UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER'S THESIS

AN ANALYSIS OF VALUE CREATION WITH A ROBO-ADVISOR

Ljubljana, February 2022 JOŽE PRESKAR

AUTHORSHIP STATEMENT

The undersigned Jože Preskar, a student at the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), author of this final written work of studies titled "An Analysis of Value Creation with a Robo-advisor", prepared under the supervision of professor Igor Lončarski, PhD

HEREBY DECLARE THAT

1. This final written work of studies is based on the results of my own research.

2. The printed form of this work is identical to the one in the electronic form.

3. The text of this works has been proofread, edited and is technically in adherence with the SEB LU's Technical Guidelines for Written Works, meaning it includes citations and/or quoted works and opinions of other authors in accordance with the SEB LU's Technical Guidelines for Writing Research Proposals or Dissertations.

4. I am aware that plagiarism (in written or graphical form) is a criminal offence and can be prosecuted in accordance with the Criminal Code of the Republic of Slovenia.

5. I am aware of the consequences a proven plagiarism charge based on this work could have for my status at the SEB LU in accordance with the relevant SEB LU Rules.

6. I have obtained all the necessary permits to use the data and works of other authors (in written or graphical form) referred to in this work and have marked them.

7. I acted abiding by ethical principles during the preparation of this work and, where necessary, obtained the permission of the Ethics Committee.

8. I have given my consent to use the electronic form of this final written work of studies for the detection of content similarity with other written work, using similarity detection software approved by the SEB LU Study Information System.

9. I transfer to the University of Ljubljana free of charge, non-exclusively, geographically, and time-wise unlimited the right of saving this work in the electronic form, the right of its reproduction and the right of making it available to the public on the World Wide Web via the Repository of the University of Ljubljana;

10. I consent to the publication of my personal data included in this work and in this declaration when the work is published.

11. I hereby also declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Ljubljana, ________________________ Author's signature: ________________________

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

sl. – Slovenian

AuM – (sl. sredstva v upravljanju); Assets under Management

B2B – (sl. poslovanje med podjetji); Business-to-Business

B2B2C – (sl. poslovanje med podjetjem in potrošnikom); Business-to-Business-to-Consumer

B2C – (sl. poslovanje s potrošniki); Business-to-Consumer

CAGR – (sl. skupna letna stopnja rasti); Compound Annual Growth Rate

COVID-19 – (sl. koronavirusna bolezen); Coronavirus Disease

ESG – (sl. okolje, družba in upravljanje); Environmental, Social and Governance

ETFs – (sl. kotirajoči investicijski skladi); Exchange Traded Funds

EU – (sl. Evropska Unija); European Union

EUR – (sl. Evro); Euro (currency)

Fintech – (sl. finančna tehnologija); Financial Technology

IRA – (sl. vrsta pokojninskega računa); Individual Retirement Accounts

IT – (sl. informacijska tehnologija); Information Technology

MDD – (sl. največji upad); Maximum Drawdown

MPT – (sl. sodobna teorija portfelja); Modern Portfolio Theory

MVO – (sl. vrsta optimizacije portfelja); Mean-Variance Optimization

NAV – (sl. neto vrednost sredstev); Net Asset Value

n/a – (sl. ni podatka); Not available

PGR – (sl. delež realiziranih dobičkov); Proportion of Gains Realised

PLR – (sl. delež realizirane izgube); Proportion of Losses Realised

RIA – (sl. registrirani investicijski svetovalci); Registered Investment Advisers

RS_{AuM} – (sl. Relativni delež sredstev v upravljanju); Relative Share of AuM

RS_{Vol} – (sl. Relativni delež povprečnega dnevnega obsega trgovanja); Relative Share of Average Daily Traded Volume

SEC – (sl. Komisija za vrednostne papirje in borzo); Securities and Exchange Commission

SRI – (sl. družbeno odgovorno vlaganje); Socially Responsible Investing

TACO – (sl. skupni letni stroški lastništva); Total Annual Cost of Ownership

TIPS – (sl. vrednostni papirji zaščiteni z inflacijo); Treasury Inflation-Protected Securities

US – (sl. Združene države Amerike); the United States

USD – (sl. ameriški dolar); US Dollar (currency)

INTRODUCTION

In recent years, robo-advisors have become one of the most popular tools in the investment management industry, challenging traditional investment solutions mainly by reducing costs and by addressing behavioural biases in investment decisions.

In its essence, a robo-advisor is an algorithm-based investment solution that automatically construct, optimize and manage portfolios on behalf of its clients, most commonly using a passive investment strategy. Robo-advisors emerged just after the global financial crisis in 2008, within the broader phenomenon called financial technology (hereafter: fintech). These technologies can promote cheaper and more efficient financial services; therefore, robo-advisors could be particularly attractive to millennials and households with low disposable income (Abraham, Schmukler, & Tessada, 2019). At the same time, individuals that already have investments might benefit from enhanced computational power and objectivity, as robo-advisors promote higher diversification and theoretically reduce behavioural biases. With the appearance of robo-advisors, the human financial advice received a valid alternative with detrimental consequences for those financial institutions that rely exclusively on human financial advisors. Moreover, Brenner & Meyll (2020) showed that the fear of being victimized by an investment fraud positively affects the use of robo-advice, as investors are seeking less biased alternative to potentially conflicted human financial advice.

With the rapid growth in assets under management (hereafter: AuM) over the past few years, the concept of robo-advice is increasingly being looked by established financial institutions which have started to replace their labour with fully automated investment programs. Such example is BlackRock, representing the first high-profile case of replacing human discretion with algorithms (Tokic, 2018). These institutions are driven by the increasing demand for cost efficient services and changing client needs, which robo-advisors are able to address (Delloite, 2016b). To adopt robo-advice model, they have started to cooperate with independent robo-advice companies or built and incorporated their own robo-advice model into the existing product offerings.

Despite the formidable growth and the praise robo-advisors have enjoyed so far, many questions of whether these automated investment solutions will disrupt the complete industry or end up a niche are yet to be answered. After all, the robo-advice concept is still in an early stage and has not been tested in strongly volatile market conditions yet. This has several implications for this master’s thesis. First of all, the academic literature is still very limited and does not provide a comprehensive understanding of the robo-advice model. Furthermore, robo-advisors are mainly start-up and privately owned companies, which additionally limits the publicly available information therefore this thesis is more descriptive in nature, using the combination of data provided by academics, global banking/consulting firms and up-to-date internet sources.

The purpose of this master's thesis is to provide a comprehensive understanding of the possibilities that robo-advice model has in the portfolio management process and evaluate whether this model can provide better investment advice than human wealth manager. The main objective is to examine the robo-advice model from the ground up and show how robo-advisors create value not only from the investors' perspective, but also from the perspective of traditional financial institutions seeking to upgrade their service offerings. The research questions based on the reviewed literature which will be discussed throughout the thesis are:

- What are the value propositions of a typical robo-advisor and how does it differentiate from a traditional wealth manager?
- How does the robo-advice model create value for investors?
- What is the value of using robo-advice services for traditional financial institutions?
- How do robo-advisors perform?

The thesis is divided into five parts, each consisting of several chapters. The first part is an introduction to automated wealth management and a general overview of robo-advisors. It gives the background about the subject of the thesis to better understand the definition of a robo-advisor given in the current literature, the history of robo-advisors and how they have evolved, the business model, the key players in the market, and how robo-advisors are supervised. The second part focuses on the portfolio management perspective. It provides an analysis of robo-advice value chain, starting with investor identification and asset universe selection, and continuing with a more elaborate discussion about three of the most valuable robo-advice features: portfolio construction with multidimensional improvement of Modern Portfolio Theory (hereafter: MPT), automated rebalancing, and integrated tax-loss harvesting service. The third part focuses on the behavioural finance perspective. It emphasises the most common behavioural biases in the investment decision-making process and elaborates on the potential of robo-advice model to mitigate them. The fourth part aims to demonstrate investing with a robo-advisor. In this part the portfolio strategy and implementation of one of the pioneering robo-advisors, Betterment, is analysed. Furthermore, it emphasises the goal-based investing and the use of the Black-Litterman model for asset allocation as these are the two main components that add value to Betterment's strategy. The last part is an evaluation of robo-advisors' performance in the period from January 2016 to December 2020, which also includes the effect of the COVID-19 pandemic.

1 BACKGROUND

1.1 Investment management

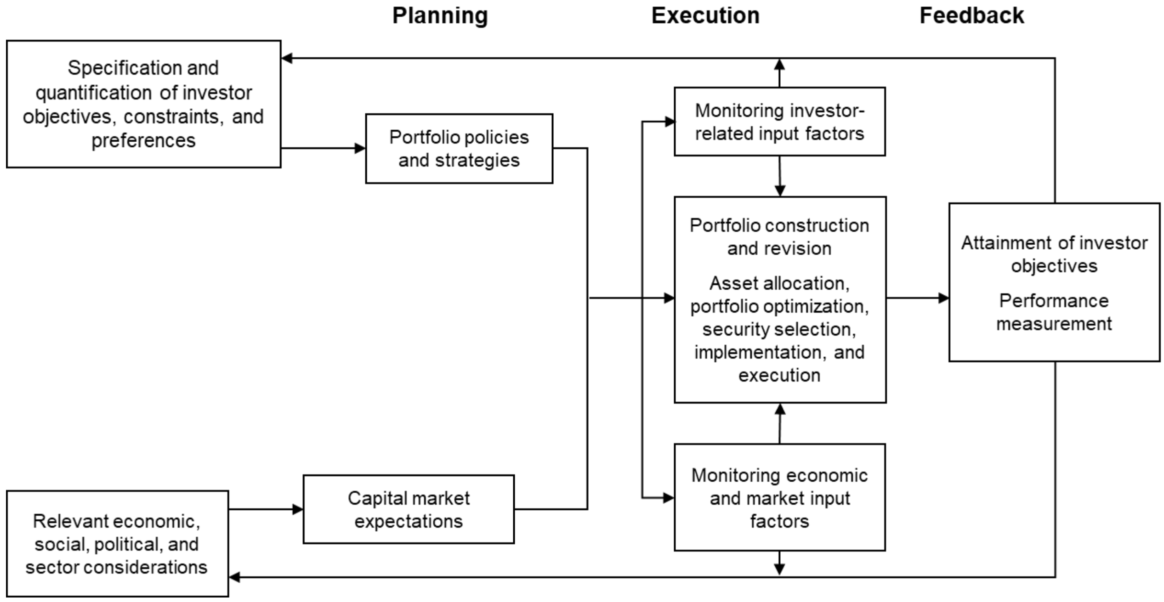
The investment management industry is built on a financial system, which according to McMillan, Pinto, Pirie, & Van de Venter (2011, p. 2) “includes markets and various financial intermediaries that help transfer financial assets, real assets, and financial risks in various forms from one entity to another, from one place to another, and from one point in time to another. These transfers take place whenever someone exchanges one asset or financial contract for another.” When the buyer and seller voluntarily arrange their trades, they both expect to be better off.

Sironi (2016) further describes investment management as a type of financial intermediary between issuers of financial products (i.e., governments, financial institutions, or corporations), and individual or institutional investors looking to optimally allocate their funds. In this so-called supply-demand mechanism, issuers search for the cheapest funding, investors seek the highest returns, and intermediaries make use of their knowledge to serve their clients and maximise intermediation margins. The latter are known as investment managers, who serve their clients and advise them on suitable portfolios by selecting from the universe of direct or indirect investments.

According to Maginn, Tuttle, McLeavey, & Pinto (2007) investment management firms generally employ portfolio managers, analytical staff, traders, marketing and support personnel. Portfolio managers use outside research, which is conducted by sell-side analysts, and in-house research. They work in line with a three-step process, consisting of planning, execution and feedback (Figure 1). The first phase refers to the identification and specification of investor-related and market-related input factors, based on which the portfolio strategies are developed and the portfolio structure is defined. The second phase refers to the integration of investment strategies with capital market expectations, whereby portfolio managers initiate and traders implement portfolio decisions. In the last phase, the performance is evaluated and the portfolio is revised as some of the input factors may change. If necessary, the rebalancing is implemented as well. Thus, the feedback and the execution phase constantly interact with each other. The whole process is based on the MPT concept and has become simpler with an increase in ever-cheaper availability of the computer processing possibilities.

While technology has downshifted the costs and the complexity of portfolio management process, the changing behaviour of investors and tighter regulation have further contributed to the investment management industry to evolve from the 1950’s highly-priced conventional portfolio managers to today’s low-priced robo-advisors. Therefore, the financial advice has become accessible not only to ultra-high net worth individuals, but to the middle class as well (Sironi, 2016).

Figure 1: Three-step process of portfolio management



Adapted from Maginn, Tuttle, McLeavey, & Pinto (2007).

1.2 Robo-advisors

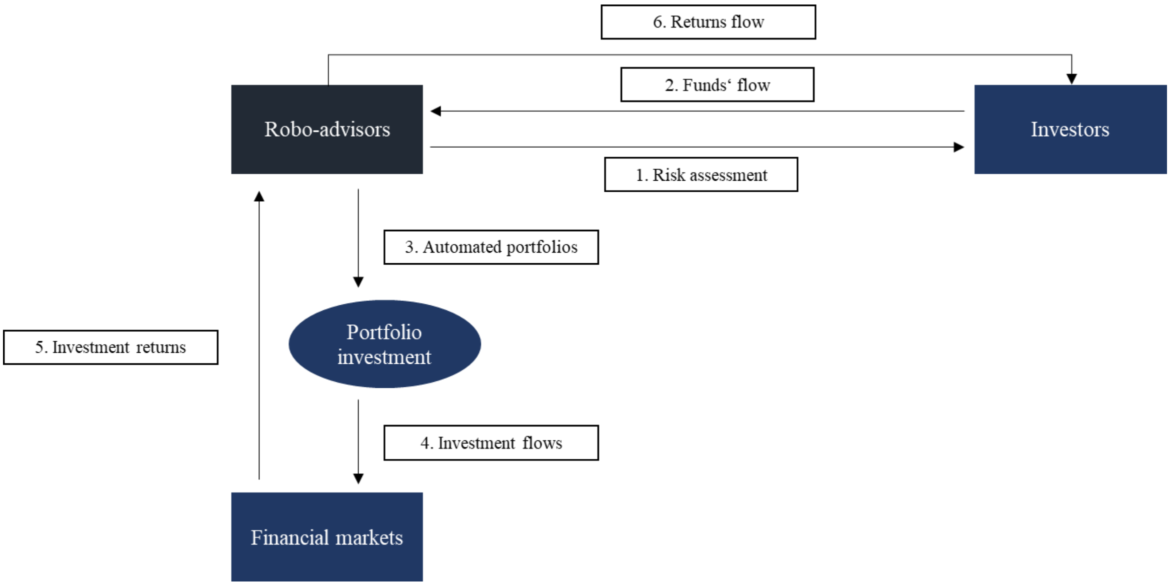
1.2.1 Definition

A brief definition has already been coined in the introduction of this master's thesis. However, robo-advisors are not just the automated investment solutions in the literal sense of the word, but rather private companies, registered under the Securities and Exchange Commission (hereafter: SEC) as Registered Investment Advisors (hereafter: RIA), and they usually provide discretionary portfolio management services.

Despite having different business models (will be discussed later), all robo-advisors bear three common characteristics; namely, with the use of (1) self-learning algorithms, they provide (2) an automated investment solution delivered through (3) online platforms to investors. They guide their clients through the process of risk assessment and help them define their investment preferences. Furthermore, according to Puhle (2016) they obtain trading authority from clients so that the buying and selling decisions can be made (discretionary) by the robo-advisors and do not need to be approved by the client.

Figure 2 briefly illustrates how a typical robo-advisor works, usually starting with risk assessment and ending with the final distribution of returns back to investors.

Figure 2: Flowchart of a typical robo-advice process



Adapted from Tao, Su, Xiao, Dai, & Khalid (2020).

1.2.2 Evolution

As briefly mentioned in chapter 1.1 the investment management industry is constantly adopting new technologies to provide cheaper and more efficient financial services. The adoption deepened after the global financial crisis in 2008, when reduced trust in financial institutions and the regulatory response by increasing capital requirements made it more difficult and expensive for traditional financial institutions to operate. Meanwhile, this created an opportunity for technology-advanced institutions to thrive, since they could offer financial services more cheaply and efficiently than other financial institutions burdened with old infrastructure and increased regulation (IFC, 2017).

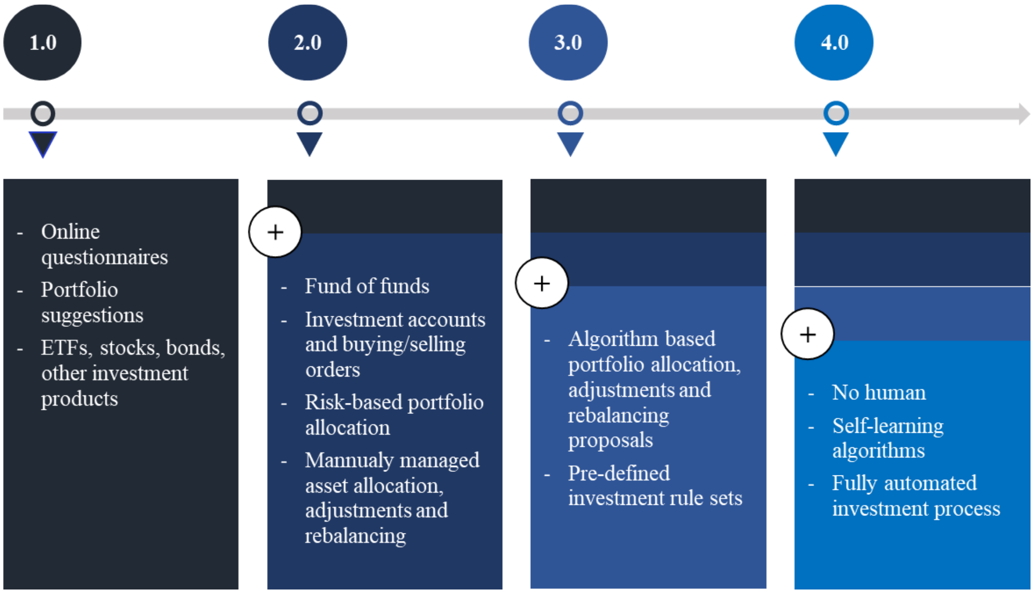
Robo-advisors officially appeared with Betterment and Wealthfront (originally called kaChing) being launched in 2008. These two US-based companies are still the largest independent robo-advisors in terms of AuM with 16.4 billion USD and 20 billion USD, respectively. A year later, Personal Capital[1] was founded. After that more and more financial institutions have started to offer robo-advice services as they recognised robo-advisors as a low-cost alternative to traditional human advisors. For example, Charles Schwab launched its first in-house robo-advisor Intelligent Portfolios in 2015 (Carey, 2021a). In the same year, Blackrock entered the robo-advice services by acquisition of Future Advisor (Reuters, 2015). The Vanguard Group also entered the market with its hybrid robo-advisor Personal Advisor Services in 2015 and complemented its offering with a fully automated Digital Advisor in

[1] Acquired by Empower Retirement in 2020 (Kauflin, 2020).

2020 (Carey, 2021b).[2] Last but not least, Bank of America through its affiliate Merrill Edge launched its robo-advisor Merrill Guided Investing in 2019 (Businesswire, 2019).

Over the years, robo-advisors have changed in term of features they provide. With the entrance of large financial players in the market, the evolution has escalated and the differences among robo-advisors increased. Delloite (2016a) outlined four development stages of robo-advisors ranging from least developed 1.0 to the most developed 4.0 (Figure 3).

Figure 3: Evolution from robo-advisor 1.0 to 4.0



Adapted from Delloite (2016a).

Robo-advisor 1.0 uses online questionnaire to filter suitable products and offer clients specific portfolio suggestions. These portfolios consist of exchange-traded funds (hereafter: ETFs), stocks, bonds, or other investment products. Buying and selling orders as well as future adjustments have to be done by clients on their own. Robo-advisor 2.0 goes one step further. Portfolios are structured as a fund of funds, while the service also includes setting up investment accounts and executing buying/selling orders. The questionnaires have two functions, they are not only used to filter products but to allocate clients to pre-defined risk-allocated portfolios as well. The asset allocation, adjustments and portfolio rebalancing are managed manually by an investment manager therefore the robo-advisor 2.0 still qualifies as a semi-automated tool. Robo-advisor 3.0 is a technological advancement compared to its predecessor. Algorithms are employed to propose asset allocation, adjustments and portfolio rebalancing, while the investment manager still supervises the final investment decision based on the pre-defined investment strategy. Clients can either accept or reject the investment recommendations and also have an option to adjust the investment decision. The

[2] The difference between hybrid and fully automated robo-advisors is described in chapter 1.2.3.

most advanced robo-advisor 4.0 eliminates the human factor from the investment process as it employs self-learning algorithms that fully automate asset allocation and portfolio rebalancing. Based on the inputs from sophisticated questionnaires (i.e., investor objectives, constraints, and preferences) and relevant market conditions, robo-advisor 4.0 automatically manages portfolios in line with the pre-selected portfolio policies and strategies (Delloite, 2016a).

1.2.3 Business model

Robo-advice companies have different business models. The most common distinction is whether they provide fully automated financial advice or involve human advisors in their portfolio management service as well (Puhle, 2016). The latter are called hybrid robo-advisors as they combine automated service with human interaction where usually an advisor in addition to online questionnaires initiates an interview with the client to gather information about their financial condition, investment goals, and risk tolerance. Investment portfolios are therefore managed by a professional but with the help of robo-advice tools. Additionally, personal review meetings can also be scheduled in case of a hybrid approach. However, this comes at the investor's expense since such robo-advice companies typically require larger initial payments and charge higher fees. Even the companies that commenced as fully automated robo-advisors have started to include human professionals in their service offerings. For example, Betterment added an option within its premium plan for clients to have phone or email conversations with their team of professionals (Tergesen, 2017).

Despite this distinction, robo-advice business model generally consists of the building blocks summarised in Appendix 3 and is further described in this chapter. Starting with the value propositions, robo-advice companies have low fee structure that is transparent and easy to understand. They typically charge an annual fee, which covers the advice, custody services, transactions, rebalancing and other account administration. Additionally, the customers are obligated to pay the expense ratio embedded in the ETFs and mutual funds that constitute the portfolio (Puhle, 2016). Total fees depend on the approach a robo-advisor is using, with hybrid being reasonably more expensive due to the higher level of human interaction. There are also differences between the countries. In the US fees are relatively lower than elsewhere, which is not surprising given the competitiveness in the market. For example, Betterment currently charges an annual fee ranging between 0.25% and 0.40%, Wealthfront charges an annual fee of 0.25%, and Personal Capital charges 0.89% (Betterment, 2021; Wealthfront, 2021a; Personal Capital, 2021). In Germany, robo-advisors charge higher annual fees, on average. Vaamo charges between 0.49% and 0.99% per annum, Scalable Capital charges 0.75% per annum and easyfolio charges 0.91% per annum, to name a few (https://robo-advisors.eu). Nevertheless, robo-advisors are still cheaper compared to human financial advisors who, for example, charge fees between 1% to 2% of AuM in the US (Fisch, Turner, & Labouré, 2019). In addition to optimised fee structure, the technologically advanced equipment enables robo-advice companies to provide automation in portfolio management process and to offer tax optimisation services, such as tax loss harvesting. Furthermore, with the limited human factor, robo-advisors are able to reduce behavioural biases in investment decisions. Both, portfolio management and behavioural finance perspectives are analysed more into details in the following sections, where also key activities of robo-advisors are described thoroughly.

Robo-advisors have emerged from Business-to-Consumer (hereafter: B2C) to Business-to-Business (hereafter: B2B) platforms, while some also combine both approaches (hereafter: B2B2C). B2Cs generally target mass market, mass affluent and affluent client segments. To put it in a context, according to McKinsey&Company (2014) the common client classification based on household assets is as follows: mass market (50,000 USD – 200,000 USD), mass affluent (200,000 USD – 1 million USD), affluent (1 million USD – 5 million USD), high net worth individuals (5 million USD – 30 million USD) and ultra-high net worth individuals (over 30 million USD). Traditional investment management institutions have focused on the last two groups given the higher AuM that provides greater profitability, while robo-advisors have initially served the first three groups only. The tendency to serve the less wealthy is still visible in their fee structure; however, with the inclusion of human financial professionals robo-advisors started to target high net worth individuals as well. For example, roughly 15% of Charles Schwab's clients using robo-advice service have their net worth in the excess of 1 million USD while Betterment also serves clients with accounts exceeding 10 million USD (Puhle, 2016). Robo-advisors interact with their clients online and are accessible through smartphones, tablets, computers, etc.

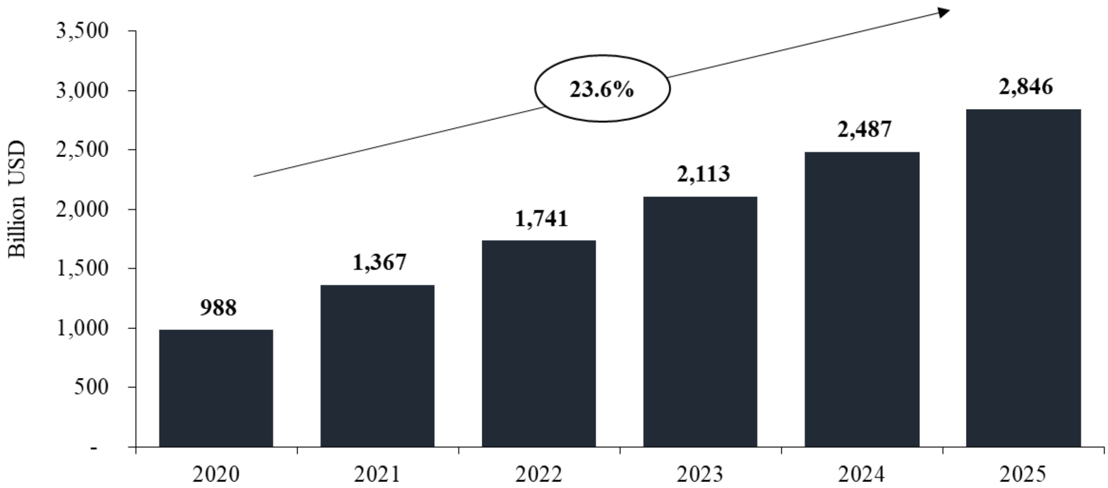
To do business, robo-advisors must cooperate with several parties. First, robo-advisors usually penetrate the market as start-up companies with extensive research and development costs, IT infrastructure costs, and marketing costs associated with online campaigns to attract new clients. Therefore, they normally approach or are approached by venture capital investors seeking to enter the fintech market. Furthermore, some robo-advisors have strategic partnerships with banks and other financial institutions to provide B2B and/or B2B2C services (if robo-advice service is not in-house already). These institutions also provide robo-advisors with custody and brokerage services. Thirdly, robo-advisors need resources to gather market inputs therefore they must cooperate with financial data providers as well (Puhle, 2016).

1.2.4 Market competitors

Robo-advisors are simply a global phenomenon with established players across the US, Europe and Asia-Pacific. The US market is the largest by number of robo-advice providers and assets managed by them. It is not surprising as the US landscape is far more fragmented and competitive than other markets and has a long tradition of investment management services (Sironi, 2016). There are roughly 200 robo-advisors in the US, followed by Europe where the number amounts to between 98 and 126. It is noteworthy that the UK and Germany dominate the market in Europe (Buchanan, 2019).

It is estimated that robo-advisors manage about 1 trillion USD AuM or approximately 0.01% of total AuM being managed by the global asset and wealth management industry. Despite being relatively small compared to the industry, robo-advisors' AuM is anticipated to grow at a compelling $CAGR_{2020\text{-}2025}$ of 23,6%, reaching almost 2.9 trillion USD by 2025 as presented in Figure 4. For comparison, the AuM in the global asset and wealth management industry has been forecast to grow at a $CAGR_{2020\text{-}2025}$ of 5.5%, reaching approx. 145.4 trillion USD by 2025 (PwC, n.d.).

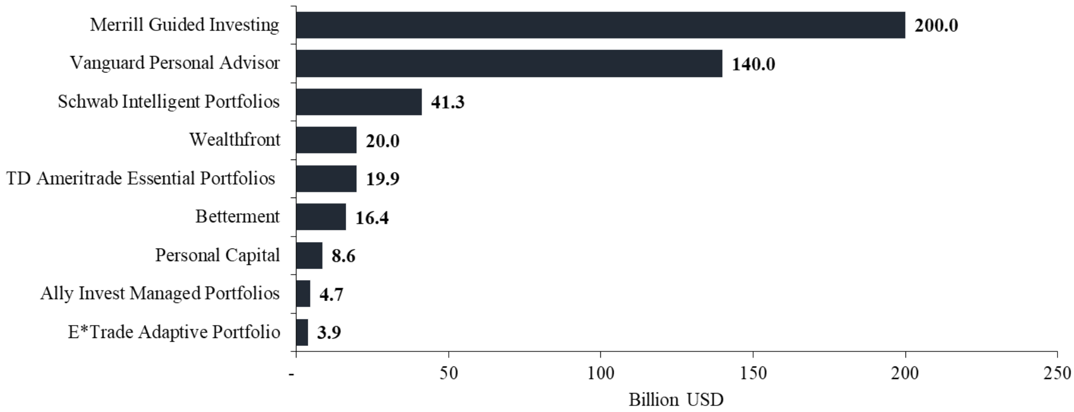
Figure 4: Projected AuM of global robo-advisors (as of May 2020)



Adapted from Statista (2021).

According to Orçun (2017) there is a growing competition for independent robo-advisors, which do not have large client networks yet, since established financial institutions have entered the market. In response, independent robo-advisors started to evolve from B2C into B2B services, while others have been taken over by established financial institutions as indicated in chapter 1.2.2. Therefore, the largest robo-advisors in the US are owned by those institutions. As presented in Figure 5, the largest US robo-advisor is Merrill Guided Investing with 200 billion USD, followed by Vanguard Personal Advisor and Schwab Intelligent Portfolios with 140 billion USD and 41.3 billion USD, respectively. The largest independent robo-advisors, Wealthfront and Betterment, are managing 20 billion USD and 16.4 billion USD, respectively.

Figure 5: Top US robo-advisors by AuM (as of May 2020)



Adapted from Statista (2021).

According to Puhle (2019) the US market is followed by Europe, where the exact AuM numbers are difficult to find since there is no mandatory reporting as it is in the US. Orçun (2017) estimates that the AuM of European robo-advisors range between 5% and 6% of assets managed by US robo-advisors. Furthermore, the European market is highly concentrated as at least five robo-advisors were estimated to manage more than 100 million EUR each, whereby Germany and the UK represent more than 90% market share.

Given the amount of AuM in Europe compared to US, the low number is however multifaceted. The retail investors who are in the heart of robo-advice services are relatively risk averse in Europe and are more reluctant to use investment management services. The level of risk aversion therefore results in a lion’s share of bank deposits, insurance and pension fund reserves in the structure of European households’ portfolios. Typical clients of the European investment management industry are therefore institutional investors and high net worth individuals, who are now switching to robo-advice services offered by established financial institutions. The European market therefore still has a strong upside potential.

The least developed market is Asia-Pacific, where robo-advisors appeared reasonably late due to the relative scarcity of available ETFs. The leading robo-advisor is Bambu, which is located in Singapore. Other reputable robo-advisors in Asia-Pacific region are Lingji from China, Smartly from Singapore, Theo from Japan, Ignition Wealth from Australia, and Chloe from Hong Kong.

1.2.5 Governance and supervision

The same conduct standards that apply to traditional advisory institutions must apply to robo-advice companies as well. In other words, robo-advisors have to provide transparency of all costs, potential threats for investors, and limitations of the services they provide. Furthermore, relevant information must be fully and fairly disclosed for investors to have a clear understanding of investment policies and potential conflict of interest. Robo-advice clients should also be informed about risk management and possible limitations of the underlying algorithms. In addition, robo-advisors must ensure that their strategies and investment recommendations are suitable for clients based on their financial condition and objective/s. Because they operate online extensively, robo-advisors must pay an extra attention to protect clients' data and maintain the log-in credentials on their websites (Orçun, 2017).

As mentioned in chapter 1.2.1 robo-advisors are registered with SEC as RIAs and therefore subject to the same regulatory requirements and supervised by the same regulatory authorities as traditional investment advisors. Fisch, Turner, & Labouré (2019) argue that the quality of robo-advice services may be easier to supervise given the traceability of electronic content. Meanwhile, it is nearly impossible to track private conversations of human advisors with the clients. However, the digitalisation of the financial advice is bringing additional challenges for the regulators and supervisors who should adopt new legal policies as soon as possible (Bayon, 2018). The reason for such a request to amend the legislation is partly due to the concerns raised by Fein (2015), who showed that some robo-advisors disregard fiduciary standard of care and may be conflicted. Furthermore, the author claims that robo-advisors not always act in the client's best interest.

2 ANALYSIS FROM PORTFOLIO MANAGEMENT PERSPECTIVE

2.1 Robo-advice value chain

Mullainathan, Noeth, & Schoar (2012) find that advisors may not systematically provide investment advice due to the biases, which help them to achieve their economic interest, i.e., maximising fees. By contrary, robo-advisors normally offer low-cost financial advice and adhere to the systematic and well-grounded finance theory. The following activities are usually performed by a robo-advice model:

- Identification of an investor's profile (e.g., financial condition, investment goals, and risk tolerance).
- The selection of asset universe based on the applied criteria (e.g., history, performance, liquidity, coverage, diversification).
- Portfolio construction based on the asset allocation and portfolio optimisation methods (e.g., MPT, Black-Litterman, full-scale optimisation, etc.).
- Monitoring the investor and market related factors, and portfolio rebalancing if necessary (e.g., threshold-based rebalancing).
- Tax-loss harvesting (additional service performed by a limited number of robo-advisors).

Figure 6: Robo-advice model value chain

Source: Adapted from FINRA (2016).

Each activity is analysed more into detail further in this chapter, following the same order as presented in Figure 6.

2.2 Investor identification

Robo-advisors must identify the specific facts about their clients, which is essential to provide sound investment advice. For such purposes, they employ online questionnaires that are designed to identify investors' financial condition, investment goals, and risk tolerance. The most commonly used questionnaire is presented in Table 1 and can be interpreted as follows. At the beginning robo-advisors ask questions about the rationale for investing and the envisioned time horizon. Then they ask specific questions about investor's financial literacy and risk tolerance. The latter is measured through risk willingness and risk capacity. As the name suggests, risk willingness measures the risk an investor is willing to take, while risk capacity measures the risk the investor is able to take. It is advised that risk willingness does not exceed risk capacity (FINRA, 2016).

Table 1: General robo-advice questionnaire

Nr.	Question	Possible answers
1	Reason for investment.	a) General savings b) Precautionary savings c) Retirement d) Other
2	You need this investment starting in _________(year) for _________ years.	/
3	You have __________ understanding of ETFs.	a) Good b) Some c) No
4	When deciding on your investments, you ____________________.	a) Maximise gains b) Minimise losses
5	Have you ever lost 25% or more of your investments in one year?	a) Yes b) No
6	If you ever were to lose 25% or more of your investments in one year, you would ____________________.	a) Sell everything b) Sell part of your investment c) Do nothing d) Reallocate your investments e) Buy more
7	Personal information about age, gender, income, mortgage debt, other assets.	/

Adapted from Orçun (2017).

Online questionnaires have several favourable features (Orçun, 2017):

- It is relatively simple to fill out the form and the process usually takes less than 15 minutes compared to traditional onboarding methods, which can be time-consuming and absurdly administrative.
- Investors can easily modify their answers without visiting their advisor as this can be done with an online setting. However, it is advised for long-term investors not to change investment preferences too often, because this could be detrimental for their portfolio.[3]
- The records of communication between a robo-advisor and an investor can be easily kept to track investor's profile and preferences. Consequently, the investor onboarding is more efficient and transparent.

However, there are some drawbacks to online questionnaires (Orçun, 2017):

- Multiple-choice questions normally give basic information about an investor without a complete understanding of their financial condition, a thing to be considered in financial planning.
- Standardised questions might be too limited or insufficient to get better understanding of a client. This can lead to a situation where two investors with different investment objectives are assigned to the same portfolio allocation.
- The subjective nature of responses to the questions may be misleading for robo-advisors since they put investors with similar responses to the same basket. However, responses may be biased in a way that one investor might think they have "some" understanding of ETFs while the other answers "good" due to their overconfidence.

These drawbacks can be mitigated in different ways. For example, explanatory videos could be used to inform investors about financial planning, financial theories, or risk concepts more in detail. Furthermore, vignette questions[4] may be used to re-scale investors' responses to subjective questions. Furthermore, Sironi (2016) suggests that robo-advisors could replace questionnaires with engaging experiences through so-called Gamification, which would allow robo-advisors to modernise the client onboarding by testing their risk willingness and educating them about the impact of uncertainty on portfolio returns, while also leading them towards more consistent investment behaviours.

2.3 Asset universe selection

The investable universe of robo-advisors generally consists of equity and fixed income securities. Because ETFs have the most lucrative features for automated trading strategies, these financial instruments are typically selected for constructing portfolios. The final set of

[3] For example, the change in risk tolerance could trigger the liquidation of some investments whereby the investor faces costs of selling and reinvesting (Orçun, 2017).

[4] Vignette in this context "is a short description of a hypothetical financial situation or decision designed to simulate key features of a real-world scenario" (Orçun, 2017, p. 3).

ETFs usually comes down to between 3% and 6% of all investable ETFs. Robo-advisors aim to minimise taxes with appropriate asset location strategies. The whole process of selecting asset universe is analysed further in this chapter.

2.3.1 Asset classes

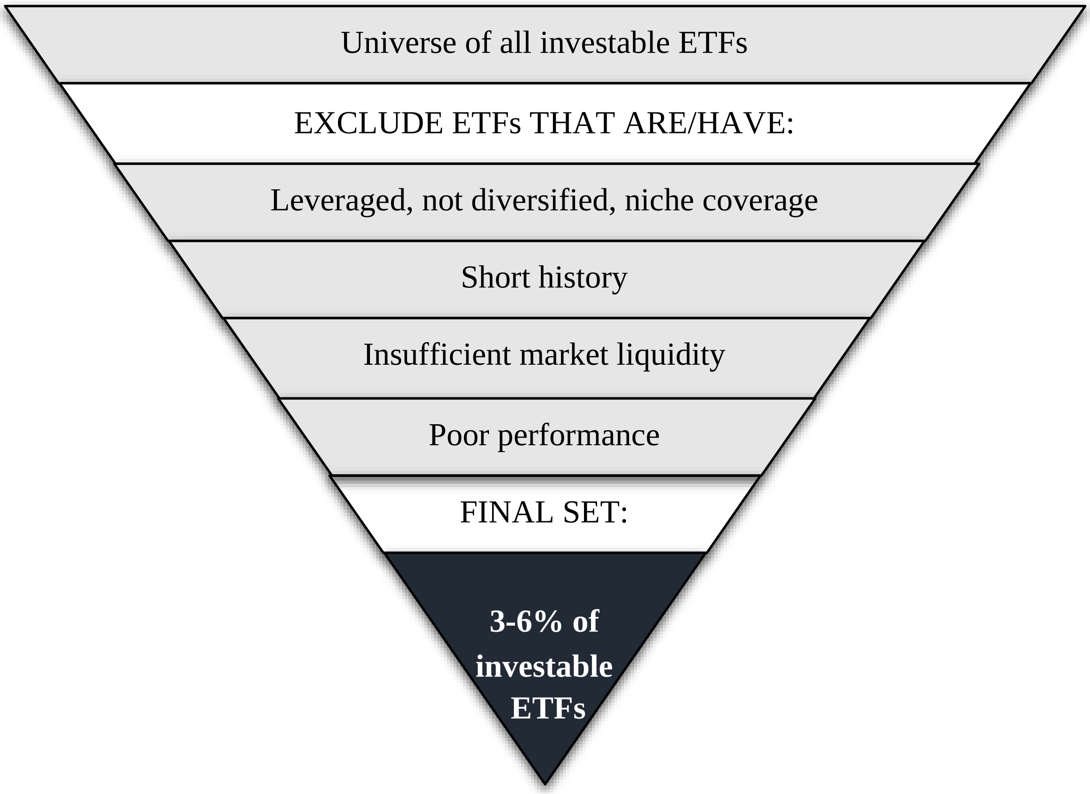
Robo-advisors foremost adhere to passive investment strategies therefore exclude any actively managed funds from their investable universe. Moreover, they prefer investing in liquid assets so that their clients may withdraw their assets without any complications. Consequently, private equity and real estate asset classes are excluded since such assets may be restricted on redemption. Robo-advisors focus on equity and fixed income asset classes, where risk and return are fundamental variables to consider. According to MPT, asset class correlation should be minimised to attain greater diversification which is why they select a broad mix of domestic/international equities and government/corporate bonds from developed and emerging markets. Some of them also include treasury inflation-protected securities (hereafter: TIPS), real estate investment trusts, precious metals and commodities to diversify even more (Puhle, 2019).

2.3.2 Selecting from the universe of investable exchange traded funds

Besides risk and return, robo-advisors also consider that asset classes are easily investable. Thus, they generally choose ETFs, while some exceptions include also mutual funds, index funds, sustainable funds, and exchange-traded commodities. ETFs have the most lucrative features for automated trading strategies, usually a passive indexing strategy. In short, an ETF is a type of security that aims to track the performance of an underlying index (e.g., national/international stock, bond, real-estate, or commodity index) as precisely as possible. ETFs are considerably less expensive than mutual funds, which may also adhere to active investment strategies. Furthermore, as an index tracking instrument they provide significant diversification benefits and serve as the main financial instruments for robo-advisors (Beketov, Lehmann, & Wittke, 2018; Orçun, 2017).

ETFs are selected by a top-down method as depicted in Figure 7. In the first step, robo-advisors focus on leverage, diversification and market coverage. Then they eliminate ETFs that have a short history because it would be difficult to calculate inputs for portfolio optimisation accurately enough with the lack of data. Furthermore, ETFs with inadequate market liquidity are excluded as well since the gap between bid and ask prices might be too broad to allow low-cost rebalancing. In the last step, ETFs with poor past performance are also eliminated from the selection. The final set of ETFs in which robo-advisors invest in usually ranges between 3% and 6% of the initial set. While the selection helps to extract the most suitable ETFs for investing, this limited final set may be restrictive in other robo-advice activities, such as tax-loss harvesting (Orçun, 2017). The entire ETF selection process is discussed more in detail in chapter 4.2.2, based on the specific case.

Figure 7: ETF selection criteria



Adapted from Orçun (2017).

2.3.3 Socially responsible investing

In the last few years, robo-advisors have acted towards the growing demand for Socially Responsible Investing (hereafter: SRI) options, which are constructed considering Environmental, Social and Governance (hereafter: ESG) criteria, as an addition to the ETF selection criteria described before (Schanmuganathan, 2020). Some robo-advice providers offer their clients an option to choose the SRI-themed portfolio. For example, Betterment offers three different types of SRI portfolios to its clients. First is Climate Impact portfolio which provides exposure to companies that are trying to mitigate climate change. Second is Social Impact portfolio which provides exposure to companies that are promoting gender and racial equality. Third portfolio, called Broad Impact, incorporates all ESG pillars and provides exposure to companies that are addressing not only the climate change, gender and racial equality, but ethical management as well. To select socially responsible ETFs for inclusion in the SRI portfolios, Betterment adopts two approaches, a scoring-based, and an engagement-based approach. According to the first approach, Betterment selects ETFs that meet certain ESG scores which are provided by MSCI, one of the leading ESG ratings provider. Under the second approach, Betterment selects the engagement-based socially responsible ETFs, which express an SRI preference through the fund manager’s active engagement with companies held through the fund, via shareholder proposals and proxy voting (Betterment, 2021b). SRI is a perfect add-on to existing portfolios since not only it attracts new clients but might provide compelling performance as well. Backend Benchmarking (2021a) finds that over the last 2-year period, nearly all SRI portfolios included in the analysis outperformed their counterparts (traditional core portfolios) at the same robo-advice provider. Furthermore, after launching the new SRI portfolio options in October 2020, Betterment's AuM related to SRI grew at an accelerating rate or roughly six times the rate of AuM in its core portfolio.

2.3.4 Asset location

When financial instruments are selected, robo-advisors then aim to minimise taxes by allocating asset classes to taxable or tax-advantaged accounts (individual retirement accounts (hereafter: IRA) and 401(k)s) accordingly (Bjerknes & Vukovic, 2017). This placement of asset classes in a client's taxable or tax-deferred accounts is commonly referred to as the "asset location" which can have a sizable effect on portfolio returns. Daryanani & Cordaro (2005) demonstrate that systematic asset location increases portfolio returns up to 20 basis points yearly, on average. Betterment offers a fully automated asset location strategy to its clients. Once an investor sets up a Tax-Coordinated Portfolio, Betterment manages assets as a single portfolio across all included legal accounts, using every dividend and deposit to optimise the location of the assets. Furthermore, Betterment also rebalances to improve asset location if necessary, without causing taxes. In general, assets, which are expected to be taxed at higher rates, are managed within tax-advantaged accounts, while assets expected to be taxed at lower rates are managed within taxable accounts. Betterment claims that by doing that, after-tax returns can be boosted by 48 basis points yearly, on average (Betterment, 2019).

2.4 Portfolio construction

The next step in the value chain is portfolio construction where robo-advisors construct portfolios based on the investor's profile and target asset allocation. The asset allocation decision is normally viewed as one of the most important decisions in investment process as it explains more than 90% of the variation in returns (Brinson, Hood, & Beebower, 1986). Therefore, most of the robo-advisors strictly adhere to the MPT methodology and use mean-variance optimisation (hereafter: MVO) to generate efficient frontiers. MVO, introduced by Nobel prize laureate Harry Markowitz, is a quantitative tool that takes correlations between a set of assets and their volatilities as input variables and then maximises the expected returns for a given level of risk. To estimate the inputs and create efficient risk-return portfolios, historical time series are used in the MVO (Markowitz, 1952). However, MVO framework has limitations of its own, which are further discussed in this chapter. It is important to understand them, because robo-advisors then apply different methods to overcome these shortcomings.

2.4.1 Limitations of mean-variance optimisation

Due to its simplicity, MVO is the most widely accepted framework for asset allocation. The model simplifies investment assumptions to increase feasibility; however, it simultaneously limits the ability to incorporate real-world asset class characteristics due to:

- *Normality assumption.* MVO assumes that security returns are distributed normally, but Swensen (2009) argues that returns are not normally distributed because markets exhibit more extreme events than it is assumed under the normal distribution.
- *Extreme input sensitivity.* MVO can lead to highly concentrated rather than well-diversified portfolios. Best & Grauer (1991) demonstrated that a slight change in the expected return of one of the portfolio's assets could force a significant share of assets out of the portfolio, while the portfolio's overall expected return and standard deviation are virtually unchanged.
- *Estimation error.* Michaud (1989, p. 34) argues that MVO “significantly overweights (underweights) those securities that have large (small) estimated returns, negative (positive) correlations, and small (large) variances. These securities are most likely to have large estimation errors.”
- *Time horizon.* MVO is based on a single-period framework and it is assumed that investors make their decisions regarding asset allocation only once, normally at the beginning of a given period. However, investors might have several goals with multi-period time horizons which cannot be accurately addressed using the MVO (Swensen, 2009).

As a result of these inter-related and well-documented limitations, portfolios optimised by the MVO approach are rather concentrated and can fail to achieve maximum diversification.

2.4.2 Methods used by robo-advisors

As mentioned before, robo-advisors apply different methods to overcome or at least to mitigate the shortcomings of MVO. These methods are widely accepted by the finance theory and nothing new to the industry. However, with robo-advisors the feasibility of such methods has become even more pronounced. Beketov, Lehmann, & Wittke (2018) find the following as the most common alternative to MVO incorporated in robo-advice models:

- Constant portfolio weights.
- Sample portfolios.
- Black-Litterman model.
- Monte Carlo simulations.
- Full-scale optimisation.
- Other (risk parity, risk parity with skewness risk, scenario optimisation, etc.).

Robo-advisors use either one or multiple above-mentioned methods to construct portfolios. The first two methods are relatively straightforward but both lack the ability for individualisation. Furthermore, robo-advice clients are generally tech savvy and demand more sophisticated approaches. That is way the most reputable robo-advisors adhere to the last three methods. Black-Litterman model is one of the most comprehensive methods incorporated into algorithms as it enables robo-advisors to generate intuitive and well-diversified portfolios. In its essence, the model introduced by Black & Litterman (1992), is a sophisticated framework for portfolio construction that helps to combine the subjective views with the market equilibrium. Furthermore, Monte Carlo simulations are used by some robo-advisors to increase the robustness of portfolio weights. The most recent advancement also used by robo-advisors is full-scale optimisation, which provides more customised portfolios and overcomes the normality assumption of the MVO (Adler & Kritzman, 2006). Other methods are relatively rare but may become more popular with the increasing competition between robo-advisors.

2.5 Monitoring and rebalancing

The technological sophistication and built-in systems that automate the monitoring and rebalancing process make robo-advice model more attractive compared to human financial advisors, who are often exposed to behavioural biases and may fail to rebalance in a strictly disciplined way. It seems unintuitive for humans to rebalance their portfolios during a financial crisis by selling their best-performing investments and buying the under-performing ones. Furthermore, manual checking for rebalancing opportunities can be a time-consuming task for humans. However, rebalancing is essential to keep portfolio in line with the initial target asset allocation, because securities perform differently or risk preferences of the investor change. If rebalancing is not undertaken, the drift can lead to a situation where asset classes are over or under-weighted compared to initial setting. Not only is regular rebalancing important to maintain the required risk profile, but it also helps to attain better performance of a portfolio (FINRA, 2016; Lam, 2016; Vanguard, 2010).

Several studies show that rebalancing can provide better risk-adjusted performance. For example, Swensen (2005) found in his study that rebalanced portfolios over the period from 1992 to 2002 realised 0.4% higher risk-adjusted returns than portfolios that were not rebalanced. In another study, Kaissar (2017) took even longer time period; namely, from from 1926 to 2016, and got similar results. He compares two portfolios, an annually rebalanced and never-rebalanced or neglected one. Both portfolios started with 60% allocation to stocks and 40% allocation to bonds. The neglected portfolio returned an average of 9.4% annually over the period 1926-2016, while the rebalanced portfolio returned 8.6% annually. The results were nearly identical for a shorter period as well, resulting in a 9.7% average annual return of the neglected portfolio and an 8.8% return of the rebalanced portfolio over the period 2006-2016. Despite higher gross returns, a standard deviation of a neglected portfolio was 16.4%, while a standard deviation of a rebalanced portfolio was

12.1%. The reason is simple, the growth of bonds lagged behind the growth of stocks resulting in a 99% stock allocation of neglected portfolio in 2016. Consequently, a rebalanced portfolio produced a better risk-adjusted return than the neglected portfolio.

Due to the automated nature, robo-advice model normally employs threshold-based rebalancing, where an algorithm daily monitors and automatically rebalances investment portfolio to the initial asset allocation once the drift surpasses a certain threshold. Additionally, clients have an option to indicate changes of their risk preferences over the website, which may also trigger rebalancing as the target allocation must be adjusted accordingly. One way to rebalance a portfolio is to use the client's cash flows, which can be sourced from their deposits, withdrawals from over-weighted assets, dividends from equity investments and reinvestments. These cash flows are then used to purchase under-weighted asset classes. The value from dividends and reinvestments can be relatively small, therefore, these cash flows are usually effective only when the drift is minimal. If the client's cash flows are insufficient to achieve the target asset allocation, then the robo-advice model would simply rebalance assets that are already in the portfolio by selling overweighted and buying underweighted asset classes. However, this is not a preferred option as it exposes the client to additional commissions and capital losses or taxable gains (Lam, 2016; FINRA, 2016).

2.6 Tax-loss harvesting

Tax efficiency is seriously considered by the robo-advice model since it improves after-tax returns. Robo-advisors not only allocate assets in taxable or tax-advantaged accounts as already discussed in chapter 2.3.4., but also perform tax-loss harvesting which is another very important feature discussed further in this chapter.

In its essence, "tax-loss harvesting is the process of selling securities at a loss and using the proceeds to buy highly correlated substitutable investments. By realizing capital losses and taking advantage of differences in tax rates between short-term and long-term capital gains, portfolios reap additional returns through both the compounding of tax savings (which come with tax filings and tax rate arbitrage. Since investments are replaced by highly correlated substitutes, the risk-return profile of the portfolio is largely maintained" (Lam, 2016, p. 23).

When tax-loss harvesting is performed, the so-called "wash sale" must be considered, because in the US the tax authorities explicitly forbid an investor to deduct losses related to wash sales. According to SEC (2021), a wash sale is an event in which an investor sells or trades securities at a loss and within 30 days before / after the sale they either buy considerably similar securities or buy an option to obtain considerably similar securities in the future. To put it in the context, an investor who buys a stock for 10 monetary units and later sells it for 5 monetary units, thus realising a loss in the amount of 5 monetary units, is not allowed to use this loss for tax purposes if they buy another considerably similar stock for 8 monetary units within 30 days. Nevertheless, the investor still has an option to use this loss for tax purposes in the future transaction, since cost basis of the new stock is now actually 13 monetary units (8 for new stock + 5 prohibited loss). Once the investor sells new stock at a loss again, the cost basis of 13 monetary units will be then considered for tax purposes (Orçun, 2017).

Wash sale can be avoided in different ways. One way is simply to wait 30 days after the sale event occurred and keep cash proceeds in the account. However, robo-advisors try to avoid such approach since it would yield a drift from the client's initial target asset allocation. Furthermore, cash portion in the account that is not invested could hurt the portfolio's long-term performance (Khentov, 2021). Alternatively, robo-advisors choose ETFs that follow non-identical but highly correlated indices (Lam, 2016). They label them as prime and alternative ETFs (see Appendix 4 and 5). However, it is difficult to find such alternatives in practice. Orçun (2017) estimates that for each ETF there is approximately 7 to 10 alternative ETFs where wash sale does not apply. In addition, some robo-advisors also adhere to more sophisticated methods of tax-loss harvesting. For example, they buy and sell highly correlated underlying stocks of indices and thus avoid wash sale directly. By doing that, tax-loss harvesting becomes an even more convenient and effective way to gaining compelling after-tax returns (Jung, Glaser, & Kopplin, 2019; Lam, 2016).

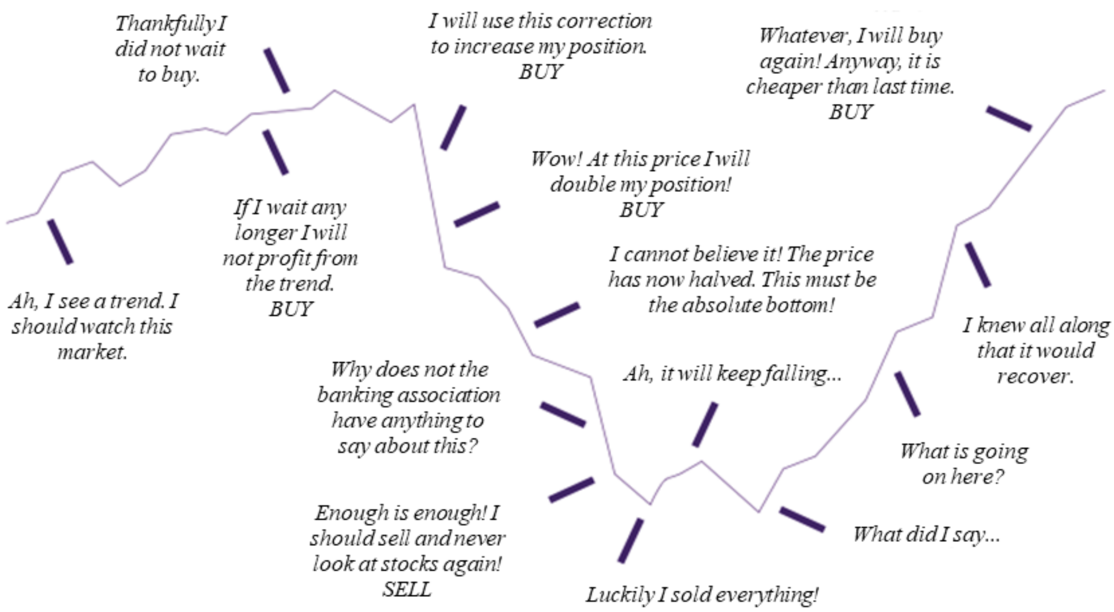
It is estimated that the additional gain or annual tax alpha moves around 1%. Tax-loss harvesting is performed by human advisors as well, but they normally offer this service only to large account holders and they do that on an annual basis. Meanwhile, robo-advisors offer tax-loss harvesting by default within their pricing plans and check for harvesting opportunities daily (Lam, 2016).

3 ANALYSIS FROM BEHAVIOURAL FINANCE PERSPECTIVE

3.1 Roller coaster of emotions

Investment process extends from obtaining information, selecting stocks, making trades, holding investments to selling and making new decisions. The process is full of psychological hazards which may be detrimental for investors as they often experience so-called "Roller coaster of emotions" as illustrated in Figure 8 below (Credit Suisse, 2016). Cognitive and emotional biases arising from investing are of human nature. Wealth managers should theoretically mitigate these biases but they usually advise their clients just as they invest personally. Linnainmaa, Melzer, & Previtero (2021) showed that wealth managers exhibit behavioural biases because they trade frequently, chase returns, sympathize actively managed funds, and above all, they underdiversify their holdings. By contrary, fully automated robo-advisors invest systematically and in line with the finance theory, thus have a potential to reduce aforementioned biases. However, algorithms are written by humans therefore robo-advice models might be biased as well (D'Acunto, Prabhala, & Rossi, 2019). Furthermore, the switch to online investing may increase the confidence among investors and as such deteriorate the performance due to increased trading (Barber & Odean, 2002), reflecting that robo-advisors could also encourage higher turnover and consequently erode some of the benefits associated with the robo-advice. It seems that opinions are divided. Some argue that robo-advisors can mitigate behavioural biases, while others say they are affected by human errors too.

Figure 8: Investment process – roller coaster of emotions



Adapted from Credit Suisse (2016).

3.2 Behavioural biases in the portfolio management

Researchers in the field of behavioural finance analyse the effectiveness of human decisions in different decision-making situations and try to address biases arising from human behaviour. However, Pompian (2006) argues that the portfolio management is inadequately addressed and advisors still lack practical understanding how to detect biases themselves and how to advise their clients with this regard. Therefore, this chapter begins with the identification of the most common biases in portfolio management context and aims to elaborate whether robo-advice model is suitable to mitigate them.

3.2.1 Overconfidence bias and active trading

First and one of the most widely addressed bias is overconfidence. Humans generally view the world positively and are usually overconfident about their expertise, skills and expectations. Overconfidence is a cognitive bias which is reflected in the financial markets in the form of active trading because investors prefer their own judgement and usually overhear thinking of others. The active trading can lead to underperformance when compared to the market, as it has been shown in many studies. For example, Barber & Odean (1999) demonstrated that households which trade extremely frequently can underperform the strategic (buy-and-hold) households by more than 7 percentage points.

Pompian (2006) distinguishes two types of overconfidence; namely, prediction overconfidence and certainty overconfidence. The first type refers to investors who are overconfident in their investing abilities and assign too narrow confidence intervals to their investment predictions. The second type refers to investors who are too certain about their common sense. When having determined that a stock is a good investment, these investors will overlook a potential loss and afterwards feel disapointed if the investment performs poorly. Such behaviour leads to frequent trading and to underdiversified portfolios.

3.2.2 Loss aversion bias

The second, loss aversion bias, is an emotional bias introduced by the behavioural finance pioneers Kahneman & Tversky (1979) as part of their prospect theory. They found that a potential loss is more powerful stimulus than a potential gain with the same probability. Meaning, it is more preffered not to lose 50 monetary units than to gain the same amount of money. In the case where the likelihood of a potential loss is insignificant, investors would prefer to take this loss rather than expose themselves to a large risk of a potential gain. For instance, when offered to take 400 monetary units or gain 500 monetary units with probability of 80%, where 20% is a probability of getting nothing, people would probably go with the first option although the expected result is the same (400 monetary units). If they were put in another situation, where they would have an option to lose 400 monetary units or take an 80% probability of losing 500 monetary units, people would probably go with the latter and thus engage in the risk-taking behaviour in hope to keep away from the potential loss (Harley, 2016).

Pompian (2006) identified the following behaviours in portfolio management pointing to loss aversion bias:

- Investors hold losing investments hoping that these investments will rebound or even when they envision no such turnaround is possible. This behaviour could have a detrimental outcome because usually the best response is to sell losing investments and reallocate the assets. Furtheremore, investors unknowingly take on more risks by holding those investments than they would in the case of eliminating them and moving into better ones.
- Investors sell winning investments because they fear the market will reverse and revoke their profits. By securing their profits, investors limit themselves to gain even more from those investment. Investors start to trade actively which further deteriorate their returns.

- Investors hold suboptimally balanced portfolios. For instance, if value of an asset fall and an investor do not sell due to loss aversion, an imbalance of the portfolio may arise. By disregarding regular rebalancing, the asset allocation may fade away from the long-term investment objectives set by an investor.

The first two behaviours are commonly referred to as the disposition effect, first identified by Shefrin & Statman (1985) in their study. Holding losers and selling winners can have detrimental consequences for the investor as already explained. Not only holding losers and selling winners increase risk and support active trading, but such behaviour limits the upside potential of the portfolio because winners are proven to outperform the unsold losers held in the portfolio (Odean, 1998).

3.2.3 Trend chasing

Investors are looking for patterns, which means they tend to buy securities that have increased recently assuming a positive trend is more likely to go forward than the negative one. This so-called trend-chasing behaviour is especially visible among unskilled investors and is, among other factors, encouraged by the aforementioned overconfidence, which causes investors to believe that forecasting trend is more an ability than a luck. An investor who is exhibiting trend-chasing behaviour will more frequently purchase a security when its price is high and then dispose it when the price is low (Thinking forward, n.d.).

3.2.4 Rank effect

Hartzmark (2015) in his study documented another interesting behaviour that is common among retail investors and portfolio managers as well. He found that they are more likely to sell the worst and the best-performing investments in the portfolio while disregarding investments with intermediate performance. The behaviour indicates that how an individual security in the portfolio is viewed depends on how it is ranked compared to other securities in the given portfolio. Consequently, the bias is named rank effect.

3.2.5 Mental accounting bias

Humans prefer to mentally categorise their investments into buckets or mental accounts. These accounts might, for example, include money for studying or retirement savings, and they often hold different risk profiles (Lin, n.d.). In other words, mental accounting is a cognitive bias where people group their assets in a way that usually violates fundamental economic logic. The bias was first coined by Thaler (1985) who analysed mental accounting for marketing purposes but the bias is being increasingly present in investing as well. Investors bucket their investments in separate accounts aiming to diversify their financial objectives. By doing that they usually neglect positions between those accounts which can lead to the unsatisfactory performance of an aggregated portfolio. Furthermore, some investors want to preserve the principal and tend to spend the interest. For instance, they see a high-dividend paying stock appealing at the time due to the dividends but can suffer a loss in the long run due to principal depreciation (Pompian, 2006). Based on the first statement, investors do not consider their aggregated portfolios as a whole but as a group of different sub-portfolios, each being associated with an objective that has a certain threshold level of return.

Das, Markowitz, Scheid, & Statman (2010) combined the fundamentals of MVO and behavioural portfolio theory to derive to what they call a "new mental accounting framework". Based on these findings, the so-called goal-based investing has occurred. It is a relatively new approach in wealth management and has grown in popularity after the financial crisis in 2008. The idea of goal-based investing is to use mental accounting bias as a strength because the division of an aggregated portfolio in multiple sub-portfolios or accounts gives investors the ability to specify several risk profiles. Furthermore, such approach ensures that the investor is saving optimally for each account and can rely on multiple sources to cover potential liabilities in the future (Egan, 2020). However, it can be difficult for investors to define those sub-portfolios as they may not have clear vision of their objectives at a specific point in time. For instance, an investor saving to make a prepayment for a new home might not know the required amount until the home is actually purchased (Lam, 2016).

Some robo-advisors, such as Betterment and Schwab, have already adopted this relatively new approach. They have incorporated investment goals that range from retirement savings to savings for an anticipated future expenditure. Goal-based investing at Betterment is further discussed in chapter 4.2.1 of this thesis.

3.2.6 Familiarity bias

Humans tend to invest in what they are comfortable with, preferring specific geographic location or company, despite the clear benefits of the diversification. This propensity is known as "familiarity bias" (Elan & Goodrich, 2010). Furthermore, investors prefer domestic securities over international ones, neglecting the benefits of diversification, a bias described as "home bias" or "equity home bias" according to some sources. However, it is difficult to explain why is that so. Originally, the bias was thought to have resulted from legal restrictions and transaction costs associated with investing in foreign securities but some investors simply prefer investing in what is known to them. Not only individual investors but fund managers prefer to invest in home market as well (Strong & Xu, 1999).

Aside from geographic familiarity bias, there is another widespread and highly harmful appearance of the bias where employees exhibit strong preferences of their employer's stock. By investing in their own company, employees suffer the diversification of their holdings and run the risk of compounding their pain if the company does badly. Not only would they lose their job and income from salary but would lose their savings for retirement as well (Elan & Goodrich, 2010).

Although the MPT suggests that the normal amount of equity holdings in a portfolio is at least 300, an investor on average holds only 3 to 4 equities, resulting in a portfolio that is severely underdiversified. The familiarity bias described in this chapter exacerbates the underdiversification even more (Statman, 2004).

3.2.7 Confirmation bias

Humans normally favor ideas that confirm their existing beliefs while devalue whatever do not coincide with them. This cognitive phenomenon is called confirmation bias and can be separated into several subgroups, such as biased research, biased interpretation or biased recall to name a few. Even tough it causes several negative effects, the bias is very common in several areas because it can increase efficiency, self-esteem and alleviate stress. Pompian (2006) identified the following behaviours in portfolio management pointing to confirmation bias:

- Investors seek confirmatory information about their investments rather than objective facts. This would leave them in the loop when the decline in a stock price is imminent. For example, they find a stock breaking through a 52-week price high a good investment, despite it has no fundamental value.
- Investors overconcentrate on the stocks of the company they work for and emphasise information demonstrating that this company will do well in the future. For example, some of the IBM’s employees were convinced that the company's operating system would be the industry flagship product in the early 1990s. They completely disregarded unfavourable information from the market that the company has a growing competition from Microsoft, which launched its own operating system (Windows). Nevertheless, IBM’s employees stuck to IBM stock, expecting that its operating system would drive the performance of the stock. However, it turned out differently. After the peak of 35 USD per share in 1991, IBM slid to a low of 10 USD over the course of the next two years and then recovered only until the beginning of 1997. During this “depression” period, many of IBM employees were laid off while they also lost their retirement savings on the account of the poor performance of the stock.
- Aside from holding the stocks of an employer company, investors sometimes obsessively stick with particular stock because they filter out negative news regarding the stock and seek the confirmation that the stock itself will pay off. Over the years, this could lead to overconcentration of the stock and ultimately to an unbalanced portfolio.

3.2.8 Anchoring bias

Anchoring bias is yet another cognitive bias that occurs when people process information. Person exhibiting this bias normally relies on the first information or an "anchor" and interprets newer information from the anchor perspective, instead of analysing it independently and objectively. Investors unconsciously set initial stock price (price of a stock where they enter an investment) or current stock price as anchors, and then cling to these figures when facing questions regarding buying or selling opportunities. For example, when asked where Apple stock will be in two years, a biased investor would first counter-question where it is today. Then based on the current stock price (the anchor), they will assume where the price is going to be in the next two years. Another common situation is when biased investors evaluate target price of a stock. If the target price they get is far from the actual stock price, they will try to match the actual market price instead of trusting their due diligence (CFI, 2015; Pompian, 2006).

3.3 Robo-advice and its potential at mitigating behavioural biases

Theoretically, robo-advice model is set to generate decisions that are unbiased and can help to mitigate common behavioural mistakes described in the previous chapter. However, opinions in the practice are still divided. That is why I turn to previous studies to elaborate on this dilemma. Table 2 summarises key findings, which are justified further in this chapter.

Table 2: Robo-advice model and behavioural biases

	Overconfidence (active trading)	Loss aversion	Trend chasing	Rank effect	Mental accounting	Familiarity bias	Confirmation bias	Anchoring bias
Can robo-advice model mitigate the bias?	Yes	Yes	Yes	Yes	Yes	Yes	Partially	Partially

Source: Own work.

If I recall the robo-advice model value chain described in chapter 2.1, the most critical in terms of behavioural biases is the first activity, where robo-advisors identify an investor's risk profile. They are not yet comprehensively self-sufficient to accurately perform risk analysis without human help (Bhatia, Chandani, & Chhateja, 2020). That is why the questionnaires are designed and fulfilled by humans, and as such prone to information processing biases (e.g., confirmation and anchoring bias). Furthermore, the clients are usually young and unexperienced individuals who are just new to investing. Such individuals can be very confident about their abilities and avoid taking investment advice from professionals (Lewis, 2018). This can translate in sub-optimal investment decisions with detrimental consequences for their long-term financial well-being. Therefore, it is important for robo-advisors to educate their clients so that they can gain the required financial literacy before using the service. Willis (2011) finds that clients can be ashamed of revealing their financial knowledge to human advisors. But with robo-advisors the case might be different.

First, robo-advisors offer more comfortable setting for investors to reveal their financial literarcy without the fear of revealing details to a human advisor (Lewis, 2018). Secondly, robo-advisors can educate their cleints through engaging experiences or Gamification (as described in chapter 2.2) due to their technological advancement.

But when it comes to investing, robo-advisors evidently mitigate behavioural biases. As already mentioned in the second part of the thesis, robo-advisors generally adhere to the systematic and well-grounded finance theory. They invest according to the passive investment strategies and choose ETFs as their primary investment assets. Furthermore, the selection of investable ETFs is performed according to the predefined rules. Therefore, robo-advisors are able to construct well-diversified portfolios and because they adhere to the passive investment strategies, they also mitigate the problem of excessive trading. But it has to be noted that robo-advisors also perform regular rebalancing to reduce portfolio drifts, which can potentially lead to frequent trading that benefits the robo-advisor (especially those owned by financial institutions) through commissions at the expense of investors (D'Acunto, Prabhala, & Rossi, 2019). However, rebalancing benefits usually exceed the expenses. Moreover, clients normally have the option to adjust their preferences in a way that may reduce the rebalancing.

Robo-advisors also reduce the mental accounting bias, which is addressed through the goal-based investing as described in chapter 3.2.5 and further elaborated in chapter 4.2.1. The main idea is that by goal-based investing approach, robo-advisors turn mental accounting bias to their advantage.

Disposition effect (as part of the loss aversion bias), trend-chasing, and rank effect have been tested on the actual data by D'Acunto, Prabhala, & Rossi (2019). They observe the investment behaviour of investors that have joined a robo-advisor introduced by an Indian brokerage company, in the time period from July 2015 to February 2017. They test the incidence of these three biases before and after investors access the robo-advisor. First, the disposition effect is measured as the difference between the proportion of gains realised (hereafter: PGR) and the proportion of losses realised (hereafter: PLR) before and after using the robo-advisor, where:

$$PGR = \frac{Realised\ gains}{Realised\ gains + paper\ gains} \tag{1}$$

and

$$PLR = \frac{Realised\ losses}{Realised\ losses + paper\ losses} \tag{2}$$

The disposition effect occurs if PGR exceeds PLR, because that means that an investor realises gains more often than losses. Furthermore, the larger the difference between the two, the more severe the disposition effect is. Figure 9 shows that the difference is positive even after using the robo-advisor, but it evidently decreases.

Secondly, the trend chasing is measured as a share of positive returns in the period of the 5 business days preceding the purchase date of a security. The same is applied for purchases before and after using the robo-advisor. The share is calculated according to the following formula:

$$Trend\ chasing = \frac{Days\ price\ increase}{Days\ price\ increase + Days\ price\ decrease} \tag{3}$$

The result in Figure 9 shows that after using a robo-advisor the share was reduced by approximately 1.2%, indicating that investors reduced the tendency to buy securities with good performance in the days just before the purchase (trend chasing).

Thirdly, to measure the extent of the rank effect, the proportions of best-, middle-, and worst-performing securities investors sell, are computed according to the following:

$$Best = \frac{Best\ sold}{Best\ sold + Best\ not\ sold} \tag{4}$$

and

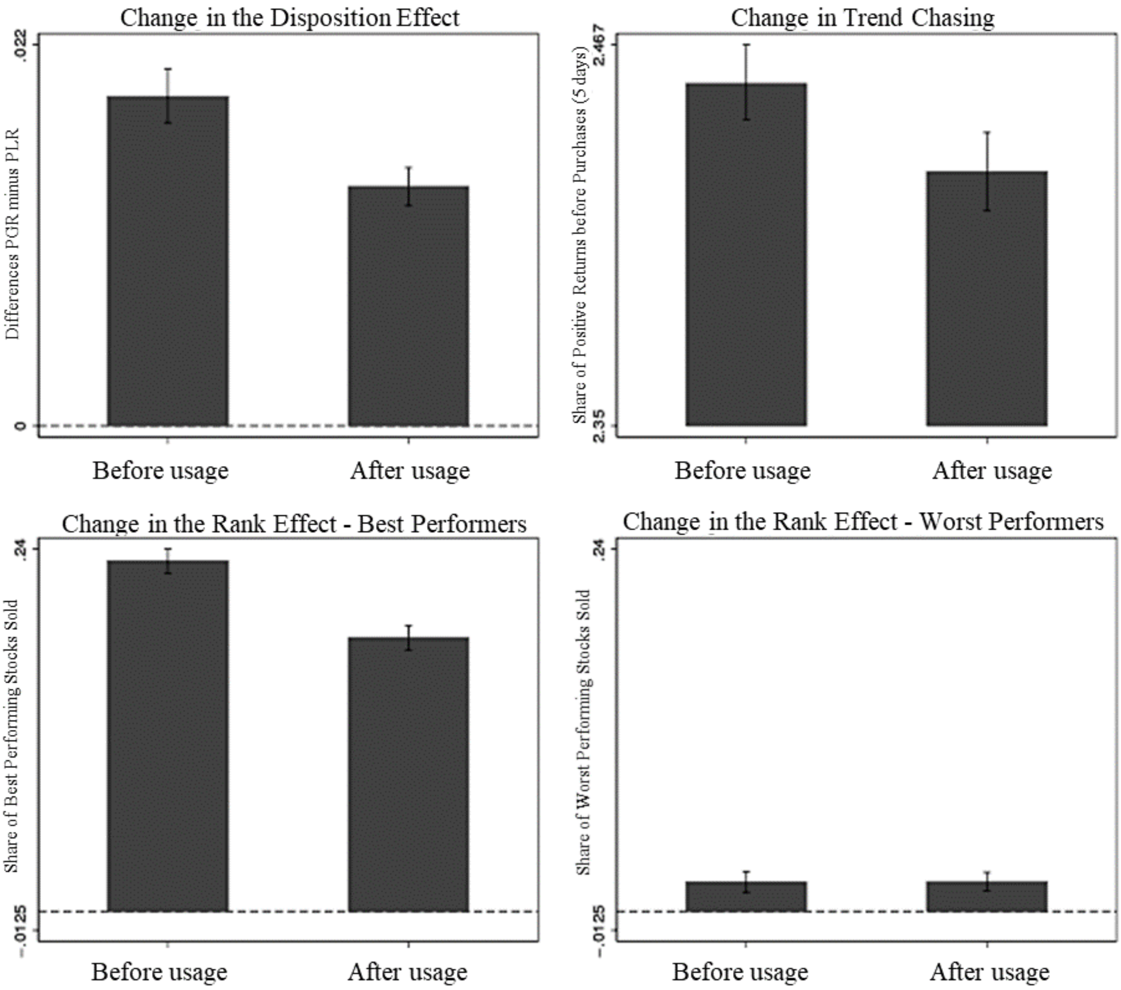
$$Middle = \frac{Middle\ sold}{Middle\ sold + Middle\ not\ sold} \tag{5}$$

and

$$Worst = \frac{Worst\ sold}{Worst\ sold + Worst\ not\ sold} \tag{6}$$

The differences between Best – Middle (best performers) and Worst – Middle (worst performers) are then computed for each investor, before and after using the robo-advisor. The results in Figure 9 show that the propensity to sell the best performers is substantially higher before using robo-advisors than after the use, indicating that robo-advisors decrease the bias to some extent, but the effect does not completely fade away. On the other hand, the propensity to sell the worst performers is quite limited, therefore it is difficult to detect any systematic differences before and after using the robo-advisor.

Figure 9: Behavioural biases before and after robo-advising



Adapted from D'Acunto, Prabhala, & Rossi (2019).

Similarily, Loos, Previtero, Scheurle, & Hackethal, (2019) in their study observe the investment behaviour of 11,145 investors that joined the robo-advice service at a German retail bank. The time horizon is from the launch of the robo-advisor in April 2014 to October 2017. 40.3% of the observed investors were existing clients of the bank, and the remaining 59.7% were new clients. Researchers demonstrate that after joining the bank's robo-advisor, all clients hold more diversified portfolios with a larger fraction of index funds and show lower trend-chasing. They also exhibit lower home bias, which is a part of the larger phenomenon- familiarity bias. As the study shows, these effects are even stronger among unexperienced clients who previously have not dealt with any financial professional. The effects of the study are both economically and statistically significant. The limitation of this study is that researchers compare the behaviours of new and existing bank clients joining its in-house robo-advisor, which limits the generalisation of the results to independent robo-advisors such as Betterment or Wealthfront.

4 EXAMPLE: INVESTING WITH ROBO-ADVISOR BETTERMENT

4.1 Description of the company

To illustrate investing with a robo-advisor, I have used one of the pioneering robo-advisors, Betterment. Betterment LLC was founded in 2008 and is the first generation robo-advice start-up that has more than 18 billion USD AuM and over 500,000 clients as of December 2020 (Backend Benchmarking, 2021). It is a US-based independent robo-advisor, without affiliation to the financial products recommended to its clients. Betterment started as a fully automated B2C robo-advisor and has also expanded into B2B over time. Most recently, it has added human financial advisors to its premium investment plan.

Betterment offers the following pricing plans to its clients (Betterment, 2021):

- *No fee plan (checking, cash reserve, advice, and planning tools).* This plan charges no fees and requires a 0 USD minimum balance.
- *Digital investing plan*. This plan charges a 0.25% annual fee and requires a 0 USD minimum balance.
- *Premium investing plan.* This plan charges a 0.40% annual fee and requires a 100,000 USD minimum balance.

Betterment prides itself on the projected added value it may provide to an investor. It is estimated that an average investor can gain between 0.90% and 1.48% more per year than if they had invested in ETFs on their own (Rollén, 2019).

4.2 Portfolio strategy and implementation

4.2.1 Client onboarding and goal-based investing

As already discussed in chapter 2.2, the robo-advice model introduces an online questionnaire to gain insight into investment capabilities and preferences of a client. While most robo-advisors assess risk preferences through a set of questions centred around loss aversion, behaviour in bearish markets, and sometimes about behavioural biases, Betterment only indirectly assesses risk tolerance (Pirner, 2018).

Betterment's strategy is centred around a personalised financial plan built on different goals. Therefore, Betterment's questionnaire is slightly different when compared to the standard one. The latter attempts to capture perceived individual risk tolerance at a given moment rather than the risk tolerance needed to achieve a certain goal. Betterment's questionnaire is presented in Table 3 below.

Table 3: Betterment's questionnaire

Nr.	Question	Possible answers	Additions
1	Let's get started. Are you retired?	a) Yes b) No	Age determines stock allocation
2	What is your primary reason for investing?	a) Saving for retirement b) General investing c) Saving for an emergency fund d) Saving for a major purchase	Determines stock allocation over time
3	Are you currently investing?	a) Yes b) No	/
4	How are you currently investing?	a) I am doing it myself b) I have an employer plan c) I have an investment advisor	/
5	What are your investable assets?	(Amount USD)	Deposit determines stock allocation
6	Would you like unlimited access to our team of CFP professionals?	a) Yes b) No	Selection of payment plan
7	Which plan would you like to start with?	a) Digital Plan (0.25% fees) b) Premium Plan (0.40% fees)	Selection of payment plan
8	Goal setting	a) Individual (usable for any goal) b) 401(k) Rollovers/Transfers c) IRAs d) Joint Account e) Trust Account	Goal, age, deposits and time horizon determine stock ratios over time. Possible advice: - Increase auto-depostis - Add one-time deposits - Adjust time horizon - Adjust stock ratio

Adapted from Pirner (2018).

Within the Betterment's questionnaire an investor can choose the rationale for investing (question nr. 2). Based on the answer an investor is then allocated to underlying goal or multiple goals, if the investor chooses more than one option. Each goal may contain one or more investment accounts, which range from taxable, retirement (401(k), traditional IRA, and Roth IRA), joint, and trust accounts. There are currently five types of investment goals at Betterment; namely, retirement savings, retirement income, general investing, safety net, and major purchase goal (Table 4). As the name suggests, the retirement savings investment goal is assigned to individuals who are saving for retirement. An investor with at least 20 years until retirement is recommended to hold 90% equity and 10% fixed income allocation (Table 4). The allocation moves to 56% equity over time as the investor is closer to retirement date. After retirement, an investor can switch to the next goal type, retirement income. By doing that, the investor gets a plan for regular withdrawals while the reminder of a portfolio is invested more conservatively in line with the lower risk profile. The third type, general investing, is assigned to individuals who are not sure about their goals and/or do not envision any specific expenditure in the future. The allocation ranges from 90% equity in aggressive portfolio to 55% equity in conservative portfolio, which primarily depends on the age of an investor. The next type, safety net, is one of the highest priority goals at Betterment, assigned to individuals who are saving for an emergency fund. The allocation is conservative all the time, aiming at 30% equity and 70% fixed income. The time horizon is not specifically determined because it is assumed that an investor can liquidate a substantial portion of the portfolio at any time. The last type, major purchase, is assigned to individuals saving for a specific future expenditure (e.g., car, house, education, etc.). The allocation usually starts with 90% equity and 10% fixed income, and shifts to more conservative percentages as the goal is near the target date. It is assumed that an investor may liquidate the entire portfolio once the target date is reached (Egan, 2021).

Table 4: Betterment's goal types

Type of investment goal	Aggressive allocation	Conservative allocation	Anticipated term	Cash-out assumptions
Retirement savings	90% equity / 10% fixed income	56% equity / 44% fixed income	Up to 50 years	Switch to retirement income
Retirement income	56% equity / 44% fixed income	30% equity / 70% fixed income	Up to 30 years	Steady drawdown with dynamic withdrawal rate until target date
General investing	90% equity / 10% fixed income	55% equity / 45% fixed income	Depends on investor age	No liquidation
Safety net	30% equity / 70% fixed income	30% equity / 70% fixed income	Not specified	Up to full liquidation at any time
Major purchase	90% equity / 10% fixed income	0% equity / 100% fixed income	Between 1 and 35 years	Full liquidation at target date

Adapted from Egan (2021).

Investors can manually change the goal type within their account even after the initial setting. Furthermore, they have an option to personalise the recommended portfolio strategies. For example, they can shift the allocation either to more aggressive or more conservative, if they wish so.

4.2.2 Selection of exchange-traded funds for portfolio construction

Betterment selects exclusively from the universe of equity and fixed income ETFs, whereby it introduces internal "fund scoring method" to rate ETFs for incorporation in the portfolios. The method encompasses three essential components; namely, cost-to-trade, cost-to-hold, and market impact. The first two components can be incorporated in a single formula, called total annual cost of ownership (hereafter: TACO):

$$TACO = (bid/ask\ spread + liquidity) + (expense\ ratio + tracking\ difference) \tag{7}$$

Cost-to-trade, which encompasses the first part of the formula, is a measure of costs that occur during trading activities and is determined by a bid-ask spread and liquidity, whereby Betterment aims to:

- Select ETFs with narrow bid-ask spreads.
- Select ETFs with high liquidity or volume.

Cost-to-hold, which encompasses the second part of the formula, is a measure of costs that occur by holding a fund and is determined by the expense ratio and tracking difference, whereby Betterment aims to:

- Select ETFs with low expense ratios.
- Select ETFs with low tracking differences.

The third component, market impact, is the change in price of an ETF caused by trading activities. While market impact is already incorporated within TACO through the liquidity measure, Betterment takes further actions to prevent significant movements of an ETF price. It incorporates two additional measures; namely the relative share of AuM (hereafter: RS_{AuM}) and the relative share of average daily traded volume (hereafter: RS_{Vol}):

$$RS_{AuM} = \frac{AuM_{Betterment}}{AuM_{ETF}} \tag{8}$$

and

$$RS_{Vol} = \frac{Vol_{Betterment}}{Vol_{ETF}} \tag{9}$$

Betterment aims to minimise both measures to avoid situations where its trading activity would lead to a significant market impact. All the aforementioned constraints are summarised in Table 5 below.

Table 5: Betterment's ETF selection criteria

Constraint	Assessment
Cost-to-trade	Narrow bid-ask spread High liqudity (volume)
Cost-to-hold	Low expense ratio Low tracking difference
Market impact	High liquidity High AuM

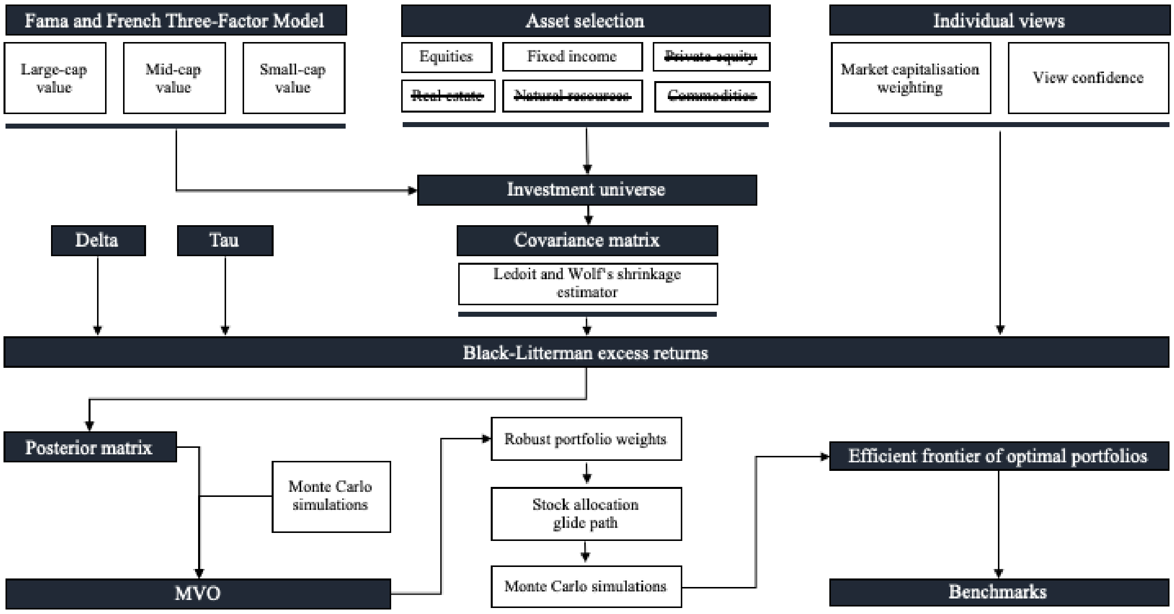
Adapted from Grealish (2021).

After applying ETF selection criteria, Betterment gets an investment universe of ETFs for both taxable and IRA accounts. See Appendix 4 and 5 for a full disclosure of Betterment's ETF selection for taxable and IRA accounts, respectively. The difference is that Betterment uses different alternative ETFs for IRA accounts. This is because Betterment uses the tax-loss harvesting feature for taxable accounts and has to avoid the wash sale rule. Furthermore, Betterment aims to improve portfolio after-tax returns by utilizing ETFs tracking municipal bonds, since the interest income is typically exempt from federal and state taxation (Grealish, 2019).

4.2.3 Customised portfolio construction

Like most of the other robo-advisors, Betterment allocates selected ETFs by using MVO, which is the foundation of MPT. However, Betterment goes one step further by estimating forward looking returns (Black-Litterman model), modifying covariance matrix (Ledoit-Wolf shrinkage method) and tilting portfolios (Fama and French model).

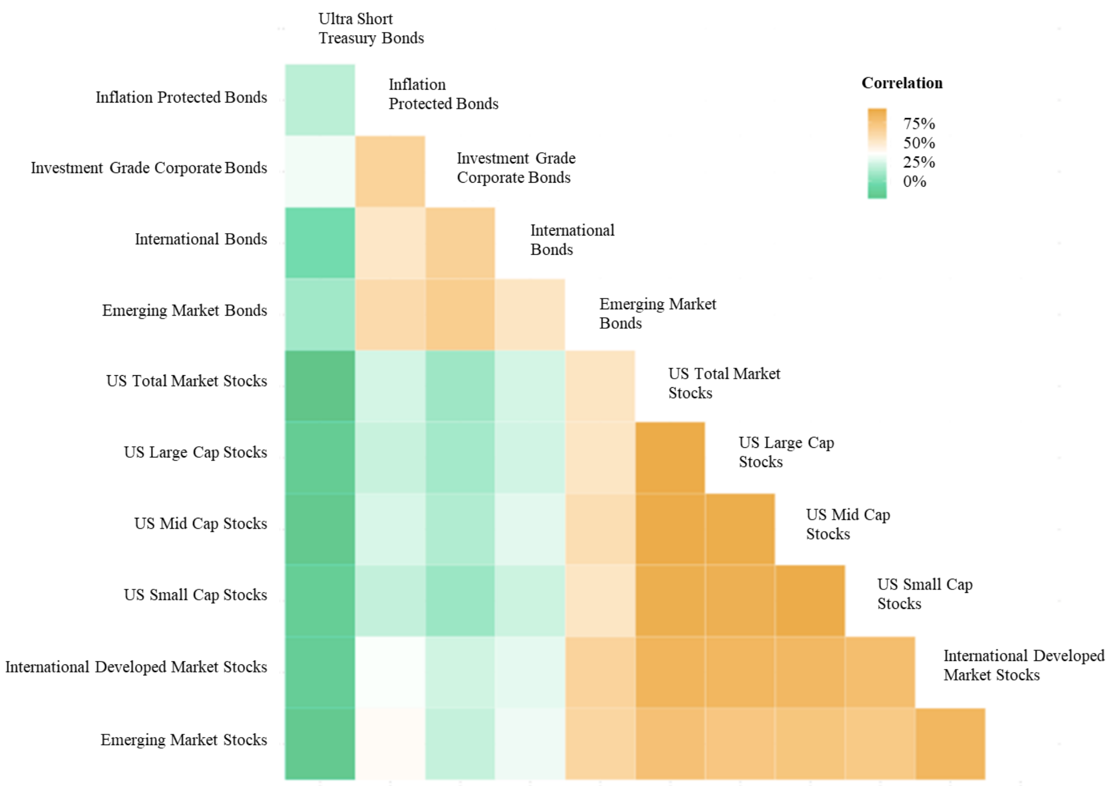
Figure 10: Betterment's asset allocation and optimisation



Adapted from Pirner (2018).

To estimate expected returns Betterment uses the Black-Litterman model with some additions. Based on the model, the selected basket of assets is considered as the global market portfolio. To capture the exposures of the asset classes, Betterment relies exclusively on the ETFs selected according to the selection criteria already discussed in the previous chapter. As a starting point of the Black-Litterman approach, Betterment uses reverse optimisation to compute implied equilibrium returns. The first required input is the risk aversion coefficient or delta. Betterment does not disclose any value regarding this input. The second input (i.e., the covariance matrix of excess returns) is calculated based on the monthly excess returns and then annualised. Betterment's addition here is that it employs Ledoit-Wolf shrinkage methodology, which systematically reduces the estimation error arising from the sample covariance matrix (Ledoit & Wolf, 2003). In his study, Pirner (2018) reconstructs this methodology using Betterment's data and finds that the upgraded matrix is more balanced and centered than the original covariance matrix. Figure 11 shows the implied correlation matrix for Betterment based on the shrinkage method.

Figure 11: Correlation matrix modified by the shrinkage method



Adapted from Grealish (2019).

The value assets are highly correlated with the US Total Stock Market ETF, while the correlation with fixed income assets is significantly lower, moving between 0% and 50%. Betterment specifically states that to select portfolios it tilts its portfolios based on the implications of the Fama and French Three-Factor Model (Grealish, 2019). It seems that a high correlation of value ETFs is therefore acceptable from Betterment's perspective, and somewhat countered with a low correlation with the fixed income ETFs (Pirner, 2018).

The third input is the market capitalisation weight of the assets. Betterment does not disclose the weights. However, these derived relative weights are then used to calculate implied equilibrium excess returns, which are relatively lower and more balanced when compared to historical averages (Pirner, 2018).

Fama & French (1992) showed that returns of equities are driven by market, size, and value factors. The first factor is already incorporated in Betterment's portfolio strategy by the underlying asset allocation, but to gain higher returns from the size and value factors, Betterment further tilts portfolios using its views and corresponding level of confidence in the views. Views are calculated from the historical data analysis, while the level of confidence or tau is determined subjectively (Grealish, 2019). However, a more robust explanation of how Betterment formulates its views or which views are used, relative or absolute, is publicly not available. For comparison, Wealthfront also tilts its portfolios by incorporating its views, which are formulated with the Wealthfront Capital Markets Model (Wealthfront, n.d.). Once the views are incorporated, the returns are adjusted upwards or downwards, if the view is positive or negative, respectively. The resulting returns are so-called Black-Litterman excess returns (Idzorek, 2007).

Before constructing an efficient frontier by MVO, Betterment calculates the posterior matrix and uses Monte Carlo simulations to further increase the robustness of portfolio weights (Pirner, 2018). Thus, final weights are a complex average of the tilted market portfolio based on the Fama and French method, and the weights produced by Monte Carlo simulations (Grealish, 2019). To argue its value added, Betterment compares its efficient frontier with the "naive portfolio", which consists of the US equity index (SPY) and the US bond index (AGG).

4.2.4 Automated rebalancing

Betterment automatically rebalances portfolios daily, if necessary. As demonstrated in Table 6, the portfolio drift according to Betterment's methodology is defined as aggregated deviation of asset classes from their target allocation weights, divided by two.

Table 6: Measuring portfolio drift for rebalancing

	Target allocation	Current allocation	Deviation (+/-)
Domestic fixed income	25%	30%	5%
International fixed income	25%	20%	5%
Domestic equtiy	25%	30%	5%
International equity	25%	20%	5%
Aggregated deviation			**20%**
Portfolio drift according to Betterment's methodology			**10%**

Adapted from Grealish (2018).

Betterment then tries to reduce this shift in either of the following ways (Grealish, 2018):

– When the portfolio drift exceeds 2%, algorithms automatically calculate the required amount to reduce the drift down to 0% and the system notify a client to make the deposit. This method is called cash flow rebalancing, since client's deposits or dividends received in the account are used to reduce the drift. The cash flows are used to buy underweighted asset classes and this is the preferred option because the need to sell is reduced or eliminated, and thus no tax obligations are generated.
– When the portfolio drift exceeds 3% and there are no (or limited) cash flows available, algorithms start to sell overweighted asset classes and use the proceeds to buy the underweighted ones. This method is called sell/buy rebalancing, since proceeds from the trades are used to reduce the drift. Because tax obligations may arise from selling,

algorithms employ additional restriction on taxable accounts. The rationale is to sell assets that have been in the portfolio long enough to realise capital gains that are taxed at a lower rate. If there are no such assets (e.g., in newly established accounts), the system notifies a client to make a deposit. If even that is not possible then the drift may stay above 3% until one of the conditions is satisfied.

– When a client changes investment preferences and thus modify the target allocation, algorithms automatically rebalance to the new target and reduce portfolio drift down to 0%. Again, this might cause tax obligations therefore the system informs a client about potential tax impact. Moreover, the tax minimisation restriction is triggered to help reduce the tax impact on sold securities.

4.2.5 Improved after-tax returns

Aside from the tax minimisation restriction already incorporated in the algorithms, Betterment offers a fully automated tax-loss harvesting service to improve after-tax returns, which is called Tax Loss Harvesting+™ or TLH+. The concepts of tax-loss harvesting have already been discussed in chapter 2.6 of this thesis. In addition, Betterment has published a white paper quantifying the value of its tax-loss harvesting service. By backtesting the performance between 2000 and 2013, Betterment found that TLH+ would have provided an estimated 0.77% annual tax alpha. Wealthfront (2021b) also found comparable results under slightly different assumptions in its white paper.

5 PERFORMANCE EVALUATION

5.1 Previous studies

Tao, Su, Xiao, Dai, & Khalid (2020) in their study compare the risk-adjusted performance figures of 100 US robo-advisors and conventional funds (equity, fixed income, money market, and hybrid funds) over a time period of four years, from January 2016 to December 2019. They find that, on average, robo-advisors outperform all standalone conventional funds. Furthermore, robo-advisors also outperform three prominent equity indices (S&P 500, DJIA, Nasdaq), and the results are robust for different risk-reward model specifications.

Puhle (2019) analyses monthly returns of five German robo-advisors over a time period of three and a half years, from May 2015 to December 2018. He documents significant performance differences between some of the analysed robo-advisors. Furthermore, he finds that asset allocation is not the only driver of performance differences between robo-advisors. Alternative drivers might be missing factors, portfolio implementation, and rebalancing.

However, both the aforementioned studies lack a longer time horizon. It is reasonable to look at the long-term returns (e.g., five years or longer) because short-term returns do not provide a complete picture. This is why some studies investigate the long-term performance of selected robo-advisors by backtesting the replicated portfolios. For example, Berg & Mhanga (2019) in their study backtest the performance of portfolios reconstructed based on Swedish robo-advisors' investment methodologies, using the data from January 2010 to February 2019. They find that macroeconomic factors play a significant role in the performance of the robo-advisors and that the portfolios with a higher proportion of stocks are the long-term winners. On the other hand, the lower the proportion of stocks, the stronger the risk-adjusted returns, emphasising the fact that robo-advisors benefit risk-averse investors the most. In another study, Bjerknes & Vukovic (2017) backtested the performance of portfolios reconstructed based on notable US robo-advisors Betterment, Future Advisor, Schwab Intelligent Portfolios, and Wealthfront, using data from January 2009 to December 2016. They found that all four robo-advisors included in the analysis outperformed the benchmark in terms of cumulative return over the investment horizon of eight years. Moreover, they observed that three out four robo-advisors outperformed the benchmark in terms of risk-adjusted return as well. They also found that the robo-advisor model benefits conservative investors the most, which is in line with Berg & Mhanga (2019) findings. Even though these findings exhibit a pattern, they are not based on the real performance data of robo-advisors, but rather on replicated portfolios. In addition, the analysis based on the actual historical performance figures of selected US robo-advisors is given in the next chapter.

5.2 Empirical analysis

5.2.1 Data and methodology

The returns data for robo-advisors is retrieved from the Backend Benchmarking internet portal, which tracks the performance of investment accounts (taxable and retirement), opened at the largest US robo-advice providers and funded with real money. Returns are provided a quarterly and are net-of-fees.

In this thesis, I focus on taxable accounts that cover the longest interval, i.e., from the first quarter of 2016 to the last quarter of 2020. After applying these selection criteria, I was left with the sample consisting of 6 robo-advisors: Betterment, Acorns, Personal Capital, Schwab, SigFig and Vanguard. Table 7 below introduces key facts about these robo-advisors and shows the underlying portfolio constitution of the accounts. There are differences in the required account minimums and advisory fees that each provider charges to its clients for the robo-advice services. Fees mostly depend on the type of robo-advisor, with those using the hybrid approach being more expensive, as can be observed from the table. Some robo-advisors also offer tax-loss harvesting services. All portfolios included in the analysis have a similar target asset allocation of a moderate risk profile (i.e., approx. 60% equities, 40% fixed income). There are, however, some minor differences between robo-advisors as they may add cash or other miscellaneous assets to their portfolios. The equity part of the portfolios is generally allocated to domestic (between 50%-70%) and international equities (between 30%-50%).

Table 7: Key facts about selected robo-advisors

Robo-advisor	Account minimum	Advisory fee	Fully automated / hybrid	Tax-loss harvesting	Weighted average expense ratio	Initial target asset allocation	Asset allocation as of 31.12.2020
Betterment	Digital investing plan: No minimum; Premium investing plan: 100,000 USD	Digital investing plan: 0.25%; Premium investing plan: 0.40% (0.30% for balances above 2 million USD)	Digital investing plan: fully automated Premium investing plan: hybrid	Yes	0,09%	65% equities / 35% fixed income	66% equities / 34% fixed income
Acorns	No minimum	Acorns Invest: 1 USD/month; Acorns Invest and Acorns Later and Acorns Spend: 3 USD/month; Acorns Family: 5 USD/month; (special offer for balances above 1 million USD)	Fully automated	No	0,05%	61% equities / 39% fixed income	63% equities / 37% fixed income
Personal Capital	100,000 USD	Balance up to 1 million USD: 0.89%; Balance over 1 million USD: reduced rate	Hybrid	Yes	0,10%	69% equities / 25% fixed income / 5% miscellaneous / 1% cash	73% equities / 23% fixed income / 4% miscellaneous / 1% cash
Schwab	Intelligent Portfolios: 5,000 USD; Intelligent Portfolios Premium: 25,000 USD	Intelligent Portfolios: 0 USD; Intelligent Portfolios Premium: 300 USD initial planning fee, 30 USD/month subscription	Hybrid	Yes	0,18%	61% equities / 23% fixed income / 5% miscellaneous / 10% cash	58% equities / 30% fixed income / 2% miscellaneous / 10% cash
SigFig	2,000 USD	Balance up to 10,000 USD; 0 USD Balance over 10,000 USD; 0.25%	Hybrid	Yes	0,07%	62% equities / 37% fixed income / 1% cash	62% equities / 37% fixed income / 1% cash
Vanguard	Vanguard Personal Advisor: 50,000 USD; Vanguard Digital Advisor: 3,000 USD	Vanguard Personal Advisor: 0.30% for balances up to 5 million USD, lower rate for balances over 5 million USD. Vanguard Digital Advisor: 0.20%	Vanguard Personal Advisor: hybrid Vanguard Digital Advisor: fully automated	No	0,07%	60% equities / 40% fixed income	62% equities / 38% fixed income

Adapted from Backend Benchmarking (2021a).

First, I have analysed the reported historical returns. To better understand the underlying performance, I analysed separately the equity, fixed income, and balanced portfolios. I took the reported quarterly returns and logarithmised them. The logarithmic returns were then the basis for the analysis. I calculated 1-year, 2-year, 3-year, 4-year, and 5-year performance by annualization. Furthermore, I introduced the benchmarks, which were taken as an alternative to the robo-advisors. For that purpose, I selected conventional funds (i.e., actively/passively managed mutual funds, an ETF and index funds). As there are a lot of providers of conventional funds in the market, I decided to go with the two financial institutions that offer both conventional funds as well as their in-house robo-advice services: Vanguard and Schwab. The selection was further limited by the asset composition of the funds and the time period, which means I selected only the funds that were available for the full analysed period. I selected twelve funds that invest either in equity or fixed income securities or have a balanced portfolio composition, i.e., approx. 60% equity and 40% fixed income.

Benchmarks for equity portfolio:

– *Vanguard Total World Stock ETF (VT).* It is an ETF that aims to invest in global equity. Regionally, the majority represents North America (63%) and is followed by Europe

(16%), Pacific (11%), emerging markets (10%), Middle East (<1%) and other (<1%) (Vanguard, 2021a).

- *Vanguard Global Equity Fund (VHGEX).* The actively managed mutual fund that invests in global equity. By the composition it is very similar to VT with North America representing more than 60% of assets (Vanguard, 2021b).
- *Schwab Total Stock Market Index Fund (SWTSX).* It is an index fund that seeks to provide exposure to small-cap, mid-cap and large-cap US equity by tracking the Dow Jones U.S. Total Stock Market Index^{SM}. Large-cap is representing more than 60% of the portfolio (Charles Schwab, 2021a).
- *Schwab Core Equity Fund (SWANX).* The actively managed mutual fund that invests in US equity. By the composition it is very similar to SWTSX with large-cap representing more than 60% of the portfolio (Charles Schwab, 2021b).

Benchmarks for fixed income portfolio:

- *Vanguard Total Bond Market Index Fund Admiral Shares (VBTLX).* Index fund that provides exposure to US investment-grade bonds by investing primarily in US Treasuries (more than 60%) with maturities up to 10 years, which represent more than 70% of the portfolio (Vanguard, 2021c).
- *Vanguard Core Bond Fund Investor Shares (VCORX).* The actively managed mutual fund that provides exposure to US investment-grade bonds. By the composition the fund is very similar to VBTLX with US Treasuries representing more than 60% of the portfolio and maturities up to 10 years representing more than 70% of the portfolio (Vanguard, 2021d).
- *Schwab Treasury Inflation Protected Securities Index Fund (SWRSX).* Index fund that aims to track the US TIPS market (Charles Schwab, 2021c).
- *Vanguard Emerging Markets Government Bond Index Fund Admiral Shares (VGAVX).* Index fund that provides exposure to the government bonds in emerging markets (Vanguard, 2021e).

Benchmarks for balanced portfolio:

- *Vanguard Balanced Index Fund Admiral Shares (VBIAX).* By tracking two benchmark indexes the fund provides exposure to roughly 60% equity and 40% fixed income (Vanguard, 2021f).
- *Vanguard Wellington Fund Admiral Shares (VWENX).* The actively managed mutual fund that similar to VBIAX offers exposure to equity, about two-thirds of the portfolio, and the remaining portion to fixed income (Vanguard, 2021g).
- *Schwab Balanced Fund (SWOBX).* The actively managed mutual fund that offers a diversified exposure to US equity, fixed income, and cash and equivalents (Charles Schwab, 2021d).

- *Schwab MarketTrack Balanced Portfolio (SWBGX).* Passively managed mutual fund that seeks both capital growth and income through investing in equity (50%-70%) and fixed income funds (Charles Schwab, 2021e).

To be consistent, I took quarterly returns of the funds, which were retrieved from Yahoo Finance. As robo-advisors' returns are calculated on a net-of-fee basis, I also subtracted an average annual management fee from the gross benchmarks' returns.[5]

In the second part of the empirical analysis, I turn to the cumulative performance of balanced portfolios and the downside risk. To measure downside risk, I introduce the maximum drawdown (hereafter: MDD) measure, which is calculated in accordance with the following formula:

$$\text{MDD} = \frac{\text{Trough Value} - \text{Peak Value}}{Peak\ Value} \tag{10}$$

In the last part, I introduce the Sharpe ratio as a measure of risk-adjusted-performance. Methodologically, the "Sharpe ratio divides average portfolio excess return over the sample period by the standard deviation of returns over that period. It measures the reward to (total) volatility trade-off" and is calculated in accordance with the following formula (Bodie, Kane, & Marcus, 2011, p. 814):

$$\text{Sharpe ratio} = \frac{\mathrm{r}_p - r_f}{\sigma_p} \tag{11}$$

where r_p is average return of the portfolio, r_f is the risk-free rate[6], and σ_p is the portfolio's standard deviation.

5.2.2 Historical returns

The results of reported historical returns and discussion are further provided in this chapter, starting with the equity portfolio, followed by the fixed income and balanced portfolios.

[5] I assumed a 0.33% annual management fee, which corresponds to the average fee of selected robo-advisors.
[6] I assumed a risk-free rate as the current yield on the 10-year US government bond, which amounts to 1.29% as of 16 July 2021 (https://www.bloomberg.com/markets/rates-bonds/government-bonds/us).

Table 8: Performance of equity portfolios as of 31 December 2020

Rank	1-year	2-year	3-year	4-year	5-year
1	SigFig 15.9%	SigFig 19.9%	SigFig 10.1%	SigFig 13.0%	SigFig 12.4%
2	Vanguard 15.7%	Vanguard 19.8%	Vanguard 10.0%	Vanguard 12.7%	Vanguard 12.0%
3	Acorns 12.7%	Acorns 18.5%	Acorns 9.5%	Acorns 11.4%	Acorns 11.3%
4	Personal Capital 12.6%	Betterment 17.5%	Personal Capital 8.0%	Betterment 10.6%	Schwab 10.4%
5	Betterment 12.3%	Personal Capital 17.3%	Betterment 7.4%	Personal Capital 10.2%	Betterment 10.3%
6	Schwab 9.5%	Schwab 15.6%	Schwab 6.6%	Schwab 9.7%	Personal Capital 10.3%
Average robo-advisor	**13.1%**	**18.1%**	**8.6%**	**11.3%**	**11.1%**
Benchmarks					
VT	15.1%	19.3%	9.3%	12.4%	11.5%
VHGEX	19.9%	22.4%	11.6%	14.8%	13.0%
SWTSX	18.5%	22.5%	13.1%	14.5%	13.9%
SWANX	11.0%	18.2%	8.8%	11.9%	10.8%
Average benchmark	**16.1%**	**20.6%**	**10.7%**	**13.4%**	**12.3%**

Source: Own work.

The average robo-advisor returned 11.1% annually on equity portfolios over the last 5-year period, while the average benchmark returned 12.3% annually in the same period, especially owing to exceptionally well-performing VHGEX and SWTSX, whereby the first is Vanguard's actively managed mutual fund and the latter is Schwab's index fund tracking solely the US stock market. With the exception of SigFig and Vanguard, robo-advisors were not able to beat the VT, which is the closest approximation of passive investing in the entire world of equities, covering developing and well-established markets.

The most successful period in terms of historical returns for both robo-advisors as well as benchmarks was the last 2-year period, when they returned on average 18.1% and 20.6%, respectively.

The best performing robo-advisor was SigFig, which outperformed its peers in all periods and returned a healthy 12.4% over the 5-year period. The reason for its outperformance might be that SigFig invests primarily in ETFs with exposure to US large-cap stocks, which have outperformed small-cap and mid-cap stocks over the past five years. Secondly, SigFig holds a higher than average portion of its international holdings in emerging markets, which have had superior returns compared to developed markets over the analysed period (Backend Benchmarking, 2021a). Despite being the most dominant among robo-advisors, SigFig still did not manage to outperform both the best performing benchmarks.

Table 9: Performance of fixed income portfolios as of 31 December 2020

Rank	1-year	2-year	3-year	4-year	5-year
1	SigFig 8.7%	SigFig 8.4%	SigFig 5.4%	Schwab 5.2%	Schwab 5.6%
2	Schwab 7.0%	Schwab 7.7%	Schwab 4.9%	SigFig 5.2%	SigFig 5.3%
3	Personal Capital 5.8%	Acorns 7.0%	Betterment 4.4%	Betterment 4.3%	Betterment 3.9%
4	Betterment 5.4%	Betterment 6.7%	Acorns 4.0%	Vanguard 3.9%	Personal Capital 3.8%
5	Acorns 5.2%	Personal Capital 6.3%	Vanguard 3.9%	Acorns 3.7%	Acorns 3.3%
6	Vanguard 4.6%	Vanguard 5.4%	Personal Capital 3.6%	Personal Capital 3.6%	Vanguard 3.2%
Average robo-advisor	**6.1%**	**6.9%**	**4.4%**	**4.3%**	**4.2%**
Benchmarks					
VBTLX	7.1%	7.6%	4.9%	4.5%	4.0%
VCORX	9.4%	9.0%	5.6%	5.0%	4.2%
SWRSX	10.0%	8.9%	5.4%	4.7%	4.5%
VGAVX	5.3%	9.0%	5.0%	5.7%	6.4%
Average benchmark	**7.9%**	**8.6%**	**5.2%**	**5.0%**	**4.8%**

Source: Own work.

The average robo-advisor returned 4.2% annually on fixed income portfolios over the last 5-year period, while the average benchmark returned 4,8% annually in the same period, owing to the emerging economies tracking index fund-VGAVX, which in the long run outperformed them all.

The most successful period in terms of historical returns for both robo-advisors and benchmarks was the last 2-year period, when they returned on average 6.9% and 8.6%, respectively. SWRSX, an index fund that tracks the US TIPS market, shows the most compelling performance in the last year period with an annual return of 10%.

In the long run, the best performing robo-advisor was Schwab, which outperformed its peers over the 4-year and 5-year periods. The advantage of Schwab is that it holds a well-diversified portfolio of fixed income, consisting of high-yield corporate, municipal and emerging market bonds, as well as mid-duration TIPS. Schwab's robo-advisor was followed by SigFig. The latter had superior performance over the shorter period compared to Schwab. SigFig also holds a broad mix of fixed income, with a strong position in investment-grade bonds, as well as allocations to TIPS and high-quality US corporate bonds (Backend Benchmarking, 2021a). It seems that robo-advisors have done a great job by exposing the fixed income part of their portfolios to a broad bond market as “emerging market bonds and corporate bonds did better at the beginning of the last five years when markets were calmer and riskier debt was under less duress, while the mid-duration TIPS have done well over the last year as investors shifted into the US government bonds and worries of inflation have spiked due to the massive stimulus packages” (Backend Benchmarking, 2021a, p. 17-18).

Table 10: Performance of balanced portfolios as of 31 December 2020

Rank	1-year	2-year	3-year	4-year	5-year
1	SigFig 14.4%	SigFig 16.0%	SigFig 8.7%	SigFig 10.3%	SigFig 9.9%
2	Vanguard 11.5%	Personal Capital 14.6%	Vanguard 7.7%	Vanguard 9.4%	Personal Capital 8.7%
3	Personal Capital 11.2%	Vanguard 14.3%	Acorns 7.4%	Betterment 8.8%	Vanguard 8.6%
4	Betterment 11.0%	Betterment 14.2%	Personal Capital 7.0%	Personal Capital 8.6%	Schwab 8.3%
5	Acorns 9.8%	Acorns 14.0%	Betterment 6.7%	Acorns 8.5%	Betterment 8.3%
6	Schwab 8.5%	Schwab 12.2%	Schwab 5.7%	Schwab 7.9%	Acorns 8.3%
Average robo-advisor	**11.0%**	**14.2%**	**7.2%**	**8.9%**	**8.7%**
Benchmarks					
VBIAX	14.9%	17.1%	10.3%	10.9%	10.3%
VWENX	9.8%	14.9%	8.7%	9.9%	10.0%
SWOBX	13.4%	15.7%	8.9%	10.2%	9.1%
SWBGX	9.6%	13.2%	6.8%	8.0%	8.1%
Average benchmark	**11.9%**	**15.2%**	**8.7%**	**9.8%**	**9.4%**

Source: Own work.

The average robo-advisor returned 8.7% annually on a balanced portfolio during the last five-year period, while the average benchmark returned 9.4% annually in the same period, with its top-performing index fund- VBIAX being the most dominant with a 10.3% annual return. The latter is also the most similar to robo-advisors in terms of the asset allocation of equity and fixed income. However, it focuses only on the US market and thus differs in terms of market diversification. Interestingly, this passively managed fund succeeded in beating both actively managed mutual funds, VWENX and SWOBX.

The best performing robo-advisor over the analysed period was SigFig, which is not surprising given its dominating equity and above-average fixed income performance. Not only was SigFig dominant among robo-advisors, but it also managed to outperform two benchmarks, SWOBX and SWBGX, while over the last four years it also outperformed VWENX. This is remarkable given the fact that SigFig was the only robo-advisor that outperformed three benchmarks and came very close to the best-performing VBIAX.

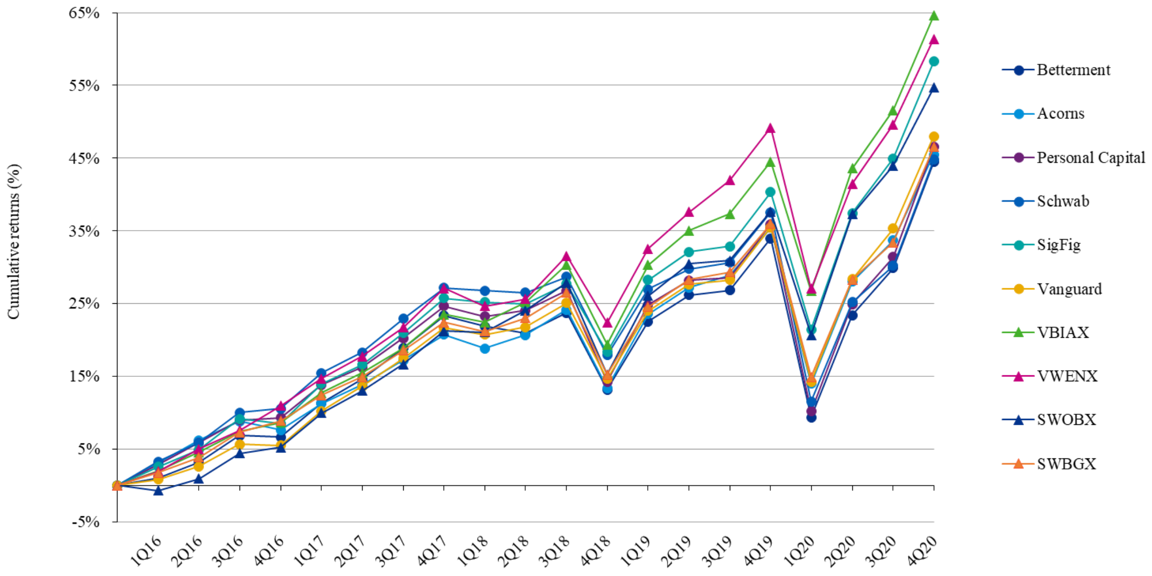
Another observation can be made about the type of robo-advisors being fully automated or using human interaction in addition to their automated portfolio management style. It seems that the latter provides better long-term returns since SigFig and Personal Capital both outperformed their fully automated peers over the 5-year period, indicating that the robo-advice model may be even more pronounced with a little human help. After all, even Betterment, which has started as a fully automated robo-advisor, now offers hybrid services within its premium plan.

One of the most important features of robo-advisors, as already discussed in earlier chapters is the tax-loss harvesting service provided by most of the analysed robo-advisors (see Table 7). However, it is almost impossible to measure the benefit of the tax-loss harvesting with the publicly available data as of today. There is, however, early evidence on the tax-loss harvesting benefit provided by Backend Benchmarking, which tracks a set of specific accounts that offer tax-loss harvesting (these accounts are different from the afore analysed accounts). High sell-off at the beginning of the global pandemic has provided an opportunity to reassess the efficacy of the tax-loss harvesting services. For example, Schwab stands out for the highest percentage of realised net losses in 2020. As of the end of 2020, it realised over 8.3% of its portfolio in net short-term losses. On the contrary, SigFig did not realise any losses in the same period. However, it has to be noted that the results are still very limited as the tax-loss harvesting occurs less often in older accounts, which are more likely to hold assets with the value above their original cost basis thus leaving no space for harvesting tax-losses. Furthermore, with the rising market, the opportunities to harvest losses fall (Backend Benchmarking, 2021b).

5.2.3 Cumulative performance and downside risk

The cumulative performance of balanced portfolios is charted in Figure 12, while Table 11 shows the downside risk measured by MDD.

Figure 12: Cumulative performance of balanced portfolios



Source: Own work.

Figure 12 shows a very similar trend for all portfolios. There were two major drops, one in the last quarter of 2018 and one in the first quarter of 2020. The latter refers to the beginning of the COVID-19 pandemic when the average robo-advisor experienced the MDD of 63.4%, as presented in Table 11. Robo-advisors exhibited higher MDD on average compared to the benchmarks, which averaged MDD of 47.2% in the same period. This indicates that robo-advisors may be riskier to invest in, and investors should expect higher losses in the event of financial turmoil in the short term. However, it has to be noted that robo-advisors generally adhere to long-term investment horizons and this may not be the case in the long run.

Table 11: Maximum drawdown

Robo-advisors	MDD (in %)	Benchmarks	MDD (in %)
Betterment	-72,4	VBIAX	-40,0
Acorns	-60,5	VWENX	-45,0
Personal Capital	-71,7	SWOBX	-45,1
Schwab	-69,2	SWBGX	-58,6
SigFig	-46,8		
Vanguard	-59,8		
Average	**-63,4**	**Average**	**-47,2**

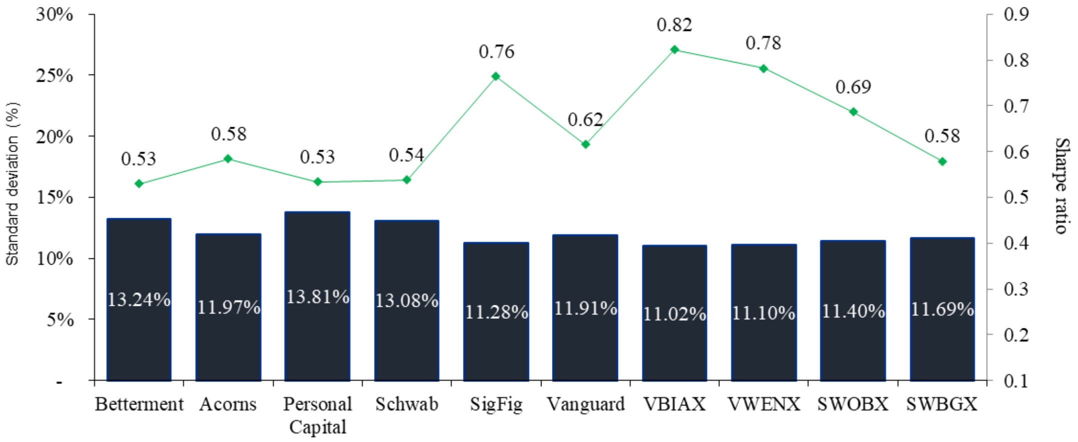
Source: Own work.

Despite the turbulent first quarter of 2020, the robo-advice market experienced a massive surge, gaining an additional 3.1% new clients (Corporate Vision, 2020). This turned out to be beneficial for the investors since the performance of robo-advisors rebounded in the second quarter of 2020. The average robo-advisor returned 12.7% in that quarter alone, which is an astonishing figure given the volatile market conditions. Furthermore, even the benchmarks were not able to beat this performance because the average benchmark returned 12.5% during that quarter.

5.2.4 Risk-adjusted performance

After introducing the Sharpe ratio as a measure of risk-adjusted performance, the following figure can be charted.

Figure 13: Risk-adjusted performance



Source: Own work.

With the inclusion of risk-adjusted measures for the 5-year period, the picture is almost identical to historical returns where the average robo-advisor performed worse than the average benchmark with the average Sharpe ratio of 0.59 compared to 0.72, respectively. On average, robo-advisors exhibited a much higher standard deviation amounting to 12.5% compared to benchmarks' 11.3%.

It has been observed that robo-advisors are generally riskier to invest in and do not reward as much as the benchmarks for the given level of risk. The obvious exception here is SigFig, which not only outperformed SWOBX and SWBGX in terms of historical returns but also in terms of risk-adjusted performance with its Sharpe ratio amounting to 0.76 over the 5-year period. It was followed by Vanguard's robo-advisor, which also managed to beat the SWBGX benchmark with a Sharpe ratio of 0.62.

CONCLUSION

The purpose of this thesis was to provide a thorough understanding of the robo-advice model's capabilities in the portfolio management process, as well as to determine whether this model can deliver sound investment advice with attractive returns for investors. The following four questions were addressed in this thesis:

- What are the value propositions of a typical robo-advisor and how does it differentiate from a traditional wealth manager?
- How does the robo-advice model create value for investors?
- What is the value of using robo-advice services for traditional financial institutions?
- How do robo-advisors perform?

I first determined the following value propositions of a typical robo-advisor by analysing past studies and comparing different robo-advice models. To begin with, robo-advisors typically offer a cost structure that is minimal, transparent and easy to understand. The amount of human engagement in the portfolio management process affects the fees. "Pure" robo-advisors, which provide fully automated robo-advice services charge lower fees, starting at around 0.25% per annum while the hybrid robo-advisors, which provide advice with human interaction, charge higher fees, starting at around 0.40% per annum (with some exceptions). This is still way below the average traditional (human) advisor who charges fees between 1% to 2% per annum. Not only the fees but the account minimums are much lower with robo-advisors as well. This is due to the target groups, because robo-advisors normally focus on less wealthy investors, while the traditional wealth managers focus on the wealthiest two target groups.

Secondly, due to their artificial intelligence nature, robo-advisors can employ advanced quantitative methods of portfolio management, resulting in diversified and tax-efficient portfolio compositions. In general, robo-advisors work based on the MPT framework and use MVO to generate the efficient frontier of optimal portfolios. However, MVO by itself has some limitations, such as normality assumption, extreme input sensitivity, estimation error, and time horizon. Therefore, robo-advisors apply different methods to overcome them. The most commonly used method is the Black-Litterman model, which helps to generate intuitive and well-diversified portfolios. Another important feature of robo-advisors is automated threshold-based rebalancing. As the theoretical and empirical evidence suggests, rebalancing leads to better risk-adjusted returns. The technological sophistication and built-in systems make robo-advisors perfectly suited for monitoring and rebalancing process. They can check portfolios daily, which can be a very time-consuming task for a human advisor to do. Last but not least, the advancement of robo-advisors from the portfolio management perspective is tax-loss harvesting, which by itself is nothing new, but a service usually provided by traditional wealth managers only to clients with large accounts, while robo-advisors also cater to clients with small accounts. Furthermore, robo-advisors are able to perform tax-loss harvesting daily and can achieve a high level of tax efficiency, which results in higher returns provided to investors.

Making investment decisions is normally considered to be difficult for investors because such a decision-making process can be risky and complex. Furthermore, the investment process requires high financial literacy and discipline as it is full of psychological pitfalls that lead to cognitive or emotional biases. Some of the most noticeable biases related to portfolio management are: overconfidence, loss aversion bias, trend-chasing, rank effect, mental accounting, familiarity bias, confirmation bias and anchoring bias. Even highly educated wealth managers appear to exhibit these behavioural biases trading frequently, chasing returns, preferring actively managed funds, and underdiversifying their portfolios. Human nature dictates this. On the contrary, the robo-advice model lays the framework for generating decisions that are unbiased or at least less prejudiced. Investment methodologies based on scholarly publications are frequently followed by robo-advisors. They avoid active (return-chasing) techniques in favour of low-cost ETFs and portfolio diversification over many different asset classes, which are chosen based on the risk and return profiles. They include both, domestic and international investments to achieve even higher diversification. Robo-advisors exhibit lower disposition effects, trend-chasing, rank effect, and familiarity bias by investing systematically in accordance with a well-grounded investment methodology. As a result, the reduction of behavioural biases is counted as the third value proposition of a typical robo-advisor.

After identifying value propositions, I focus on the part where investing with one of the pioneering robo-advisors is analysed to show how the robo-advice model creates value for investors. I use the robo-advisor pioneer Betterment, founded in 2008, which is the first-generation start-up company offering fully automated robo-advice services. It has more than 18 billion USD in AuM and over 500,000 clients as of December 2020. Betterment's investment strategy is centred around goal-based investing, the concept that has grown in popularity after the financial crisis in 2008. Goal-based investing uses mental accounting bias as a strength and emphasizes the division of the total portfolio into several subportfolios, where each subportfolio has a specific life goal of an investor assigned. Betterment currently offers five types of investment goals: retirement savings and income, general investing, safety net, and major purchases. For each goal, Betterment then recommends aggressive and conservative target allocations, which can be adjusted based on the client's preferences. After the client's profile identification, Betterment starts with the implementation of its portfolio strategy. First, it selects appropriate assets to be included in the portfolio. In general, robo-advisors choose ETFs, which have the most lucrative features for automated trading strategies when compared to other investment instruments. Betterment selects exclusively from the universe of equity and fixed income ETFs, while it excludes other traditional asset classes such as commodities, real estate, private equity, and natural resources. For the selection, Betterment employs tight constraints, where the primary goal is to select funds that provides the lowest TACO and exhibits the lowest market impact, which means that selected ETFs have sufficient AuM and average daily traded volume so that the price of an ETF is unaffected when Betterment trades on behalf of its clients. By doing so, Betterment filters the universe of all investable ETFs down to the final set, which usually consists of around 20 ETFs, labelled as the prime or alternative selection. The alternative ETFs are usually used for tax-loss harvesting service because the wash sale rule has to be considered. To optimally allocate assets, Betterment then makes use of the Black-Litterman model and the MVO, with some additions for robustness. Such additions are the Ledoit-Wolf shrinkage for the covariance matrix, a market-capitalisation-based weighting scheme for the view matrix, and Monte-Carlo simulations. The portfolios are checked by an algorithm daily for rebalancing opportunities. Betterment uses three types of rebalancing: cash flow, sell/buy, and allocation change rebalancing, always with an eye on tax efficiency. To improve after-tax returns, Betterment also offers a fully automated tax-loss harvesting service, which can provide roughly 0.77% additional performance benefit.

The final part of the thesis is an evaluation of the robo-advisors' performance. Previous studies have shown that robo-advisors can outperform their traditional counterparts in terms of cumulative returns and risk-adjusted returns. However, these studies lack longer time periods, or measure the performance based on the replicated portfolios. Furthermore, the studies conducted in relatively non-volatile market conditions exclude any effects of the financial turmoil. This is why an additional empirical analysis was performed within the thesis. I analysed quarterly return data for six US robo-advisors and their benchmarks, ranging from the first quarter of 2016 to the fourth quarter of 2020. The results show that the average robo-advisor returned 11.1% annually on an equity portfolio, 4.2% annually on a fixed income portfolio, and 8.7% annually on the balanced portfolio (with a target asset allocation of the moderate risk profile of 60/40), over the last 5-year period. Meanwhile, the average benchmark returned 12.3% annually on an equity portfolio, 4.8% on a fixed income portfolio, and 9.4% on the balanced portfolio over the same period. The balanced counterparts of robo-advisors exhibited lower MDD, observed in the first quarter of 2020, with an average of 47.2% compared to robo-advisors' 63.4%. The higher riskiness of robo-advisors was reflected in risk-adjusted performance as they displayed lower Sharpe ratios, an average of which amounted to 0.59 compared to the benchmarks' 0.72. The notable exception is the best performing robo-advisor, Sig-Fig, which not only dominated in terms of historical returns, but also managed to outperform two of the benchmarks in terms of risk-adjusted performance with a Sharpe ratio of 0.76.

In conclusion, technological advancements on top of the financial crisis in 2008 have translated in many structural changes in the finance industry, whereby wealth management has been one of the most affected. In the last few years, there has been a rapid rise of companies providing automated financial services, so-called robo-advisors. These virtual advisors are set to provide advanced portfolio management features and can mitigate behavioural biases that usually occur when people invest on their own or with the help of human financial advisors. Furthermore, robo-advisors are easy to use, have low initial investment requirements, and are cost-effective as they provide financial services at considerably lower rates compared to their traditional counterparts. However, as much as robo-advisors seem to disrupt wealth management services, traditional financial institutions view them as a healthy and complementary option to their existing services. First, there is a growing demand for robo-advising services that have boosted their AuM in recent years, thus increasing the appetites of large financial institutions. Secondly, robo-advisors attract a less wealthy population, the one that traditional wealth managers do not cover themselves. Thirdly, the automated nature of robo-advisors drives down costs and enables better control and compliance. Fourthly, robo-advisors can help to address the growing demand for digital experiences that clients, especially millennials, seek. Last but not least is the aforementioned reduction of behavioural biases that even the most experienced wealth managers are prone to. These are some of the reasons why traditional financial institutions have started developing their in-house robo-advisors, or have taken over established robo-advisory firms in the market. Moreover, I have illustrated that robo-advisors may provide sound investing advice with compelling performance. There are, however, some potential limitations of the analysis that we should be aware of. The robo-advisors are still in an early stage; hence the data is not very exhaustive and historical returns are provided only on a quarterly basis. Despite considering a 5-year period, the analysis still lacks a larger sample with more robo-advisors and a longer time span. Furthermore, not enough is known about the tax-loss harvesting benefits, although this is one of the key advertised benefits robo-advisors offer to their clients. It would, therefore, be sensible and logical to review these findings once a larger dataset is available.

REFERENCE LIST

1. Abraham, F., Schmukler, S., & Tessada, J. (2019). Robo-Advisors: Investing through Machines. *World Bank Policy Research Working Paper* (21).
2. Adler, T., & Kritzman, M. (2006). Mean–variance versus full-scale optimisation: In and out of sample. *Journal of Asset Management, 7*(5), 302-311.
3. Backend Benchmarking. (2021a). *Robo Report Fourth Quarter 2020*. Retrieved May 20, 2021, from https://www.backendbenchmarking.com/the-robo-report/report-archives/
4. Backend Benchmarking. (2021b). *Tax-Loss Harvesting Study 2021 – Which Robos Took Your Tax Bill Seriously*. Retrieved July 30, 2021, from https://www.backendbenchmarking.com/blog/2021/05/tax-loss-harvesting-same-name-but-different-service-at-different-providers/
5. Barber, B. M., & Odean, T. (1999). The Courage of Misguided Convictions. *Financial Analysts Journal*, *55*(6) 41-55.
6. Barber, B. M., & Odean, T. (2002). Online Investors: Do the Slow Die First. *The Review of Financial Studies, 15*(2), 455-487.
7. Bartram, S. M., Branke, J., & Motahari, M. (2020). *Artificial intelligence in asset management.* CFA Institute Research Foundation.
8. Bayon, P. (2018, February). *A legal framework for robo-advisors.* Retrieved January 15, 2021, from https://www.researchgate.net/publication/326838133_A_legal_framework_for_robo-advisors
9. Beketov, M., Lehmann, K., & Wittke, M. (2018, September 27). *Robo Advisors: quantitative methods inside the robots.* Retrieved November 15, 2020, from https://link.springer.com/article/10.1057/s41260-018-0092-9
10. Berg, A., & Mhanga, S. (2019). *Robo-advisors on the Swedish Market: From a Portfolio Management Perspective.* Jönköping: Jönköping University, International Business School.
11. Best, M. J., & Grauer, R. R. (1991). On the Sensitivity of Mean-Variance-Efficient Portfolios to Changes in Asset Means: Some Analytical and Computational Results. *The Review of Financial Studies, 4*(2), 315-342.
12. Betterment. (2019). *The Benefits of Tax Coordination*. Retrieved May 20, 2021, from https://www.betterment.com/resources/benefits-of-tax-coordination/
13. Betterment. (2021a). *Pricing at Betterment*. Retrieved May 20, 2021, from https://www.betterment.com/pricing/
14. Betterment. (2021b). *Socially responsible investing portfolio strategy disclosure*. Retrieved July 30, 2021, from https://www.betterment.com/legal/socially-responsible-investing-portfolio-strategy/
15. Bhatia, A., Chandani, A., & Chhateja, J. (2020). Robo advisory and its potential in addressing the behavioral biases of investors - A qualitative study in Indian context. *Journal of Behavioral and Experimental Finance, 25*(5).

16. Bjerknes, L., & Vukovic, A. (2017). *Automated Advice: A Portfolio Management Perspective on Robo- Advisors.* Norwegian University of Science and Technology.
17. Black, F., & Litterman, R. (1992). Global Portfolio Optimization. *Financial Analysts Journal, 48*(5), 28-43.
18. Bodie, Z., Kane, A., & Marcus, A. J. (2011). *Investments* (11th ed.). New York: McGraw-Hill/Irwin.
19. Brenner, L., & Meyll, T. (2020). Robo-advisors: A substitute for human financial advice? *Journal of Behavioral and Experimental Finance, 25*(1).
20. Brinson, G. P., Hood, R. L., & Beebower, G. L. (1986). Determinants of Portfolio Performance. *Financial Analysts Journal, 42*(4), 39-44.
21. Buchanan, B. G. (2019). *Artificial intelligence in finance.* The Alan Turing Institute.
22. Businesswire. (2019). *Bank of America Introduces Powerful Solution Combining Merrill Digital Capabilities With Advice and Guidance From a Financial Solutions Advisor*. Retrieved April 16, 2021, from https://www.businesswire.com/news/home/20190603005304/en/Bank-of-America-Introduces-Powerful-Solution-Combining-Merrill-Digital-Capabilities-With-Advice-and-Guidance-From-a-Financial-Solutions-Advisor
23. Carey, T. W. (2021a). *Charles Schwab Intelligent Portfolios Review*. Retrieved March 30, 2021, from https://www.investopedia.com/charles-schwab-intelligent-portfolios-review-4692523
24. Carey, T. W. (2021b). *Vanguard Digital Advisor Review*. Retrieved March 30, 2021, from https://www.investopedia.com/vanguard-digital-advisor-review-5078066
25. CFI. (2015). *Anchoring Bias*. Retrieved August 25, 2021, from https://corporatefinanceinstitute.com/resources/knowledge/trading-investing/anchoring-bias/
26. Charles Schwab. (2021a). *Schwab Total Stock Market Index Fund*. Retrieved October 1, 2021, from https://www.schwabassetmanagement.com/products/swtsx
27. Charles Schwab. (2021b). *Schwab Core Equity Fund*. Retrieved October 1, 2021, from https://www.schwabassetmanagement.com/products/swanx
28. Charles Schwab. (2021c). *Schwab Treasury Inflation Protected Securities Index Fund*. Retrieved October 1, 2021, from https://www.schwabassetmanagement.com/products/swrsx
29. Charles Schwab. (2021d). *Schwab Balanced Fund*. Retrieved October 1, 2021, from https://www.schwabassetmanagement.com/products/swobx
30. Charles Schwab. (2021e). *Schwab MarketTrack Balanced Portfolio*. Retrieved October 1, 2021, from https://www.schwabassetmanagement.com/products/swbgx
31. Corporate Vision. (2020, July 2). *The Rise in Robo Advisory Services During Covid-19*. Retrieved June 16, 2021, from https://www.corporatevision-news.com/about-us/
32. Credit Suisse. (2016). *Behavioural finance: The psychology of investing*. Zurich: Credit Suisse Group AG.
33. D'Acunto, F., Prabhala, N., & Rossi, A. G. (2019). The Promises and Pitfalls of Robo-Advising. *The Review of Financial Studies, 32*(5), 1983-2020.

34. Daryanani, G., & Cordaro, C. (2005). Asset Location: A Generic Framework for Maximizing After-Tax Wealth. *Journal of Financial Planning, 18*(1), 44-54.
35. Das, S., Markowitz, H., Scheid, J., & Statman, M. (2010). Portfolio Optimization with Mental Accounts. *The Journal of Financial and Quantitative Analysis, 45*(2), 311-334.
36. Delloite. (2016a). *The expansion of Robo-Advisory in Wealth Management.* Retrieved January 15, 2021, from https://www2.deloitte.com/content/dam/Deloitte/de/Documents/financial-services/Deloitte-Robo-safe.pdf
37. Deloitte. (2016b). *Cost-Income Ratios and Robo-Advisory*. Retrieved June 15, 2021, from https://www2.deloitte.com/content/dam/Deloitte/de/Documents/financial-services/Robo-Advisory-in-Wealth-Management.pdf
38. Egan, D. (2020, April 23). *9 Reasons Goal-Based Investing Leads to Success*. Retrieved May 30, 2021, from https://www.betterment.com/resources/goal-based-investing/
39. Egan, D. (2021, March). *Using Investment Goals At Betterment.* Retrieved May 30, 2021, from Betterment: https://www.betterment.com/resources/goals-advice-explained/
40. Elan, S. L., & Goodrich, M. K. (2010, August). *Behavioral patterns and pitfalls of U.S. investors.* Retrieved May 16, 2021, from https://www.loc.gov/rr/frd/pdf-files/SEC_Investor-Behavior.pdf
41. Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance, 47*(2), 427-465.
42. Fein, M. L. (2015, June 30). *Robo-Advisors: A Closer Look.* Retrieved November 2020, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2658701
43. FINRA. (2016, March). *Report on Digital Investment Advice.* Retrieved May 5, 2021, from https://www.finra.org/sites/default/files/digital-investment-advice-report.pdf
44. Fisch, J., Turner, J. A., & Labouré, M. (2019). The Emergence of the Robo-Advisor. In J. Agnew, & O. S. Mitchell, *The Disruptive Impact of FinTech on Retirement Systems.* Oxford: Oxford Scholarship Online.
45. Grealish, A. (2018, May 22). *How Portfolio Rebalancing Works to Manage Risk*. Retrieved April 6, 2021, from Betterment: https://www.betterment.com/resources/portfolio-drift-rebalancing/
46. Grealish, A. (2019). *The Betterment Portfolio Strategy*. Retrieved April 6, 2021, from https://www.betterment.com/resources/betterment-portfolio-strategy/
47. Grealish, A. (2021, May). *ETF Selection For Portfolio Construction: A Methodology*. Retrieved May 29, 2021, from https://www.betterment.com/resources/etf-portfolio-selection-methodology/
48. Harley, A. (2016, June 19). *Prospect Theory and Loss Aversion: How Users Make Decisions*. Retrieved May 17, 2021, from https://www.nngroup.com/articles/prospect-theory/

49. Hartzmark, S. H. (2015). The Worst, the Best, Ignoring All the Rest: The Rank Effect and Trading Behavior. *The Review of Financial Studies, 28*(4), 1024-1059.
50. Idzorek, T. (2007). A step-by-step guide to the Black-Litterman model: Incorporating user-specified confidence levels. In S. Satchell, *Forecasting expected returns in the financial markets* (pp. 17-38). Academic Press.
51. IFC. (2017, August). *Digital Financial Services: Challenges and Opportunities for Emerging Market Banks.* Retrieved January 16, 2021, from https://openknowledge.worldbank.org/bitstream/handle/10986/30368/118736-BRI-EMCompass-Note-42-DFS-Challenges-and-Opportunities-PUBLIC.pdf?sequence=1&isAllowed=y
52. Jung, D., Glaser, D., & Kopplin, W. (2019, January). *Robo-Advisory: Opportunities and Risks for the Future of Financial Advisory: Recent Findings and Practical Cases.* Retrieved November 30, 2020, from https://www.researchgate.net/publication/328390383_Robo-Advisory_Opportunities_and_Risks_for_the_Future_of_Financial_Advisory_Recent_Findings_and_Practical_Cases
53. Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica, 47*(2), 263-291.
54. Kaissar, N. (2017, January 19). *The Ups and Downs of Portfolio Rebalancing*. Retrieved April 4, 2021, from https://nirkaissar.com/the-ups-and-downs-of-portfolio-rebalancing/
55. Kane, L. (2014, September). *Here's Where The Term 'Robo-Advisor' First Appeared.* Retrieved April 2, 2021, from https://www.businessinsider.com/where-robo-advisor-started-2014-9
56. Kauflin, J. (2020, June 29). *Fintech Personal Capital Sells To Canadian Insurer For $825 Million Plus Contingency Bonus*. Retrieved April 5, 2021, from https://www.forbes.com/sites/jeffkauflin/2020/06/29/robo-advisor-personal-capital-to-be-acquired-for-up-to-1-billion/?sh=e5604cd67e3a
57. Khentov, B. (2021, April 23). *Tax Loss Harvesting+™ Methodology*. Retrieved April 4, 2021, from https://www.betterment.com/resources/tax-loss-harvesting-methodology/
58. Lam, J. W. (2016, April). *Robo-Advisors: A Portfolio Management Perspective.* Retrieved February 15, 2021, from https://economics.yale.edu/sites/default/files/files/Undergraduate/Nominated%20Senior%20Essays/2015-16/Jonathan_Lam_Senior%20Essay%20Revised.pdf
59. Ledoit, O., & Wolf, M. (2003). *Honey, I Shrunk the Sample Covariance Matrix.* Retrieved April 5, 2021, from http://www.ledoit.net/honey.pdf
60. Lewis, D. R. (2018, June). *Computers May Not Make Mistakes but Many Consumers Do.* Retrieved April 10, 2021, from https://www.researchgate.net/publication/325563547_Computers_May_Not_Make_Mistakes_but_Many_Consumers_Do

61. Lin, M. (n.d.). *Why Investors Are Irrational, According to Behavioral Finance*. Retrieved May 15, 2021, from https://www.toptal.com/finance/financial-analysts/investor-psychology-behavioral-biases
62. Linnainmaa, J. T., Melzer, B. T., & Previtero, A. (2021). The Misguided Beliefs of Financial Advisors. *The Journal of Finance, 76*(2), 587-621.
63. Loos, B., Previtero, A., Scheurle, S., & Hackethal, A. (2019, May). *Robo-advisers and Investor Behavior.* Retrieved April 4, 2021, from https://www.vgsf.ac.at/fileadmin/vgsf/Papers/Archive/FRS_2019-20/20191018_FRS_Previtero.pdf
64. Maginn, J. L., Tuttle, D. L., McLeavey, D. W., & Pinto, J. E. (2007). *Managing Investment Portfolios* (3rd ed.). Hoboken: John Wiley & Sons.
65. Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance, 7*(1), 77-91.
66. McKinsey&Company. (2014). *McKinsey Global Wealth Management Survey 2014: An attractive sector in transition.* Retrieved April 2, 2021, from https://www.bourbonfm.com/sites/default/files/users/PatrickBourbon/file/Global_Wealth_Management_Survey_2014%20%281%29%20%281%29.pdf
67. McMillan, M. G., Pinto, J. E., Pirie, W. L., & Van de Venter, G. (2011). *Investments: Principles of Portfolio and Equity Analysis.* Hoboken: John Wiley & Sons.
68. Michaud, R. (1989). The Markowitz Optimization Enigma: Is 'Optimized' Optimal. *Financial Analysts Journal*, 31-42.
69. Mullainathan, S., Noeth, M., & Schoar, A. (2012, March). *The Market for Financial Advice: An Audit Study.* Retrieved May 15, 2021, from https://www.researchgate.net/publication/254072294_The_Market_for_Financial_Advice_An_Audit_Study/link/5eebda84458515814a6aa2c5/download
70. Odean, T. (1998). Are Investors Reluctant to Realize Their Losses. *The Journal of Finance*, *53*(5), 1775-1798.
71. Orçun, K. (2017, August 10). *Robo-advice – a true innovation in asset management.* Retrieved November 22, 2020, from Deutsche Bank Research: https://www.dbresearch.com/PROD/RPS_EN-PROD/PROD0000000000449125/Robo-advice_–_a_true_innovation_in_asset_managemen.pdf?undefined&realload=q/WxvP7Uwv/5/0aUO4NKWDO5hYGXfFtXZdGAY9~Qxg3/4x5izlXlo7S5jks10teo7b4w6CSlqZNRxaJcWCetqA==
72. Personal Capital. (2021). *Our Fee Structure*. Retrieved May 20, 2021, from https://www.personalcapital.com/wealth-management
73. Pirner, D. (2018, August). *Asset Allocation with Black-Litterman in a case study of Robo Advisor Betterment.* Retrieved November 22, 2020, from https://www.researchgate.net/publication/326878665_Asset_Allocation_with_Black-Litterman_in_a_case_study_of_Robo_Advisor_Betterment
74. Pompian, M. M. (2006). *Behavioral Finance and Wealth Management: How to Build Optimal Portfolios That Account for Investor Biases.* Hoboken: John Wiley & Sons.

75. Puhle, M. (2016). The FinTech Revolution: A Closer Look at Robo-Advisors. *Economy and Finance, 3*(4), 256-271.
76. Puhle, M. (2019). The Performance and Asset Allocation of German Robo-Advisors. *Society and Economy, 41*(3), 331-351.
77. PwC. (n.d.). *Global Assets under Management set to rise to $145.4 trillion by 2025*. Retrieved August 16, 2021, from https://www.pwc.com/ng/en/press-room/global-assets-under-management-set-to-rise.html
78. Reuters. (2015, August 26). *BlackRock to acquire robo-adviser*. Retrieved May 21, 2021, from https://www.reuters.com/article/us-futureadvisor-m-a-blackrock-idUSKCN0QV1HU20150826
79. Rollén, S. (2019, April 25). *How We Estimate the Added Value of Using Betterment.* Retrieved June 4, 2021, from https://www.betterment.com/resources/investor-returns-methodology/
80. Schanmuganathan, M. (2020, September). Behavioural finance in an era of artificial intelligence: Longitudinal case study of robo-advisors in investment decisions. *Journal of Behavioral and Experimental Finance, 27*(1).
81. SEC. (2021). *Wash Sales*. Retrieved December 15, 2021, from https://www.investor.gov/introduction-investing/investing-basics/glossary/wash-sales
82. Shefrin, H., & Statman, M. (1985). The Disposition to Sell Winners Too Early and Ride losers Too Long: Theory and Evidence. *The Journal of Finance, 40*(3), 777-790.
83. Shefrin, H., & Statman, M. (2000). Behavioral Portfolio Theory. *The Journal of Financial and Quantitative Analysis, 35*(2), 127-151.
84. Sironi, P. (2016). *FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification.* Chichester: John Wiley & Sons.
85. Statista. (2021). *FinTech Report 2021: Statista Digital Market Outlook-Market report.* Hamburg: Statista.
86. Statman, M. (2004). The Diversification Puzzle. *Financial Analysts Journal, 60*(4), 44-53.
87. Strong, N., & Xu, X. (1999, December 9). *Understanding the equity home bias: evidence from survey data.* Retrieved May 25, 2021, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=191401
88. Swensen, D. F. (2005). *Unconventional Success: A Fundamental Approach to Personal Investment.* New York: Free Press.
89. Swensen, D. F. (2009). *Pioneering Portfolio Management: An Unconventional Approach to Institutional Investment.* New York: Free Press.
90. Tao, R., Su, C.-W., Xiao, Y., Dai, K., & Khalid, F. (2020). Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets. *Technological Forecasting and Social Change, 163*(3).

91. Tergesen, A. (2017, July 26). *Betterment Adds More Human Advice to Its Robo Services.* Retrieved May 24, 2021, from https://www.wsj.com/articles/betterment-adds-more-human-advice-to-its-robo-services-1501074001
92. Thaler, R. (1985). Mental Accounting and Consumer Choice. *Marketing Science, 4*(3), 199-214.
93. Thinking forward. (n.d.). *Trend-Chasing Bias*. Retrieved May 24, 2021, from http://thinkingforward.site/trend-chasing-bias/
94. Tokic, D. (2018). BlackRock Robo-Advisor 4.0: When artificial intelligence replaces human disrection. *Strategic change, 27*(4), 285-290.
95. Vanguard. (2010, July). *Best practices for portfolio rebalancing.* Retrieved May 20, 2021, from https://www.pattonfunds.com/pdf/Best-Practices-for-Rebalancing-Vanguard-(00030673).PDF
96. Vanguard. (2021a). *Vanguard Total World Stock ETF*. Retrieved October 1, 2021, from https://investor.vanguard.com/etf/profile/VT
97. Vanguard. (2021b). *Vanguard Global Equity Fund*. Retrieved October 1, 2021, from https://investor.vanguard.com/mutual-funds/profile/VHGEX
98. Vanguard. (2021c). *Vanguard Total Bond Market Index Fund Admiral Shares*. Retrieved October 1, 2021, from https://investor.vanguard.com/mutual-funds/profile/VBTLX
99. Vanguard. (2021d). *Vanguard Core Bond Fund Investor Shares*. Retrieved October 1, 2021, from https://investor.vanguard.com/mutual-funds/profile/VCORX
100. Vanguard. (2021e). *Vanguard Emerging Markets Government Bond Index Fund Admiral Shares*. Retrieved October 1, 2021, from https://investor.vanguard.com/mutual-funds/profile/VGAVX
101. Vanguard. (2021f). *Vanguard Balanced Index Fund Admiral Shares*. Retrieved October 1, 2021, from https://investor.vanguard.com/mutual-funds/profile/vbiax
102. Vanguard. (2021g). *Vanguard Wellington Fund Admiral Shares*. Retrieved October 1, 2021, from https://investor.vanguard.com/mutual-funds/profile/VWENX
103. Wealthfront. (2021a). *Fees for Investment Accounts*. Retrieved May 20, 2021, from https://support.wealthfront.com/hc/en-us/articles/211003683-Fees-for-Investment-Accounts
104. Wealthfront. (2021b, February 5). *Wealthfront Tax-Loss Harvesting*. Retrieved June 14, 2021, from https://research.wealthfront.com/whitepapers/tax-loss-harvesting/
105. Wealthfront. (n.d.). *Wealthfront Investment Methodology White Paper*. Retrieved November 25, 2020, from https://research.wealthfront.com/whitepapers/investment-methodology/
106. Willis, L. E. (2011, May). The Financial Education Fallacy. *The American Economic Review, 101*(3), 429-434.

APPENDICES

Appendix 1: Povzetek (Abstract in Slovenian language)

Avtomatizirani upravljalci premoženja (v nadaljevanju: robo-svetovalci) so v zadnjih letih doživeli vzpon popularnosti v industriji upravljanja naložb, saj predstavljajo izziv za tradicionalne naložbene rešitve, predvsem z zniževanjem stroškov in z odpravljanjem vedenjskih pristranskosti pri naložbenih odločitvah. Robo-svetovalci so še posebej privlačni za skupino vlagateljev z nižjimi dohodki ter za mlajšo, tehnološko napredno populacijo. Poleg tega pa so zaradi svoje hitre rasti v zadnjih nekaj letih pritegnili pozornost tudi večjih, že uveljavljenih tradicionalnih finančnih institucij, ki v svoje portfelje storitev dodajajo stroškovno učinkovite produkte in hkrati sledijo spreminjajočim potrebam svojih strank. Kljub temu pa so robo-svetovalci še vedno v razvojni fazi in še vedno je malo znanega o njihovi uspešnosti pri upravljanju portfeljev. Nenazadnje so se številni prvič soočili z visoko volatilnimi tržnimi razmerami šele z izbruhom pandemije COVID-19 v letu 2020. Namen magistrske naloge je torej pomagati bralcu k boljšemu razumevanju delovanja robo-svetovalcev in oceniti, ali lahko takšen model zagotovi zanesljiv naložbeni nasvet s privlačnimi donosi.

Robo-svetovalec je v osnovi avtomatiziran naložbeni produkt, ki s pomočjo algoritmov samodejno sestavi, optimizira in upravlja naložbeni portfelj, najpogosteje z uporabo pasivne naložbene strategije. Stroka deli robo-svetovalce na tiste, ki so popolnoma avtomatizirani in hibridne, kjer se v sam naložbeni proces vključi tudi človeški svetovalec. Ne glede na tip, pa v principu vsak robo-svetovalec deluje po načelu uveljavljenih finančnih teorij, med katerimi je najpogosteje uporabljena sodobna teorija portfelja. To je tudi ena ključnih prednosti robo-svetovalcev, saj striktno razpršijo naložbene portfelje svojih strank in s tem dokazano zmanjšujejo vedenjske pristranskosti, ki se pogostokrat pojavijo pri vlagateljih ob sprejemanju investicijskih odločitev. Čeprav robo-svetovalci v povprečju dosegajo nekoliko nižje donose kot njihova merila uspešnosti (vključujoč aktivne in pasivne sklade), pa določeni med njimi že kažejo svojo zmožnost doseganja zavidljivih donosov. Lep primer je ameriški robo-svetovalec SigFig, ki je v analiziranem 5-letnem obdobju presegel nekatere sklade tudi v smislu tveganja prilagojenih donosov. Skozi celotno magistrsko nalogo tako ugotavljam, da je sama ideja robo-svetovalca zelo zanimiva in donosna ter privlačna ne le za male, ampak tudi za premožnejše in institucionalne vlagatelje. To nakazuje tudi dejstvo, da se vedno več uveljavljenih finančnih institucij na trgu upravljanja naložb odloča bodisi za razvoj lastnega robo-svetovalca ali za prevzem obstoječega podjetja z že obstoječim modelom robo-svetovalca.

Appendix 2: Abstract

Recently, robo-advisors have become one of the hottest buzzwords in the investment management industry, challenging traditional investment solutions mainly by reducing costs and by addressing behavioural biases in investment decisions. They are particularly attractive to young, technologically advanced individuals, and households with lower disposable income. Furthermore, they have become extremely popular among the established financial institutions, which are challenged by the cost-efficiency and changing client needs. Nevertheless, robo-advisors are still in the development phase and little is known about their performance. Furthermore, many of them faced highly volatile market conditions for the first time with the outbreak of the COVID-19 pandemic in 2020. Therefore, the purpose of this master's thesis is to provide a comprehensive understanding of the possibilities that the robo-advice model has in the portfolio management process and evaluate whether this model can provide sound investment advice with compelling returns for investors.

A robo-advisor is an algorithm-based investment solution that automatically construct, optimize and manage portfolios on behalf of its clients, most commonly using a passive investment strategy. In general, robo-advisors are either fully automated or hybrid, where a human financial advisor is also involved in the investment process. Regardless of the business model, all robo-advisors normally adhere to adhere to the systematic and well-grounded finance theory. MPT is the most typical method they use. One of the key advantages is that robo-advisors systematically diversify investment portfolios, reducing behavioural biases that even the most experienced wealth managers are prone to. Although robo-advisors underperform their benchmarks on average, some of them have already demonstrated the capacity to generate compelling returns. Over the last five years, SigFig, a US robo-advisor, has beaten several actively and passively managed funds even in the risk-adjusted terms. I see the robo-advice model as a value-adding instrument that benefits both new and unexperienced investors, as well as wealthy and institutional investors. This is even more pronounced by the fact that an increased number of established financial institutions have recognised the opportunity in the robo-advice market.

Appendix 3: Business model Canvas for a robo-advice model

Refers to chapter 1.2.3.

<table>
<tr><th>Key Partners</th><th>Key Activities</th><th>Value Propositions</th><th>Customer Relationships</th><th>Customer Segments</th></tr>
<tr>
<td rowspan="3">– Venture capital investors
– Strategic partnerships with banks and other financial institutions (if not in-house)
– Financial data providers</td>
<td>– Investor identification, asset universe selection, portfolio construction, monitoring and rebalancing, tax loss harvesting</td>
<td rowspan="3">– Low, transparent, and easy to understand fee structure
– Automated process of portfolio management
– Reduced behavioural biases in investment decisions</td>
<td>– Automated online relationships
– Calls and emails with financial professionals (hybrid robo-advisors)</td>
<td rowspan="3">– B2C
– B2B
– B2B2C

– Mass market, mass affluent, affluent and high net worth investors</td>
</tr>
<tr><th>Key Resources</th><th>Channels</th></tr>
<tr>
<td>– Sophisticated IT environment
– Analytical research tools</td>
<td>– Online
– Accessible through smartphones, tablets, computers, etc.</td>
</tr>
</table>

<table>
<tr><th>Cost Structure</th><th>Revenue Streams</th></tr>
<tr>
<td>– Personnel expenses (account or portfolio managers; mostly for technical support)
– Partnership costs, R&D costs, IT infrastructure costs, marketing & client onboarding costs
– Other operating expenses (insurance costs, rent, equipment, etc.)</td>
<td>– Single all-inclusive annual fee (inversely correlated to the invested amount, the higher the AuM, the lower the fees, and vice versa)
– Additional source of income -> additional human advice for affluent clients in some cases (hybrid robo-advisors)</td>
</tr>
</table>

Source: Own work.

Appendix 4: Betterment's portfolio ETFs for taxable accounts

Refers to chapter 4.2.2.

Asset Class	Selection	Asset name	Expense Ratio (%)
US Total Stock Market	Prime	Vanguard Total Stock Market ETF (VTI)	0.03
	Alternative	iShares Core S&P Total US Stock Market ETF (ITOT)	0.03
US Large-Cap Value Stocks	Prime	Vanguard Value ETF (VTV)	0.04
	Alternative	SPDR® Portfolio S&P 500 Value ETF (SPYV)	0.04
US Mid-Cap Value Stocks	Prime	Vanguard Mid-Cap Value ETF (VOE)	0.07
	Alternative	iShares Russell Mid-Cap Value ETF (IWS)	0.24
US Small-Cap Value Stocks	Prime	Vanguard Small-Cap Value ETF (VBR)	0.07
	Alternative	iShares Russell 2000 Value ETF (IWN)	0.24
International Developed Stocks	Prime	Vanguard FTSE Developed Markets ETF (VEA)	0.05
	Alternative	iShares Core MSCI EAFE ETF (IEFA)	0.07
Emerging Market Stocks	Prime	Vanguard FTSE Emerging Markets ETF (VWO)	0.10
	Alternative	iShares Core MSCI Emerging Markets ETF (IEMG)	0.13
Short-Term Treasuries	Prime	Goldman Sachs Access Treasury 0-1 Year ETF (GBIL)	0.12
US Short-Term Bonds	Prime	JPMorgan Ultra-Short Income ETF (JPST)	0.18
TIPS	Prime	Vanguard Short-Term Inflation-Protected Securities ETF (VTIP)	0.05
US Municipal Bonds	Prime	iShares National Muni Bond ETF (MUB)	0.07
	Alternative	SPDR® Nuveen Blmbg Barclays Muni Bd ETF (TFI)	0.23
US High Quality Bonds	Prime	iShares Core U.S. Aggregate Bond ETF (AGG)	0.04
International Developed Bonds	Prime	Vanguard Total International Bond ETF (BNDX)	0.08
Emerging Market Bonds	Prime	iShares JP Morgan USD Em Mkts Bd ETF (EMB)	0.39
	Alternative	Vanguard Emerging Mkts Govt Bd ETF (VWOB)	0.25
Average expense ratio			**0.12**

Adapted from Grealish (2021).

Appendix 5: Betterment's portfolio ETFs for IRA accounts

Refers to chapter 4.2.2.

Asset Class	Selection	Asset name	Expense Ratio (%)
US Total Stock Market	Prime	Vanguard Total Stock Market ETF (VTI)	0.03
	Alternative	Schwab US Broad Market ETF™ (SCHB)	0.03
US Large-Cap Value Stocks	Prime	Vanguard Value ETF (VTV)	0.04
	Alternative	Schwab US Large-Cap Value ETF™ (SCHV)	0.04
US Mid-Cap Value Stocks	Prime	Vanguard Mid-Cap Value ETF (VOE)	0.07
	Alternative	iShares S&P Mid-Cap 400 Value ETF (IJJ)	0.18
US Small-Cap Value Stocks	Prime	Vanguard Small-Cap Value ETF (VBR)	0.07
	Alternative	SPDR® S&P 600 Small Cap Value ETF (SLYV)	0.15
International Developed Stocks	Prime	Vanguard FTSE Developed Markets ETF (VEA)	0.05
	Alternative	Schwab International Equity ETF™ (SCHF)	0.06
Emerging Market Stocks	Prime	Vanguard FTSE Emerging Markets ETF (VWO)	0.10
	Alternative	SPDR® S&P Emerging Markets ETF (SPEM)	0.11
Short-Term Treasuries	Prime	Goldman Sachs Access Treasury 0-1 Year ETF (GBIL)	0.12
US Short-Term Bonds	Prime	JPMorgan Ultra-Short Income ETF (JPST)	0.18
TIPS	Prime	Vanguard Short-Term Infl-Prot Secs ETF (VTIP)	0.05
US High Quality Bonds	Prime	iShares Core U.S. Aggregate Bond ETF (AGG)	0.04
International Developed Bonds	Prime	Vanguard Total International Bond ETF (BNDX)	0.08
Emerging Market Bonds	Prime	iShares JP Morgan USD Em Mkts Bd ETF (EMB)	0.39
	Alternative	PowerShares Emerging Markets Sov Dbt ETF (PCY)	0.50
Average expense ratio			**0.12**

Adapted from Grealish (2021).