016-05	32
Growney	2017-05	20
Investify	2017-05	20
VisualVest	2017-05	20
cominvest	2018-05	8
Prosperity	2018-05	8
ROBIN	2018-05	8
Solidvest	2018-05	8
WeltInvest	2018-05	8

Source: author’s calculations based on data from BrokerVergleich.

4.2. Empirical Results

4.2.1. Distribution of monthly returns

First, we analyze the reported monthly returns and estimate parameters of the sample return distributions. We report the results in Table 2.

There exists considerable variation between the return distributions of the robo-advisor portfolios. The monthly sample mean varies between -0.055% and 0.064% and the sample standard deviation between 1.827% and 2.102% . All portfolios exhibit negative skewness and excess kurtosis. The monthly minimum and maximum returns in the sample vary between -5.3% and -4.2% and 4.3% and 5.1% respectively.

We also constructed benchmark returns. We construct the benchmark as an equally weighted portfolio consisting of the MSCI World Index (EUR) and the Bloomberg Barclays Global Aggregate Total Return Index (Hedged in EUR). Because the robo-advisors in our sample do not engage in active portfolio management and hence are not trying to beat the benchmark, we calculated both before-fee (gross) benchmark returns and after-fee (net) benchmark returns. We calculated net benchmark returns by subtracting typical ETF management fees

Table 2. Descriptive statistics for robo-advisor and benchmark returns (monthly data)

	Arithmetic Mean (%)	Standard Deviation (%)	Skewness	Excess Kurtosis	Min (%)	Max (%)
Robo-advisor						
Easyfolio	-0.055	1.827	-0.363	1.175	-5.000	4.900
Fintego	-0.002	1.840	-0.472	0.766	-4.400	4.600
Quirion	0.041	1.868	-0.407	0.774	-4.200	4.900
SutorBank	-0.043	2.102	-0.410	0.661	-5.300	5.100
Vaamo	0.064	1.834	-0.250	0.175	-4.600	4.300
Benchmark						
Before fees	0.174	1.707	-0.346	0.856	-4.112	4.669
After fees	0.063	1.707	-0.346	0.856	-4.224	4.557

Note: Benchmark data is from Bloomberg.

Source: author.

and typical robo-advisor fees from the gross benchmark returns.⁴ In our opinion, after-fee benchmark returns are more appropriate for contrasting with robo-advisor returns.

Only Vaamo has a mean return that is higher than the after-fee benchmark return. No robo-advisor achieved an average monthly return that is higher than the gross benchmark mean return. Implementation costs, i.e. ETF management fees and robo-advisor fees reduce portfolio performance considerably.

The monthly returns of the five robo-advisors are highly correlated as the covariance/correlation matrix in Table 3 shows. This is not surprising since the tracked portfolios have a similar asset allocation (on average 50% equity and 50% fixed income). The minimum correlation coefficient is 85.9% (between Fintego and Vaamo) and the highest correlation coefficient exists between Quirion and SutorBank (94.8%).

Table 3. Covariance/correlation matrix of robo-advisor portfolios

	Easyfolio	Fintego	Quirion	SutorBank	Vaamo
Easyfolio	3.262	0.939	0.943	0.944	0.933
Fintego	3.084	3.309	0.931	0.899	0.859
Quirion	3.143	3.128	3.408	0.948	0.920
SutorBank	3.542	3.398	3.635	4.317	0.930
Vaamo	3.053	2.831	3.078	3.502	3.285

Source: author.

⁴ We assumed a management fee of 0.38% p.a. for an ETF that tracks the MSCI World Index and a management fee of 0.3% p.a. for an ETF that tracks the Bloomberg Barclays Global Aggregate Index. Furthermore, we assume a typical robo-advisor fee of 1% p.a.

4.2.2. Cumulative performance

After having analyzed the monthly returns, we turn our attention to the cumulative performance of robo-advisors from May 2015 until December 2018, which is shown in *Figure 3*.

Figure 3. Cumulative performance of robo-advisors in percentage, from May 2015 to December 2018

Source: author.

Cumulative performance is similar between the robo-advisors except for SutorBank and Easyfolio. SutorBank drops much more in the beginning of 2016 but gains more on a relative basis during the period until December 2018. In risk terminology, this refers to a much higher maximum drawdown of 10.6% for SutorBank. Maximum drawdowns (MDD) for all robo-advisors are reported in *Table 4*.

Table 4. Maximum drawdown for robo-advisors

Robo-Advisor	MDD (%)
Easyfolio	8.7
Fintego	7.6
Quirion	8.6
SutorBank	10.6
Vaamo	9.2

Source: author.

Table 5 reports the cumulative performance in each calendar year and since inception.

Table 5. Cumulative performance per calendar year

	2015*	2016	2017	2018	Since inception
Robo-advisor					
Easyfolio	-5.1%	6.1%	2.5%	-6.0%	-3.1%
Fintego	-4.8%	6.6%	1.4%	-3.6%	-0.8%
Quirion	-3.5%	7.0%	2.9%	-5.0%	1.1%
SutorBank	-5.7%	6.3%	5.7%	-8.2%	-2.8%
Vaamo	-4.8%	8.6%	3.5%	-4.6%	2.1%
Benchmark					
Before fees	-1.2%	6.7%	4.3%	-2.4%	7.3%
After fees	-2.1%	5.3%	2.9%	-3.7%	2.2%

* from 30 April

Source: author.

When we look at the returns since inception, no robo-advisor has been able to beat the benchmark on a before-fee basis and only Vaamo has achieved nearly the same performance after fees. Vaamo is the best-performing robo-advisor and Easyfolio the worst performing, with a 5.2% performance gap between them.

When we analyze the individual years, we find that in 2016 Quirion and Vaamo have been able to beat the index even before fees. In 2015, on the other hand, all robo-advisors performed worse than the index even on an after-fee basis. This might suggest that the asset allocation of the robo-advisors does not closely follow the 50% MSCI World and 50% Bloomberg Barclays Global Aggregate composition, but includes other asset classes as well. In addition, different rebalancing methodologies or ETF choice might have had an influence.

We report the relative performance of the individual robo-advisors in *Table 6*. In our small sample, we observe that no robo-advisor was consistently better or worse than its peers. Monthly robo-advisor returns also do not display significant autocorrelations.

In the next sections, we compare the robo-advisors regarding different risk-adjusted performance measures.

Table 6. Annual robo-advisor rankings with annual performance in percent

Rank	2015*	2016	2017	2018
1	Quirion −3.5%	Vaamo 8.6%	SutorBank 5.7%	Fintego −3.6%
2	Vaamo −4.8%	Quirion 7.0%	Vaamo 3.5%	Vaamo −4.6%
3	Fintego −4.8%	Fintego 6.6%	Quirion 2.9%	Quirion −5.%
4	Easyfolio −5.1%	SutorBank 6.3%	Easyfolio 2.5%	Easyfolio −6.0%
5	SutorBank −5.7%	Easyfolio 6.1%	Fintego 1.4%	SutorBank −8.2%

* from 30 April

Source: author.

4.2.3. Sharpe Ratio

The Sharpe ratio measures the excess return earned per unit of total risk. SR_i is computed as

$$SR_i = \frac{\mu_i - r_f}{\sigma_i},$$

where, for robo-advisor i , μ_i is the sample mean monthly return, r_f is the mean monthly 1-month EURIBOR return, and σ_i is the standard deviation of the monthly return for robo-advisor i . We report Sharpe ratios for robo-advisors and the benchmark in Table 7.

Table 7. Sharpe-ratios for robo-advisors and benchmark.

Sharpe Ratio	
Robo-advisor	
Easyfolio	−0.02
Fintego	0.01
Quirion	0.04
SutorBank	−0.01
Vaamo	0.05
Benchmark	
Before fees	0.26
After fees	0.20

Source: author.

4.2.4. Jensen's alpha

We also evaluate robo-advisors using the following model (Jensen 1968):

$$r_{it} = \alpha_i + \beta_i r_M + \varepsilon_i,$$

where r_{it} is the excess monthly robo-advisor return, r_M is the monthly excess return of the market. We use the MSCI World Index as a proxy for the market and calculate the excess return over the 1M Euribor returns. The estimated α_i and β_i for all robo-advisors and the benchmark are reported in *Table 8*.

Table 8. Jensen's alpha and beta.

	Beta	Jensen's alpha
Robo-advisors		
Easyfolio	0.494	-0.192
Fintego	0.491	-0.139
Quirion	0.520	-0.106
SutorBank	0.567	-0.205
Vaamo	0.487	-0.072
Benchmark		
Before fees	0.486	0.039
After fees	0.486	-0.072

Source: author.

The estimated values for Jensen's alpha are all negative and not statistically significant even at the 10% level. Negative values for alpha indicate that the robo-advisors performed worse than their exposure to the market portfolio would warrant. In our case, this is not surprising since robo-advisors do not perform active portfolio management and robo-advisor returns are after fees. Their stated goal is not to beat the market but simply to invest the clients' money in the markets in a way that suits their risk preference.

Next, we look at the asset-allocation decision of the robo-advisors in our sample to gain some further understanding of why some robo-advisors performed better than others.

4.2.5. Asset allocation

To capture exposures to typical asset classes, we analyze each robo-advisor return time series using a common factor set across all portfolios. To run our analysis, we selected five typical asset classes in which robo-advisors invest: developed market bonds (government and corporate), developed market equity, emerging

market equity, treasury inflation-protected bonds (TIPS) and commodities. We report summary statistics for these asset classes in *Table 9*.

Table 9. Summary statistics for monthly asset class returns, from May 2015 to December 2018

Asset class	Arithmetic Mean (%)	Standard Deviation (%)	Skewness	Excess Kurtosis	Min (%)	Max (%)
Bonds DM	0.043	0.696	-0.063	0.751	-1.832	1.792
Equity DM	0.306	3.442	-0.442	0.845	-8.485	9.057
Equity EM	0.045	3.849	-0.234	0.319	-10.315	8.258
TIPS	0.017	1.218	-0.337	-0.741	-2.378	2.241
Commodities	-0.596	3.479	-0.106	0.629	-9.859	7.981

Source: author.

The covariance/correlation matrix for the asset class (factor) returns is given in *Table 10*.

Table 10. Covariance/correlation matrix of asset class returns

	Bonds DM	Equity DM	Equity EM	TIPS	Commodities
Bonds DM	0.580	-0.073	0.029	0.663	-0.132
Equity DM	-0.197	12.632	0.755	0.207	0.376
Equity EM	0.116	13.912	26.901	0.273	0.448
TIPS	0.738	1.074	2.071	2.140	0.072
Commodities	-0.403	5.344	9.298	0.420	15.979

Source: author.

The asset classes are quite uncorrelated to each other. The highest correlation (75.5%) is observed between developed market equity and emerging market equity, the lowest correlation (-13.2%) exists between developed market bonds and commodities.

Figure 4 reports the cumulative performance of the individual asset classes over the sample period.

Emerging markets equity and commodities were the big losers until Q1 2016. Afterwards, emerging markets equity rebounded. Commodities markets were the worst performer with a return of approximately -20%. Over our period, a portfolio fully invested in developed markets equity would have outperformed all peers, whereas even a small exposure to commodities would have been a serious drag on performance.

Figure 4. Cumulative performance of different asset classes in percentages, from May 2015 to December 2018

Source: author.

We employ style analysis developed by Sharpe (1992) to infer the effective exposures of each robo-advisor to mutually exclusive asset classes. The effective mix method contrasts with one that measures the asset class exposure based on the reported holdings – return-based versus holdings-based style analysis. The results provide a guide for assessing the source of robo-advisor returns.

In order to estimate the exposure, we run a constrained regression. We regress monthly robo-advisor returns on the above-mentioned returns of the five asset classes. We also require that the asset class weights sum to one and that all weights are non-negative. The model is:

$$r_{it} = \sum_{j=1}^r \beta_j R_j + \varepsilon_i,$$

where r_{it} is the monthly return for robo-advisor i and R_j is the monthly return for asset class j . We further require $\sum_{j=1}^r \beta_j = 1$ and $\beta_j \geq 0 \forall j = 1, \dots, 5$. The estimates for β_j are reported in Table 11.

The selection of asset classes for our style analysis seems to be suitable: between 88.3% (SutorBank) and 94.6% (Easyfolio) of returns can be explained by exposures to the five asset classes. We report the explained R^2 and unexplained parts of the return variability in Table 12.

Table 11. Estimated asset allocation for robo-advisors and benchmark

	Bonds DM (%)	Equity DM (%)	Equity EM (%)	TIPS (%)	Commodities (%)
Robo-advisors					
Easyfolio	35.2	38.3	13.9	11.7	1.0
Fintego	27.7	43.3	3.4	23.5	2.1
Quirion	42.6	48.8	7.0	0.0	1.6
SutorBank	37.8	47.6	14.6	0.0	0.0
Vaamo	45.6	40.5	13.9	0.0	0.0
Benchmark					
Before fees	50.0	50.0	0.0	0.0	0.0

Source: author.

Table 12. Explained and unexplained return variability for robo-advisors

	Explained	Unexplained
Easyfolio	94.6	5.4
Fintego	90.1	9.9
Quirion	90.1	9.9
SutorBank	88.3	11.7
Vaamo	88.7	11.3

Source: author.

In general, the results of our style analysis confirm the reported asset allocation of the robo-advisors. All robo-advisors in our sample have roughly 50% exposure to equity and 50% to bonds. However, when one looks deeper, one finds several deviations from the reported asset allocation. Fintego, for example, seems to have a large exposure to TIPS according to our style analysis, but the reported asset allocation does not mention TIPS as a target asset class. According to the company’s website, Fintego invests into commodities, which, on the other hand, only shows up as a very small percentage in our style analysis. The reason could be our relatively small historical sample of only 44 monthly returns. Furthermore, our asset class universe might not be suited for all investment styles: Fintego invests only in European government bonds and corporate bonds. Other robo-advisors allocate assets not geographically but according to factors, e.g. value or growth.

In order to compare the styles of the different robo-advisors, we calculate their common style⁵ CS_{ij} as the sum of the overlap of the exposure to the individual asset classes as follows:

⁵ A concept used for example by Markov Processes International, Inc.

$$CS_{ij} = \sum_{a=1}^5 \min \{ \beta_{i,a}, \beta_{j,a} \},$$

where $\beta_{i,a}$ denotes the exposure of robo-advisor i to asset class a . We report the common style for the five robo-advisors in our sample in *Table 13*.

Table 13. Common style in percentage points for robo-advisors

	Easyfolio	Fintego	Quirion	SutorBank	Vaamo
Easyfolio	100.0	82.1	81.5	87.4	87.4
Fintego	82.1	100.0	76.0	74.4	71.6
Quirion	81.5	76.0	100.0	92.4	90.1
SutorBank	87.4	74.4	92.4	100.0	92.2
Vaamo	87.4	71.6	90.1	92.2	100.0

Source: author.

The result shows that the investment style of robo-advisors is very similar. Quirion and SutorBank seem to have the same style, i.e. the same exposure to asset classes. Fintego is the robo-advisor that differs in its investment style most from its peers.

Style analysis enables us also to create mimicking portfolio for reach robo-advisor, which can provide further performance insights. We calculate the mimicking portfolio returns as follows:

$$r_{it} = \sum_{j=1}^r \beta_j R_{jt},$$

where r_{it} is the return of mimicking portfolio for robo-advisor i and R_{jt} is the monthly return for asset class j . The resulting summary statistics of mimicking portfolio returns are reported in *Table 14*.

Table 14. Summary statistics for mimicking portfolio returns

Mimicking Portfolio	Arithmetic Mean (%)	Standard Deviation (%)	Skewness	Excess Kurtosis	Min (%)	Max (%)
Easyfolio	0.166	1.717	-0.338	1.036	-4.255	4.788
Fintego	0.137	1.718	-0.384	1.275	-4.455	4.824
Quirion	0.161	1.874	-0.436	1.064	-4.750	5.123
SutorBank	0.168	2.044	-0.465	1.216	-5.390	5.622
Vaamo	0.150	1.791	-0.440	1.255	-4.777	4.941

Source: author.

Figure 5. Cumulative returns of mimicking portfolios

Source: author.

When we compare *Table 14* and *Table 2*, we observe that the mimicking portfolios have nearly the same volatility as the original portfolios. The means of the mimicking portfolios are higher since these are before-fee returns. What is evident from *Figure 5* on the cumulative returns of mimicking portfolios is that differences in factor exposures alone cannot explain the observed differences in mean returns. The returns of Easyfolio and Vaamo should have been nearly identical given the estimated exposures to asset classes but from *Table 5* we know that Vaamo returned cumulatively 5.2% more than Easyfolio until December 2018.

In addition, management fees cannot explain the Easyfolio-Vaamo difference since Vaamo charges about 13 bps p.a. more than Easyfolio. We can also safely assume that the average ETF-management fees charged by the funds, in which the robo-advisors invest, are similar.

Table 15. Robo-advisor fees

	Annual management fee
Easyfolio	0.66%
Fintego	0.95%
Quirion	0.48%
SutorBank	0.70%
Vaamo	0.79%

Source: Finanztest (2017).

Given the way robo-advisors manage money and if asset allocation and management fees cannot explain the performance differences, then the following characteristics must be the reason. First, exposure to other factors. Vaamo's style analysis only explained 89% of the return variability; 11% remains unexplained. This 11% might result from exposure to asset classes/factors (e.g. small cap, value stocks, or momentum) that our analysis did not include. This is even more plausible since Vaamo invests into funds managed by US fund manager Dimensional Fund Advisors, which is famous for employing the Fama/French (1993) factor methodology. Second, portfolio implementation might play a role. The specific funds the robo-advisor invests in and how the fund buys and sells these ETFs may differ. In addition, the portfolio management techniques of the ETFs play a role. Third, rebalancing is important, i.e. how and how often the current portfolio weights are brought back to the target weights. If re-balancing is done at (ex-post) not optimal points in time, it has a negative effect on portfolio performance.

5. CONCLUSIONS

We analyzed monthly return data for five German robo-advisors over the May 2015 – December 2018 period. We documented significant performance differences between some of these robo-advisors. Using returns-based style analysis, we found their effective asset mix. Mimicking portfolios have been constructed for each robo-advisor and using these, we tried to explain differences in performance with differences in asset allocation. We found that differences in asset allocation cannot fully explain the observed differences in performance between different robo-advisors. Alternative reasons for these performance differences include missing factors, portfolio implementation, and re-balancing.

This result is significant since we demonstrated that portfolios with a similar (stated) asset mix of around 50% bonds and 50% equities (which would be suitable for people with a similar risk preference) can show large differences performance. Hence, finding the right robo-advisor is of critical importance.

Given the ongoing debate about the relative merits of traditional financial advice and robo-advice, it would also be interesting to contrast performances between portfolios recommended by traditional financial advisors and robo-advisors for the same person. Robo-advisors typically recommend a portfolio based on very few data points / attributes from a client. A traditional financial advisor would be able to use much more information from the client in order to recommend a portfolio that would be much more suitable for them.

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