

ROBO-ADVISORS AS PART OF INDUSTRY 4.0 IN FINANCIAL MARKETS: EVOLUTIONARY DEVELOPMENT, METHODS, AND FIRST PERFORMANCE INSIGHTS

Thomas Holtfort^{*}, Andreas Horsch^{**}, Joachim Schwarz^{***}

^{*} Corresponding author, FOM University of Applied Sciences, Essen, Germany

Contact details: FOM University of Applied Sciences, Leimkugelstr. 6, 45151 Essen, Germany

^{**} Chair of Investment and Finance, Technische Universität (TU) Bergakademie, Freiberg, Germany

^{***} Faculty of Business Studies, University of Applied Sciences Emden-Leer, Emden, Germany



Abstract

How to cite this paper: Holtfort, T., Horsch, A., & Schwarz, J. (2022). Robo-advisors as part of industry 4.0 in financial markets: Evolutionary development, methods, and first performance insights. *Risk Governance and Control: Financial Markets & Institutions*, 12(2), 38–46. <https://doi.org/10.22495/rgcv12i2p3>

Copyright © 2022 The Authors

This work is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0). <https://creativecommons.org/licenses/by/4.0/>

ISSN Online: 2077-4303

ISSN Print: 2077-429X

Received: 12.05.2022

Accepted: 05.07.2022

JEL Classification: G11, O16, O31

DOI: 10.22495/rgcv12i2p3

Today, an essential disruptive trend of the fourth industrial revolution is robo-advisors that offer innovative asset management services (Tao, Su, Xiao, Dai, & Khalid, 2021). They are automated investment platforms that use quantitative algorithms to produce advice to investors to help them manage their portfolios and are accessible to clients online (Beketov, Lehmann, & Wittke, 2018). Until now, there has been no comprehensive analysis of the development of these innovative advisors, the asset allocation methods used, and the performance (also concerning the Corona crisis). Thus, the paper takes robo-advisory-related research a step further by analyzing the development of robo-advisory on a global scale from an evolutionary point of view, at the same time focusing on the variety of methods applied by the advisors and the factors influencing their performance between 2018 and 2021 by regression analysis. Our results show that modern portfolio theory remains the primary framework used by robo-advisors, even though some use new approaches. The average performance of robo-advisors appears to beat the market benchmark, however not significantly during the Corona-crash period. Important factors influencing their performance are the number of allocation methods applied and, specifically, the technique of rebalancing. The findings demonstrate that in the context of Industry 4.0, robo-advisors can offer advantages not only in terms of costs and technical processes but also in terms of performance.

Keywords: Robo-Advisors, Industry 4.0, Innovation, Evolutionary Economics

Authors' individual contribution: Conceptualization — T.H. and A.H.; Methodology — T.H., A.H., and J.S.; Formal Analysis — J.S.; Investigation — T.H.; Data Curation — T.H.; Writing — Original Draft — T.H., A.H., and J.S.; Writing — Review & Editing — T.H., A.H., and J.S.; Visualization — T.H.

Declaration of conflicting interests: The Authors declare that there is no conflict of interest.

1. INTRODUCTION

Innovative information technology is in the foreground of the fourth industrial revolution (nicknamed Industry 4.0, and also understood as the “digital transformation” of the economy (Culot, Nassimbeni, Orzes, & Sartor, 2020). The speed of the disruption that has been advanced by Industry 4.0 is so tremendous that some economies have found it challenging to keep up with the progress (Kim, 2018; Su, Qin, Tao, & Umar, 2020). The emergence of innovative technologies affects the level of management in firms as well as organizational and regional structures in a disruptive sense (Horvath & Szabo, 2019; Muscio & Cifforilli, 2020). Traditional financial intermediaries such as banks and insurers are among those organizations exposed to substantial change resulting in new opportunities and new risk factors that can be put forth by this revolution (Tao, Su, Xiao, Dai, & Khalid, 2021; Grove, Clouse, & Xu, 2020). Against this backdrop, the adaption and diffusion of technology in the financial service area is expediting extremely fast, including a Schumpeterian shift from traditional to more innovative financial products (Liu, Li, & Wang, 2020; Ahmad, Kowalewski, & Pisany, 2021).

In this regard, robo-advisors can be defined as FinTech institutions that offer financial services employing new (information) technology (see basically on FinTechs, Thakor, 2020; Holtfort, Horsch, and Schwarz, 2021; Eickstädt and Horsch, 2021). As such, robo-advisors are considered one of the most important disruptive trends (re-)shaping the asset management industry (Tao et al., 2021; Siddiqui & Rivera, 2022). In a nutshell, a robo-advisor can be defined as a mechanized investment platform that operates with automated algorithms to provide financial advice to investors (Beketov, Lehmann, & Wittke, 2018; Jung, Dorner, Glaser, & Morana, 2018). Based on this general classification of robo-advisors, four generations can be distinguished (Deloitte, 2016; Beketov et al., 2018).

Robo-advisors of the first and second generation focused information transmission, including, for example, online questionnaires and proposals, thereby providing a combination of advice and online access to traditional asset management services. In contrast, robo-advisors of the third and fourth generation include systems that cover the entire investment process, starting from the selection of the instrument universe and finishing with periodic portfolio rebalancing and performance reporting. In doing so, these institutions utilize quantitative methods and algorithms to construct and rebalance the portfolios they manage (Deloitte, 2016).

The growth prospects for these institutions are considerable, as different forecasts predict them to manage almost 2.14 trillion USD by 2023, which would be nearly 10% of the total global assets under management (Statista, 2021; Abraham, Schmukler, & Tessada, 2019). Overall, Industry 4.0 can lead to two benefits in the area of asset management (Brenner & Meyll, 2020):

1. Robo advisors could provide retail investors access to financial advice that was unavailable for them before.

2. They aim to deliver this advice at lower transaction costs, which could turn them more efficient than conventional setups (due to savings in fixed costs and reduced minimum investment requirements).

The emergence of robo-advisory, which can be explained in more detail by evolutionary economics, gained momentum after the 2007–2008 global financial crisis, when tighter regulations of traditional banks on the one hand, and developments in computer science, on the other hand, increased incentives to develop non-bank, technology-based financial companies (Abraham et al., 2019). The ideas and fundamentals of evolutionary economics can be traced back to early Austrian and institutional economics, as represented by Menger (1871), Veblen (1898), Marshall (1898), Schumpeter (1911), Hayek (1945), and von Mises (1949), who provided seminal contributions. As well, the fundamental work of Nobel Laureate North (1990) on the relevance of institutions and institutional change, especially the effects of (formal/informal) rules on economic processes in general, contributes to a deeper understanding of the emergence and development of robo-advisory in particular.

The first robo-advisors, i.e., US-American companies Wealthfront and Betterment, started operations already in 2008, but neither company offered financial advice to investors until 2010 (Fisch, Labouré, & Turner, 2019). Wealthfront began as a mutual fund company and originally used human advisors, not robots, pursuing a business model based on providing high-quality asset management services at a lower cost and without the substantial minimum investments required by other professional advisors at that time (Ha, 2010). Wealthfront’s founders Andy Rachleff and Dan Carroll, who consequently can be seen as alert entrepreneurs (on the concept of the alert entrepreneur, see the seminal contributions of Kirzner, 1973, 1997), shifted the company’s focus after they discovered the potential that computer software offered for making investment advice accessible to more people at even lower cost (thus Rachleff and Carroll put an idea of new software technology for advisory into practice, see Fisch et al., 2019; Wealthfront, n.d.). Betterment’s founder Jon Stein developed a method that automated the process of selecting and managing investments (according to Hayek, he generated a unique form of technological knowledge, enabling him to penetrate traditional banking markets; on the economic relevance of knowledge, see the seminal work of Hayek, 1945, 1973), and thus turned an abstract opportunity into actual market processes and even competitive advantage. Although Betterment claims to offer financial advice at a lower cost than traditional financial advisers, the key component of the company’s strategy appears to be making investing simple for its clients (Stein, 2016; Fisch et al., 2019). Meanwhile, the automated business models of the first robo-advisors have been imitated by various competitors in North America, Europe, and Asia (for the relevance of imitation and adaptation for institutional change see, Nelson and Winter, 1982), with the US having become the largest market according to assets under management (Statista, 2021). Altogether, it can be stated that

the first robo-advisors (in the sense of North they can be seen as new institutions, which set novel structures and drive market processes within the framework of the applicable market rules, see North, 1990) added to the competitiveness of (financial advisory) market processes and structures of banking markets (Schumpeter, 1911, 1942) by using digital technology/products embedding them into the Industry 4.0 phenomenon and caught traditional financial intermediaries unaware, as particularly banks struggled with the consequences of the financial crises since 2007.

Despite the popularity and outreach of robo-advisors (Eule, 2018; Fisch et al., 2019), there is scant empirical research on their methods, performance, and especially factors influencing the latter. In this paper, we attempt to fill the gap by providing insights on the asset allocation/portfolio methods and the performance of robo-advisors of the third and fourth generation (only these types of robo-advisors can be considered as “true” robo-advisors according to their performing of portfolio management and optimization, see Beketov et al., 2018). Our findings suggest that the robo-advisors have, on average, outperformed the benchmark recently (2018–2021). Moreover, the results show that the allocation method of rebalancing is advantageous for the performance of robo-advisors.

Keeping these previous findings in mind, the rest of the paper is structured as follows. Section 2 presents a review of current literature, followed by an introduction to data and methodology in Section 3. Sections 4 and 5 present and discuss the results. Finally, Section 6 concludes the paper.

2. LITERATURE REVIEW

Previous research on robo-advisory topics predominantly focused on definitions, processes, characteristics/benefits, and market overviews of robo-advisors (Phoon & Koh, 2018; Abraham et al., 2019; Brenner & Meyll, 2020; Jung et al., 2018; Torno, Metzler, & Torno, 2021). At the same time, robo-advisors have been focused with respect to problems of the (economics of) law and regulation (Seidt, Zaharis, & Jarrett, 2019; Treleaven, Barnettt, & Koshiyama, 2019; Ringe & Ruof, 2021). Regarding the allocation methods and especially the performance of robo-advisors, there is only scant empirical literature. Grealish and Kolm (2022) state in their recent paper (however without empirical data) that most robo-advisors build and manage portfolios by modern portfolio theory, while some robo-advisors employ other allocation methods like balancing portfolios. Beketov et al. (2018) also confirm for a dataset of 28 robo-advisors the relevance of the portfolio theory as most occurred allocation framework, modified by some other methods like, for example, value at risk. Helms, Hölscher, and Nelde (2021) analyze a sample of 15 US, UK, and German robo-advisors using different performance measures (e.g., Sharpe ratio) that for the US robo-advisors the Sharpe ratio is highest, followed by the UK. Puhle (2019) evaluate the performance of five German robo-advisors between 2015 and 2018 using Sharpe ratios. The findings show that no robo-advisor was able to beat the benchmark and the performance in the sample varies greatly. That performance data for

robo-advisors are hard to find and vary widely confirms Scholz and Tertilt (2020) by analyzing only the one or two biggest robo-advisors in the US, the UK, and Germany. They state that by and large, the performance of robo-advisors seems to be reasonable. Finally, Torno and Schildmann (2020) show for a dataset of 35 robo-advisors considering different recommended portfolio structures (in terms of risk) for the months of September and October 2019 that within the portfolio structures a higher risk-affinity leads to a higher Sharpe ratio and vice versa.

3. RESEARCH METHODOLOGY AND DATA

Meanwhile, available information about robo-advisors is tremendous and truly diverse in terms of topics covered and the quality of writings (Beketov et al., 2018). Despite this abundance, little is known about the core portfolio optimization, asset allocation methods, and the respective assets under management volumes of robo-advisors (as an early, yet small-sample primer, see Park, Ryu, and Shin, 2016). Subsequent analyses were based on a set of 119 companies listed as robo-advisors (information was derived, e.g., from www.adviserinfo.sec.gov or www.techfluence.eu; on the use of websites as a scientific method in finance, see, e.g., Adhami et al., 2018). This list was compiled during extensive prior research¹ (to ensure the quality of information of the robo-advisor, the respective web pages of these robo-advisors were verified twice). The web pages of these robo-advisors were analyzed, and all of the information about the asset allocation and portfolio optimization methods were collected. The data set included robo-advisors from 18 countries, with 32% of the companies located in the US, 21% in Germany, 9% in the UK, 7% in Canada, and the remaining 31% in other countries (e.g., India and China). The robo-advisors in the dataset were founded between 2007 and 2021, with the average year being 2014 (the most frequent years are: 2014, 2015, and 2017). Referring to the use of an active, passive or mixed investment strategy/allocation, 55% of the robo-advisors work with a purely passive strategy (Exchange Traded Funds), 26% with a mixed approach (Exchange Traded Funds and active management funds), and 19% with a pure active strategy (active management funds). Regarding whether a bank is the parent company of the robo-advisor, the data show that for 18% of the robo-advisors, this is the case (above all in Germany), whereas the other robo-advisors work independently. The assets under management volumes of the examined robo-advisors ranged from 1 to 161,000 million USD, with the average value being 5,762 million USD.

Some robo-advisors also have specific features that set them apart from others. Fincite (Germany), Fidelity Go (the US), or Opti (Sweden), for example, are robo-advisors that use kind of a hybrid model by working with both mathematical algorithms and human advisors. Especially in times of crisis, such as the Corona pandemic and the associated price declines on the stock markets in spring 2020, this can be future-oriented for clients regarding the possibility of having an additional human advisor. Furthermore, some robo-advisors offer their clients mostly sustainable investments, like, for

¹ The list is available upon request from the corresponding author.

example, June (Denmark) or Sustainfolio (the US). The Swedish robo-advisor Robosave asks its clients about financial literacy as part of the investment process to better classify the clients' risk attitudes. COCOA, an Islamic finance-oriented robo-advisor from Bahrain, only works with halal-compliant investment products. Finally, Ellevest (the US) is a robo-advisor specializing in women as clients.

To analyze the frequency of the methods in robo-advisors (i.e., the number of robo-advisors applying a particular method), a table was compiled based on method names and definitions the robo-advisors used to describe their methodology, regardless of the specificity or clarity of their websites. Thus, the terms "Portfolio theory" or "Value at risk" refer to methodological frameworks that may include other more specific methods. Other names, such as "Black-Litterman model" or "Factor model", refer to such particular methods. Ultimately, the terms "Sample portfolio" and "Rebalancing" are defined generally and ambiguously, and therefore, the actual methods applied to derive such portfolios are unclear. As part of the next step in the analysis, the occurrences of all methods irrespective of their generality and definition clarity were counted (from one to four terms per robo-advisor). This analysis aimed to describe and display the overall methodological situation in robo-advisors.

Furthermore, publicly available information on the companies' assets under management was collected and related to the methods applied by the respective companies. This approach can indicate the assets under management volumes managed by different methods, but the results are only approximate, as the actual information on the methods' assets under management is not available. All of the methods' names were considered to cover the entire methodological landscape in this analysis. The most recent information on the assets under management was retrieved either from the companies' websites or from other robo-advisor-related websites (e.g., www.adviserinfo.sec.gov or www.techfluence.eu).

To evaluate the first performance insights of robo-advisors (the necessary information was available on different websites, e.g., www.nerdwallet.com, www.biallo.de, www.boringmoney.co.uk, or from individual websites of the robo-advisors analyzed); first, the average cumulative 3-year performance (this was the only performance information that was common to all websites) of the robo-advisors (for a mixed portfolio of stocks and bonds) was compared with a standard (Clare, O'Sullivan, Sherman, & Zhu, 2019) benchmark (50% Morgan Stanley Capital International (MSCI) World/50% Barclays Global Aggregate Bonds) and, on the other hand, the particular Corona-pandemic situation was taken into account by also comparing the performance of the robo-advisors during the Corona-crash in spring 2020 with this benchmark (this against the background to what extent robo-advisors/algorithms do their job well even in times of crisis). Finally, to gain more in-depth knowledge about the performance of robo-advisors, possible influencing factors (which have already been described in this section and document a particular relevance) are analyzed with regard to the 3-year cumulative long-term performance from March 31, 2018, to March 31, 2021 (short-term influences on the performance are therefore not of great impact and longer periods are

not yet widely available) employing a regression analysis (an alternative for the regression analysis might be — depending on the regression diagnostic — a specific nonparametric method, see basically Dickhaus, 2018; for the use of nonparametric tests in robo-advisory research, see Torno and Schildmann, 2020; Warchlewska and Waliszewski, 2020). These influencing factors (and thus the independent variables) are assets under management, asset allocation/risk management method, year of foundation, country of origin, active or passive investment style, and whether a bank is involved in the robo-advisor in terms of capital or not.

4. RESULTS

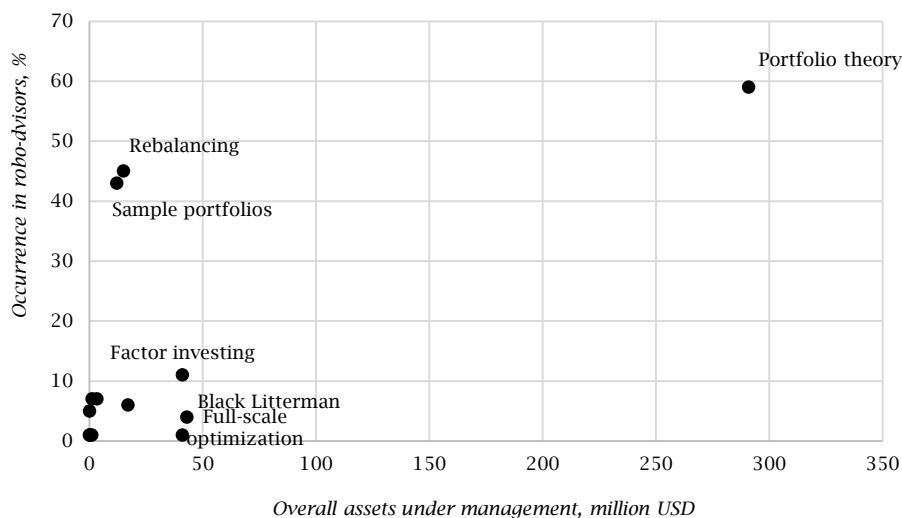
The analysis of the 119 robo-advisors has shown that information about the asset allocation/risk methods is only available for 109 of them. The others either do not provide such information or do not use any formal asset allocation methods (this holds in particular for robo-advisors of the first and second generation like, e.g., US-American Robin Hood, British RiskSave, or French FundShop). Therefore, only the aforementioned 109 robo-advisors were considered for the analysis of the methods used. Altogether, these 109 robo-advisors explicitly refer to 14 various methods, most frequently to Markowitz's Portfolio theory (Markowitz, 1952), followed by Rebalancing and Sample portfolios (Table 1). Among these three terms, only the first can be called a genuinely quantitative method, whereas the other two are general definitions provided on the companies' websites, which may include various methods unknown to us (therefore, a general overview is provided hereafter).

Table 1. Occurrence of different methods of analyzed robo-advisors (multiple answers possible)

<i>Method</i>	<i>Occurrence of the framework in %</i>
Portfolio theory (diversification)	59
Rebalancing	45
Sample portfolio	43
Factor investing	11
Value at risk	7
Artificial intelligence (neural networks)	7
Dynamic investing	6
Downside protection	5
Black-Litterman model	4
Full-scale optimization	1
Constant proportion portfolio insurance	1
Liability driven	1
Behavioral finance (prospect theory)	1
Technical analysis (moving averages)	1

The analysis of the correspondence between the methods' occurrence and the respective assets under management (if available) demonstrates that most robo-advised assets are managed according to the insights of Portfolio theory (Figure 1). Furthermore, we detected that comparably advanced methods, such as the Black-Litterman model (Black & Litterman, 1991), Full-scale optimization (Cremers, Kritzman, & Page, 2005), or factor investing (Fama & French, 1993), are applied to comparably high assets under management volumes in general, although the number of robo-advisors using these methods is small.

Figure 1. Relation between the methods' occurrence (%) and volumes of robo-advisors' assets under management in million USD



Referring to — until now rather underresearched — the performance of the robo-advisors, a dataset of only 58 robo-advisors could be found (data on the other robo-advisors were not available) to get the cumulative 3-year performance (for a 50:50 mixed portfolio of stocks and bonds) from March 31, 2018, to March 31, 2021. These robo-advisors are based predominantly in the US, Germany, the UK, Canada, and India. Concerning the performance of the robo-advisors compared to a standard benchmark (as mentioned before), it becomes apparent (Table 2) that robo-advisors beat the benchmark and therefore seemed to have performed well.

Table 2. Benchmarking the performance of robo-advisors (March 31, 2018, to March 31, 2021)

Performance of robo-advisors	Performance of the benchmark
24.28%	20.68%

In the next step, we separately analyze the performance of the robo-advisors with the aforementioned benchmark during the crash in spring 2020 caused by the Corona-pandemic situation (the dataset for this precisely selected period in spring 2020 was here only available for 20 German robo-advisors and a few others, but not for robo-advisors in the US or the UK; furthermore, the data for the Corona-crash period are only available as separate data and not as part of the previously examined 3-year period). Hence, the period from February 1, 2020, to March 31, 2020, was used to analyze how the asset allocation/risk management systems of the robo-advisors worked in

times of crisis, and on the other hand, how influential the investment style (active, mixed or passive) turned out during that particular period. Table 3 displays that, in total, the robo-advisors performed slightly better than the benchmark (taking into account the small and above all German sample here).

Table 3. Benchmarking the performance of robo-advisors during the Corona-crash period (February 1, 2020, to March 31, 2020)

Performance of robo-advisors	Performance of the benchmark
-11.36%	-12.57%

Finally, the results of the linear regression are considered. As indicated above, the assets under management, asset allocation/risk management method, year of foundation, country of origin (measured by two dummy variables: Germany compared to other countries and the US compared to other countries), active, mixed, or passive investment style (measured by two dummy variables: mixed compared to other investment styles and passive compared to other investment styles), and whether a bank holds shares of the robo-advisor were considered as independent variables. For the asset allocation/risk management method, only the three methods with the highest occurrence (see Table 1) were used for the sake of clarity. A further variable refers to the number of asset allocation and risk management methods a robo-advisor applies. This resulted in an overall number of eleven independent variables and the following regression equation:

$$\begin{aligned}
 \text{Cumulative 3-year performance} = & \beta_0 + \beta_1 * \text{Germany} + \beta_2 * \text{US} + \beta_3 * \text{Assets under management} + \\
 & \beta_4 * \text{Bank} + \beta_5 * \text{Number of methods} + \beta_6 * \text{Year of foundation} + \beta_7 * \text{Portfolio theory} + \\
 & + \beta_8 * \text{Rebalancing} + \beta_9 * \text{Sample portfolio} + \beta_{10} * \text{Mixed style} + \beta_{11} * \text{Passive style}
 \end{aligned}
 \tag{1}$$

Germany, US, Bank, Portfolio theory, Rebalancing, Sample portfolio, Mixed style, and Passive style are 0/1 indicator variables (dummy variables), and the others are metric variables.

Evidently, it is possible to perform regression for those 58 robo-advisors only for which we were able to calculate the cumulative 3-year performance. Unfortunately, for a substantial part of this

subsample, information on assets under management (22) and year of foundation (4) turned out to be unavailable.

Therefore, only 35 robo-advisors remain for the regression, 13 from Germany, 16 from the US, and 6 from other countries. This is a comparably small sample size, but the best available for the time being, and not unusual for the early analysis of innovative types of institutions compared to the 11 independent variables requiring thorough consideration of the stability of the regression results. For this purpose, we ran the standard regression diagnostics.

First, we checked for unusual observations, i.e., outliers. A single observation is called unusual if the regression line follows a significantly different trend without this single observation compared with the regression line including this single observation. This results in different estimates for the regression coefficients, and Cook's distance measures this difference to the original parameter estimates (Cook, 1977). The higher Cook's distance, the more unusual is the corresponding single observation. Another indicator is the leverage values (Everitt & Skrondal, 2010). They measure the distance of the independent variables' values for one observation to all other independent variables' values. The higher the leverage values, the more unusual is the corresponding single observation. Both Cook's distance and leverage values revealed one unusual observation, the robo-advisor Vanguard: the assets under management of Vanguard amount to 161 billion USD, which is around four times as high as the second largest value of 41 billion USD (Schwab). Further, 161 is more than three standard deviations ($sd = 27.8$) away from the average value ($mean = 9.1$). Therefore, this observation was omitted from further analyses.

Next, we checked for model misspecification, especially for the linearity assumption, which states that the relationship between dependent and independent variables is linear. Standard measures are Ramsey's test (Ramsey, 1969) and a scatter plot of the regression residuals against the fitted regression line. If this relationship is not linear, a linear regression model would be an inappropriate approach. Non-linearity results in systematic deviation of the residuals from the regression line, which a scatter plot can reveal. Ramsey's test compares the linear model with an extended model by adding nonlinear independent components to the original model. If the nonlinear independent components are significant, then misspecification is present. Both Ramsey's test ($p = 0.9122$) and the scatter plot did not indicate any model misspecification, so the linearity assumption holds.

An important assumption for the regression analysis is the independence of the observations from each other. The economic interpretation of this assumption is that the cumulative 3-year performance of each robo-advisor is independent of the performance of any other robo-advisor. Independence can be assessed by considering

the autocorrelation of the residuals. The Durbin-Watson test tests if a residual's value depends on the value of the adjacent residual (Verbeek, 2017), and the (first-order) Breusch-Godfrey test (Breusch, 1978) extends the regression model for the adjacent residual and tests if the adjacent residual has a significant effect. Both, Durbin-Watson test ($p = 0.8055$) and Breusch-Godfrey test ($p = 0.5666$) revealed no autocorrelation.

The next assumption to be tested is the homoscedasticity assumption. Homoscedasticity means that the accuracy of the regression line is the same, no matter if the independent variables have low or high values, i.e., the explanatory power of the regression coefficients is the same for every value of the independent variables. Under homoscedasticity, the scatter plot of the residuals against the fitted line shows no pattern of the residuals. However, if a funnel-shaped pattern is present, then the variance of the residuals changes substantially along the regression line, indicating heteroscedasticity. Both the Goldfeld-Quandt test (Griffiths, Hill, & Judge, 1993) and the Breusch-Pagan test (Breusch & Pagan, 1979) test this. The Goldfeld-Quandt test ($p = 0.5267$) and the Breusch-Pagan test ($p = 0.0517$), however, showed unequal results. Still, the scatter plot revealed no funnel-shaped pattern so that homoscedasticity can be assumed.

Another critical assumption is absent (or at least low) multicollinearity, meaning that every independent variable is independent of the other independent variables. If one independent variable is dependent on all other independent variables, then this variable contains no additional information and can be omitted. For the assessment of multicollinearity, regression analyses are performed for every independent variable on all other independent variables. Then, the R^2 values from these regression models are taken, and the inverses of $(1 - R^2)$ are calculated. These values are called variance inflation factors and should not exceed 5. All variance inflation factors were below 1.5, indicating no multicollinearity.

The final assumption to be examined is the normality of the residuals. This is necessary for the test theory and the calculation of p-values and can be examined by the Shapiro-Wilk test (Shapiro & Wilk, 1965), a histogram of the residuals, and the quantile-quantile-plot (qq-plot). The Shapiro-Wilk test ($p = 0.5435$), the slightly right-skewed histogram, and the qq-plot showed no significant deviation from the normality of the residuals. Overall, the regression diagnostics showed that all regression assumptions listed above are met.

As a further robustness check, regressions have been performed, reducing the number of independent variables by one. This checking has been done for each non-significant independent variable, resulting in seven reduced regressions. This resulted in slight changes in regression coefficients' estimates and p-values, but not in significance levels, indicating the stability of the regression results, which Table 4 displays.

Table 4. Regression results of robo-advisors according to their cumulative 3-year performance

<i>Variable</i>	<i>Estimate</i>	<i>Standard error</i>	<i>t-value</i>	<i>p-value</i>
Intercept	973.70	1308.55	0.74	0.465
Germany vs. other countries	-0.46	5.15	-0.09	0.929
US vs. other countries	-3.51	4.48	-0.78	0.442
Assets under management	-0.12	0.22	-0.52	0.607
Bank	6.38	5.93	1.08	0.293
Number of methods	-6.91	2.71	-2.55	0.018*
Year of foundation	-0.47	0.65	-0.72	0.480
Portfolio theory	3.86	4.30	0.90	0.378
Rebalancing	10.30	4.28	2.41	0.025*
Sample portfolios	6.15	4.65	1.32	0.199
Mixed style vs. active style	-8.14	8.40	-0.97	0.343
Passive style vs. active style	-5.69	8.93	-0.64	0.531

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

The results show a significant positive effect of the Rebalancing method (the other two methods also show positive, albeit not significant, effects). A robo-advisor applying the Rebalancing method realized a significantly higher cumulative 3-year performance. Further, a significant adverse effect can be observed concerning the number of methods a robo-advisor applies: the more methods used, the lower the cumulative 3-year performance.

5. DISCUSSION

Table 2 has made clear that robo-advisors are able to outperform the benchmark on average, at least for the period 2018–2021. One reason for their superior performance could be found in their asset allocation/risk management method or investment style (active, mixed, or passive). Furthermore, it could be rooted in the data analysis' innovative automation that leads to better investment screening processes and portfolio management. With regard to the Corona crash in spring 2020, Table 3 displays that on average the robo-advisors performed slightly better than the benchmark. This could be a hint for the suitability of their allocation/risk methods in times of crisis. However, a closer look at the data clarifies that robo-advisors applying a mixed/active style performed better (-9.26%) than those investing in a passive style (-13.22%) during this crisis period. This could be since, during a downswing, a more active investment style can consciously reduce the risk, while this does not work for a passive style. Altogether, it can be stated that since the robo-advisors did not perform significantly better than the benchmark in times of crisis, this could increase the clients' desire for at least a hybrid model (combined use of robo and human advisors), especially in a retreating market (on this "warm body effect", see Fisch et al., 2019).

As the regression analysis in Table 4 has shown, a number of different methods for allocation and risk management (used at the same time) applied by the robo-advisor is not really advantageous (only the Rebalancing method for its own shows significant positive effects). This could mean that too much optimization of the asset allocation process by various methods does not bring any added value. A positive but not significant effect can be seen in bank ownership. Reasons for this could be based on more extensive funding, and

also technology support of the robo-advisors with the help of the bank. Finally, it can be stated that the variables country of origin, assets under management and year of foundation tend to have a slightly negative impact on the performance. Thus, one could conclude that small robo-advisors with low assets under management have a better chance of good performance (or to put it another way: perhaps high volume robo-advisors are too big to perform).

6. CONCLUSION

Technological innovations have resulted in various disruptions in the financial services area. In this context, robo-advisors are a disruptive trend in asset management, which is linked with a rapid evolution (explained by evolutionary economics) of these new financial institutions in recent years. These automated investment advisors claim to offer various benefits to investors. Besides their assumed cost-effectiveness and low minimum investment requirements, which make them accessible to a larger number of investors, the robo-advisors' good performance compared to the benchmark is to be mentioned. In addition, the analysis displays selected positive influencing factors (e.g., the Rebalancing method) on the performance. However, the use of various allocation methods is not fundamentally advantageous. Robo-advisors, who use not only standard methods (e.g., Portfolio theory) but also relatively modern methods such as, e.g., value at risk (like Scalable), show that precisely this value at risk model has proven to be vulnerable in the Corona crisis (Deloitte, 2020).

There are, however, limitations to our analysis. On the one hand, it remains to be tested by future research based on a larger dataset to what extent robo-advisors deliver good performance in general and in times of crises in particular, especially against the backdrop of the use of different and modern allocation/risk methods. On the other hand, the regulatory framework of robo-advisors — which is evolving, too — should also be examined more closely in the future. Finally, the hybrid advisor model should be analyzed more intensively concerning future performance compared to full automated robo-advisors on the one hand, and traditional human advisors on the other hand.

REFERENCES

1. Abraham, F., Schumaker, S. L., & Tessada, J. (2019). Robo-advisors: Investing through machines. *Worldbank Research & Policy Briefs*, 21. Retrieved from <http://documents.worldbank.org/curated/en/275041551196836758/Robo-Advisors-Investing-through-Machines>
2. Adhami, S., Giudici, G., & Martinazzi, S. (2018). Why do businesses go crypto? An empirical analysis of initial coin offerings. *Journal of Economics and Business*, 100, 64–75. <https://doi.org/10.1016/j.jeconbus.2018.04.001>
3. Ahmad, M. F., Kowalewski, O., & Pisany, P. (2021). What determines initial coin offering success: A cross-country study. *Economics of Innovation and New Technology*. <https://doi.org/10.1080/10438599.2021.1982712>
4. Beketov, M., Lehmann, K., & Wittke, M. (2018). Robo advisors: Quantitative methods inside the robots. *Journal of Asset Management*, 19, 363–370. <https://doi.org/10.1057/s41260-018-0092-9>
5. Black, F., & Litterman, R. (1991). Asset allocation: Combining investor views with market equilibrium. *The Journal of Fixed Income*, 1(2), 7–18. <https://doi.org/10.3905/jfi.1991.408013>
6. Brenner, L., & Meyll, T. (2020). Robo-advisors: A substitute for human financial advice? *Journal of Behavioral and Experimental Finance*, 25, 100275. <https://doi.org/10.1016/j.jbef.2020.100275>
7. Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian Economic Papers*, 17(31), 334–355. <https://doi.org/10.1111/j.1467-8454.1978.tb00635.x>
8. Breusch, T. S., & Pagan, A. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, 47(5), 1287–1294. <https://doi.org/10.2307/1911963>
9. Clare, A., O'Sullivan, N., Sherman, M., & Zhu, S. (2019). The performance of US bond mutual funds. *International Review of Financial Analysis*, 61, 1–8. <https://doi.org/10.1016/j.irfa.2018.12.001>
10. Cook, R. D. (1977). Detection of influential observation in linear regression. *Technometrics*, 19(1), 15–18. <https://doi.org/10.1080/00401706.1977.10489493>
11. Cremers, J.-H., Kritzman, M., & Page, S. (2005). Optimal hedge fund allocations: Do higher moments matter? *The Journal of Portfolio Management*, 31(3), 70–81. <https://doi.org/10.3905/jpm.2005.500356>
12. Culot, G., Nassimbeni, G., Orzes, G., & Sartor, M. (2020). Behind the definition of Industry 4.0: Analysis and open questions. *International Journal of Production Economics*, 226, 107617. <https://doi.org/10.1016/j.ijpe.2020.107617>
13. Deloitte. (2016). *The expansion of robo-advisory in wealth management*. Retrieved from <https://www2.deloitte.com/content/dam/Deloitte/de/Documents/financial-services/Deloitte-Robo-safe.pdf>
14. Deloitte. (2020, June 10). *The COVID Value-at-Risk (VaR) challenge: Making sense of calculated Value-at-Risk (VaR) numbers versus management and board risk limits*. Retrieved 2021, December 20, from <https://www2.deloitte.com/au/en/blog/assurance-advisory-blog/2020/covid-value-at-risk-var-challenge.html>
15. Dickhaus, T. (2018). *The theory of nonparametric tests*. <https://doi.org/10.1007/978-3-319-76315-6>
16. Eickstädt, A., & Horsch, A. (2021). Financial technologies and systemic risk: Some general economic observations. In I. H.-Y. Chiu, & G. Deipenbrock (Eds.), *Routledge handbook of financial technology and law* (pp. 95–115). <https://doi.org/10.4324/9780429325670-6>
17. Eule, A. (2018, February 3). As robo-advisors cross \$200 billion in assets, Schwab leads in performance. *Barron's*. Retrieved 2021, July 30, from <https://www.barrons.com/articles/as-robo-advisors-cross-200-billion-in-assets-schwab-leads-in-performance-1517509393>
18. Everitt, B. S., & Skrondal, A. (2010). *The Cambridge dictionary of statistics* (4th ed.). Cambridge: Cambridge University Press.
19. Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56. [https://doi.org/10.1016/0304-405X\(93\)90023-5](https://doi.org/10.1016/0304-405X(93)90023-5)
20. Fisch, J. E., Labouré, M., & Turner, J. A. (2019). The emergence of the robo-advisor. In J. Agnew, & O. S. Mitchell (Eds.), *The disruptive impact of fintech on retirement systems* (pp. 13–37). <https://doi.org/10.1093/oso/9780198845553.003.0002>
21. Grealish, A., & Kolm, P. N. (2022). Robo-advisory: From Investing principles and algorithms to future developments. In A. Capponi, & C. A. Lehalle (Eds.), *Machine learning in financial markets: A guide to contemporary practice*. <https://doi.org/10.2139/ssrn.3776826>
22. Griffiths, W. E., Hill, R. C., & Judge, G. G. (1993). *Learning and practicing econometrics*. New York, NY: John Wiley.
23. Grove, H., Clouse, M., & Xu, T. (2020). New risks related to emerging technologies and reputation for corporate governance. *Journal of Governance and Regulation*, 9(2), 64–74. <https://doi.org/10.22495/jgrv9i2art4>
24. Ha, A. (2010, October 19). Investing site KaChing gets classier as Wealthfront. *VentureBeat*. Retrieved 2021, July 29, from <https://venturebeat.com/2010/10/19/kaching-wealthfront/>
25. Hayek, F. A. (1945). The use of knowledge in society. *The American Economic Review*, 35(4), 519–530. Retrieved from <https://www.jstor.org/stable/1809376>
26. Hayek, F. A. (1973). *Law, legislation and liberty: A new statement of the liberal principles of justice and political economy* (Volume 1: Rules and order). London, the UK: Routledge & Kegan Paul.
27. Helms, N., Hölscher, R., & Nelde, M. (2021). Automated investment management: Comparing the design and performance of international robo-managers. *European Financial Management*. Advance online publication. <https://doi.org/10.1111/eufm.12333>
28. Holtfort, T., Horsch, A., & Schwarz, J. (2021). Global fintech entrepreneurship and its influencing factors: An evolutionary economic analysis. *Risk Governance & Control: Financial Markets & Institutions*, 11(1), 61–79. <https://doi.org/10.22495/rgcv11i1p5>
29. Horvath, D., & Szabo, R. Z. (2019). Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technological Forecasting and Social Change*, 146, 119–132. <https://doi.org/10.1016/j.techfore.2019.05.021>
30. Jung, D., Dorner, V., Glaser, F., & Morana, S. (2018). Robo-advisory: Digitalization and automation of financial advisory. *Business & Information Systems Engineering*, 60(1), 81–86. <https://doi.org/10.1007/s12599-018-0521-9>
31. Kim, J. (2018). Are countries ready for the new meso revolution? Testing the waters for new industrial change in Korea. *Technological Forecasting and Social Change*, 132, 34–39. <https://doi.org/10.1016/j.techfore.2017.11.006>
32. Kirzner, I. (1973). *Competition and entrepreneurship*. Retrieved from <https://cutt.ly/ULrHCPK>
33. Kirzner, I. (1997). Entrepreneurial discovery and the competitive market process: An Austrian approach. *Journal of Economic Literature*, 35(1), 60–85. Retrieved from <https://www.jstor.org/stable/2729693>

34. Liu, J., Li, X., & Wang, S. (2020). What have we learnt from 10 years of fintech research? A scientometric analysis. *Technological Forecasting and Social Change*, 155, 120022. <https://doi.org/10.1016/j.techfore.2020.120022>
35. Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91. <https://doi.org/10.1111/j.1540-6261.1952.tb01525.x>
36. Marshall, A. (1898). Distribution and exchange. *The Economic Journal*, 8(29), 37–59. <https://doi.org/10.2307/2956696>
37. Menger, C. (1871). *Grundsätze der Volkswirtschaftslehre*. Retrieved from <https://oll.libertyfund.org/title/menger-grundsätze-der-volkswirtschaftslehre>
38. von Mises, L. (1949). *Human action: A treatise on economics*. New Haven: Yale University Press.
39. Muscio, A., & Cifollilli, A. (2020). What drives the capacity to integrate Industry 4.0 technologies? Evidence from European R&D projects. *Economics of Innovation and New Technologies*, 29(2), 169–183. <https://doi.org/10.1080/10438599.2019.1597413>
40. Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Retrieved from http://inctpped.ie.ufrj.br/spiderweb/pdf_2/Dosi_1_An_evolutionary-theory-of_economic_change.pdf
41. North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge University Press. <https://doi.org/10.1017/CBO9780511808678>
42. Park, J. Y., Ryu, J. P., & Shin, H. J. (2016). Robo-advisors for portfolio management. *Advanced Science and Technology Letters*, 141, 104–108. Retrieved from <https://docplayer.net/53183925-Robo-advisors-for-portfolio-management.html>
43. Phoon, K. F., & Koh, C. C. F. (2018). Robo-advisors and wealth management. *Journal of Alternative Investments*, 20(3), 79–94. <https://doi.org/10.3905/jai.2018.20.3.079>
44. Puhle, M. (2019). The performance and asset allocation of German robo-advisors. *Society and Economy*, 41(3), 331–351. <https://doi.org/10.1556/204.2019.41.3.4>
45. Ramsey, J. B. (1969). Tests for specification errors in classical linear least-squares regression analysis. *Journal of the Royal Statistical Society*, 31(2), 350–371. <https://doi.org/10.1111/j.2517-6161.1969.tb00796.x>
46. Ringe, W.-G., & Ruof, C. (2021). Robo advice: Legal and regulatory challenges. In I. H.-Y. Chiu, & G. Deipenbrock (Eds.), *Routledge handbook of financial technology and law* (pp. 193–212). <https://doi.org/10.4324/9780429325670-11>
47. Scholz, P., & Tertilt, M. (2020). Robo-advisory: The rise of the investment machines. In P. Scholz (Ed.), *Robo-advisory: Investing in the digital age* (pp. 3–20). https://doi.org/10.1007/978-3-030-40818-3_1
48. Schumpeter, J. A. (1911). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. Cambridge: Harvard University Press.
49. Schumpeter, J. A. (1942). *Capitalism, socialism and democracy*. New York, NY: Harper.
50. Seidt, A. L., Zaharis, N., & Jarrett, C. (2019). Paying attention to that man behind the curtain: State securities regulators' early conversations with robo-advisors. *University of Toledo Law Review*, 50(3), 501–523. Retrieved from <https://heinonline.org/HOL/LandingPage?handle=hein.journals/utol50&div=38&id=&page=>
51. Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, 52(3–4), 591–611. <https://doi.org/10.1093/biomet/52.3-4.591>
52. Siddiqui, Z., & Rivera, C. A. (2022). Fintech and fintech ecosystem: A review of literature. *Risk Governance and Control: Financial Markets & Institutions*, 12(1), 63–73. <https://doi.org/10.22495/rgcv12i1p5>
53. Statista. (2021). *Assets under management of robo-advisors worldwide 2017 to 2025*. Retrieved 2021, November 30, from <https://www.statista.com/forecasts/1262614/robo-advisors-managing-assets-worldwide>
54. Stein, J. (2016, July 25). *The history of Betterment: How we started a company that changed an industry* [Post]. LinkedIn. Retrieved from <https://www.linkedin.com/pulse/history-betterment-how-we-started-company-changing-industry-stein/>
55. Su, C.-W., Qin, M., Tao, R., & Umar, M. (2020). Financial implications of fourth industrial revolution: Can bitcoin improve prospects of energy investment? *Technological Forecasting and Social Change*, 158, 120178. <https://doi.org/10.1016/j.techfore.2020.120178>
56. Tao, R., Su, C.-W., Xiao, Y., Dai, K., & Khalid, F. (2021). Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets. *Technological Forecasting and Social Change*, 163, 120421. <https://doi.org/10.1016/j.techfore.2020.120421>
57. Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, 41, 100833. <https://doi.org/10.1016/j.jfi.2019.100833>
58. Torno, A., Metzler, D. R., & Torno, V. (2021). Robo-what?, robo-why?, robo-how? — A systematic literature review of robo-advice. Paper presented at *the twenty-fifth Pacific Asia Conference on Information Systems*. Retrieved from <https://www.researchgate.net/publication/352519187>
59. Torno, A., & Schildmann, S. (2020). What do robo-advisors recommend? — An analysis of portfolio structure, performance and risk. In B. Clapham, & J.-A. Koch (Eds.), *Enterprise applications, markets and services in the finance industry* (pp. 92–108). https://doi.org/10.1007/978-3-030-64466-6_6
60. Treleaven, P., Barnett, J., & Koshiyama, A. (2019). Algorithms: Law and regulation. *Computer*, 52(2), 32–40. <https://doi.org/10.1109/MC.2018.2888774>
61. Veblen, T. (1898). Why is economics not an evolutionary science? *The Quarterly Journal of Economics*, 12(4), 373–397. <https://doi.org/10.2307/1882952>
62. Verbeek, M. (2017). *A guide to modern econometrics* (5th ed.). New York, NY: Wiley.
63. Warchlewska, A., & Waliszewski, K. (2020). Who uses robo-advisors? The Polish case. *European Research Studies Journal*, 23(1), 97–114. <https://doi.org/10.35808/ersj/1748>
64. Wealthfront. (n.d.). *Here's how it all started*. Retrieved 2021, July 29, from <https://www.wealthfront.com/origin>