Veli Joel Katajarinne

The effect of Robo-Advisor adoption in retail investors

A Behavioral Finance Perspective

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Author: Veli Joel Katajarinne

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ABSTRACT:

The purpose of this thesis is to explore the relationship between the adoption of robo-advisory services and retail investors' investing behavior. More specifically, the main objective of this thesis is to understand the effects of robo-advisors in mitigating retail investors' behavioral biases by influencing their approach to portfolio diversification, trading frequency and risk tolerance. As more and more retail investors turn to robo-advisors for advice, understanding their influence on retail investor behavior is crucial. This is particularly important in today's volatile and complex financial markets. The thesis is based on a comprehensive literature review of existing research on robo-advisors and behavioral finance. The existing literature often agrees on the beneficial effects robo-advisory adoption has on retail investor portfolio diversification, trading frequency and risk tolerance, but there are some outliers. This thesis contributes to understanding how robo-advisors reshape retail investing by promoting rational decision-making and mitigating common behavioral biases.

KEYWORDS: Robo-advisor, Behavioral Finance, Portfolio Diversification, Trading Frequency, Risk Tolerance

Contents

1 Introduction

The popularization of technology in financial services has significantly changed the way individuals approach investing, especially through the adoption of robo-advisors. Robo-advisors are automated platforms that provide algorithm-driven investment advice with minimal human intervention (Lewis, 2018). This paper aims to explore how the adoption of robo-advisors affects the behavior of individual investors.

In recent years, artificial intelligence has evolved at a rapid pace, bringing significant changes to investment advice. As retail investors increasingly turn to robo-advisors for advice, understanding their influence on retail investor behavior is crucial. This is particularly important in today's volatile and complex financial markets. Robo-advisors offer personalized investment strategies at a lower cost, making them an attractive alternative to traditional human advisors amid growing economic uncertainty.

Historically, seeking advice from experts has helped to reduce the stress associated with decision making, thereby increasing consumer loyalty and satisfaction. For example, when shopping, consumers often turn to store employees for assistance (Beatty et al., 1996) and subsequently experience increased loyalty and satisfaction with their choices (Reynolds & Arnold, 2000). Regarding investing, such advice often leads to better-informed and optimal investment decisions that generate higher investment returns at lower risk (Bluethgen et al., 2008). However, human financial advisors have been shown to exhibit behavioral biases and cognitive limitations (Rossi & Utkus, 2024), which can negatively impact the quality of advice provided. As a result, AI-powered robo-advisors have become increasingly popular in recent years as investors seek affordable and automated investment advice (Rossi & Utkus, 2024).

Given the psychological complexity of investment decisions, this paper seeks to determine the extent to which robo-advisors can help retail investors overcome these challenges by mitigating behavioral biases. Understanding how the adoption of these AI-powered tools influence retail investor behavior is critical for both individual investors and the broader financial landscape, as it could change the dynamics of investment decision-making in an increasingly automated world.

Purpose and objectives of the thesis

The purpose of this paper is to examine how the increasing use of AI-powered robo-advisors affects the investment behavior of retail investors. The study will examine behavioral finance concepts and phenomena relevant to robo-advisors and their impact on investor decision-making.

To structure the study, the main objective of the study is to investigate the overarching hypothesis that robo-advisors mitigate behavioral biases in retail investors, potentially influencing their portfolio diversification, trading behavior, and risk tolerance.

The first area of research will focus on portfolio diversification. Research suggests that retail investors often tend to be under-diversified in their investment portfolios. This thesis examines whether the introduction of robo-advisors exacerbates or mitigates this bias. It is hypothesized that by providing perceived expertise and simplified recommendations, robo-advisors may either lead to overconfidence and less diversified strategies or promote greater awareness of the benefits of diversification.

Secondly, the study analyses the trading frequency of retail investors who use robo-advisors compared to those who do not. The hypothesis is that robo-advisors may facilitate increased trading due to their accessibility and reduced cognitive load, leading to potentially more frequent, though not necessarily optimal, trading decisions.

The third focus of the thesis will be on risk tolerance, investigating whether the use of robo-advisors affects the risk profiles of retail investors. This analysis will consider the extent to which the framing effects of risk information presented by robo-advisors influence investors' perceptions of risk, potentially leading to discrepancies between their stated risk preferences before using a robo-advisor and their actual risk exposure afterwards.

In summary, this study aims to investigate the impact of robo-advisors on the behavior and decision-making processes of retail investors, specifically how these automated services may mitigate or influence common behavioral biases in the context of portfolio management, trading activities, and risk assessment. The first and only hypothesis of the study is therefore:

H1: Robo-advisors mitigate retail investors' behavioral biases by influencing their approach to portfolio diversification, trading frequency, and risk tolerance.

Structure of the thesis

The structure of this thesis is as follows. The motivation, research questions, and hypothesis of the study are introduced in the first section. The second section of the thesis covers the theoretical background, and it focuses on relevant behavioral finance theories. The section is categorized into three main groups: Theories Related to How Retail Investors Process Information, Decision-Making Frameworks, and Information Dynamics in Retail Investing. Section three covers the literature review of related literature concerning the topic of this thesis. The fourth and final section concludes the findings.

2 Theoretical background

When examining the adoption of AI-powered robo-advisors and their impact on retail investors, it is important to understand the behavioral patterns that influence investor decisions. This section categorizes relevant theories into three main groups: Theories Related to How Retail Investors Process Information, Decision-Making Frameworks, and Information Dynamics in Retail Investing.

2.1 Theories Related to How Retail Investors Process Information

2.1.1 Cognitive Biases

Home Bias

Home bias in equities is a well-known behavioral finance phenomenon, first studied in an academic context by Kenneth French and James M. Poterna in 1991. The clear benefits of international diversification have been recognized for several decades, but most individual investors still hold almost all of their assets in domestic assets (French & Poterna, 1991). In 1991, French and Poterna found that investors in each country expect returns in their domestic stock market to be much higher than returns in other markets, and that this lack of diversification appears to be the result of investor choice rather than institutional constraints. Individual investors choose to invest in domestic equity markets. They feel they have more accurate information about the returns of domestic assets because they watch domestic television, listen to domestic radio, and read domestic newspapers, and therefore investing domestically is less risky for them than investing on their own (Dziuda & Mondria, 2012).

Familiarity bias

Another common psychological bias relevant to this study is the familiarity bias. Both overconfidence bias and familiarity bias can be used to further understand the concept of home bias. Huberman (2001) refers to familiarity bias as a preference to invest in

assets that are known or easily understood, even if they are less profitable or riskier than more diversified alternatives. According to Huberman (2001), familiarity bias can involve real or perceived information bias, overconfidence, and emotional attachment. Investors may believe that they have better information about familiar companies than about unfamiliar ones. Investors may also overestimate their knowledge about familiar investments. In addition, familiarity creates a sense of comfort and trust, leading to emotional investment (Huberman, 2001). Massa & Simonov (2006), on the other hand, pointed out that investors affected by the familiarity bias invest in companies located near the investor's residence and in companies within the same industry as the investor's profession. In addition, investors affected by this bias tend to invest in stocks that have been held by the investor for a longer period (Massa & Simonov, 2006). Huberman (2001) points out that investors who hold a disproportionate amount of their assets in a single stock or similar types of stocks are significantly more vulnerable to losses if that company underperforms. By neglecting diversification, investors may miss out on potentially more profitable opportunities in other, less familiar investments (Huberman, 2001).

Overconfidence

Behavioral finance phenomena, such as home bias, often stem from or can be further explained by other behavioral biases. Another psychological bias relevant to financial markets and individual investors is overconfidence. As Odean said in 1998, people are overconfident, and overconfidence affects financial markets. Daniel, Hirshleifer & Subrahmayam (1998) define overconfidence in the context of financial markets as investors overestimating the accuracy of their private information. Crucially, the article by Daniel et al. (1998) does not assume that investors are overconfident about public information. The overconfidence is specifically focused on the accuracy of their unique insights and judgments.

Overconfidence has many implications in the context of individual investors. According to Barber & Odean (2001), in its simplest form, overconfidence is associated with excessive trading and poorer investment outcomes. Barber & Odean (2001) found that individual investors who trade more actively do worse than those who trade less. In addition, overconfident traders tend to hold under-diversified portfolios (Odean, 1998).

Loss aversion

Kahneman & Tversky (1979) show that the displeasure associated with losing a given amount of money is substantially greater than the pleasure associated with gaining the same amount of money. This psychological asymmetry is at the heart of loss aversion. Kahneman & Tversky also show that preferences for gains and losses are mirror images of each other. Risk aversion in the domain of gains is mirrored by risk-seeking behavior in the domain of losses (Kahneman & Tversky, 1979). This "mirror effect" is a direct consequence of loss aversion. In addition, the framing effect mentioned above has a significant impact on the influence of loss aversion. Framing outcomes as losses rather than gains tends to increase risk-averse behavior in the gain domain and risk-seeking behavior in the loss domain. In essence, Kahneman & Tversky (1979) show that investors' reactions to losses are psychologically different from and more powerful than their reactions to comparable gains.

2.1.2 Emotional Biases

Disposition effect

The disposition effect is a well-documented behavioral bias that leads investors to make suboptimal trading decisions. People often tend to seek out actions that make them feel proud or good and avoid actions that make them feel regretful or bad. Shefrin & Statman (1985) provide a broad theoretical framework that explains this effect. Shefrin & Statman (1985) combine elements of prospect theory and various cognitive biases such as mental accounting, regret aversion, and self-control. Shefrin & Statman (1985) explain that the pursuit of pride and the avoidance of regret leads to a disposition to realize gains

and defer losses. The disposition effect leads to suboptimal investment decisions in multiple ways. For example, investors give up potential future gains by selling winners too early. Investors also often suffer even greater losses by holding onto losers for too long before finally selling them. The combined effects of selling winners too early and holding losers for too long result in lower overall portfolio returns (Shefrin & Statman, 1985).

Regret aversion

Regret aversion is the tendency to avoid making decisions out of concern that the selected path of action would prove less than ideal in retrospect. It is an emotional bias that prioritizes avoiding the pain of regret over maximizing potential gains (Ising & Pompian, 2006, pp. 243-251). Ising & Pompian distinguish regret from disappointment, emphasizing that regret involves a sense of personal responsibility for a negative outcome.

According to Frydman & Camerer (2016), regret aversion leads to suboptimal trading decisions. Investors are less likely to repurchase a stock that has recently risen in price after having previously sold it. This avoidance of repurchasing a winning stock, despite its potential for further gains, is strong evidence of regret aversion. The investor avoids the painful feeling of regret associated with a missed opportunity. Frydman & Camerer (2016) refer to this effect as the repurchase effect. Frydman & Camerer (2016) show that regret aversion is a significant factor influencing the behavior of retail investors.

2.1.3 Decision-Making Frameworks

Prospect theory

One of the most widely accepted theories in behavioral finance is prospect theory. Prospect theory is a theory of behavioral economics, judgment, and decision making. It was first developed in 1979 by Daniel Kahneman and Amos Tversky. Kahneman & Tversky (1979) propose that investors evaluate decisions based on potential gains and losses rather than final asset positions. According to Kahneman & Tversky's theory, investors make suboptimal decisions because they overreact to losses. Investors may also hold on to losing investments for far too long, hoping for a recovery. In addition, investors may sell winning investments too soon, locking in a smaller gain to avoid the possibility of a larger loss (Kahneman & Tversky, 1979). Kahneman & Tversky's prospect theory does not directly study retail investors, but subsequent research relies heavily on its principles to explain numerous observed biases in investor behavior, such as the disposition effect, the framing effect, and risk seeking or risk aversion.

Mental accounting

Mental accounting describes the heuristics people use to break down complex financial decisions into smaller, more manageable pieces (Frydman, Hartzmark & Solo-mon, 2018). Mental accounting is shaped by psychological factors that influence how people perceive, experience, and make financial decisions (Thaler, 1999). Both Thaler (1999) and Frydman et al. (2018) define mental accounting through some core ideas, such as grouping and reference points.

According to Frydman et al. (2018), grouping is a phenomenon where investors categorize financial decisions and outcomes into mental accounts, for example, separate accounts for different stocks. Outcomes within one account are evaluated together, while outcomes in different accounts are considered separately. In essence, success in one account does not offset failure in another. Reference point, on the other hand, refers to the tendency to evaluate gains and losses relative to a reference point, not total wealth.

This reference point has a significant impact on an investor's experience (Frydman et al., 2018).

Overall, Thaler (1999) suggests that while mental accounting helps organize and manage personal finances, it can also lead to systematic biases in investment decisions, undermining optimal portfolio management for individual investors.

Framing effect

The framing effect is another significant cognitive bias that can lead to suboptimal investment decisions among retail investors. Tversky & Kahneman (1981) define the framing effect as the influence of the way choices are presented, or the so-called "frame", on decisions. Even when the underlying options are economically equivalent, different framings can lead to different preferences (Tversky & Kahneman, 1981). This is because investors do not always process information objectively. Instead, investors rely on cognitive shortcuts and heuristics that can be manipulated by the way information is presented.

How investment options are presented influences investors' risk tolerance (Tversky & Kahneman, 1981). For example, an investor may reject a high-risk investment presented as a 50% potential loss, but accept the same investment presented as a 50% potential gain, even though both represent the same risk (Tversky & Kahneman, 1981). Investors can also be overly influenced by an initial piece of information and often fail to sufficiently adjust their subsequent judgments (Tversky & Kahneman, 1981), also known as anchoring bias.

Tversky & Kahneman (1981) emphasize that by understanding how the framing effect bias works, retail investors can potentially reduce its impact on their financial decisions. Investors could become more aware of how information is presented and actively seek out alternative perspectives to avoid being so heavily influenced by misleading frames.

Self-control

Self-control bias is a human behavioral tendency that causes people to prioritize short-term gratification over long-term goals. Thaler (1981) does not offer a single definition of self-control. Instead, he explains self-control problems as an internal conflict between two metaphorical agents within an individual, the planner and the doer. The planner represents the individual's long-term goals and preferences. The planner is rational and future-oriented. The doer represents the individual's immediate desires and impulses. The doer acts in the present without full consideration of future consequences. The doer's actions are often inconsistent with the planner's long-term goals (Thaler, 1981). Successful self-control, according to Thaler (1981), occurs when the planner successfully influences the doer's actions to align with long-term goals. Conversely, when the doer's actions prevail, it is considered a failure of self-control (Thaler, 1981).

2.2 Information Dynamics in Retail Investing

Information Bias and Asymmetry

Another issue related to retail investor behavior that has been of interest to researchers for some time is information bias, or asymmetric information. Biais, Bossarts, and Spatt (2010) introduce asymmetric information by distinguishing between two types of investors, informed and uninformed investors. Informed investors have private signals about the future cash flows of risky assets. On the other hand, uninformed investors lack private signals and must trust publicly available information, such as prices and past returns, to form their expectations about future asset payoffs. The information asymmetry lies in the fact that informed investors have private signals. The uninformed rely on the information contained in market prices, which are partially influenced by the private signals of the informed investors (Biais et al., 2010).

Herd Behavior

One of the most prominent information dynamics within retail investing is known as herding or herd behavior. Hirshleifer & Hong Teoh (2001) conduct a review of the theory behind herd behavior and evidence related to it. “We are influenced by others in almost every activity, and this includes investment and financial transactions” (Hirshleifer & Hong Teoh, 2003). The study by Hirshleifer & Hong Teoh (2001) refers to herd behavior as the merging of behavior, which results from interactions between individuals. The decisions and actions driven by these interactions align with each other rather than private information. Hirshleifer & Hong Teoh (2001) divide herd behavior into two primary mechanisms: rational and irrational herding. Rational herding refers to the “rational” imitation of a peer or an institution due to the perception of them having superior information. Irrational herding, on the other hand, is referred to by Hirshleifer & Hong Teoh (2001) as driven by psychological factors. Such psychological factors could be social pressures such as panic or frenzy (Hirshleifer & Hong Teoh, 2001). I.e., retail investors might disregard personal analysis due to irrational herding.

Efficient Market Hypothesis

It is commonly accepted that the Efficient Market Hypothesis (EMH) is the central proposition of finance. The Efficient Market Hypothesis, as defined by Fama, E.F. (1970), hypothesizes that a market is efficient if prices fully reflect all available information at any given time. This means that asset prices adjust quickly and accurately to new information. Fama (1970) categorizes EMH into three forms based on the type of information reflected in prices. Firstly, Weak Form Efficiency implies that technical analysis based on past trends cannot consistently yield excess returns. Secondly, the Semi-Strong Form Efficiency suggests that fundamental analysis cannot consistently outperform the market. Lastly, Strong Form Efficiency posits that no individual or group can consistently find higher returns even with “monopolistic” access to information. It is important to note that the Efficient Market Hypothesis is a very broad framework, but it is crucial for

understanding market behavior. It is widely used in academic and practical analyses of capital markets.

2.2.1 Information Dynamics and Robo-advisors in Retail Investors

Information dynamics in retail investing, such as information asymmetry, herd behavior, and efficient market hypothesis, face new challenges and opportunities in today's volatile and complex financial markets as a result of the rise of robo-advisors. As mentioned previously, retail investors often face asymmetrical information, i.e., lack private signals and rely on information contained in the market prices, which can be seen as one of the primary drivers of herd behavior. This, combined with cognitive and emotional biases, would suggest, contrary to the efficient market hypothesis, that investors are not purely rational. However, robo-advisors can change these information dynamics by giving access to complicated portfolio strategies that are traditionally kept to themselves by institutional investors. As Shanmuganathan (2020) mentions in his study, the robo-advisor model holds the promise of finally including the masses into the realm of investing. The following section will review existing literature in the context of the central hypothesis of this paper.

3 Literature review

The adoption of robo-advisors by retail investors and its effects have been studied extensively in financial literature. However, the literature on robo-advisors is still relatively young, and there are some different views on how retail investor behavior is influenced by the adoption of robo-advisory services. This section deals with previous research on the subject.

3.1 Robo-advisors and Behavioral Biases

D'Acunto et al. (2019) conduct a comprehensive study examining the effects of robo-advisory adoption on retail investor financial decision-making and found supporting evidence for the aforementioned central hypothesis. The researchers gather data between 1.4.2015 and 27.1.2017. During this time, D'Acunto et al. follow the daily trading activities and monthly portfolio holdings of individuals and compare their financial decision-making and investor behavior before and after robo-advisor adoption.

D'Acunto et al. (2019) directly address the mitigation of emotional biases such as the disposition effect. The researchers find that this bias is substantially less pronounced, although not completely eliminated, in robo-advisor users compared to non-users. The study by D'Acunto et al. (2019) also addresses the problem of mental accounting. This previously mentioned decision-making framework is potentially mitigated by robo-advisory adoption, according to the researchers. Robo-advisors are a way to simplify the set of decisions investors have to make to rebalance their portfolios (D'Acunto et al., 2019). In other words, robo-advisors might indirectly mitigate the mental accounting bias in retail investors through their simplicity and automated execution.

Another study relevant to this thesis by Rossi & Utkus (2024) also studies the effects of robo-advisory adoption on retail investor financial decision-making. Rossi & Utkus (2024) focus more specifically on the diversification and welfare effects of robo-advisor adoption, but this section focuses on the potential mitigation of cognitive biases such as home

bias and overconfidence. In their study, Rossi & Utkus examine changes in portfolio composition, diversification, and other characteristics and compare their findings between before and after individuals adopt robo-advisory services.

Rossi & Utkus (2024) find that across all investors, robo-advisor adoption increases indexing and diversification and thus reduces home bias. Even though Rossi & Utkus do not directly mention familiarity bias, robo-advisors expose individual investors to a broader range of potential investments, potentially steering them away from familiar investments or assets. In other words, robo-advisor adoption increases indexing and international diversification, which may reduce familiarity bias.

While D'Acunto et al. (2019) and Rossi & Utkus (2024) do not directly address it, robo-advisory adoption can potentially mitigate biases such as self-control, overconfidence, loss aversion, regret aversion, and information bias and asymmetry. Rossi & Utkus (2024) show that individuals who have adopted robo-advisors spend less time monitoring their portfolios. Retail investors who have adopted robo-advisors save on average six hours per year. This finding by Rossi & Utkus suggests that robo-advisors may help mitigate self-control issues related to exaggerated portfolio monitoring and trading. D'Acunto et al. (2019) also indirectly suggest that robo-advisors could mitigate the decision-making framework known as self-control bias through the automation of investment decisions. This reduces the need for constant self-control when implementing an investment strategy. On the other hand, D'Acunto et al. (2019) find that a large portion of their test subjects increased their trading volume after adopting robo-advisors, which could suggest that some individuals might have even less self-control due to the automated investment decisions and simplicity of robo-advice. Additionally, as mentioned before, robo-advisor adoption increases indexing and reduces the number of assets held (Rossi & Utkus, 2024). This might suggest that robo-advice could indirectly reduce overconfidence in e.g., stock-picking behavior.

When talking about the overconfidence bias, Singh et al. (2024) find that other cognitive and emotional biases, as well as decision-making frameworks, are interrelated with the overconfidence bias. Most notably, the framing effect is heavily interrelated with overconfidence in retail investors. Similar to D'Acunto et al. (2019) and Rossi & Utkus (2024), Singh et al. (2024) suggest that robo-advisor adoption could mitigate the overconfidence bias in retail investors. Based on the findings of Singh et al. (2024) on the relation between overconfidence and the framing effect, one could assume that the reduction in overconfidence bias would potentially mitigate the framing effect as well.

Yet another study touching on the effects of robo-advisor adoption in retail investors is by Bhatia et al. (2020). The researchers' findings are very similar to those of D'Acunto et al. (2019) and Rossi & Utkus (2024). Bhatia et al. (2020) find that, by preventing investors from either holding onto unsuccessful investments or selling successful investments too early, robo-advisors can reduce the disposition effect, much like the findings of D'Acunto et al. (2019). In addition, the researchers find that the automation brought by robo-advisors reduces excessive trading driven by emotional reactions or overconfidence. The reduction of excessive trading, coupled with the potentially more consistent investment advice provided by robo-advisors, could lessen the possibility of regret. In other words, robo-advisor adoption could potentially mitigate one of the most prominent emotional biases within retail investors, regret aversion.

When examining the cognitive bias, loss aversion, it is important to consider its close relation to the disposition effect. As mentioned before, the disposition effect is in part driven by the individuals' desire to avoid realizing losses. D'Acunto et al.'s (2019) findings on the mitigation of the disposition effect could suggest that robo-advisory adoption might lessen the emotional harm of losses and encourage more objective investment decisions by providing a more rational framework. Additionally, both D'Acunto et al. (2019) and Rossi & Utkus (2024) show that robo-advisor adoption leads to more diversified portfolios and reduced volatility. This could potentially mitigate loss aversion bias, as more diversified portfolios are less likely to show large losses that would, in turn, activate loss-averse behavior.

Robo-advisors may also potentially reduce one of the most prominent information dynamics in retail investing, information asymmetry or information bias. Hong et al. (2023) directly address the potential mitigation of information asymmetry. Financial robo-advisors proactively interpreting to clients how the algorithm works to develop the optimal portfolio can enhance information transparency and reduce information asymmetry (Hong et al., 2023). Additionally, Sanga & Aziakpono (2023) find that many emerging financial technology (FinTech) solutions, such as robo-advisors, cut costs and reduce information asymmetry. Even though they do not mention it directly, D'Acunto et al. (2019) find similar evidence supporting the claim that robo-advisors mitigate the information bias. Robo-advisors provide access to a wider range of information and increase indexing and international diversification in retail investor portfolios. This broader market exposure could reduce information asymmetry.

Even though both .'sD'Acunto et al.'s (2019) and Rossi & Utkus' (2024) findings strongly support the central hypothesis of this thesis, one must never take these findings at face value. There are some real methodological limitations. In the case of D'Acunto et al. (2019), the data gathered for their study comes from a single brokerage firm in India. The researchers' findings are not necessarily generalizable across different investor populations or geographies. Additionally, the period when the researchers gather data is

relatively short, especially the period post-adoption (approx. 6 months). This heavily limits the ability to study the long-term effects of robo-advisor adoption in retail investors. This is also true in the study by Rossi & Utkus (2024). Rossi & Utkus (2024) study gathered data over approximately two years, which closely resembles the findings of D'Acunto et al.'s (2019) study. On the other hand, the research by Rossi & Utkus (2024) takes place in the United States of America, which could suggest that the strong evidence for the central hypothesis of this paper could be applicable across different investor populations. It is also extremely important to note that changes in market conditions or other events during the data collection period could influence the results. Lastly, both studies gathered their data around the years 2015-2017. While relatively young in the context of all financial literature, robo-advisors are much more advanced nowadays, and it is important to critically analyze the applicability of the findings of D'Acunto et al. (2019) and Rossi & Utkus (2024).

In the case of Bhatia et al. (2020), even though the data gathered is from India, similar to D'Acunto et al. (2019), the methodology of the research by Bhatia et al. (2020) has a qualitative nature. The researchers interviewed 34 experts from different fields within finance, e.g., wealth management, digital strategy, behavioral finance, and artificial intelligence. As the findings of Bhatia et al. (2020) are based on expert opinions rather than empirical data, it limits the generalizability. In addition, the sample size of 34 experts is relatively small and might not cover the full range of diverse perspectives within the industry. Furthermore, the opinions of experts could reflect personal views and biases rather than objectively addressing the effects of robo-advisor adoption in retail investors. On the other hand, the non-contradictory results of the studies by Bhatia et al. (2020), D'Acunto et al. (2019), and Rossi & Utkus (2024) suggest that the findings of Bhatia et al. (2020) are trustworthy.

All these possible bias reductions and mitigations examined in this section create the conditions for improved portfolio diversification. The next section of this literature review will tackle the impact of robo-advisory adoption on retail investor portfolio diversification.

3.2 Impact on Portfolio Diversification

Building on the previous section, research reveals concrete portfolio diversification improvements tied to robo-advisor adoption. One of the most prominent studies examined in this thesis, D'Acunto et al. (2019), studying the impact of robo-advisory adoption on portfolio diversification and investor behavior, find that investors holding fewer than 10 stocks before robo-advisory adoption increased their holdings by approximately 100 percent using the robo-advisor. Additionally, their market-adjusted portfolio volatility declined significantly. While the study provides incredibly supportive evidence to the hypothesis of this paper, it is essential to note that the study was conducted on a single brokerage platform in India, which heavily limits the generalizability of their findings to other markets or robo-advisor designs. Additionally, as mentioned in the previous section, the study measured the effects only over 1-2 months.

Another heavily referenced study in this thesis by Rossi & Utkus (2024) examining how adopting robo-advisors affects retail investors' portfolios find similar evidence as D'Acunto et al. (2019). As mentioned before, robo-advice reduces home bias and increases indexing, leading to better-diversified portfolios. Similar to D'Acunto et al. (2019), Rossi & Utkus (2019) find that investors holding fewer individual assets before adoption benefited the most. Once again, the findings of this study are not fully generalizable since the results are based on a single US robo-advisor.

Another study examining the influence of robo-advisory adoption on retail investors' portfolios is by Onabowale (2024). AI-driven trading systems analyze real-time market data to execute trades at optimal moments, improving portfolio performance (Onabowale, 2024). Additionally, portfolio optimization, driven by AI, ensures that assets are

allocated in a manner that balances risk and return effectively, benefiting both institutional and retail clients (Onawobale, 2024). Onabowale (2024) finds that robo-advisors increased retail investors' exposure to non-correlated asset classes by 32% compared to self-managed portfolios. This was primarily thanks to the automated balancing and risk-assessment algorithms provided by the robo-advisor. Even though the portfolio outcomes in this study were analyzed only over 12-18 months, the research focused on three different fintech platforms, which gives the study at least some generalizability. In addition to the findings of the studies mentioned in this section, robo-advisors can replicate the same products as the more expensive and time-consuming human-advisors, such as a properly diversified and efficient portfolio (Todd & Seay, 2020).

The evidence in this section directly supports the claim about portfolio diversification discussed in the first objective of this thesis. I.e., algorithmic allocation or diversification helps mitigate insufficient diversification caused by familiarity bias or other biases mentioned in the sections above. However, it is important to note that the investment strategies and financial knowledge held by the investors before adoption heavily influence the effects robo-advisors have on the investor's portfolio diversification.

3.3 Influence on Trading Frequency

While diversification improves in most cases, the trading frequency affects robo-advisors have on retail investors is not as straightforward as the mitigation of well-known behavioral biases or portfolio diversification. D'Acunto et al. (2023) find that retail investors whose portfolios were already rather diversified before adopting robo-advice perform worse after adoption because they use the robo-advisor often, which includes more frequent trading than before adoption. In other words, overconfident investors tend to believe that their signals about the expected return of an asset are more precise than they actually are. And this form of overconfidence leads these individuals to trade too much. Contrary to D'Acunto et al. (2023), Bianchi & Biere (2021) find that robo-users showed reduced trading after adoption, shifting to passive instruments (e.g., index funds). Also,

Li et al. (2023) suggest that the automated nature of robo-advisors reduces the need for manual trading. Furthermore, one of the most referenced studies in this thesis, D'Acunto et al. (2019), find that investors who were well diversified before robo-advisor adoption traded more actively without experiencing significant performance gains.

Based on the differing findings of the studies mentioned in this section, the effect of robo-advisory adoption on retail investors' trading frequency depends on the design of the robo-advisory service. Some robo-advisors are entirely automated, whilst others give the investors the freedom to trade freely. More automated robo-advisors tend to mitigate excessive trading, but some robo-advisors that leave the option to trade to the investors tend to lead the investors to make excessive trades. More importantly, the differing outcomes of the studies examined in this section suggest that trading frequency changes depend mainly on the investors' strategies and knowledge before adoption, which is very similar to the findings of the previous section about portfolio diversification.

3.4 Effects on Risk Tolerance

Regarding the risk tolerance effects of robo-advisory adoption in retail investors, Todd & Seay (2020) provide some promising evidence for the hypothesis of this thesis. Todd & Seay (2020) find that robo-advisor users show higher risk tolerance than non-users, with 34% of adopters self-reporting a willingness to accept above-average investment risks, while only 22% of traditional advisor clients. While this provides valuable evidence for this thesis, the risk tolerance metrics of the study rely on survey responses rather than observed behavioral or portfolio data. Additionally, the survey participants were U.S.-based, with 92%, and college-educated, with 78% of participants. This limits the generalizability of the findings of the survey-based study by Todd & Seay (2020).

Another study tackling the effects of robo-advisory adoption on retail investors' risk tolerance is by Li et al. (2023). Their study finds that participants with above-average fintech knowledge preferred robo-advised portfolios 23.8% more. This would suggest that investors who are more optimistic about robo-advisors could indirectly exhibit higher risk

tolerance. Again, the study has some methodological limitations. The portfolio valuations and preferences were measured in a 17-day laboratory environment, which might not reflect long-term real-world behavior. Additionally, the study was conducted exclusively with Chinese investors, which limits the applicability to Western markets with potentially different attitudes toward automation.

The results of the studies examined in this section about risk tolerance demonstrate that robo-advisor users have a higher tolerance for risk, but again, very similar to the two previous sections, the prior knowledge and attitudes towards robo-advisors heavily influence the impact robo-advisors have on investors' risk tolerance.

4 Conclusion

This thesis examines the effects of robo-advisory adoption on retail investors. To be more specific, the focus of the thesis is on how robo-advisory adoption affects the investing behavior of retail investors by influencing their approach to portfolio diversification, trading frequency, and risk tolerance. The thesis includes a theoretical background section explaining some of the most well-known behavioral finance theories that are relevant to the central hypothesis and research questions of this thesis.

The objective of this thesis is to review current literature regarding the topic and examine the potential mitigation of some of the most common behavioral biases. The thesis highlights that this area of finance should be researched more, as the current, relatively young literature does not seem to have a clear understanding of how robo-advisor adoption affects the behavior of retail investors by influencing their approach to portfolio diversification, trading frequency, and risk tolerance.

The research questions and central hypothesis of this paper were reviewed and examined extensively. They are as follows:

RQ1: How does the adoption of robo-advisors affect retail investors' portfolio diversification?
RQ2: How does the adoption of robo-advisors affect retail investors' trading frequency?
RQ3: How does the adoption of robo-advisors affect retail investors' risk tolerance?
H1: Robo-advisors mitigate retail investors' behavioral biases by influencing their approach to portfolio diversification, trading frequency, and risk tolerance.

Many previous studies reviewed in this thesis show that the adoption of robo-advisors has a beneficial effect on portfolio diversification in retail investors by, e.g., automating asset allocation, mitigating behavioral biases, and introducing investors to a broader market exposure. In other words, robo-advisors' automated rebalancing and algorithmic allocation mitigate insufficient portfolio diversification caused by biases such as home

bias and familiarity bias. The simplified decision-making introduced by robo-advisors, automated rebalancing reduces biases such as mental accounting and self-control. Thus, the central hypothesis of this study is supported. On the other hand, the knowledge the investor has before robo-advisor adoption plays a significant role in how robo-advisory adoption affects the investor's portfolio diversification. According to the literature reviewed in this study, investors with insufficient knowledge of financial literacy benefited the most from robo-advisory adoption.

Further reviewing the literature reveals that trading frequency and risk tolerance are not directly or single-handedly influenced by robo-advisor adoption, but the knowledge, attitudes, and investment strategies investors have before robo-advisor adoption seem to be the key factor in determining the changes in risk tolerance and trading frequency. Some studies suggest that investors with already sufficiently diversified portfolios trade more frequently after adopting robo-advisors, likely due to overconfidence in automated tools. On the contrary, other studies find robo-advisor users shift to passive strategies, e.g., index funds, which decreases trading activity. The impact robo-advisors have on trading activity in retail investors depends on platform design, e.g., the level of automation, and the investors' pre-existing knowledge of financial literacy. The same applies heavily to how robo-advisory adoption affects retail investors' risk tolerance: the more the investor has knowledge about AI-powered investment advisors, i.e., robo-advisors, and the more optimistic the individual is about robo-advisors, the more risk tolerant they will be after the adoption of robo-advice.

While the findings of this study robustly support the central hypothesis, it is important to consider that the research reviewed is from different years and might not be up to date. Additionally, literature uses data from robo-advisors in different countries. Therefore, for future research, this thesis suggests that robo-advisors should be studied with the most recent robo-advisory designs, in multiple different countries, and for a long period to examine the long-term effects of robo-advisory adoption in retail investors.

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