SCHOOL OF
ECONOMICS AND
MANAGEMENT

From Biased to Balanced:

Overcoming Behavioral Biases with Robo-Advisors in Sweden

Disa Roth & Sara Ricklander

Bachelor Thesis

Department of Economics

Supervisor: Anders Vilhelmsson

January 2024

Abstract

In recent years, the emergence of artificial intelligence and automated algorithms in financial advisory services have democratized financial advice and have the potential to revolutionize investment strategy. This shift is of importance for retail investors, as they deal with behavioral biases affecting their investment decisions. This thesis investigates robo-advisors' ability to mitigate these biases and outperform portfolios of Swedish retail investors. Based on real data of stock prices, a robo-advisor portfolio as well as portfolios influenced by different biases are calibrated using MatLab to answer our research question. Our findings reveal that robo-advisors, by offering more objective, data-driven advice, can significantly enhance portfolio performance, particularly for less experienced investors.

Keywords: Robo-advisors, Behavioral Finance, Retail Investors, Markowitz Optimization, Portfolio Performance, Investment Strategies

Acknowledgments

We would like to thank our supervisor Anders Vilhelmsson for both his support during the project and for all his help in figuring out MatLab. Your support was crucial to the success of our project.

1. Introduction

The use of artificial intelligence and automated algorithms is being increasingly included in all aspects of society, especially since it is now easier than ever to access. The financial industry is one of these areas, and artificial intelligence has since the 2000's revolutionized trading and investment strategies. This is much due to the development of robo-advisors, which are algorithms that can be used as an alternative to traditional financial advisors (Sironi, 2016). Robo-advisors make financial advice more accessible as they offer advice for a smaller cost than ever before while investors are still able to personalize their investments with their own risk aversion and preferences (Berg and Mhanga, 2019; Reher and Solinski, 2021). The lower cost has opened the formerly expensive market of financial advisors to less wealthy individuals, making more investors from low and medium-income populations now able to access financial advice (D'Acunto and Rossi, 2022). Another angle of the introduction of data-driven algorithms is the possibility to offer objective investment strategies which decreases the risk of making decisions influenced by psychological factors rather than rational analysis. The decisions that are made from psychological factors are called behavioral biases and can lead to suboptimal investment choices, as investors might either take on excessive risk or become overly cautious. Understanding and mitigating these biases is crucial for achieving long-term investment success, which is explained in Rossi and Utkus' (2020) paper that enlightens the biases' significant impact on portfolio performance and risk management.

Building on the transformative impact of robo-advisors in financial advice, research has delved into various dimensions of these AI-driven platforms, examining their efficiency, user experience, and their impact on behavioral biases. Reher and Solinski (2021) explores the potential of robo-advisors democratization in the financial services, and the relationship to behavioral biases. They found that more inexperienced investors are more likely to be affected by these biases and that these advisors make financial advice more accessible to this group. Furthermore, other studies (D'Acunto et al, 2019; Odean, 1998; Rossi and Utkus, 2020) have researched this relationship and found that robo-advisors reduce behavioral biases such as trend-chasing, the disposition effect, and home bias.

Previous research on the performance of robo-advisors has focused on comparing different robo-advisors' portfolios to each other, as well as with a benchmark or to a traditional advisor's portfolio. As robo-advisors hold the potential to democratize access to financial advice, this study aims to evaluate if they can enhance investment performance for a broader segment of the population. We will therefore compare the robo-advisors portfolio with portfolios similar to household savers and apply behavioral biases to the comparable portfolios. Behavioral biases have, to our knowledge, not been researched in combination with robo-advisors for a Swedish retail investor, making our study the first one to examine this relationship. Additionally, most of the previous studies have used real data, also making our study one of the first to simulate these portfolios using MatLab. This approach enables us to study the effect of different biases more precisely as real data would consist of a combination of an uncertain number of unknown biases. The research question that we aim to answer through our study is the following: *Can Swedish retail investors with biased portfolios benefit from using a robo-advisor tool when investing?*

Through collected data from Capital IQ, Fama French Data Library, and Riksbanken, this study displays how a robo-advisor based on Markowitz optimization model can decrease a retail investor's potential to influence their portfolios with behavioral biases. With the help of MatLab, a portfolio mimicking the investment strategy of a robo-advisor as well as several portfolios with different biases are simulated and compared to each other. In accordance with former studies, the results of this study will find that a robo-advisor is a tool for less frequent investors to access financial advice and to improve the performance of their portfolios. The biases that are discussed throughout this essay are home bias, the disposition effect, the rank effect, and under-diversification. The results first and foremost show that biased portfolios are costly in terms of investment performance. Secondly, we find that all biases can be completely eliminated through the use of a robo-advisor. Moreover, these results will be compared to previous studies, as well as analyzed in a broader context in terms of wealth distribution.

The disposition of the thesis will be as follows: chapter 2 gives an introduction to the theories used for the rest of the thesis. After this, chapter 3 introduces a literature review that covers previous studies on robo-advisors as well as on behavioral biases in investing. This chapter will be followed by a description of our data collection and the missing and excluded data. In the subsequent chapter, we clarify our methodological approach, detailing the construction of the robo-advisor portfolio as well as the portfolios influenced by different biases. The pivotal section of the thesis, chapter 6, is dedicated to the presentation and discussion of the results. This chapter includes the core analytical segment of the thesis, presenting a comparative analysis of the constructed portfolio's performance as well as setting our thesis side-by-side with previous research. The final chapter concludes our essay, underscoring the broader application of our results in both investment theory and practice.

2. Theory

This section outlines the theoretical foundation on which this thesis is based. Initially, the theories that the robo-advisor's algorithms are built upon will be introduced. Central to this discussion is Markowitz's Modern Portfolio Theory (1952) and its integrations with concepts such as the Efficient Market Hypothesis (EMH). Secondly, the focus will shift to the dynamics of behavioral biases in investing, examining how individuals with different biases act and deviate from rational decision-making. Lastly, we will delve into fund evaluation tools, which will later be used to measure the performance of the portfolios. This includes descriptions of the Sharpe Ratio, Jensen's alpha, and the Capital Asset Pricing Model (CAPM), upon which Jensen's alpha is based.

2.1 The Markowitz model

Harry Markowitz's introduction of Modern Portfolio Theory in 1952 marked a fundamental transformation in investment portfolio management. This theory, detailed in Markowitz (1952), advocated for an approach where risk and return are evaluated not in isolation, but in the context of the portfolio as a whole, thereby altering the conventional methods of portfolio management.

The cornerstone of the Markowitz model is diversification, which is applied to minimize portfolio risk by investing in several assets with low correlation. This specifically minimizes the idiosyncratic risks, i.e. risks specific to a certain asset, but does not eliminate risk entirely as the systematic risk remains. The key lies in balancing the portfolio with assets that, while individually risky, collectively increase the expected return due to their low correlations.

Through this, it is possible to achieve a higher risk-return trade-off (Markowitz, 1952). This is visually presented through the efficient frontier:

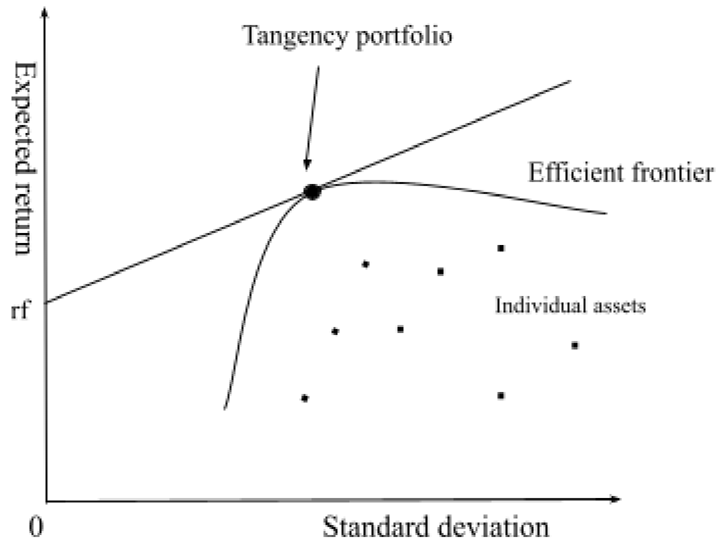


Figure 2.1 The Efficient Frontier

The efficient frontier represents a set of portfolios that offer the highest expected return for a given level of risk or the lowest risk for a given level of expected return. This is typically represented in a graph where the horizontal axis denotes risk and the vertical axis represents the expected return. The dots represent individual assets, with their own risk-return profile. The curve, known as the efficient frontier, describes the best level of return you can get for a given level of risk. This implies that every point on the curve is considered an optimally diversified portfolio. The portfolios below this line are considered suboptimal as they yield a lower return for the same level of risk. The straight line, originating from the risk-free rate (denoted rf) is called the capital market line (CML).

2.2 Efficient Market Hypothesis

The Efficient Market Hypothesis or EMH, is a traditional portfolio theory introduced by Eugene Fama (1970), which suggests that information is fully reflected in stock prices. The theory further emphasizes that all investors are rational and make decisions based on rationality. As all buyers and sellers access the same information, price movements are unpredictable. Fama's work was built upon research done by Maurice Kendall (1953), which showed that prices follow a random walk. As stock prices reflect all known information, nothing except for new information will cause the price to change. This leads to the stakeholders only reacting to information that is not yet known to the market. The efficient market hypothesis comes in three forms; weak, semi-strong, and strong efficiency.

This theory is a central concept in financial economics and has revolutionized the investment selection process for a diverse range of stakeholders, regardless of their investment strategies and philosophies. It is a foundation in investing as stakeholders either believe that all available information is fully reflected in the stock price, posing that the hypothesis holds, or they remain skeptical of this idea. Investors who are skeptical of this idea believe that there are price inconsistencies in the market that they can capitalize on. This is crucial as this newer interpretation acknowledges that markets are mostly efficient, but that these investors help align the stock prices with their intrinsic value thereby maintaining market efficiency.

2.3 Behavioral biases in investment decisions

Historically, rational investor behavior is an assumption made by traditional economic theories. However, the emergence of behavioral economics in the 1980s highlighted how emotions, attitudes, and psychological biases, such as overconfidence, mental accounting, and herding behavior, affect decision-making (Zahera and Bansal, 2018). One of the early studies about behavioral finance was conducted by Kahneman and Tversky (1974) who investigated the prospect theory and representativeness. Behavioral finance emphasizes how these biases can lead to irrational and inefficient investment decisions. For instance, overconfidence and regret aversion are found to significantly affect investor's behavior (Sahi, 2017). Another bias that is well-documented and discussed is home bias that Saivasan and Lokhande (2022) found is crucial for understanding portfolio diversification challenges. This bias implies that investors choose to invest disproportionately in domestic assets, despite the potential benefits of international diversification (French and Poterba, 1991). Research from Coval and Moskowitz (1999) linked this bias to information asymmetry and the investor's preference for familiar and local assets.

Multiple behavioral biases refer to the past profits and losses of investments. One of these is the disposition effect. This bias was first introduced by Hersh Shefrin and Meir Statman (1985), where they further built upon the research previously made by Kahneman and Tversky. Shefrin and Statman suggest that investors tend to sell winning investments too early and hold onto losing investments, causing the investors to make suboptimal investments where they have larger losses and limit potential gains. The disposition effect is further calculated by comparing the proportion of gains that are taken, against the proportion of losses that are realized (Madaan and Singh, 2019). This causes a bias as investors are more likely to act on their fear of losses rather than the probability of gains (Zahera and Bansal, 2018). The disposition effect bias is not the only behavioral bias that enlightens the issue concerning investors focusing too much on the previous performance of their investments. Another bias that shows this tendency is the rank effect. The rank effect, first introduced by Hartzmark in 2014, explores the likeliness of selling extreme winners and losers. The bias indicates that, rather than selling and buying assets rationally, the investment decision is based on how poor or good they perform, and therefore not leading to an optimal portfolio.

Another bias, that is not seen solely as a behavioral bias, is the tendency of investors not to diversify their portfolios. This means that the investor holds too few assets in their portfolio, leading to a portfolio with excessive idiosyncratic risk. Early research has concluded that 10 assets would indicate that the portfolio is well diversified, however, Statman (1987) concluded in his study that an investor should have at least 30 assets in order to achieve a well diversified portfolio.

2.4 Fund Evaluation; Sharpe Ratio and Jensen's Alpha

When evaluating an investment decision, it is important to make the assessment not only taking the raw returns into account but rather looking at the returns in context with the undertaken risk. Sharpe ratio and Jensen's alpha are both risk-adjusted measures to evaluate the performance of an investment, meaning that a higher Sharpe or Jensen value is more beneficial for the investor. The Sharpe ratio, introduced by Nobelist William F. Sharpe (1966), is a reward-to-volatility measure. The measure is calculated by dividing the risk premium by the standard deviation, see the following formula:

$$S = \frac{E(R) - R_f}{\sigma}$$

S = Sharpe Ratio

E = expected value

R = asset return

Rf = risk-free rate

σ = standard deviation of the assets return

Jensen's alpha, named after Michael Jensen (1967), measures the additional risk-adjusted return associated with an investment in comparison to the expected return according to the CAPM model. The alpha is calculated as follows:

$$\alpha = R_p - (R_f + \beta(R_m - R_f)$$

α = Jensen's alpha

R_p = real return of the portfolio

R_f= risk-free rate

β = the portfolio's beta

R_m= market return

2.5 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) was introduced by Jack Treynor, William Sharpe, John Lintner, and Jan Mossing individually, expanding upon the research from Markowitz and modern portfolio theory (Elbannan, 2014). In contrast to modern portfolio theory, CAPM also includes the possibility of lending and borrowing at a risk-free rate and the assumption that all investors have homogeneous beliefs. CAPM is used to evaluate the pricing of securities with a defined risk level. It assists in estimating the potential return of an investment, taking into account the market's risk-free rate and the specific risk measure (beta) of the investment (Berg and Mangha, 2019). The CAPM is expressed as follows:

$$E(r_i) = r_f + \beta[E(r_M) - r_f)]$$

The assumptions of the CAPM are:

1. Investors have homogeneous expectations

2. Investors are risk-averse
3. Investors act rationally and invest in efficient portfolios
4. There are no transaction costs or taxes

3. Literature review

3.1 Robo-Advisors

The discussion of robo-advisors and their impact on portfolio selection has risen since the introduction of artificial intelligence. Using robo-advisors has changed the previous conditions of investing in portfolios and is a tool to construct portfolios that are based on the investor's risk aversion and preferences (D'Acunto et al, 2019). Lam (2016) notes that robo-advisors operate on foundational financial principles, with a preference for strategies such as passive indexing and tax-efficient asset placement, employing algorithms to methodically allocate assets in a manner that is consistent with established financial theory.

An advantage that robo-advisors have is that they reduce the cost of financial advice, as it no longer requires a human advisor (D'Acunto et at, 2019). Several studies (Berg and Mhanga, 2019; Reher and Solinski, 2021) find that this, paired with a lower initial investment, makes financial advice more accessible. Robo-advisory therefore widens the scope of financial advisory services, enabling a new group of investors from low to middle-income brackets to seek guidance. Further evidence (Brenner and Meyll, 2020) indicates that the utilization of robo-advisors diminishes the demand for human financial advisors, with users being 16 percentage points less inclined to seek human advice. In addition to enhanced accessibility, D'Acunto and Rossi (2020) describe that robo-advisors employ pre-programmed algorithms that enable continuous monitoring and optimization of investments, simplifying the user experience and ongoing improvement. The simplified user experience is something that Rossi and Utkus (2020) also recognize, and that when investors start using a robo-advisor, it increases the portfolio performance and decreases the effort of managing the portfolio. To track this, they use a platform and examine how often the investor logs onto the platform. The reduced effort of managing the portfolio is visible in their study as the investors spent 30 minutes or less on the website, compared to their previous time spent there. Reher and Solinksi's paper (2020), further strengthens the case for superior performance of robo-advisors, evidenced by their ability to significantly improve the Sharpe ratio and returns of portfolios while simultaneously reducing risk. They base their analysis on data from a major U.S. robo-advisor and reveal that middle-class households particularly benefit from these improvements. In their study, there is a notable increase in the Sharpe ratio by 0.298 for middle-class portfolios and 0.297 for upper-class portfolios when managed by robo-advisors compared to self-managed portfolios. Additionally, the study shows an increase in expected returns of 2.3 percentage points for both middle and upper-class portfolios managed by robo-advisors. This superior performance is accompanied by a significant reduction in total volatility. This is largely due to the robo-advisors' effective diversification strategies and their capability to optimize exposure to priced risks, factors that might be challenging for individual investors to manage effectively.

Robo-advisors, while offering a cost-effective and time-saving approach to portfolio management, display certain limitations. A notable drawback, as Waliszewski and Zięba-Szklarska (2020) highlight, is the trade-off between lower costs and reduced personalization. The algorithm-driven nature of robo-advisors might lead to standardized investment strategies that may not fully align with an individual investor's unique financial situation, goals, and preferences. Furthermore, the reliance on questionnaires for assessing risk tolerance raises concerns about the accuracy and depth of understanding these automated systems have regarding an investor's real risk tolerance. Unlike human advisors who can interpret nuances and adjust strategies based on small changes in an investor's life or market conditions, robo-advisors may lack the capability to make such intuitive adjustments. This could potentially result in investment recommendations that are not entirely tailored to the investor's specific needs, leading to suboptimal asset allocation and risk exposure.

3.2 Behavioral biases

Behavioral biases represent fundamental aspects of human behavior and pose challenges in constructing diversified asset portfolios. Historically, mitigating these biases has relied on the expertise of financial human advisors (D’Acunto and Rossi, 2021). Since the introduction of robo-advisors two decades ago, the question has risen if this can affect behavioral biases in investing. D’Acunto et al (2019) analyze the adoption of the instrument and evaluate its influence on the financial decision-making processes of investors. They differentiate between well-diversified and diversified investors. The results indicate that the disposition effect, trend-chasing, and rank effect are less pronounced when using the robo-advisor for both types of investors (D'Acunto et al, 2019). Specifically, the disposition effect decreases by 30% when using a robo-advisor, and the rank effect decreases by 26%. D'Acunto and Rossi's (2021) research paper reveals that another behavioral bias that decreases significantly is home bias. Other reports (Rossi and Utkus, 2020) claim home bias is completely eliminated, and that the investors that benefit the most from robo-advisors are those with less diversification in their primary portfolios. However, it is worth mentioning that D'Acunto's study looks at a robo-advisor that offers advice that can be rejected by the investor, whilst Rossi and Utkus look at a robo-advisor that invests automatically. Furthermore, D'Acunto et al (2019) also find that robo-advisors help undiversified investors to hold a higher number of stocks and therefore obtain a lower portfolio variance. In contrast, investors who had well-diversified portfolios before using the robo-advisor could not see any significant change in their portfolio diversification and performance after the adoption. Under-diversification is an issue as it exploits the investor for excess volatility, and it is possible to reduce this risk by holding more assets. Studies (Barber and Odeon, 1998; Gargano and Rossi, 2018; D'Acunto et al, 2019) find that the median investors in the US and India hold as few as three, four, or five assets in their portfolio. This finding stands in contrast to the previously mentioned statement by Statman (1987), who argues that 30 assets should be included in a portfolio to be considered well-diversified.

Another study concerning behavioral biases was conducted by Hartzmark in 2014. In his study (2014), Hartmark delved into the behavioral bias known as the rank effect, however, not with any connection to robo-advisors. Hartzman studies the rank effect through two large datasets from a brokerage fund and a mutual fund, where he confirms the tendency of investors making investment decisions influenced by this bias. Moreover, he finds that there is a probability of 26-31% of an investor selling either the worst performing, or the best performing assets in their portfolio further presenting evidence for this bias. Further research on losses and gains under behavioral biases was provided by Odean (1998). In his study, he found that it is common for investors to sell their winners too soon and keep their losers, i.e. the disposition effect, with December being the only exception due to tax reasons. He further concludes that the bias leads to the investors receiving lower returns. Some explanations for this bias might be that investors sell winners as a measure to rebalance their portfolios or due to higher transaction costs for low priced stocks. However, this should not mean that they sell all their winners, but only a small proportion of them. When taking both rebalancing and transaction costs into account, Odean (1998) found that the investors still seem to sell their winners instead of losers, suggesting that the bias does not depend on rational choices. Grosshaus and Zeisberger (2015) go beyond examining only the behavioral biases that affect investment decisions and research the psychological factors that influence investment strategies. This research specifically explores how investors' decisions are impacted by varying price paths. While some behavioral biases emphasize reactions to past profits and losses, they often overlook the significance of the price path, implying a focus solely on final returns. However, Grosshans and Zeisberger discover that investor satisfaction is significantly influenced by the trajectory of investment prices. Their findings suggest that the disposition effect might not be as universally applicable as previously believed, indicating that incorporating price paths could enhance our understanding of such behavioral patterns in investments.

4. Data

This section outlines the data collection process as well as the specific data used in the thesis.

4.1 Data gathering

The data for this study covers a time period that stretches from 2013-11-22 to 2023-10-31. The timeframe is chosen to capture different market conditions, including more recent episodes of heightened volatility. By including data from both turbulent and tranquil periods, the analysis aims to offer a comprehensive view of the market dynamics and their impact on portfolio performance as well as limiting the effect of economic cycles. Additionally, it was considered valuable to understand how the robo-advisor would perform during these conditions. The data used in this thesis was mainly gathered from Capital IQ. This included data on stock prices of companies listed on the OMX Nordic Exchange Stockholm, market capitalization of these companies as well as stock prices of the S&P 500 companies. The reason for including American companies is its ability to provide a more comprehensive analysis. This is due to the size and influence of the American economy which therefore enables it to represent the world market in our study instead of only using Sweden which has a limited perspective on the stock market as a whole. Furthermore, we are interested in simulating portfolios of Swedish investors as no studies analyzing robo-advisors' ability to outperform behavioral biases have been conducted in Sweden before and see this as an interesting environment as the population is receptive to digital solutions. Further alterations on the datasets were performed in MatLab which are explained thoroughly in the code that is found in the appendix. A key aspect of our data gathering involved converting S&P 500 stock prices from USD into SEK using the exchange rates, enabling a relevant comparison for Swedish investors. These stock prices were manually converted using daily spot rates of USD/SEK, retrieved from Riksbanken.

To compute the Sharpe Ratio and Jensen's alpha, a market index and a risk-free rate are needed. For this purpose, we chose the American economy and specifically its financial market as our benchmark. This decision is based on the influence and representation that the U.S. market contributes to in global dynamics. The data consisting of market return, risk-free rate, and excess market return is gathered from the Fama French Data Library. This data source uses the performance of all NYSE, AMEX, and NASDAQ[1] companies to compute the market return and the American treasury bill rate as the risk-free rate. At the time of the data collection, the most recent information from this source extended up to the end of October 2023, and therefore we collected data from 2013-11-22 until 2023-10-31. We calculated the risk-free rate continuously over time from the imported data, integrating it into our financial models in both daily and annual forms.

In addition, we divided the data into a sample and evaluation period. The sample period consists of 358 days between 2013-11-22 and 2015-05-22. The evaluation period consists of 2072 days between 2015-05-23 and 2023-10-31. The data is split into two periods to train the robo-advisor in the sample period and then test how it performs out-of-sample. Giving the advisor data it has not seen before, in the second period, makes it possible to analyze its performance in real-world conditions.

[1] New York Stock Exchange, American Stock Exchange and National Association of Securities Dealers Automated Quotations

4.2 Missing and excluded data

In our original data sets over stock prices of companies on the Stockholm Stock Exchange as well as the S&P 500 companies, the days when the stock exchange was closed were still included. On these non-trading days, the dataset defaulted to the last known sale price from the previous trading day. This approach can introduce inaccuracies when computing the return and in analyzes that assume daily price fluctuations. Recognizing this problem, the dataset was reviewed to identify and exclude all non-trading days. This process involved cross-referencing the stock exchange calendars to confirm days of closure due to weekends, American as well as Swedish holidays, or other non-trading circumstances. This led to the dataset being narrowed down from 3652 days to containing 2431 trading days over the analyzed decade. This adjustment ensures that the analysis reflects real trading activity and provides a more precise representation of stock market behavior during the stated period.

Moreover, some of the stocks in the datasets exhibited missing data during certain periods. The absence of complete data for these assets was primarily attributed to two scenarios: either the stocks did not exist at the beginning of the time period, or the companies ceased to exist at some point during this time frame. We decided to exclude these assets from our dataset, to maintain the consistency of our analysis. Originally, the dataset of Swedish stock prices contained 818 companies and the S&P 500 consisted of 500 companies. After the reduction of companies with incomplete data, our data consisted of 288 Swedish stocks and 465 American stocks. An important consideration when doing this is the possibility of a survivorship bias. Survivorship bias occurs when an analysis is skewed by concentrating only on the companies that "survived" or remained operational through the entire sample period, ignoring those that failed or ceased to exist. Since our research question is to investigate the difference in performance between a robo-advisor portfolio and behavioral bias portfolios, survivorship bias is not a central concern; its impact on results would only arise if its magnitudes differ between the robo-advisor and behavioral bias portfolios, but as the same data is used for all portfolios this should not be of any concern. This scenario would also occur if any behavioral bias strategy is more inclined to retain stocks facing delisting due to factors such as bankruptcy or buyouts. The optimal way of conducting this research would be to use delisting returns, however, these are not available in

Sweden. Additionally, after removing certain days and assets, these were compared to the original datasets to minimize errors.

5. Method

The calculations for this thesis have been done entirely in MatLab. Before anything else, the analysis starts by setting a fixed seed for the random number generator to get a consistent sequence of random numbers every time the code is run. This enables reproducibility and ensures that any random processes are identical across different runs of the program. In order to calculate the robo-advisor portfolio and the portfolios that include behavioral biases, various data files, including stock prices, market capitalizations, and risk-free rate data, are loaded into MatLab. This allowed for initial calculations of the daily and annual risk-free rate as well as the establishment of a comprehensive stock universe, containing assets from both the American and Swedish stock markets. The four behavioral bias portfolios we created in MatLab were an undiversified portfolio, a portfolio with home bias, a portfolio with the disposition effect, and finally a portfolio with the rank effect bias. These biases were chosen as we believe that they are relevant when looking at biases that a retail investor might exhibit, and also to limit our study to get more detailed information about each portfolio instead of choosing additional biases to analyze. Moreover, we have chosen to have 100 assets in the robo-advisors portfolio and 30 assets in the rest of the portfolios except for the undiversified portfolio, as 30 assets are considered to be a well-diversified portfolio. When calculating the annual values in our code, we assume 250 trading days in a year as the stock exchange market is open approximately 250 days per year.

5.1 Robo-advisor

This section outlines the methodology used to compute the portfolio of a hypothetical robo-advisor. The computation was done by leveraging market data and applying modern portfolio theory principles. The dataset is divided into two key periods: an estimation period, which spans 18 months starting from November 22, 2013, and an evaluation period covering the remaining 8,5 years. This division allows for robust backtesting of the robo-advisor's strategy, evaluating the model's performance on unseen data after training on the estimation sample. The assets chosen for this portfolio are the 50 largest stocks in our Swedish stock universe and 50 random stocks from the American stock data. To determine which Swedish stocks are the largest, the market cap of each company in the Swedish stock dataset was weighed against the total market cap to derive daily value weights. In the evaluation period, a portfolio object is created and the optimal weights to maximize the Sharpe ratio are calculated using the MatLab formula 'estimateMaxSharpeRatio'. Furthermore, some limitations were selected including no short-selling as well as a maximum weight of 10% in a single asset. This decision is grounded in limiting the risk in the robo-advisor's portfolio, where limiting the weight of any single asset to 10% is a strategy aimed at achieving diversification and controlling risk. Furthermore, short-selling is considered a high-risk strategy as it allows for unlimited losses, which is the rationale behind limiting the robo-advisor from doing this. The optimal portfolio was then created and to determine the performance of this portfolio some key financial metrics were calculated for both the estimation and evaluation period. However, the results from the evaluation period are what we base our comparative analysis on as this calculation mimics the real-world scenario where an investor would be investing in the robo-advisor's recommendations.

5.2 Portfolios containing behavioral biases

5.2.1 Undiversified portfolio

To study the effect of under-diversification, we assume that an investor will only invest in three of all available stocks. Therefore, the portfolio was calculated by only choosing three of all the available Swedish and American assets. This selection was randomized and further repeated 10,000 times, simulating 10,000 random portfolios containing only three stocks. Repeating the process multiple times is a Monte-Carlo simulation which is a technique used to understand the variability and risk of a certain strategy under different scenarios. By choosing the assets 10,000 times, the randomness in selection imitates the uncertainty and variety an individual investor might experience when choosing a small number of stocks for investment and gives us a more robust result. After the three stocks in each portfolio were selected, they were equally weighted in each portfolio.

5.2.2 Home bias portfolio

The second portfolio that was constructed was the one containing home bias. As this behavioral bias means that investors invest too much in their home country, this was simulated by creating a portfolio consisting only of Swedish assets. The selection, like the undiversified portfolio, was randomly selected using ‘randperm’, and thereafter simulating this selection 10,000 times. However, for this portfolio, we chose to have 30 assets in the portfolio as that amount is seen as what is needed for a well-diversified portfolio. In order to simulate home bias, this portfolio is limited to using only the assets within the OMX Nordic Exchange. After selecting the 30 stocks, we compute the equally weighted portfolio return for each day by averaging the returns of the selected stocks.

5.2.3 Disposition effect portfolio

For the disposition effect portfolio, all stocks are now available to choose from, which is represented by a timetable that refers to the combination of all Swedish and American stocks. From these, 30 stocks are chosen through a random selection, also this time to have a well-diversified portfolio. For each month, we calculated the performance of the market with the help of daily returns based on all NYSE, AMEX, and NASDAQ companies. Based on the market's performance, we adjusted our criteria for significant gains and losses within the portfolio. Specifically, in bear market conditions (monthly performance less than -5%), we set lower thresholds for recognizing gains (10%) and losses (-10%). Conversely, in bull markets (performance exceeding 5%), these thresholds were increased to 20% for gains and -20% for losses, while moderate thresholds of 15% and -15% were applied in neutral market conditions. In accordance with the disposition effect, the portfolio was recomposed by selling off the 'extreme gainers' (stocks exceeding the gain threshold) and retaining the 'extreme losers' (stocks below the loss threshold). This adjustment process was carried out monthly, aiming to reflect the investor’s response to short-term performance fluctuations. After selling assets, we also ensure that the portfolio reinvests in another asset, making sure the portfolio contains 30 assets for the full time period.

5.2.4 Rank effect portfolio

The fourth, and final portfolio that we construct is the one mimicking an investor with the rank effect bias. In the analysis of the rank effect portfolio, we start by running 10,000 simulations to evaluate the performance of a dynamically adjusted stock portfolio. Each portfolio initially consists of 30 randomly selected stocks from both the American and Swedish stock market, representing a diverse market selection. The approach depends on a monthly evaluation of stock performance, followed by a strategic adjustment based on their returns. Each month, stocks are ranked according to their performance, and the portfolio is adjusted by removing the best and worst-performing stocks. These are then replaced with new, randomly chosen stocks that are not currently in the portfolio, reflecting an investment strategy influenced by the rank effect bias where investors often sell high-performing stocks to capture gains and avoid potential losses from underperformers.

5.3 Calculations made for all portfolios

After simulating the portfolios in Matlab, we continue to investigate their performance and risks, and these calculations are done for all of the portfolios with behavioral biases as well as for the robo-advisor. The daily returns of each portfolio are calculated by taking each asset's daily return and scaling it by its weight in the portfolio:

$$r_{p,t} = \sum_{i=1}^{n} w_i r_{i,t}$$

The daily excess return is also computed by subtracting the daily risk-free rate from the daily return, to later be able to do further calculations on Jensen's alpha.

$$r_{p,t} = \sum_{i=1}^{n} (w_i r_{i,t} - r_f)$$

To get a more comprehensive and comparative result, we take the mean of all portfolio returns and annualize them by multiplying by 250 trading days to get the average annual return for the portfolio.

$$r_{p,t} = 250 * \left(\frac{\sum_{i=1}^{n} w_i r_{i,t}}{n} \right)$$

Furthermore, this is followed up by estimating several critical financial metrics; the standard deviation, Sharpe ratio, beta, and Jensen's alpha. The standard deviation for the portfolio was first calculated using the following formula, and then annualized through the second formula below:

1. $$\sigma_i = \sqrt{\sigma_i^2}$$

2. $$\sigma_i = \sqrt{\sigma_i^2 * 250}$$

The calculation of Sharpe ratio is computed by subtracting the average annual risk-free rate from the mean annualized return and then dividing it by the portfolio's annualized standard deviation.

$$S_p = \frac{r_p - r_f}{\sigma}$$

The beta of the portfolio is calculated by creating a covariance matrix between each portfolio return and the market return as well as calculating the market variance. To get the beta of each simulated portfolio, the covariance is divided by the market variance.

$$\beta_p = \frac{\sigma_{p,m}}{\sigma_m^2}$$

After this, the average of these values is calculated to get the mean for the portfolio. Jensen's alpha was calculated by taking the excess daily return and subtracting it with the expected return according to CAPM. The mean of these values is the abnormal return of the portfolio i.e. the alpha of the portfolio.

$$\alpha = r_p - (r_f + \beta(r_m - r_f)) = \sum_{i=1}^{n} (w_i r_{i,t} - r_f) - \beta(r_m - r_f)$$

6. Results and discussion

6.1 Results

As stated previously, the datasets did not fully align with the number of observations when we imported them, which meant that we had to adjust these to get matching sets for our portfolio calculations. When conducting the estimations, this led to 2431 days that were analyzed. For all portfolios, we calculated the average return, standard deviation, beta values, Sharpe-ratio and Jensen's alpha, and the results for these calculations will be displayed in this section. Moreover, the returns, Sharpe ratio, and Jensen's alpha will be visualized in order to see the distribution of these values, as well as how they compare against the robo-advisor out-of-sample which is represented by the black line in each figure.

6.1.1 Robo-advisor, in sample

The first portfolio that we compute is the Markowitz optimized portfolio, which is the robo-advisor in our study. The result from this portfolio in the sample period was that the annual return was 32.1% and the annual standard deviation was 11.6%. Besides standard deviation as a risk measure, we estimated the beta values as well which was 0.0038174% for this period. The high return and low standard deviation resulted in a high Sharpe ratio of 272.88% and Jensen's alpha for this period was 0.1265%.

6.1.2 Robo-advisor, out-of-sample

When calculating the results for the robo-advisor in the evaluation period, the annual return was 6.8143% and the standard deviation for the same period was 14.94%. Calculating the beta for the evaluation period resulted in a value of 0.0082326%. The Sharpe ratio for the evaluation period was 42.754%. Jensen's alpha for the evaluation period was a positive value of 0.025226%. In the figures below, these results are represented by the black line.

6.1.3 Undiversified portfolio

For the undiversified portfolio, three stocks were chosen through a random selection process, which was explained in the methodology section. When computing the calculations for this undiversified portfolio, the average annual return was 5.05%. The figure below shows the distribution of the returns for all 10,000 simulations that were performed. It is evident that most of the portfolios have a positive return as the returns are positively skewed, however, there is a larger negative tail meaning that more of the outliers are negative than positive. When looking at the standard deviation, which is a risk measure that takes both the systematic and non-systematic risk into account, it is slightly higher than the other portfolios with a standard deviation of 22.983%. We also calculated the average beta for the portfolio, which was 0.62744%.

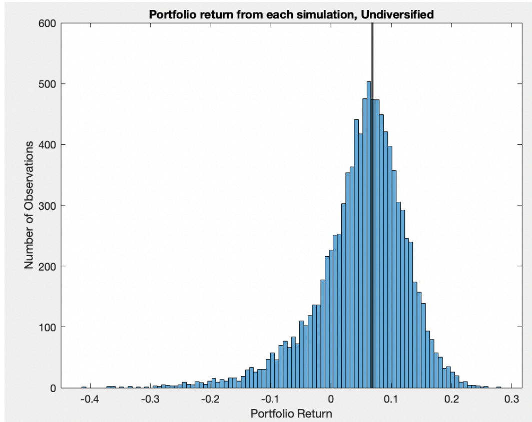
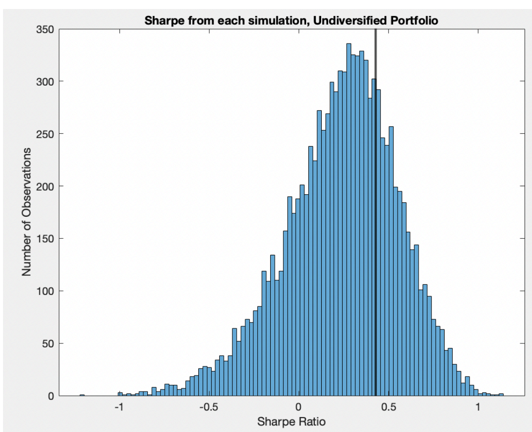
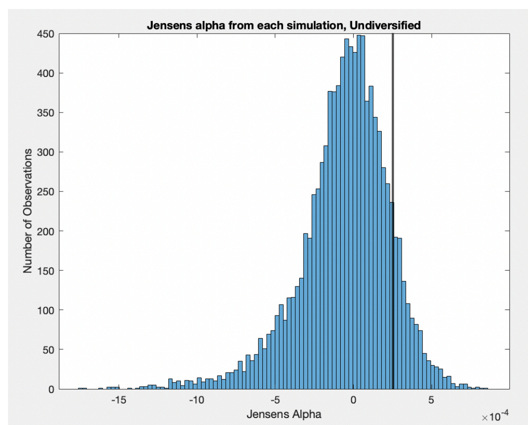


Figure 1. Illustrating the 10,000 simulated undiversified portfolios' annual portfolio return

The average Sharpe ratio for the portfolio was 23.75%. In the figure below, it is seen that most of the portfolios that were simulated have a positive Sharpe ratio, although it is visible that approximately one-third of the portfolios still have a negative ratio. The average Jensen's alpha for the undiversified portfolio was -0.0056449% and for this figure it is seen that, in comparison to the Sharpe ratio, most of the values are below zero.





Figures 2 and 3. Illustrating the 10,000 simulated portfolios' Sharpe ratio and Jensen's alpha values.

6.1.4 Home bias

For the portfolio with home bias, we performed the same calculations as for the undiversified portfolio. The return that we got from each simulation is presented in the graph below, and for this portfolio, the average return is 1.6586%. As seen in the figure, multiple simulations held both a higher and lower return than the average, but once again, the negative tail seems to be slightly larger than the positive tail. When examining the average standard deviation for this portfolio it is evident that it has an average standard deviation of 14.446%. The average beta value for the home bias portfolio is 0.34243%.

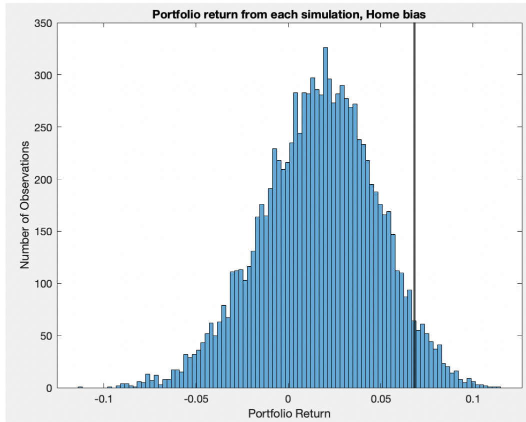
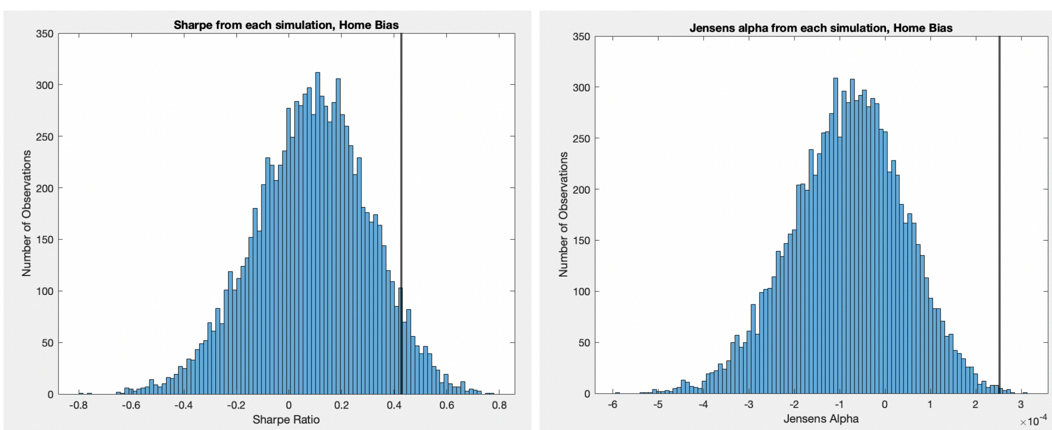


Figure 4. Illustrating the 10,000 simulated home bias portfolios' annual portfolio return

The average Sharpe ratio for the home bias portfolio is 8.71% which seems reasonable as it lies in the middle of the histogram where most values are centered. This figure follows a normal distribution as there are roughly the same amount of observations that are negative and positive. For the Jensen's alpha, this portfolio has a negative value of -0.0082448%. Similar to the previous portfolio, this distribution indicates that most of the observations hold a negative value.



Figures 5 and 6. Illustrating the 10,000 simulated home bias portfolios' Sharpe ratio and Jensen's alpha.

6.1.5 Disposition effect

For the portfolio simulating an investor with disposition effect bias, the average annual return is 5.0284%. As seen in the graph, this is a value that is found in the middle of the figure, with other values reaching from about -2% to 12%, implying that most of the values are positive. The perceived average standard deviation of this portfolio is 14.389%. For the beta value, this particular portfolio had a value of 0.631%.

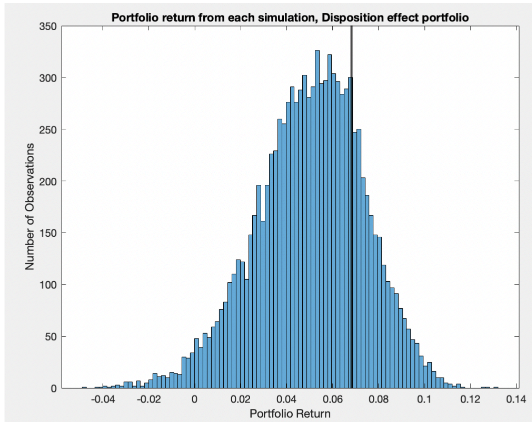
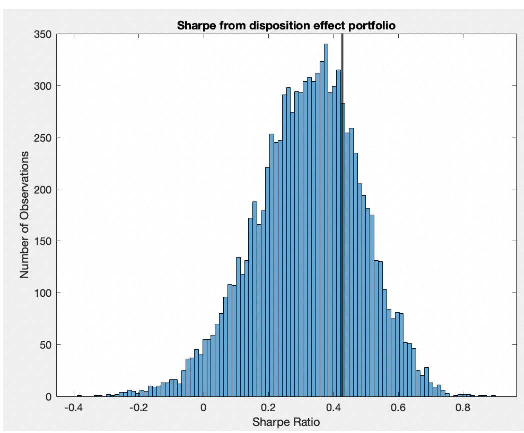
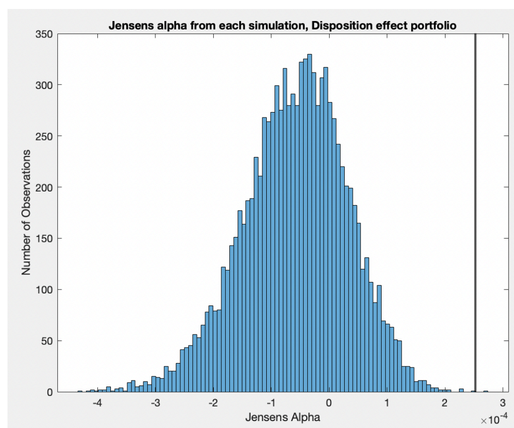


Figure 7. Illustrating the 10,000 simulated disposition effect annual portfolio return

The average Sharpe ratio for the disposition effect portfolio is 32.07% which also is found in the middle of the figure of all Sharpe values for the 10,000 simulations. The average Jensen's alpha value for the portfolio is -0.005849%, and once again, we observe more negative values than positive ones in accordance with the two previous portfolios.





Figures 8 and 9. Illustrating the 10,000 simulated disposition effect portfolios Sharpe ratio and Jensen's alpha values.

6.1.6 Rank effect

The final portfolio that we computed was for the portfolio with the rank effect. For this portfolio, the average return was 4.5626%. The average standard deviation for each simulation of this portfolio was 14.24%. Moreover, the beta value was calculated and the average beta for the rank effect portfolio was 0.59%.

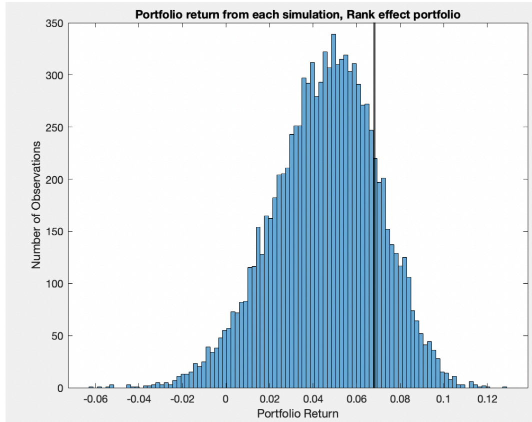
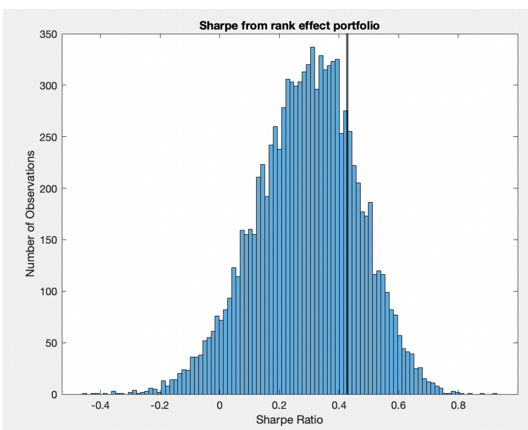


Figure 10. Illustrating the 10,000 simulated rank effect portfolios annual portfolio return.

Further calculations on the rank effect portfolio were performed, and we calculated both the average Sharpe ratio and the average Jensen's alpha value. For this portfolio, the average Sharpe ratio was 29.213% and the average alpha value was -0.00615%. The pattern that was seen with the previous portfolios is also seen here as this portfolio too has mostly negative alpha values.



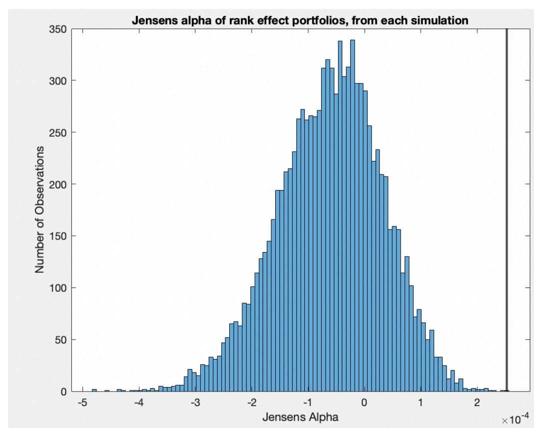


Figure 11 and 12. Illustrating the 10,000 simulated rank effect portfolios Sharpe ratios and Jensen's alpha values.

6.2 Comparing the portfolios

After having presented the results from all the portfolios above, it is possible to compare and assess the performance of the portfolios against each other. The return of the portfolios reveals that the home bias portfolio has the lowest return out of all of the portfolios with a return of 1.66%. The rank effect, disposition effect, and undiversified portfolios demonstrated progressively higher returns, recorded at 4.56%, 5.028%, and 5.05%, in that order. The robo-advisor portfolio outperformed these portfolios with an out-of-sample return of 6.81% and an in-sample return of 32.09%.

Table 1 *Average returns for the different portfolios*

Home Bias	Disposition effect	Rank effect	Undiversified	Robo advisor, out of sample	Robo advisor, in sample
1.66%	5.028%	4.56%	5.05%	6.81%	32.09%

When comparing the portfolios' standard deviations it is apparent that most of them have a similar standard deviation, except for the undiversified portfolio which has a significantly higher value. In this calculation, it is further visible that the robo-advisor did not outperform the other portfolios in the way it did in the previous calculation. In fact, all portfolios except for the undiversified one, had a slightly lower standard deviation compared to the robo-advisor out-of-sample. However, the in-sample standard deviation was still significantly lower than all the other portfolios which once again shows the superiority of the portfolio.

Table 2 *Average Standard deviations for the different portfolios*

Home Bias	Disposition effect	Rank effect	Undiversified	Robo advisor, out of sample	Robo advisor, in sample
14.45%	14.39%	14.24%	22.98%	14.94%	11.6%

The next value that is compared between the portfolios is their beta value. In this case, the biased portfolios had similar values and differed from 0.34% to 0.63%. This indicates that they have approximately the same amount of idiosyncratic risk. The robo-advisor out-of-sample had a beta value of 0.0082% which is significantly smaller than the biased portfolios, and had an in-sample beta value of 0.0038% which is even smaller. The robo-advisor reduces the portfolio's overall sensitivity to the movements of any single market, the US stock market in this case, by spreading investments across various asset types and markets. This results in a portfolio that is less volatile compared to the market benchmark, which explains the lower beta.

Table 3 *Average beta values for the different portfolios*

Home Bias	Disposition effect	Rank effect	Undiversified	Robo advisor, out of sample	Robo advisor, in sample
0.34%	0.63%	0.59%	0.63%	0.0082%	0.0038%

When comparing the Sharpe ratios of the portfolios, it is evident that the home bias portfolio performed worse than the rest of the portfolios with a Sharpe ratio of 8.87%. This was followed by the undiversified portfolio that showed a slight improvement in risk efficiency with a Sharpe ratio of 23.75%. The rank and disposition effect portfolios exhibited higher values of 29.21% and 32.07%, respectively. As expected, the Markowitz portfolios outshined the rest; the out-of-sample variant achieved a Sharpe ratio of 45.63%, while the in-sample analysis soared to 276.57%, reflecting a highly efficient balance of risk and return.

Table 4 *Average Sharpe ratios for the different portfolios*

Home Bias	Disposition effect	Rank effect	Undiversified	Robo advisor, out of sample	Robo advisor, in sample
8.87%	32.07%	29.21%	23.75%	42.754%	272.88%

When comparing the portfolios in terms of their Jensen’s alpha value, all portfolios with behavioral biases received a negative value. This is expected as we did not believe that any of those portfolios would yield an abnormal return. In comparison, the robo-advisor out-of-sample value was 0.025% which indicates that it yields a small abnormal return. The robo-advisor in-sample has an abnormal return of 0.13% which is superior to all other portfolios.

Table 5 *Average Jensen's alpha for the different portfolios*

Home Bias	Disposition effect	Rank effect	Undiversified	Robo advisor, out of sample	Robo advisor, in sample
-0.00824%	-0.00585%	-0.00615%	-0.00564%	0.025%	0.13%

Looking at all the portfolios together, it is visible that the robo-advisor portfolio outperformed all the portfolios that contain behavioral biases. The only exception to this is for the standard deviation where all biased portfolios but the undiversified ones hold a lower value than the robo-advisors out-of-sample value. However, the robo-advisor still performs better than the other portfolios when looking at the in-sample value. It is therefore possible to conclude that the Markowitz optimization portfolio is always performing better than the ones that contain any of these four biases.

6.3 Discussion

From our calculations of the portfolios in MatLab, it is noticeable that the Markowitz computed robo-advisor outperformed the biased portfolios in all of the calculations that were presented. This aligns with the literature, which emphasizes the efficiency of algorithm-based portfolio management (D'Acunto et al, 2019; Walter Lam, 2016). One explanation for this efficiency can be attributed to the robo-advisor's ability to optimize asset allocation based on systematic data analysis, minimizing the impact of human behavioral biases.

In line with Reher and Solinski (2020), our robo-advisor also demonstrated a significant improvement in Sharpe ratio, due to higher return and lower standard deviation than the biased portfolios. While Reher and Solinski focused on the general performance improvements with robo-advisors, our research delves deeper into how specific biases like home bias, disposition effect, and rank effect are addressed through algorithm-based portfolio management. This comparative analysis strengthens the argument for the efficiency of robo-advisors in diverse investment contexts, including the Swedish market, which we particularly focused on. In their paper, the Sharpe ratio improved by 0.298 and 0.297 for middle-class and upper-class portfolios, respectively, under robo-advisor management compared to self-management. Our results show similar improvements when compared to the biased portfolios. For instance, against the home bias portfolio, with the lowest Sharpe ratio, the robo-advisor portfolio showed a significant increase in Sharpe of 0.339. Compared to the disposition effect portfolio, which had the highest Sharpe ratio among the biased portfolios, our robo-advisor demonstrated an enhanced performance with a Sharpe ratio that was 0.107 points higher.

In our analysis, we can observe a distinct ranking in terms of costliness of different biases, indicated by the Sharpe ratio of the portfolio. Notably, the portfolio with disposition effect held the highest Sharpe ratio, followed by the rank effect portfolio, the undiversified portfolio, and lastly the home bias portfolio. As the Sharpe ratio is a calculation made from both the return and standard deviation, it is evident that this performance measurement indicates that the disposition effect had the best performance throughout the time period, besides the robo-advisor portfolio. A possible reason for the portfolio with disposition bias performing best could be that investors are predisposed to hold onto losing stocks longer and sell winning stocks too soon, potentially leading to a more balanced, though conservative, portfolio in certain market conditions. The finding that the home bias is the most costly in terms of the Sharpe ratio is particularly striking. It underscores the impact of geographic preference on portfolio performance, suggesting that investors benefit from a more global diversification strategy. Besides being the most costly portfolio in terms of Sharpe ratio, the home bias portfolio also displayed the largest negative alpha. As a home bias, in this study, refers to an individual entirely invested in the Swedish market, one explanation for this could be that the Swedish stocks have performed worse than the American ones during the studied time period. This underperformance could also be attributed to a limited diversification scope and potential vulnerabilities of the Swedish market during the studied period. It highlights the risks linked with overconcentration in a single market, especially in smaller, more volatile markets like Sweden's, compared to more diversified, global markets.

From the earlier research that has been discussed in this study, it is evident that robo-advisors decrease the behavioral biases that are studied. However, different research papers do not present the exact same results when using the robo-advisors, which can be expected since their research is based on different data. What they all have in common, however, is that the robo-advisor seems to help investors decrease their exposure towards behavioral biases, although this is seen in multiple degrees. Former research has shown a significant decrease in the rank effect and the disposition effect (D'Acunto et al, 2019), and the elimination of home bias (Rossi and Utkus, 2020). Moreover, the research also demonstrated how robo-advisors can help diversify the investor's portfolio (D'Acunto et al, 2019). In accordance with this research, our study presents the same results in that it does reduce home bias, undiversified bias, the disposition effect bias, and the rank effect bias.

Previous research, based on real data, states that some biases are less pronounced after using a robo-advisor whilst others can be entirely eliminated. However, in contrast to previous research concerning robo-advisors and behavioral finance, our study is done in a simulation setting and makes our robo-advisor able to eliminate biases completely. The complete elimination of home bias aligns with the findings of Rossi and Utkus (2020). However, regarding the undiversified portfolio, our results differ from those of D'Acunto et al. (2019). While they observed an improvement in the bias's impact on the portfolio, our study indicates that the robo-advisor can construct a portfolio entirely free from this bias. A possible explanation for the difference in the results of the undiversified portfolio could be that D'Acunto et al's paper looked at how investors behave after the guidance of a robo-advisor, meaning that the investor could choose whether to take the advice or not, while we computed a portfolio based solely on how the investments would be done using Markowitz optimization. This is also in line with the similar results we get with Rossi and Utkus' study, as they looked at a robo-advisor that trades automatically. The complete elimination of the rank effect as well as the disposition effect indicates a larger reduction than the the findings observed in D'Acunto et al's (2019) study, where there was a 30% decrease in the disposition effect and a 26% decrease in the rank effect when investors could intervene with the advisor's suggestions. This further underscores that robo-advisors with less human interaction display better results in terms of limiting behavioral biases, while those where investors have the possibility to interfere with the suggestions still display some biases.

For our research question regarding whether robo-advisors can benefit retail investors with biased portfolios in Sweden, it seems that the algorithm-driven platform is able to help less experienced investors with portfolio selection and asset allocation. This conclusion can be drawn since robo-advisors have the possibility of providing more objective suggestions which can decrease some of the potential biases that the investor has, leading to a more beneficial risk-return trade-off. This is continuously shown throughout our results and is also consistent with past research. Another advantage with a robo-advisor that trades automatically is the fact that investors can spend less time managing their portfolios which Reher and Solinksi (2021) also saw in their study. However, while the robo-advisor portfolio demonstrates superior results in comparison to the other portfolios, portfolios of this nature are not without limitations. Our study resonates with Waliszewski and Zięba-Szklarska (2020), who pointed out the trade-off between cost-effectiveness and personalized investment strategies. The standardized approaches of robo-advisors, while efficient, may not cater to the unique needs of every investor, potentially leading to suboptimal asset allocations for certain individual scenarios.

7. Conclusion

The objective of this thesis is to evaluate if the use of robo-advisors can be an effective alternative for retail investors, and more specifically answer the question: *Can Swedish retail investors with biased portfolios benefit from using a robo-advisor tool when investing?* Our results show that robo-advisors' ability to provide data-driven and less subjective investment advice can lead to improved portfolio performance for these investors. Moreover, robo-advisors have become more accessible than ever, and obtaining assistance from them is likely to become even more convenient in the future. The improved availability of financial advisors could also lead to other important changes in society, such as a change in the wealth distribution in the future. As financial advisors have previously demanded a large amount of initial capital, the lower limit opens the market for a new group of investors (Berg and Mhanga, 2019; Reher and Solinski, 2020). The opportunity for retail investors to grow their wealth over time will therefore increase and could lead to a change in the distribution of wealth in society in the future. However, this is not a conclusion that we can draw from our study but only speculate upon. Therefore, we think that it would be interesting to further research the possible relationship between robo-advisors and wealth distribution, which perhaps would need to be done in the future when there is more available data that can be analyzed. Although we believe that robo-advisors might have an impact on wealth distribution, it would need future studies to further evaluate this potential relationship.

This study opens up for future research, particularly in understanding the long-term societal impacts of robo-advisors, including their potential role in wealth distribution and financial inclusivity. Even though it is possible to draw conclusions from our study, we want to address the fact that this study is based on data from a limited time period of ten years. To truly grasp the influence of robo-advisors on portfolios with behavioral biases, a future study should contain more data and perhaps be based on real investors' portfolios instead of simulated portfolios.

Another possibility for future studies would be to further develop the analysis of the disposition effect bias and address the price path pattern that Grosshans and Zeisberger (2015) highlights in their study. We also acknowledge that by deleting assets from our calculations, our study might contain survivorship bias which in that case could shape the results in a certain direction.

8. References

Barber, B.M. and Odean, T. (1998). Boys will be Boys: Gender, Overconfidence, and Common Stock Investment. *SSRN Electronic Journal* , 116(1). doi:https://doi.org/10.2139/ssrn.139415.

Berg, A. and Mhanga, S. (2019). Robo-advisors on the Swedish Market: From a Portfolio Management Perspective. Master thesis, Jönköping University. https://www.diva-portal.org/smash/get/diva2:1319499/FULLTEXT01.pdf

Brenner, L. and Meyll, T. (2020). Robo-advisors: A substitute for human financial advice? *Journal of Behavioral and Experimental Finance*, 25, p. 100-275. doi:https://doi.org/10.1016/j.jbef.2020.100275.

Coval, D. J. and Moskowitz, J.T. (1999). Home Bias at Home: Local Equity Preference in Domestic Portfolios. *The Journal of Finance,* 54(6), pp. 2045-2073. Available at: https://www.jstor.org/stable/797987

D'Acunto, F., Prabhala, N. and Rossi, A.G. (2019). The Promises and Pitfalls of Robo-Advising. *The Review of Financial Studies*, 32(5), pp. 1983–2020. doi:https://doi.org/10.1093/rfs/hhz014.

D'Acunto, F. and Rossi, A.G. (2021). Robo-Advising. *The Palgrave Handbook of Technological Finance*, pp. 725–749. doi:https://doi.org/10.1007/978-3-030-65117-6_26.

D'Acunto, F. and Rossi, A. (2022). Robo-advice: An effective tool to reduce inequalities?, *Brookings*. Available at: https://www.brookings.edu/articles/robo-advice-an-effective-tool-to-reduce-inequalities/

Elbannan, M.A. (2014). The Capital Asset Pricing Model: An Overview of the Theory. *International Journal of Economics and Finance*, 7(1). doi:https://doi.org/10.5539/ijef.v7n1p216.

Fama, E.F. (1970) Efficient Capital Markets: a Review of Theory and Empirical Work, *The Journal of Finance*, 25(2), pp. 383–417. Available at: https://doi.org/10.2307/2325486

French, R.K. and Poterba, M.J. (1991). Investor Diversification and International Equity Markets, *The American Economic Review,* 81(2), pp.222-226. Available at: https://www.jstor.org/stable/2006858?seq=1

Gargano, A. and Rossi, A.G. (2018). Does It Pay to Pay Attention? *The Review of Financial Studies*, 31(12), pp. 4595–4649. doi:https://doi.org/10.1093/rfs/hhy050.

Grosshans, D. and Zeisberger, S. (2015). All's Well that Ends Well? On the Importance of How Returns are Achieved. *SSRN Electronic Journal*. doi:https://doi.org/10.2139/ssrn.2579636.

Hartzmark, S.M. (2014). The Worst, the Best, Ignoring All the Rest: The Rank Effect and Trading Behavior. *The Review of Financial Studies*, 28(4), pp. 1024–1059. Available at: https://doi.org/10.1093/rfs/hhu079.

Jensen, C.M. (1967). The Performance of Mutual Funds in the Period 1945-1964. *Journal of Finance*, 23(2), pp. 389-416. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=244153

Kendall, M. G., and Hill, A. B. (1953). The Analysis of Economic Time-Series-Part I: Prices. *Journal of the Royal Statistical Society. Series A (General)*, *116*(1), 11–34. Available at: https://doi.org/10.2307/2980947

Lam, J.W. (2016). Robo-advisors: A portfolio management perspective. Senior thesis, Yale College, 20. Available at: https://economics.yale.edu/sites/default/files/2023-01/Jonathan_Lam_Senior%20Essay%20Revised.pdfhttps://economics.yale.edu/sites/default/files/2023-01/Jonathan_Lam_Senior%20Essay%20Revised.pdf

Madaan, S., and Singh S. (2019). An Analysis of Behavioral Biases in Investment Decision-Making. *International Journal of Financial Research*. pp 55-67. Available at: https://doi.org/10.5430/ijfr.v10n4p55

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), pp.77–91. Available at: https://www.jstor.org/stable/2975974

Odean, T. (1998). Are Investors Reluctant to Realize Their Losses? *The Journal of Finance*, 53(5), pp. 1775–1798. Available at: https://doi.org/10.1111/0022-1082.00072.

Reher, M. and Solinski, S. (2020). Robo Advisors and Access to Wealth Management. *SSRN Electronic Journal*. Available at: https://doi.org/10.2139/ssrn.3515707.

Reher, M. and Solinski, S. (2021) Automation and Inequality in Wealth Management *. Available at: https://bpb-us-e2.wpmucdn.com/sites.utdallas.edu/dist/8/1090/files/2021/09/finance-conference-paper-automation-inequality-wealth-management.pdf

Rossi, A.G. and Utkus, S.P. (2020). Who Benefits from Robo-advising? Evidence from Machine Learning. *SSRN Electronic Journal*. Available at: https://doi.org/10.2139/ssrn.3552671.

Sahi, S.K. (2017). Psychological biases of individual investors and financial satisfaction. *Journal of Consumer Behaviour*, 16(6), pp.511–535. Available at: https://doi.org/10.1002/cb.1644.

Saivasan, R. and Lokhande, M. (2022). Influence of risk propensity, behavioral biases and demographic factors on equity investors' risk perception. *Asian Journal of Economics and Banking*, 6(3), pp.373-403. Available at: https://www.emerald.com/insight/content/doi/10.1108/AJEB-06-2021-0074/full/html

Sharpe, W. F. (1966). Mutual Fund Performance. *The Journal of Business,* 39(1), 119-138. Available at: https://www.jstor.org/stable/2351741

Shefrin, H. and Statman, M. (1985). The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. *The Journal of Finance*, 40(3), pp. 777–790. Available at: https://doi.org/10.1111/j.1540-6261.1985.tb05002.x.

Sironi, P. (2016). FinTech Innovation: From Robo‐Advisors to Goal Based Investing and Gamification. Available at: https://onlinelibrary.wiley.com/doi/book/10.1002/9781119227205

Statman, M. (1987). How Many Stocks Make a Diversified Portfolio? *The Journal of Financial and Quantitative Analysis*, 22(3), pp. 353–363. Available at: https://doi.org/10.2307/2330969.

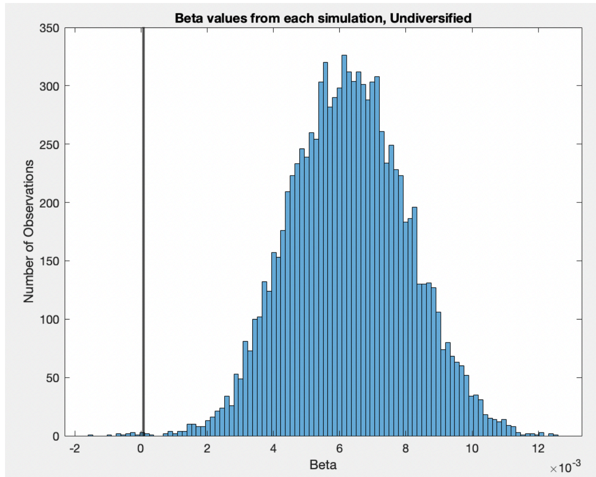
Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and Biases. *Science*, 185(4157), pp. 1124–1131. Available at: https://doi.org/10.1126/science.185.4157.1124.

Waliszewski, K. and Zięba-Szklarska, M. (2020). Robo-advisors as Automated Personal Financial Planners – SWOT Analysis. *Finanse i Prawo Finansowe*, 3(27), pp. 155–173. Available at: https://doi.org/10.18778/2391-6478.3.27.09.

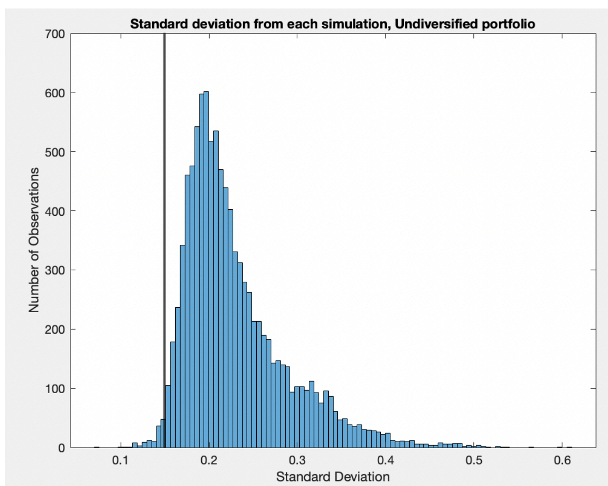
Zahera, S.A. and Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, 10(2), pp. 210-251. Available at: https://www.researchgate.net/publication/323861317_Do_investors_exhibit_behavioral_biases_in_investment_decision_making_A_systematic_review

Appendix A.

Undiversified Portfolio, figures over standard deviation and beta

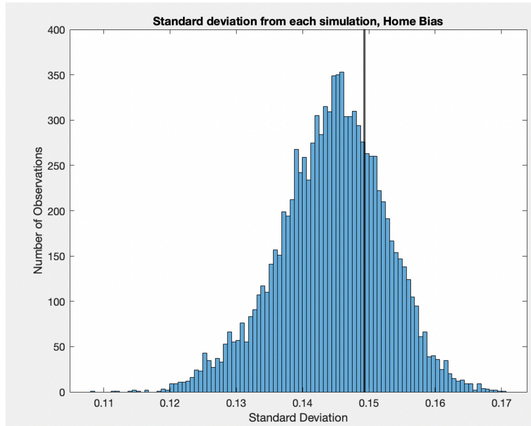


As seen in the graph of all beta values from each calculation, this seems to lie in the middle of the values and the graph somewhat follows a normal distribution.

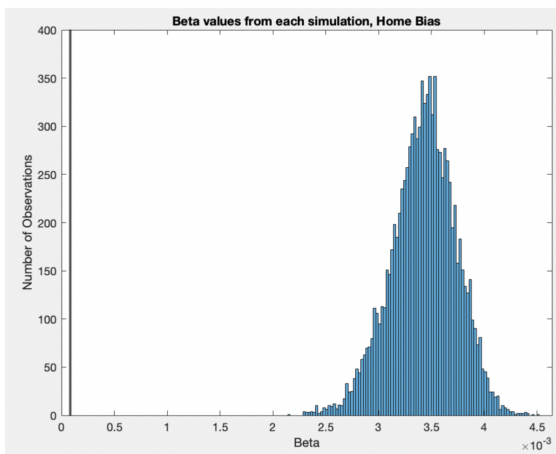


In the histogram of the standard deviation, the values do not seem to be normally distributed as they have a negative skewness and larger positive tail than the negative one.

Home Bias Portfolio, figures over standard deviation and beta

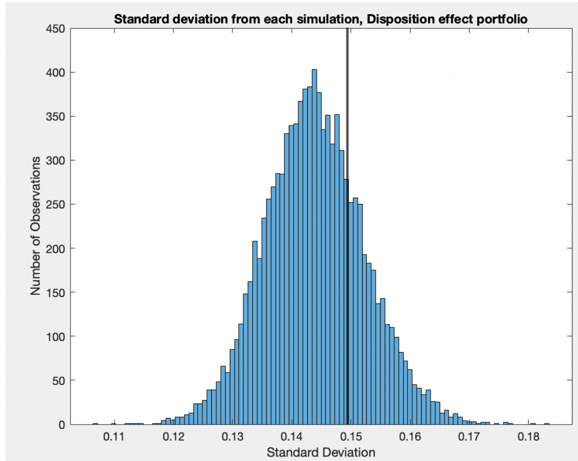


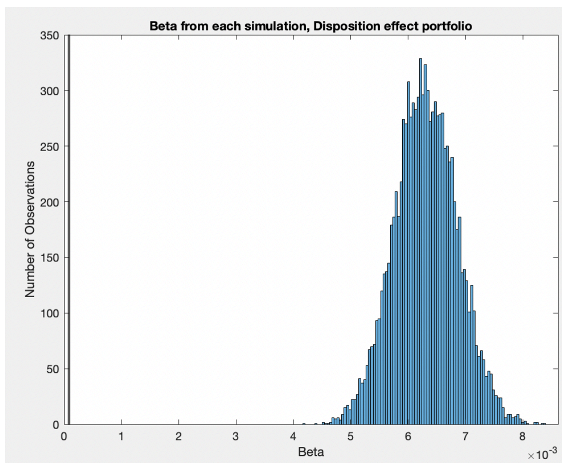
The standard deviation for the home bias portfolio has a larger negative tail. As seen in the figure over the standard deviations, this value seems to lie in the middle and the values seem to be relatively normally distributed.



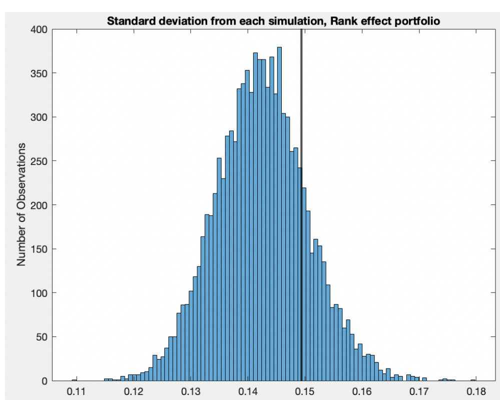
The beta value for home bias is positive for all simulations.

Disposition Bias Portfolio, figures over standard deviation and beta

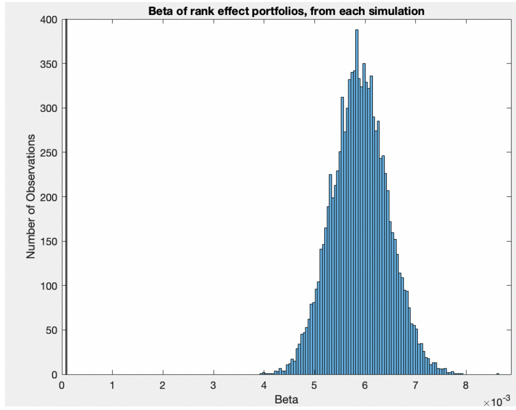




Rank Effect Portfolio, figures over standard deviation and beta



In the histogram of the standard deviation from each iteration below, it is evident that the standard deviation has a slightly negative skewness and a positive tail.



Appendix B - Code in MatLab

Can be obtained upon request.