Through the Lens

Myopic financial decisions

Institute for Management Research

Markus Strucks

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Radboud Dissertation Series

Through the Lens: Myopic Financial Decisions

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Author: Markus Strucks
Title: Through the Lens: Myopic Financial Decisions

Radboud Dissertations Series
ISSN: 2950-2772 (Online); 2950-2780 (Print)

Published by RADBOUD UNIVERSITY PRESS
Postbus 9100, 6500 HA Nijmegen, The Netherlands
www.radbouduniversitypress.nl

Design: Proefschrift AIO
Cover: Guntra Laivacuma
Printing: DPN Rikken/Pumbo

ISBN: 9789465150062
DOI:10.54195/978946515002
Free download at: www.boekenbestellen.nl/radboud-university-press/dissertations

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Through the Lens: Myopic Financial Decisions

Proefschrift ter verkrijging van de graad van doctor
aan de Radboud Universiteit Nijmegen
op gezag van de rector magnificus prof. dr. J.M. Sanders,
volgens besluit van het college voor promoties
in het openbaar te verdedigen op

dinsdag 7 januari 2025
om 12.30 uur precies

door

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geboren op 11 december 1993
te Kleve (Duitsland)

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Acknowledgements

Embarking on the odyssey of a PhD candidate has forced me to navigate unknown waters, where each wave of discovery brought about feelings ranging from fascination and excitement to occasional disenchantment. This journey, filled with its various twists and turns, has fundamentally shaped my academic but also personal development. In this moment of reflection, I am thinking about the numerous guiding stars providing light in times of storms and disorientation. Without such guidance, I would not have been able to navigate this vast sea. It is with profound gratitude that I acknowledge these luminaries in my life.

First and foremost, I express my deep gratitude to my supervisor **Stefan Zeisberger**, who has always been an inspiring role model to me. You have shown me the qualities of good academic research and encouraged me to pursue my interests around investor myopia. You also taught me about the various facets of the psychology of investment behavior, how to think outside of the box, and encouraged me to develop an independent working style. Your critical insights helped me to improve my work and approach my research questions with rigor. During the last months, more often than not, Stefan could expect me to drop by his office for a quick chat about our research, or some practical advice regarding the academic job market, which has helped me immensely. Thank you Stefan, for your invaluable insights and expertise, your patience, mentorship, and your unwavering support of my efforts.

I am also grateful to my second supervisor **Sven Nolte**, as well as the other members of my dissertation committee, **André van Hoorn**, **Jan Potters**, and **Anita**

Kopányi-Peuker, for their constructive feedback and guidance. Their perspectives and expertise are crucial in broadening my understanding of the field. I am also grateful to **Christopher Strucks** and **Rinze Hartman** for supporting my defense as paranymphs.

My research wouldn't have developped this far without the support of the Chair of Finance. **Sascha Füllbrunn**, your insights and feedback on my work have been invaluable. When I struggled to see the bigger picture of my work, your feedback during our discussions always brought me back on track. In addition, you have supported my academic endeavours greatly. **Jorgo Goossens**, we had such an engaging exchange of research articles and ideas, and I learned so much about the Dutch pension landscape from you. **Sven Nolte**, **Jianying Qiu** and **Jan Schmitz**, your perspectives on the theoretical nature of my research allowed me to think deeply about its foundations. **Anita Kopányi-Peuker**, you gave me great tips about theoretical and practical aspects of my research. **Utz Weitzel** and **Dirk-Jan Janssen**, thank you for engaging discussions and tips for my research. Many thanks also to my PhD student colleagues in the Chair of Finance, **Sara Arts**, **Ben Hiepler**, **Michel Rötter** and **Liu Shi**, and, formerly, **Jiangyan Li**, **Charlotte Borsboom**, and **Achiel Fenneman**, with whom I have shared great discussions about research, teaching and beyond.
Collaborating together with my co-authors has been a blessing. **Stephan Siegel** has taught me a great deal about rigorous academic research. His patience and detailed understanding of concepts around behavioral finance have always inspired me. **Christine Laudenbach**'s integrity, fascination for research and openness to exploring different topics have become a leading example for my research ambitions. **René Schwaiger**, we have spent afternoons of long discussions about small yet important details in our project. Your perseverance is infecting and has motivated me. I am particularly thankful for a great research visit at the University of Innsbruck, which you have made possible.

As a teacher at the Economics and Business Economics Department, I want to thank everybody who has inspired and helped me become a better educator. **Gaby**

Contreras, it is impossible to capture how much you have taught me about university education. From my beginning as a junior lecturer until the end of my PhD trajectory, you were always willing to help, involve and encourage me to reflect on course design and didactic approaches. I was also lucky to work together with **Anita Kopányi-Peuker** in different courses. Anita, we have been a great teaching team. I am really grateful for our fruitful collaboration in the Bachelor's Thesis course, and I enjoyed our interesting discussions on our courses and beyond. Your compassion and organization make you an inspiring educator. **Jana Vyrastekova** and **Jan Verhoeckx**, I have always admired your passion for teaching innovation. Similarly, I have been fascinated by **Thomas Niederkofler**'s original approach in our R course. **Rutger Schilpzand**, you have shown me countless tricks to improve my teaching and teaching organization. **Ludger Buijs**, you provided countless support to help me teach a complex and theoretical subject like Mathematics effectively and comprehensively.

My office mates **Rinze Hartman**, **Ben Hiepler**, and **Siem Smeets** never failed to make my day. The *gezellige* atmosphere in our office allowed us to have both insightful conversations about research and babble about our lives. Particularly memorable are funny incidents like the disappearance and subsequent reappearance of computer mice or our ocasional "Paperball" competitions. It was remarkable that even though we worked on different topics, we made a great team, always supporting each other. Having to leave this office now makes me realize that it has become like a second home. Thank you also to my former office mates **Timo Lange**, **Jiangyan Li**, and **Daniël Speldekamp**, for a great atmosphere at work. Many other colleagues contributed to this great atmosphere as well, including, but not limited to, **Aaron, André, Anne Lieke, Annemiek, Charan, Charlotte, Daniel, Gaby, Geert, Giacomo, Hatice, Jan, Jet, Katarzyna, Kim, Konstantina, Laura, Muskan, Olexiy, Oskar, Rein, Roben, Roel, Rutger, Sara, Simon, Thomas, Vincent and Wouter**.

Lastly, I thank my friends and family who have provided invaluable support throughout this journey. Most notably, as the wind in my sails, my partner, my parents, and my brother have helped me to stay on track by supporting and encouraging me. **Bruna**, in the short time that you have been a part of my journey, your support has already been invaluable. You have always had an open ear for my issues and gave me great advice. **Angelika**, you have demonstrated how important it is to persevere and be committed to your ambitions. When I was clueless and doubts clouded my judgment, you always had an open ear about my issues and gave me reasonable advice. The mental support you have provided also helped me immensely. **Heinz**, you are always interested in my research and initiate interesting discussions about related topics like technology or health, which I have enjoyed a lot. My brother **Christopher** has been the person to whom I could talk about everything as we share similar interests. After the Covid-pandemic lockdowns, you suggested to start playing table tennis together again, which helped me free my mind in times of stress. Thank you Christopher, for always being there as well as sharing many of my favorite moments in life.

Chapter 1

General Introduction

> "We possess inadequate power to imagine and to abstract, or we are not willing to put forth the necessary effort, but in any event we limn a more or less incomplete picture of our future wants and especially of the remotely distant ones."
>
> — von Böhm-Bawerk (1890), quoted in Frederick, Loewenstein, and O'Donoghue (2002).

Individual economic decisions involve a nexus of different factors, ranging from intrinsic preferences, cognition and beliefs to actions and experiences. Up until the first half of the twentieth century, the academic literature has largely neglected psychology and cognition but focused on modelling the *homo oeconomicus*, a rational decision maker who maximizes payoff given a known distribution of future states and outcomes. Simon (1955) was the first to recognize bounded rationality of individuals, i.e., the fact that there are limits to both cognitive processing capabilities and disposable information. This has shifted economic decision-making research from a normative toward a descriptive approach. Notable advances include Daniel Kahneman and Amos Tversky's well-known cumulative prospect theory (CPT), describing individual aversion against losses, reference dependence, differing risk attitudes in the gain versus the loss domain, and probability weighting (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). On the empirical side, recognition of departures from full rationality has opened the way for research into numerous behavioral tendencies and cognitive biases characterizing real-world behavior, which have informed policy decisions to facilitate and to improve decision-making (Thaler & Sunstein, 2021).

As one of such departures from rationality, individual short-sightedness, or temporal myopia, has been increasingly scrutinized by academic research. Myopia describes the individual tendency to overweight short-term (or segregated) compared to long-term (or aggregated) information or outcomes. It can be associated with a wide range of everyday behaviors, from daily spending decisions (Bartels & Urminsky, 2015) to effort allocation (Augenblick, Niederle, & Sprenger, 2015). Even in contexts that inherently require a long-term perspective—like retirement planning—short-sighted financial decisions remain pertinent (Benartzi & Thaler, 1999). Financial service providers, by setting the temporal frame for the information they communicate, can also induce myopia through the use of short-term defaults (e.g., Gerhard, Hoffmann, & Post, 2017). Given its wide relevance, temporal framing and its behavioral implications have so far received limited attention in academic discourse. Most empirical studies exclusively consider the effects of myopia on risk-taking in stylized decision contexts. This dissertation contributes by mapping the consequences of myopia and temporal framing for trading behavior and risk perception in realistic investment settings. In particular, we address the following research question:

To what extent does myopia affect investor risk perception and trading behavior?

Implementing controlled online experiments, we demonstrated how myopic loss aversion (Benartzi & Thaler, 1995) reduces financial risk-taking in more realistic decision scenarios. Moreover, widely displayed short-term presentations of stock price developments reinforce a focus on short-term outcomes, causing reactive trading behavior and thereby hurting investment performance. Finally, we also examined and contrasted how individual risk perceptions define behavior under short- versus long-term stock investment frames.

Stock markets offer a suitable setting for studying myopic behavior. On the short run, diversified stock portfolios may fluctuate and losses occur on a frequent basis. For long horizons, however, stock portfolios perform substantially better than other investment strategies. Historically, CPT predicts that a behavioral investor allocates funds to a pure-stock portfolio for any investment horizon exceeding five years (Dierkes, Erner, & Zeisberger, 2010). If households do not hold any equity, it may be because they adopt a myopic stance and focus on the short-term risks rather than the long-run benefits of investing (Barberis, Huang, & Thaler, 2006). Yet, several important financial decisions are geared toward the long run, such as the accumulation of long-term savings for retirement. Recent reforms in the pension landscape now involve employees actively by indicating how and how much of their salary they want to save for retirement. In the Netherlands, as well as in many other countries, contributions are in part invested in equity funds determining savings returns, meaning that households indirectly make long-term decisions under uncertainty. In the United States, households save directly via 401(k) retirement savings accounts offering attractive tax benefits. Under-appreciating the long-run returns from stock investing may have detrimental effects for long-run savings and, by extension, the financial welfare of households. Besides, facilitated access of stock market investing via financial technologies has led to increases in both the supply and the demand of stocks, making stock investing a topic for the broad population.

In this chapter, we examine the general relevance and implications of short-sighted cognition and behavior in section 1.1 and outline personal finance applications in section 1.2. section 1.3 explains the research method of the three articles included in this dissertation. section 1.4 provides an overview of the contributions of our research. Finally, section 1.5 details short summaries of each research article.

1.1 Myopic Decision-Making

Consider a simple example: After a long and tiring day at work, Vanessa faces a choice: To start planning her much-anticipated summer trip to Japan next month or to take the evening to rest and read a book, a thought that promises immediate relaxation. She struggles to visualize the incremental benefits of better flight deals, more accommodation options, and a thorough itinerary, which could enhance her travel experience. Eventually, she tells herself she will have time to plan the trip later, possibly tomorrow or the next week, without considering her already packed schedule.

Such behavior is not uncommon and likely resonates with many. When it comes to everyday decisions, there is a pronounced tendency to overemphasize immediate outcomes. The benefits of rigorous planning are not only uncertain but also manifest in the distant future, while costs in terms of mental effort are required immediately. Short-sightedness, or myopia, thus arises due to an inherent difficulty to envision future consequences.[1] If our simulations of (the utility of) future outcomes become increasingly noisy with longer decision horizons, we underweight such projections relative to short-term outcomes, biasing our decisions in favor of short horizons (Loewenstein, O'Donoghue, & Rabin, 2003; Gabaix & Laibson, 2022). Importantly, Gabaix and Laibson (2022) note that myopia is distinct from a mere preference for sooner over later rewards, referred to as time preference or impatience. Perfectly patient individuals can exhibit *as-if* discounting due to their underweighting of noisier outcomes materializing in the more distant future.

By itself, myopia need not be exclusively characterized as a cognitive bias. Instead, there may be adequate reasons for focusing on short-term outcomes. From an evolutionary perspective, relying on impulses geared toward immediacy ensured quick and proper judgment necessary during potential "fight-or-flight" situations (Durand, Fung, & Limkriangkrai, 2019). Nowadays, people rely on fast-and-frugal heuristics to navigate their daily decisions, helping them deal with an overload of information or choice alternatives in a world abundant of such (Gigerenzer, 2004). For instance, one could intuitively deduce a restaurant's quality from its present occupancy, following the "wisdom of the crowd", without considering other quality signals. Such narrow bracketing strategies may be a rational adaptive response to individual limitations in time and cognitive effort (Gabaix, 2014). Differences in global cultural institutions (see Hofstede, 1984) and socio-economic factors (see Mani, Mullainathan, Shafir, & Zhao, 2013) also suggest that myopia can serve as an effective coping mechanism to background risks. Yet, relying on impulses while disregarding or inaccurately assessing broader consequences can be detrimental. Previous research has shown that individuals tend to underestimate the perils of temporal myopia, which adversely affects their well-being. Sutter, Kocher, Glätzle-Rützler, and Trautmann (2013) show

[1] Throughout this dissertation, we refer to myopia in cognition and behavior, which is distinct from its optometric interpretation of impaired vision.

that short-sighted monetary choices relate to unhealthy behaviors such as smoking and over-eating. At the organizational level, myopic management practices can compromise long-term financial health and sustainability. For instance, Shive and Forster (2020) demonstrate that listed company CEOs' short-term goals to optimize profits in quarterly reports conflict with environmental stewardship. Similarly, undervaluing the long-run returns to schooling can adversely affect academic achievement, thereby impeding long-run human capital development (e.g., Jensen, 2010).

1.2 Myopia in Personal Finance

Personal finance requires numerous long-run considerations. Households might contemplate decisions around house purchases, healthcare spending, insurance coverage, educational investments, lifestyle inflation, bequests, and savings for retirement. For instance, if households underestimate their cost of living during retirement relative to their accumulated buffer and ongoing benefits, they may be unprepared and forced to work longer than expected. This could not only be detrimental for their long-term financial situation, but also expose them to additional health risks. There is mounting evidence that households adopt a myopic stance toward their finances in a variety of ways:

(i) **Financial Horizons:** Life-cycle models of consumption assume that individuals desire smooth consumption patterns and therefore start accumulating savings for retirement early in their lives. Drawing from empirical survey data, however, Lusardi (1999) found that less than 10% of households has financial planning horizons of more than 10 years, and 9% plan for one year ahead. Investors have a preference for evaluating their portfolios frequently when they face ambiguous stock returns (Bellemare, Kröger, & Sossou, 2022). The estimated size of the equity premium puzzle aligns most with investor evaluation periods of 1 year (Benartzi & Thaler, 1995). When it comes to information acquisition, people tend to focus on recent financial asset performance (e.g., Nolte & Schneider, 2018). In this dissertation, we complement the evidence by showing that individuals focus on short-term rather than long-term price trends, even when both are displayed jointly.

(ii) **Narrow Framing:** Individuals do not only rely on short decision and information horizons (temporal myopia), but tend to frame other aspects of the environment narrowly as well. For instance, they may invest in few single stocks rather than index funds or apply naive diversification strategies—e.g., applying a $1/n$-heuristic or neglecting the correlation of different stock returns (Laudenbach, Ungeheuer, & Weber, 2023). Moreover, managers or investors may exhibit spatial myopia in their investment decisions by focusing on exclusively on local markets or disregarding international stocks (French & Poterba, 1991; Benos & Jochec, 2013).

(iii) **Aggregation Failures:** Prima facie, it could be argued that the above manifestations of myopia emerge from individual *preference* toward shorter evaluation horizons, concentrated stock ownership or geographical limits. A rivalling explanation focuses on individual *inability* to aggregate information or decision consequences. There is substantial evidence that such aggregation failures (also) play a role. For example, Stango and Zinman (2009) found that understanding of exponential growth is poor among individuals: Since people intuitively linearize such processes, they systematically undervalue long-run returns, leading to lower saving and higher borrowing. More broadly, myopia and associated aggregation failures may stem from a dominating fast and intuitive system thinking, inhibiting deliberate and logical reasoning (Kahneman, 2003). In this dissertation, we provided evidence suggesting that individuals are able to gauge the short-term risks of stock investing, but fail to aggregate such information over longer investment horizons.

1.3 Method

This dissertation employs empirical research through online decision experiments to scrutinize individual behavior, preferences and expectations. In general, empirical methods enable real-world testing of theories and concepts by collecting primary or secondary data. Primary data collection through experiments offers distinct advantages over secondary data collection. Firstly, experiments offer a high internal validity of tested predictions, evidenced by replicable research findings (Camerer et al., 2018). Internal validity stems from the random assignment of participants to treatment(s), which vary solely in the aspect under investigation compared to a baseline control group. Random treatment assignment and controlled parameters of the decision environment both reduce the influence of potentially confounding variables. By defining and communicating a homogeneous set of information, such as the complete return distribution of a risky asset, any influence of heterogeneous underlying beliefs about future return developments can be ruled out. For instance, in chapter 2 and chapter 3 we explicitly communicate risky asset return distributions during an investment task. Secondly, decision experiments unveil behaviors and mechanisms elusive in real-world observations or inaccessible through secondary data. By mimicking real-world institutions in incentive-compatible settings with salient rewards, experiments can reveal insights into the psychological mechanisms driving economic decisions (Friedman & Sunder, 1994). In public goods game experiments, for example, participants are incentivized to contribute to a group fund that multiplies total contributions and redistributes the result equally among all participants. Such a reward structure allows to capture individual preferences toward coordination and free-riding behavior. The challenge lies in configuring experimental parameters potentially influencing decisions—like initial endowments, multiplier, or group sizes. Minor modifications of seemingly arbitrary parameters of the decision environment can affect behaviors in unanticipated ways. Given the heterogeneity of findings across studies using similar experimental designs (C. Huber et al., 2023) or analytical approaches (Menkveld et al., forthcoming), the question arises to what extent findings from controlled experiments transfer to real-world settings. In this way, critics argue that high internal validity of experiments comes at a cost of external validity.[2]

Due to their customizability, however, it is possible to design experiments to closely mimic reality or a subset of critical features. Behavioral economics research has traditionally relied on the revealed-preferences paradigm, assuming that preferences

[2] Note that potential concerns like unknown individual background risks as well as different analytical choices by researchers likely also apply to findings based on other research methods.

can be measured by looking at standalone behaviors. Self-reported preferences or expectations were asssumed to be too noisy, offering low predictive validity. In order to establish the link between behavior and preferences, however, strong assumptions about the homogeneity and rationality of underlying expectations must be maintained (Manski, 2004). Addressing such unrealistic assumptions, the stated-preferences paradigm is based on direct elicitation of preferences and beliefs, enabling delineation between them. Giglio, Maggiori, Stroebel, and Utkus (2021) highlight the importance of expectations for investment decisions and argue that survey evidence is “here to stay”. In chapter 4, we highlight the pivotal role of economic expectations for investment decisions, considering loss likelihood beliefs in particular. In doing so, we demonstrate the potential of information experiments, harnessing the power of a controlled experiment while providing practical information potentially identical to real-world displays (Haaland, Roth, & Wohlfart, 2023). We address potential measurement error concerns commonly associated with belief elicitation, like belief inconsistency (Drerup, Enke, & Von Gaudecker, 2017; Merkoulova & Veld, 2022) or cognitive uncertainty (Enke & Graeber, 2023).

Traditionally, decision experiments have been exclusively conducted in the laboratory. Increasingly, researchers have made use of online settings. Running experiments online implies giving up some of the control provided by the laboratory setting. For example, participants may get more distracted more quickly when they participate at home. However, even in laboratory settings, it is not possible to completely eliminate all potential background influences, affecting for instance the current mood of participants, which in turn may influence behavior. Whereas laboratory experiments are subject to time and capacity constraints, online experiments offer scalability so that higher statistical power can be achieved, reducing the likelihood of not rejecting a false null hypothesis (beta error). Moreover, online experiments do not require physical presence, enabling access to a more diverse target pool of participants (if desired). Platforms such as Amazon Mechanical Turk and Prolific have proven invaluable for recruiting diverse samples, facilitating broader replication efforts and ensuring consistency across global research activities (Palan & Schitter, 2018).

1.4 Contributions

This dissertation contributes to the academic discourse by elucidating the impact of temporal framing on individual investment behavior.

Historically, intertemporal choice has been modeled using a discount factor, $0 < \delta < 1$, to quantify the preference for immediate over delayed payoffs of equal size, implying that immediate consumption is valued more due to its certainty compared to uncertain future consumption (Merton, 1969). This framework categorizes individuals as more impatient if they discount future rewards heavily, based on their high time preference. However, advances in behavioral finance have occasionally overlooked and conflated the nuanced effect of temporal myopia on time preference, misinterpreting high impatience as evidence for myopia. In contrast to impatience, temporal myopia does not encompass a preference but rather a cognitive failure or behavioral bias. In this way, a perfectly patient agent may exhibit discounting behavior if they suffer from imperfect foresight (Gabaix & Laibson, 2022). In order to understand how individuals make choices over short and long horizons, it is essential to study myopia as a construct distinct from time preference.

Benartzi and Thaler (1995) pioneered the study of individual myopic tendencies and stock market engagement. Their findings suggested that investors reduce equity allocations due to short evaluation and decision time frames as well as loss aversion, which describes a disproportionately strong investor distaste against losses compared to gains (Kahneman & Tversky, 1979). This notion of myopic loss aversion has garnered support by several studies in both lab (among others, Gneezy & Potters, 1997) and field environments (Lee & Veld-Merkoulova, 2016). Yet, recent inquiries challenge the robustness of myopic loss aversion to changes toward more realistic experimental configurations. Based on a number of heterogeneous research findings, it has remained unclear whether myopic loss aversion is an empirical reality, or an experimental artifact that holds only under specific configurations of the decision environment. We reexamine the evidence and conduct comprehensive robustness tests of myopic loss aversion in chapter 2, providing broader evidence on its existence and underscoring the negative repercussions it may have for long-run financial health.

Features of the decision environment themselves can magnify myopic tendencies. Research by Gerhard et al. (2017) linked short-term portfolio return visualizations with fluctuating return expectations, while Shaton (2017) observed that long-term cumulative return displays could enhance voluntary savings contributions. It is unclear however whether such behavior is also provoked when people view more widely used price charts. As an accessible and comprehensive financial information tool, price charts have increasingly gathered scholarly attention in recent years (e.g., Borsboom & Zeisberger, 2020; Diacon & Hasseldine, 2007; Nolte & Schneider, 2018). Unlike aggregated returns, long-run price charts do not obfuscate intermediate performance, making transitory losses a salient feature, which potentially limits the effects of broad framing under such presentation formats. Our investigation of price path display horizon effects in chapter 3 revealed that individuals react more strongly to price developments under short-term performance presentation. In contrast to previous studies on the effects of narrow framing, we introduced a trading fee which allowed us to quantify the detrimental effects of short-term price visualizations.

Finally, going beyond previous exogenous myopia manipulations, this dissertation probes whether myopia is an inherent characteristic of people's perceptions or beliefs toward stock market investments. In chapter 4, we study individual expectations of short and long-run stock market investing risks. Despite the importance of long horizons for investment decisions, few previous studies have differentiated between short and long-term expectations. Notably, Breunig, Grabova, Haan, Weinhardt, and Weizsäcker (2021) documented a severe underestimation of long-term investment returns by households, beyond what can be explained by exponential growth alone. Our focus shifted to perceptions of investment risk on stock markets. While individuals are able to gauge short-run risks accurately, they severely overestimate long-run counterparts. Such a discrepancy may potentially explain why households adopt short horizons and refrain from investing, in line with the theory of myopic loss aversion. The study further contributes to the literature by highlighting the relevance of expected loss likelihoods for real planned investment allocations, complementing the findings of related recent experimental (Zeisberger, 2022) and empirical (Cao, Rieger, & Zhao, 2023) studies.

The landscape of retail investing has transformed significantly, driven by demographic shifts and advancements in FinTech, which has led to a democratization of personal finance and to placing individual investment decisions at the forefront.

Understanding cognitive and behavioral investment pitfalls has never been more crucial. While academic research has bridged numerous gaps between normative and actual individual risk-taking behavior, the link between considered time variation and investment behavior has remained underexplored. This dissertation aims to forge these essential connections, offering new insights into the cognitive biases that shape financial decision-making in an era of increasingly self-directed investing.

1.5 Summary of Chapters

1.5.1 The Consequences of Narrow Framing for Risk-Taking: A Stress Test of Myopic Loss Aversion

We reevaluated the evidence on myopic loss aversion in an online experiment. Myopic loss aversion, the tendency to pay attention to short-term portfolio losses, has been shown to reduce individual propensity to invest in risky assets, consequently hampering investment in risky long-term savings vehicles. Following the seminal study of Gneezy and Potters (1997), numerous articles have shown the robustness of myopic loss aversion with financial professionals, retail investors, advisors, crowd-workers, or teams as decision-makers. Yet, recent evidence implementing more realistic features of the decision environment called the generalizability of the concept into question (Beshears, Choi, Laibson, & Madrian, 2017). We provided a more holistic stress test of myopic loss aversion by addressing two prevalent issues in related literature: (i) Statistical power concerns, inhibiting the detectability of small- to medium-sized effects and (ii) lack of a systematic approach toward features which potentially reduce myopia. In a partial factorial design, we therefore tested the influence of return down-scaling, a compound return structure and long investment horizons separately on myopic loss aversion. 2,245 university students participated in an online experiment varying the degree of myopia (High versus Low) in treatments and investment environment features in conditions. We replicated the original results of Gneezy and Potters (1997) and demonstrated that myopic loss aversion persists in all variants of the decision context. Interestingly, the effect came closest to the baseline effect in our most realistic condition involving down-scaled and compound returns as well as a long investment horizon. In all other conditions, the investment gap between HIGH and LOW is substantially smaller, although cross-condition differences remain statistically not significant. We address potential concerns of analytical heterogeneity across studies by adopting a multiverse analysis of results. Our findings underscore the benefits of aggregated returns disclosure.

1.5.2 History Matters: How Short-Term Price Charts Hurt Investment Performance

By default, widely used price charts often communicate the most recent short-term information about past stock performance. Such a short information horizon may encourage investors to take a myopic view on their investments, resulting in reduced risk-taking and more trading as a result of intermediate price fluctuations. We tested the influence of short versus long price chart information horizons on investment and trading behavior in an online experiment with 1,041 retail investors. The chart in treatment SHORT displayed the one-period price changes of a risky asset with independent and identically distributed (iid.) returns, whereas LONG featured price movements of the last 25 periods. In each treatment, buying or selling assets was subject to a trading fee of 2% of the transacted amount. Because the risky asset return distribution was clearly communicated to experimental participants, price charts should not influence investment allocations, as past performance does not affect future price developments. Yet, we found that both trading frequency and trading volume are significantly higher when investors faced short-term price charts. As a result, participants in SHORT paid on average approximately 50% higher transaction fees, causing lower overall portfolio performance. The effect persisted even when both charts are presented jointly and are robust to increasing the number of ticks. Investors in SHORT did not exhibit significantly lower risk-taking, which may be due to the intermediate price fluctuations visible in both treatments. To alleviate investor overtrading as a response to short-term price fluctuations, financial regulation could require minimum (default) performance display horizons for financial assets, as has recently been introduced for Israeli pension funds (Shaton, 2017).

1.5.3 Why Do People (Not) Invest? The Role of Return and Risk Expectations

Empirical studies typically focus on short horizon measures when investigating the link between investor expectations and behavior. Moreover, most studies focus on expected return and return volatility, assuming that individuals care about both upside and downside fluctuations rather than an investment's loss potential in particular. We addressed this gap by examining investor and non-investor expectations of stock market investment loss likelihoods. Historically, the likelihood of a stock market loss was reduced over longer investment horizons. Responses in our survey experiment however did not reflect such difference, i.e., investors did not perceive the long-run benefits from stock investing. While deviations from historical averages were small for one-year investments, both investors and non-investors substantially overestimated the low loss likelihood of twenty-year investments, by 16 and 26 percentage points, respectively. We argue that such a large difference in perception gaps may explain why many households do not invest in equity. To improve long-term stock market risk perception, we implemented a simple information intervention allowing participants to compare their estimates with historical benchmarks. The intervention led to belief convergence between groups and prompts increased planned allocations to stock investments by non-investors (relative to investors). Updates in planned allocations for short-term investors were directly associated with revisions in future loss likelihood beliefs, whereas long-term allocations were associated with return updates. Our results show that simple and effective information provision can enable households to make long-term investment decisions, calling for increased transparency on the long-run risks of investing. Such communication has the potential to lower the barriers to stock market participation.

Chapter 2

The Consequences of Narrow Framing for Risk-Taking: A Stress Test of Myopic Loss Aversion[1]

Abstract. Narrow bracketing in combination with loss aversion has been shown to reduce individual risk-taking. This is known as myopic loss aversion (MLA) and has been corroborated by many studies. Recent evidence has contested this notion indicating that MLA's applicability is confined to highly artificial settings. Given the impact of these findings, we reevaluated the evidence on MLA involving a total of 2,245 university students, thereby achieving substantially higher statistical power than in almost all previous studies. To clarify inconsistencies in the literature, specifically under more realistic investment environments, we systematically modified the seminal study design by Gneezy and Potters (1997) to include five key adjustments. These involved realistic, down-scaled returns, return compounding, and extended investment

[1] The study is co-authored with R. Schwaiger and S. Zeisberger. The appendix is found in chapter 5. Experimental instructions and screenshots are included in the online version of the paper: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4726856

horizons. Contrary to some prior studies that have raised doubts about the robustness of MLA, our results—which are highly robust to analytical heterogeneity—consistently document the presence of MLA across all experimental conditions. Our findings substantiate the widespread applicability of MLA and underscore the benefits of disclosing aggregated returns in practical financial decision-making contexts.

2.1 Introduction

Individuals often frame decisions narrowly, segregating outcomes or frequently evaluating them (Kahneman & Tversky, 1984; Kahneman & Lovallo, 1993; Read, Loewenstein, Rabin, Keren, & Laibson, 2000; Thaler, 1985; Thaler, Tversky, Kahneman, & Schwartz, 1997). In an investment context, this particularly applies when investors evaluate their portfolios on a short-term basis. This temporal myopia demonstrates individuals' difficulty in foreseeing long-term outcomes and their implications for decisions. Coupled with prevalent loss aversion (Kahneman & Tversky, 1979), this myopia diminishes individuals' propensity to allocate investments in riskier assets. This combination of temporal myopia and loss aversion is referred to as myopic loss aversion (MLA). Given its intuitive appeal and its explanatory power regarding significant stock market anomalies, such as the equity premium puzzle (Benartzi & Thaler, 1995), MLA has garnered considerable interest in the economics and finance literature. For example, Benartzi and Thaler (1995)'s seminal work has received more than 4,500 citations, and Gneezy and Potters (1997)'s groundbreaking experimental verification of MLA has exceeded 1,600 citations, according to Google Scholar.

Research has extensively documented behavior consistent with MLA across a wide range of demographics and settings. A majority of studies have identified the manifestation of MLA among university students (Keren & Wagenaar, 1987; Gneezy & Potters, 1997; Thaler et al., 1997; Bellemare, Krause, Kröger, & Zhang, 2005; T. Langer & Weber, 2008; Fellner & Sutter, 2009; Wendy & Asri, 2012). Furthermore, observations of MLA extend beyond students to the general population (Van der Heijden, Klein, Müller, & Potters, 2012), financial experts and traders (Haigh & List, 2005; Eriksen & Kvaløy, 2010; Larson, List, & Metcalfe, 2016; Iqbal, Islam, List, & Nguyen, 2021), decision-making teams (Sutter, 2007), and private investors

(Wendy & Asri, 2012). Notably, natural field experiments have revealed that financial professionals exhibit MLA behaviors within their daily work environments (Larson et al., 2016). Evidence of MLA-compliant behavior extends to retirement planning and insurance (Benartzi & Thaler, 1999; Papon, 2008) as well as to experimental markets (Gneezy, Kapteyn, & Potters, 2003). Collectively, these studies underscore MLA's contribution to conservative decision-making and its association with generally suboptimal financial outcomes (Thaler et al., 1997; Clayton A Looney & Andrew, 2009; Larson et al., 2016).

Nevertheless, recent empirical evidence has increasingly called the concept of MLA into question. Several of the aforementioned studies have implemented the design by Gneezy and Potters (1997) as a benchmark. Their investment task extended across nine periods, featuring linear return calculations. Their risky asset yielded rates of return of either $+250\%$ or -100%, which resembles an "all-or-nothing" gamble. These experimental settings and parameters markedly deviate from the more realistic scenarios of annual investment returns, compound returns, and the extended investment horizons typically observed in financial markets. Although some field studies, including that of Larson et al. (2016), have featured compound return calculations and more realistic rates of return, these studies primarily focused on financial professional traders and involved alterations beyond the scaling of returns and compounding. This complexity makes it challenging to isolate and evaluate the singular effect of these characteristics on MLA, especially within the traditional framework established by Gneezy and Potters (1997). In a substantial and resource intensive study, Beshears et al. (2017) have taken this as an impetus to examine whether MLA is robust to more realistic, scaled-down rates of return, return compounding, and extended investment horizons.[2] Their findings suggest that behaviors consistent with MLA may not be prevalent in more realistic investment contexts. In a series of tests they came to the conclusion that the artificial "all-or-nothing" gamble is responsible for the non-replication and that the results do not extend to settings with less extreme and more realistic risk profiles. This necessitated a thorough reevaluation of the

[2] Moreover, Beshears et al. (2017) have introduced longer delays between periods in their post-lab conditions in order to move away from short laboratory settings toward more realistic real-world investment horizons. The study cost more than $200,000 in participant payoffs, by magnitudes more than comparable studies.

multitude of studies utilizing Gneezy and Potters (1997)'s experimental design, thereby challenging the overarching validity of the MLA literature. By contrast, T. Langer and Weber (2008) found MLA-compliant behavior in a small sample of university students when applying similar modifications to the scaling of the risky asset's return, return compounding, and investment horizon. Recently, Schwaiger and Hueber (2021) found that the original protocol by Gneezy and Potters (1997) replicates only among the more attentive crowdworkers on Amazon MTurk. Additionally, a variation of the original lottery, which only differed in terms of the probabilities of winning and losing (50% each instead of 33% and 66%, respectively) did not lead to behavior consistent with MLA. Nevertheless, the vast majority of studies primarily maintained or minimally altered the original framework set by Gneezy and Potters (1997). Apart from the study by Beshears et al. (2017), no other research has undertaken a comprehensive and systematic revision of the experimental parameters.[3] The path-dependent nature of research, with the vast majority of studies applying the original parameters by Gneezy and Potters (1997), thus seriously questions the external validity of the whole research field. Furthermore, different analytical choices for testing MLA behavior in published studies, such as the choice of regression models or covariates, could (partly) explain the heterogeneity of MLA results in the literature (Menkveld et al., forthcoming; Simonsohn, Simmons, & Nelson, 2020; Holzmeister et al., 2023).[4] Considering the divergent findings from studies deviating from Gneezy and Potters (1997)'s original protocol, a clear consensus remains elusive about whether MLA is a universal feature of investment decisions or a fragile artifact that crucially depends on stylized experimental designs and analytical choices. Furthermore, it is crucial to acknowledge the potential impact of publication bias when evaluating the scientific arguments for and against the relevance of MLA.

Previous studies questioning its robustness to real-world financial contexts as well as studies confirming the original findings by Gneezy and Potters (1997) suffered from at least one—and most often two—of the following two issues ex ante: (i) insufficient statistical power to reliably detect small- to medium-sized standardized effects and (ii)

[3] Table 5.3 offers a detailed overview of the applied modifications in studies based on the experiment by Gneezy and Potters (1997). We will elaborate below on our important extensions to Beshears et al. (2017).

[4] Table 5.8 depicts the implemented analytical pathways in published studies that adopted the Gneezy and Potters (1997) design.

non-isolated alterations of characteristics of the original Gneezy and Potters (1997) setting. The first issue raises the question of whether MLA's absence in more realistic contexts is genuine, or if its effects are simply diminished—rendering it unlikely to detect in studies lacking sufficient statistical power. The power curves presented in Figure 2.2 illustrate that even slight reductions in the true standardized effect, potentially resulting from alterations in the experimental design, lead to a notable decrease in statistical power. This would markedly hamper the ability to reliably identify diminished yet economically significant effects.[5] The second issue, that of concurrent modifications, complicates the attribution of specific design changes to MLA's observed fragility. In their study, Beshears et al. (2017) not only reduced the rates of return on the risky asset but also simultaneously transitioned from the original model with periodic endowments and linear returns to a singular initial endowment and compound returns. In this modified version, each decision impacts not only the immediate outcomes but also the available funds for investment in subsequent periods, potentially prompting participants to frame the investment decision more broadly overall. Adopting a broader perspective might inherently mitigate myopia in decision-making by underscoring the long-term ramifications of present choices (T. Langer & Weber, 2008). However, the compound nature of returns heightens the significance of each choice as it affects the capital that is available for investments for the next periods, potentially leading to more conservative investments due to loss aversion. Increased caution may offset the mitigating effects of a broader decision-making frame on MLA. The cumulative impact on MLA from transitioning from periodic endowments without compounding to a singular initial endowment with compounding has yet to be isolated, leaving its overall effect ambiguous. Specifically, compound returns, down-scaling of returns, or the combination of both including potential interaction effects, might diminish MLA-compliant behavior compared to the original setting. The literature also only incorporated adjustments to the investment horizon alongside simultaneous reductions in rates of return. For example, T. Langer and Weber (2008) increased the number of investment periods to 30 and combined this with lowered return rates. The discrete effects of each modification have not been distinctly isolated in the analysis. It is plausible that some of the described alterations

[5] For the detailed power calculations see the *R* script in the project's OSF repository.

could counteract each other. Therefore, the degree to which MLA findings can be generalized to scenarios that differ from the common paradigm established by Gneezy and Potters (1997), as well as the specific factors influencing this generalizability, continue to be unclear.

To illuminate these critical gaps and assess the comprehensive MLA literature's relevance and impact, we enrich the field through extensive, pre-registered online experiments with students from two large universities, in the Netherlands and in Austria. In light of conflicting findings, our objective was to ascertain the robustness of MLA and identify specific modifications to the Gneezy and Potters (1997) design that potentially mitigate individuals' inclination toward MLA-consistent behavior. Our methodology is distinguished by its capacity for the meticulous isolation of disparate elements of experimental design choices, such as realistic rates of return, return compounding, and investment horizons. Employing a (partial) factorial design, we were able to precisely discern the impact of each of the more realistic investment attributes on MLA tendencies. Furthermore, we conducted our study with a substantially larger number of participants compared to almost all prior studies that applied the Gneezy and Potters (1997) design (detailed in Table 5.3). This ensured that we were sufficiently powered to reliably identify even minor to moderate standardized effects, as illustrated in Figure 2.2. Lastly, acknowledging the diverse statistical analyses of MLA in existing research, we introduce innovation through the adoption of a multiverse approach complemented by specification curve analysis (Simonsohn et al., 2020). This method addressed potential variations in our results arising from analytical heterogeneity, thereby enhancing the reliability of our conclusions. We based the choice of the analytical pathways on an extensive examination of the applied analyses in the related MLA literature.

Our analysis uncovered compelling evidence for the persistence of MLA across all examined setting, including more realistic, down-scaled rates of return, a compound return scheme following a single initial endowment, and longer investment horizons. The outcomes derived from the multiverse approach underscored the consistency and reliability of our findings across more than 10,000 distinct analytical specifications, including varied sample exclusion criteria, sets of covariates, and regression methodologies. Collectively, our results present a stark contrast to prior research challenging

MLA's robustness, as we found significant evidence for the relevance of MLA in all of our conditions and, thus, for more realistic investment settings. A potential explanation for this divergence lies in the inadequate statistical power of preceding studies to reliably detect the smaller standardized effects we report for some of the more realistic investment contexts.

Our results highlight MLA's capacity to undermine long-term wealth accumulation, particularly in an era where individuals shoulder greater responsibility for their retirement savings due to the transition from "Defined-Benefit" to "Defined-Contribution" pension schemes. Technological advancements facilitating quick and intuitive information processing may foster short-term thinking and impulsive decisions, detracting from a strategic, long-term investment approach (see, e.g., Kalda, Loos, Previtero, & Hackethal, 2021). Adopting policies that promote a holistic investment perspective—via tax incentives, loyalty programs for long-term financial products, or educational initiatives—could significantly improve long-term financial well-being for individuals. The success and configuration of such strategies critically depend on the presence or absence of MLA in particular investment contexts. We undertook this research to elucidate this crucial distinction by addressing and resolving prevailing inconsistencies within more authentic investment environments.

2.2 Experimental Design

The experimental design of this study is based on the protocol by Gneezy and Potters (1997). In the original study across nine periods, participants allocated a financial windfall between a risky asset, which had a positive expected value, and a risk-free cash option. In one of the two treatment groups, designated as HIGH, the authors introduced a higher frequency in which participants made decisions and received feedback on investment outcomes. Participants randomly assigned to treatment HIGH received outcome feedback and made decisions in each period, while the feedback and decisions in LOW always applied to three consecutive periods. Behavior aligning with MLA theory manifests when individuals in the LOW treatment group average higher investments in the risky asset compared to those in the HIGH group. Investments with a positive expected return are characterized by an increasing (non-monotonic) likelihood of aggregate positive outcomes over time, irrespective of whether returns are compound or linear. On average, this makes the investment more attractive under infrequent evaluation for a loss-averse investor. Furthermore, the commitment to decisions across multiple periods encourages more prospective thinking in the LOW group (Redelmeier & Tversky, 1992). The risky asset in Gneezy and Potters (1997) is characterized by a binary distribution, yielding periodic outcomes where there is a one-third probability of achieving a +250% gain and a two-thirds probability of incurring a total loss (-100%). As a theoretical underpinning, we consider cumulative prospect theory (CPT) to explain behavior consistent with MLA (T. Langer & Weber, 2005). In an extension of MLA to myopic prospect theory, T. Langer and Weber (2005) highlighted the relevance of other characteristics, such as probability weighting and value function curvature, as crucial factors. To assess the lotteries' attractiveness, we assumed a CPT agent with parameters $\alpha = \beta = 0.88$, $\gamma = 0.61$, $\delta = 0.69$, and $\lambda = 1.6$.[6] Based on the above parameters, a myopic decision maker rejects a gamble following such a distribution since its periodic CPT value is negative (-2.2 for an investment of 100). In contrast, an aggregate evaluation of the three-period lottery results in a positive CPT value (4.3 for an investment of 100), predicting investment in the risky asset.[7]

2.2.1 Conditions

For this study, we replicated the original design and additionally modified it in relation to the following three critical dimensions. These changes allowed us to examine the robustness of MLA to more realistic conditions and to distinguish effects between relevant dimensions of the design.

(1) **Rates of Return**: The properties of the risky asset in Gneezy and Potters (1997) do not resemble those of typical retail investment products. To enhance realism, we adjusted the rates of return, scaling them down to +25% and -10%,

6 Value function curvature and probability weighting parameters are based on Tversky and Kahneman (1992). In line with empirical estimates, however, we assumed a lower magnitude of loss aversion (Walasek, Mullett, & Stewart, 2018). Applying the loss aversion parameter of Tversky and Kahneman (1992), $\lambda = 2.25$, the three-period lottery would still be preferred, but CPT would predict rejection of both gambles.

7 For the detailed calculations see the *R* script in the project's OSF repository.

mirroring the approach by Beshears et al. (2017). The authors came to the conclusion that MLA in the Gneezy and Potters (1997) experiment only holds true under unrealistic return scenarios as they did not find evidence for MLA with such down-scaled rates of return. In our setting, scaling down rates of return reduces the CPT values of one- vs. three-period prospects to around -0.3 and 0.6, respectively. Theoretically, a decision-maker guided by CPT still only accepts the three-period prospect. However, the practical impact of such a slight absolute value difference between the one- and three-period prospects on empirical outcomes might be reflected in smaller true effect sizes. Such a consideration could potentially explain why previous studies without sufficient statistical power have detected no effect. Should the effect disappear or lose economic significance, determining whether the cause is the reduced overall appeal of the prospect or the manner in which returns are scaled becomes challenging. Therefore, we introduced an additional condition featuring asset rates of return of +230% and −90%. By reducing the potential periodic loss to −90% of the invested amount, we were able to examine whether MLA behavior persists when the asset profile does not follow an "all-or-nothing" return framing. Again, a narrow one-period evaluation predicts rejection by a CPT decision maker, whereas a broader and aggregate evaluation of the three-period return distribution predicts acceptance of the gamble ($CPT_1 = -1.2$; $CPT_3 = 6.1$).[8]

(2) **Compound Returns**: In the original Gneezy and Potters (1997) study, participants received a new endowment in each of the nine periods for making investment decisions specific to each period. Periodic earnings were calculated for each of these separate decisions, and total earnings equaled the sum of all independent periodic earnings. However, subsequent studies by T. Langer and Weber (2008) and Beshears et al. (2017) highlighted that this approach,

[8] We adjusted the up-scaling from 250% to 230% to align the CPT values more closely with those in Gneezy and Potters (1997). We strongly believe that variances in MLA behaviors, compared to the original study, would mainly be due to the reduced risk of total loss rather than the slight change in up-scaling. Keeping the up-scaling at 250% would have led to two simultaneous changes: a move away from the risk of total loss *and* a significant deviation in CPT values. In particular, CPT would have predicted acceptance of both the one-period and the aggregated three-period lottery ($CPT_1 = 2$; $CPT_3 = 15.1$).

resulting in linear returns, diverges from typical investment practices. In real investment contexts, investors benefit from the compounding of capital gains and the reinvestment of dividends. Moreover, investors usually do not invest for predetermined periodic intervals and are not forced to liquidate their position after each period. Therefore, building upon the framework of Beshears et al. (2017), to simulate compound returns, we provided participants with an initial endowment (I), set as the product of the number of periods (K) and the periodic endowment (P), that is, $I = K \times P$. This endowment was allocated at the start, and the balance was adjusted at each period's end to reflect any gains or losses, effectively carrying the balance forward through the experiment. For instance, if participants invested a fraction x of their initial endowment I in the first period with a return of r_1, the endowment for the second period I_2 would be recalculated to include the gains or losses from that investment, that is, $I_2 = I \cdot (1 - x) + I \cdot x \cdot (1 + r_1)$. Figure 2.1 illustrates the comparison between linear and compound return calculations across the experiment's duration.

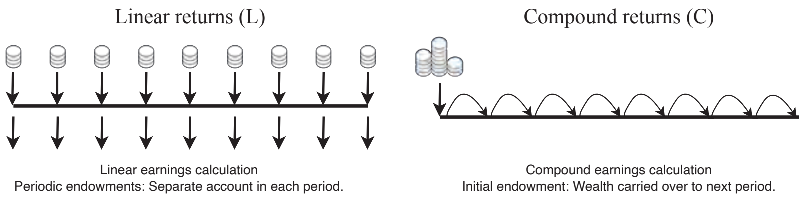

Figure 2.1: Linear versus compound return calculation.

We argue that the decision of which return calculation method to adopt is potentially consequential in an experiment testing MLA. Compared to Gneezy and Potters (1997), allocating a one-time initial endowment may shape participants' investment strategies by highlighting the enduring consequences of their initial choices on future investment balances. Consequently, this upfront endowment has the potential to counteract narrow bracketing, particularly in condition HIGH, and to promote a more far-sighted approach to investment evaluations. Conversely, this approach might predispose participants to adopt more conservative strategies upfront, mindful of their decisions' prolonged repercussions. The net effect of these potentially opposing influences is complex and remains an open question. Klos (2013) found that highlighting the final outcome distribution might mitigate MLA. Notably, Beshears et al. (2017) altered both the return scaling *and* return compounding and concluded that it is likely the former that drives their insignificant results, but that the latter is a possible reason as well.

(3) **Investment Horizon**: When participating in the investment task over nine periods, participants in condition LOW only make three decisions. Shorter investment horizons may skew myopic evaluations of risky assets, particularly if their effects differ between the LOW and HIGH treatment groups. Generally, the tendency to overestimate loss risks increases with longer investment horizons, subsequently dampening risk-taking propensities (Ponti & Tomás, 2021). By elevating decision-making and feedback instances—from 3 to 10 in the LOW condition, and from 9 to 30 in the HIGH condition—might lead to more uniform investment behaviors across treatments due to sufficiently prolonged decision and investment horizons in both groups, especially in group LOW. This is also consistent with the first experiment in Beshears et al. (2017). Here, the authors implemented the return histogram design by Benartzi and Thaler (1999) and extended the investment horizon to 52 periods with real-time delays of one week. They did not find behavior consistent with MLA. To systematically examine the investment horizonâĂŹs effect on MLA, we introduced extended periods of 30 to guarantee a multiple of three based on the original design in Gneezy and Potters (1997). This is consistent with T. Langer and Weber (2008) and adapts our experiment to reflect more conventional long-term investment scenarios. This modification allows us to delve into how extended decision-making frames might mitigate or accentuate MLA tendencies.

Table 2.1 depicts the characteristics of the six different conditions under which we tested the robustness of MLA. Alongside a baseline condition (250-100L9) identical to Gneezy and Potters (1997)'s design, our study was structured to isolate the effects of scaled-down rates of return and a departure from "all-or-nothing" gamble framing on MLA (top left box with conditions 250-100L9, 230-90L9, and 25-10L9).

The CPT value differences between the LOW and HIGH treatments under the 230-90L9 setup closely mirrored those in the original lottery, maintaining the value relationship between the LOW versus HIGH scenarios. Thus, condition 230-90L9 primarily deviates from the original by not featuring the potential for a total loss. Additionally, our experiment featured a 2 (linear vs. compound returns) × 2 (short vs. long horizon) design contrasting linear versus compound returns and short versus long investment horizons, all under more realistic, scaled-down rates of return (all four boxes with conditions 25-10L9, 25-10L30, 25-10C9, and 25-10C30). In contrast to prior research on the robustness of MLA, we were thus able to disentangle the influence of the return scaling and the influence of the return calculation.

Table 2.1: Experimental Conditions Overview: This figure delineates the between-subjects experimental setup. First, our design enables us to examine the isolated impact of scaled-down rates of return and the shift from an "all-or-nothing" gamble framing on MLA (top left box with conditions 250-100L9, 230-90L9, and 25-10L9. Furthermore, it illustrates how the investment horizon and return calculation variables are systematically varied within a 2 × 2 factorial design, incorporating realistic return rates (all four boxes with conditions 25-10L9, 25-10L30, 25-10C9, and 25-10C30.

<table>
<tr><th colspan="2"></th><th colspan="2">Investment Horizon</th></tr>
<tr><th colspan="2"></th><th>9 Periods</th><th>30 Periods</th></tr>
<tr><th rowspan="4">Return Calculation</th><th rowspan="3">Linear</th><td>250-100L9</td><td rowspan="3">25-10L30</td></tr>
<tr><td>230-90L9</td></tr>
<tr><td>25-10L9</td></tr>
<tr><th>Compound</th><td>25-10C9</td><td>25-10C30</td></tr>
</table>

2.2.2 Procedure

After providing informed consent to the study's terms and conditions,[9] participants viewed an elaborate description and illustration of the asset's return distribution.

[9] The study has been approved by the ethics board of the University of Zurich.

To maintain comparability, our instructions were identical to those of Beshears et al. (2017) except for necessary minor edits due to the online experimental setting (see OSF repository for the full set of the experimental instructions). In conditions with linear returns (250-100L9, 25-10L9, 25-10L30, and 230-90L9), participants received 100 experimental currency units (ECU) in each period, whereas in conditions with compound returns (25-10C9 or 25-10C30) participants received either 900 ECU or 3,000 ECU in Period 1 to be invested over either 9 or 30 periods. Participants in the LOW treatment were informed that each of their decisions would apply to the subsequent three periods and that their investment results would be presented in three-period blocks. In contrast, participants in the HIGH treatment were informed that they would make decisions and receive feedback on a period-by-period basis.

In each of the six conditions and each of the two treatments, HIGH and LOW, participants indicated their investment as a percentage of the endowment in ECU. This standardized approach ensured that the set of investment allocations was consistently scaled across all conditions. Requesting investments as percentages facilitates consistent scaling across conditions, irrespective of the fluctuating absolute amounts in compound return scenarios. Furthermore, these percentages could be readily converted to their corresponding absolute amounts, ensuring comparability across different conditions. On each feedback screen, we presented the return outcome(s) of the risky asset, the amount gained or lost, and the total earnings from the previous period (HIGH) or the previous three periods (LOW). Importantly, as in earlier studies (with the exception of Hardin & Looney, 2012), single-period outcomes and earnings were also displayed for participants in LOW. After the final period, participants received information about their final payoff. Due to the different structures and lengths of conditions, incentives varied slightly in magnitude.[10]

The experiment concluded with pre-registered survey questions on perceptions of ambiguity and risk associated with the lottery, which were aimed at uncovering potential explanations for variations in risk-taking across conditions (Venkatraman,

[10] In the conditions with nine periods, the payment in Euro equalled the total ECU earnings in the experiment divided by 1,200. In the conditions with thirty periods, we divided the total ECU earnings by 400 to achieve similar payments and also to compensate participants for the slightly longer time spent on the additional investment periods.

Aloysius, & Davis, 2006).[11] In addition, as pre-registered, we included three questions on the understanding of the risky asset return distribution to identify and exclude participants who were inattentive or did not understand relevant information from the sample that we used for a robustness check. Finally, we collected basic demographic data to be used in sample balancing checks and to be added as control variables in our regression analyses.

2.3 Results

2.3.1 Statistical Power and Sample

All analyses presented herein, unless noted otherwise, were pre-registered on "AsPredicted".[12] We adhered to significance levels (α) of 5%, 1%, and 0.1%, respectively, for all analyses. Our final sample consists of data we collected via online experiments in three waves with students at Radboud University in the Netherlands (Wave 1 & 2) and the University of Innsbruck in Austria (Wave 3). We invited students from different universities to ensure a sufficient number of participants. This enabled us to achieve a high statistical power to reliably detect small to medium-sized standardized effects.

We conducted ex-ante statistical power analyses for which we used Cohen's d as a standardized effect size. With our 2,245 participants (pre-registered: 2,200) in total, we generated on average 187 independent observations per treatment—HIGH and LOW—across all six conditions. Thus, we had a statistical power of at least 80% (90%) to reliably detect a standardized effect size equal to or larger than Cohen's $d = 0.29$ ($d = 0.34$), given a Type I error rate of $\alpha = 0.05$ in pairwise comparisons via two-sided unpaired-sample t-tests (see Figure 2.2—also for a comparison to related studies in the literature).

The median duration of the experiment in the full sample was 10 minutes, with a median compensation of €2.49, corresponding to an hourly rate of €14.94. As pre-registered, we excluded the fastest and slowest 2.5% of participants in terms of total processing time from the analyses to increase the signal-to-noise ratio in our data.

[11] Since these questions were exclusively pre-registered and asked during Wave 3, we have detailed their corresponding results in chapter 5. This approach allowed us to focus on the most relevant findings based on the combination of all waves in the paper's analysis section.

[12] See the pre-registration under the following links: Wave 1, Wave 2, Wave 3.

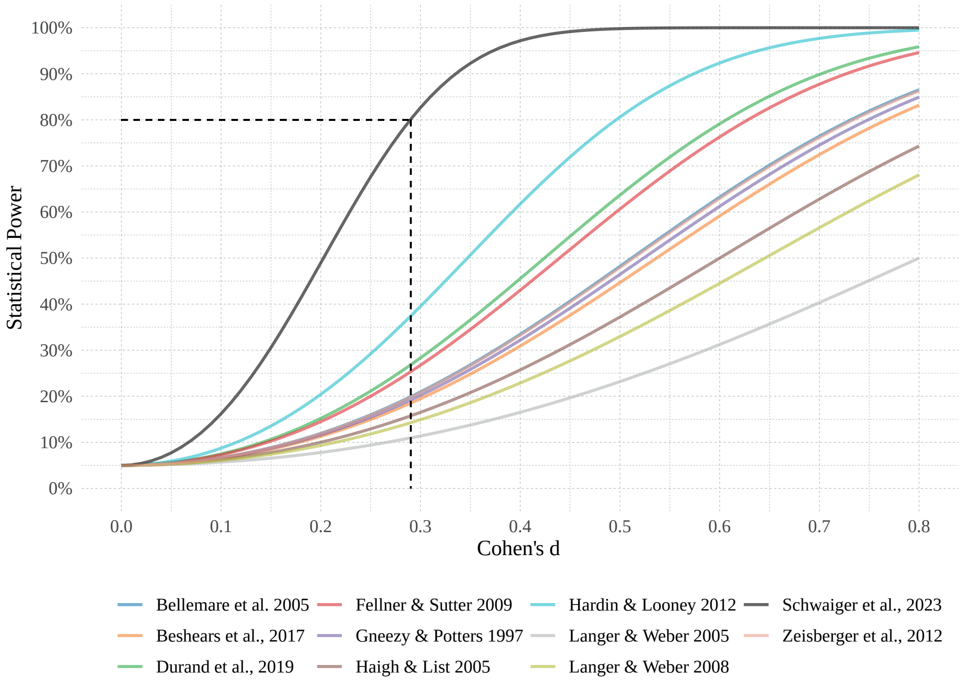

Figure 2.2: Statistical power calculations for the treatment comparison HIGH versus LOW based on the sample size of our study and of major experimental studies in the field of MLA, applying a variant of the Gneezy and Potters (1997) design. $\alpha = 0.05$.

Clicking through quickly may be an indicator of a lack of focus and understanding of the procedure and the lottery (Chmielewski & Kucker, 2020; Downs, Holbrook, Sheng, & Faith Cranor, 2010). As a result, behavior consistent with MLA may not unfold as it would in real-world investment decisions. Conducting the experiment too slowly could also be a problem as participants may take longer breaks and forget parts of the instructions (Abbey & Meloy, 2017; Downs et al., 2010). This trimming procedure led to 2,131 observations in the final sample, which we used for the main analyses. As a robustness check, we also ran our main analysis with the full sample, for which we found consistent results, which we report in Table 5.6 in the Appendix. Furthermore, as pre-registered, we applied another robustness check, excluding participants who gave too many incorrect answers and those who indicated that they "did not understand at all" in a set of comprehension check questions (see instructions in OSF repository). Compared to our final sample, this robustness sample also provided qualitatively identical results.

Prior to conducting our main analyses, we assessed the balance of observable characteristics within our final sample following the trimming procedure. To accomplish this, we conducted tests to identify any discrepancies in self-reported participant demographics and traits, such as gender, risk preferences, statistical knowledge, and university affiliations, across the different conditions and two treatments. This step was undertaken to address endogeneity concerns by pinpointing potential confounders due to imbalances that need to be included as control variables in our analysis. The results of the sample balancing checks are presented in Table 5.2 in the Appendix. We found that the measured covariates did not statistically significantly differ from each other in all but one condition (250-100L9), which was characterized by higher self-assessed statistical knowledge in group HIGH compared to group LOW. For our analyses, we exercised caution and estimated econometric specifications that controlled for self-reported participant characteristics. We also tested for multicollinearity among the covariates by calculating the variance inflation factors (VIFs), all of which were below 2. Thus, multicollinearity did not pose an issue.

2.3.2 Main Analyses

Participants' average invested amount in the lottery in percent of the periodic endowment or the current balance served as our main outcome variable. Figure 2.3 shows the average investment in percent in treatment HIGH and LOW across all six conditions, 250-100L9, 230-90L9, 25-10L9, 25-10L30, 25-10C9, and 25-10C30.[13] The whiskers indicate 95% confidence intervals, and the stars indicate ranges of p-values obtained by running unpaired-sample t-tests and—as robustness check—permutation tests comparing average investment amounts between treatments LOW and HIGH in each condition. As indicated by Figure 2.3, we found statistically significant evidence for behavior consistent with MLA in each of the six conditions (see Table 5.4 in the Appendix for the statistical details of the applied unpaired-sample t-tests for each condition). Consistent with MLA, we report universally higher risk-taking among

[13] Average round-level investments are visualized in Figure 5.2 in the Appendix.

participants in treatment LOW compared to participants in treatment HIGH. MLA behavior was most prevalent in condition 250-100L9—our Gneezy and Potters (1997) replication—with the standardized average investment difference (LOW − HIGH) amounting to $d = 0.45$, followed closely by condition 25-10C30 with $d = 0.42$ and condition 230-90L9 with $d = 0.36$. In conditions 25-10L30 with $d = 0.29$, 25-10C9 with $d = 0.28$, and 25-10L9 with $d = 0.27$, we observed small-to-medium standardized differences. Our findings present a coherent and consistent view: MLA emerges as a behavioral phenomenon even when we scaled down returns to more realistic levels. This pattern held true not only under the traditional linear framework of Gneezy and Potters (1997) but also in settings involving more realistic compound returns. Importantly, behavior consistent with MLA under realistic returns persisted across both shorter and longer investment horizons, regardless of whether the returns were calculated on a linear or compound basis. In particular, the significant difference in condition 25-10C30—our most realistic condition featuring down-scaled and compound returns as well as a longer investment horizon—reveals important insights into the economic significance of our results. Participants who received aggregated feedback and experienced decision commitment (LOW) allocated, on average, an additional 12.03 percentage points of their balance (see Table 5.4 in the Appendix) compared to those with more frequent feedback and decision-making (HIGH). To accurately reflect this in monetary terms, consider that if participants in the HIGH condition invested a certain percentage of their balance in a given period, say 40% of 3,000 ECU, their starting balance, resulting in an actual investment amount of 1,200 ECU, then participants in the LOW condition would be expected to invest $40\% + 12.03pp. = 52.03\%$ of their balance. Given a balance of 3,000 ECU, this specific investment behavior would translate to an actual investment amount of 1.561 ECU, which is larger by 361 ECU compared to group HIGH. Therefore, this effect is not just statistically significant but also reflects a considerable economic impact, underscoring the importance of MLA in investment decisions.

Our results stand in contrast with those questioning MLA in broader contexts, for example, Beshears et al. (2017), who did not observe evidence of MLA in a setting with compound returns and with returns scaled down to 25% and -10% (identical to 25-10C9). Overall, our analysis revealed that MLA remains a persistent phenomenon when the risky asset return profile deviates from the original Gneezy and Potters (1997) asset, independent from altering the earnings calculation and the investment horizon. This underscores the robustness of the original results even under modified properties of the risky asset.

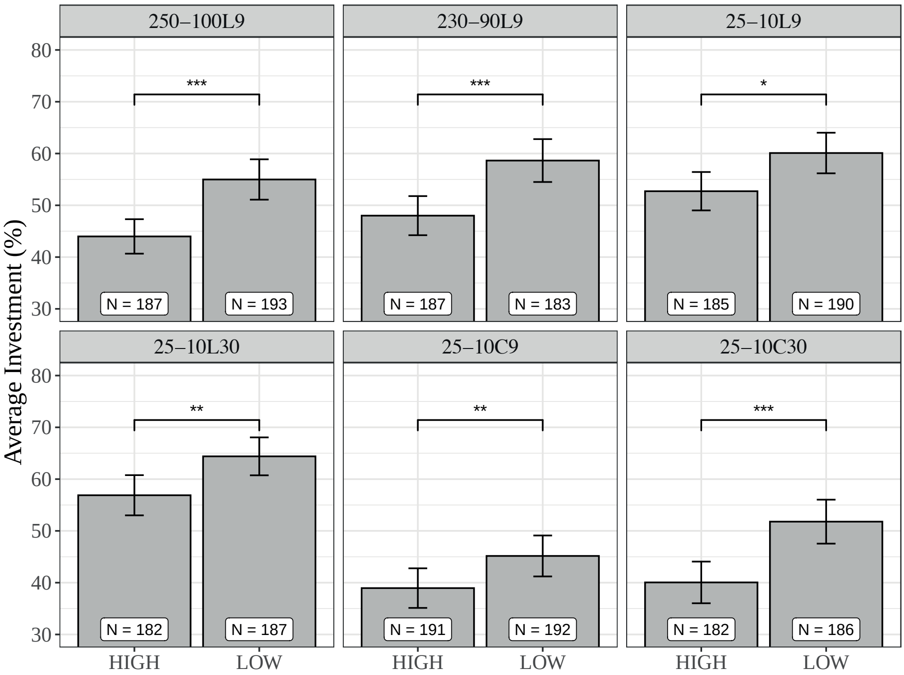

Figure 2.3: Average investment percentages between treatments HIGH and LOW across different conditions. HIGH features periodic feedback and decisions, whereas these are binding for three periods in LOW. 250-100L9 implements the Gneezy and Potters (1997) design, whereas the other conditions represent the different modifications (see Table 2.1). Error bars indicate 95% confidence intervals around mean investments in each treatment and condition. The stars indicate ranges of p-values obtained by running unpaired-sample t-tests and—as robustness check—permutation tests comparing average investment amounts between treatments LOW and HIGH in each condition (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$). Details on differences in risk-taking and the results of pairwise unpaired-sample t-tests are provided in Table 5.4.

To further inform our analyses, we ran multivariate fractional response regression models with logit links and heteroskedasticity-robust standard errors for each of the six conditions with the average proportional lottery investments over all respective periods (9 or 30) as the dependent variable.[14] We report the results in Table 2.2, which shows average marginal effects. For each model we also included the five covariates as control variables to verify the validity of our results. The coefficient LOW represents a binary dummy that equals 0 for participants in treatment HIGH or 1 for participants in treatment LOW. FEMALE is a binary dummy variable that equals 0 for male participants or 1 for female participants. INVESTOR is a dummy variable that equals 1 if participants stated to have already invested in financial products. RISKTOLERANCE indicates the self-reported risk preferences of participants, which were measured using the German SOEP questionnaire (Dohmen et al., 2011) on Likert scales from 0 to 10. STAT.KNOWLEDGE represents participants' self-reported statistical knowledge compared to their fellow students on a seven-point scale. INNSBRUCK is a binary dummy that equals 0 for participants from the Radboud University in Nijmegen or 1 for participants from the University of Innsbruck.

As can be seen from the coefficient LOW in each specification of Table 2.2, the results on MLA-compliant behavior are consistent with those presented in Figure 2.3 and Table 5.4 in the Appendix when we control for all elicited covariates. Specifically, for condition 250-100L9, which corresponds to the original setting by Gneezy and Potters (1997), Model (1) predicts that participants in treatment LOW invest on average 11.60 percentage points more in the lottery compared to their counterparts in treatment HIGH. Simply scaling the rates of return in the 25-10L9 condition, our regression predicts a difference in risk-taking between LOW and HIGH of only 7.00 percentage points and, additionally, switching to 30 instead of 9 periods corresponds to a predicted investment difference between both treatments of 5.90 percentage points. 25-10C30, the condition most closely mimicking realistic settings, produced the largest average gap in risk taking between treatments LOW and HIGH. Despite the fact that behavior consistent with MLA is a robust finding in our data, it appears that MLA is not equally pronounced in all conditions. Similarly, other studies modifying the design properties of Gneezy and Potters (1997) find attenuated evidence of MLA (see, e.g., Charness & Gneezy, 2010; Schwaiger & Hueber, 2021). Because of the low

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[14] As the investments represent the only variable exhibiting variation across different periods, we averaged the investments for our models. Our results remained qualitatively consistent when we repeated the analyses using periodic data and applied clustered standard errors at the individual level (see Table 5.5).

Table 2.2: Average marginal effects fractional response models with logit links and the amount invested in percent of the endowment as dependent variables. The binary dummy variable LOW is coded 0 for participants in the HIGH treatment and 1 for those in the LOW treatment. FEMALE is a binary dummy variable that equals 0 for male participants or 1 for female participants. INVESTOR is a dummy variable that equals 1 if participants stated to have already invested in financial products. RISKTOLERANCE indicates the self-reported risk preferences of participants, which were measured using the German SOEP questionnaire (Dohmen et al., 2011) on Likert scales from 0 to 10. STAT.KNOWLEDGE represents participants' self-reported statistical knowledge compared to their fellow students on a seven-point scale. INNSBRUCK is a binary dummy that equals 0 for participants from the Radboud University in Nijmegen or 1 for participants from the University of Innsbruck.

	Dependent variable: Investment (%)					
	Conditions:					
	250-100L9	230-90L9	25-10L9	25-10C9	25-10L30	25-10C30
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
LOW	0.116***	0.102***	0.070*	0.078**	0.059*	0.118***
	(0.025)	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)
FEMALE	-0.088**	-0.052	-0.039	-0.104**	-0.061	-0.148***
	(0.028)	(0.035)	(0.031)	(0.034)	(0.032)	(0.036)
INVESTOR	-0.017	-0.011	0.023	-0.015	0.071*	-0.027
	(0.027)	(0.033)	(0.033)	(0.033)	(0.031)	(0.034)
RISKTOLERANCE	0.040***	0.031***	0.019*	0.034***	0.026***	0.030***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
STAT.KNOWLEDGE	0.014	0.011	0.030*	-0.001	0.004	0.007
	(0.011)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
INNSBRUCK	0.090**	0.074*	0.087**	0.049	0.079**	0.074*
	(0.028)	(0.031)	(0.030)	(0.030)	(0.031)	(0.031)
Permutation p-value LOW	0.0000	0.0002	0.0096	0.0045	0.0333	0.0002
Observations	350	359	348	359	360	355

Heteroskedasticity-robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

statistical power of most studies (see Figure 2.2), smaller true MLA effect sizes that might result from deviations from the original design of Gneezy and Potters (1997) would only be detected with a low likelihood.

Furthermore, in most conditions, we observed a large and statistically significant association between gender and risk-taking behavior. Averaging coefficients of FEMALE across the six different models, we found that male participants invested 8.2 percentage points more in the lottery than female participants. This finding aligns with prior research indicating that men tend to take greater risks than women, particularly in financial contexts (Charness & Gneezy, 2012). Additionally, the results demonstrate that participants who identify themselves as more risk-seeking in financial matters invested higher amounts in the lottery, which can be seen from the statistically significant coefficient RISKTOLERANCE in all models of Table 2.2. With respect to general risk-taking behavior, we found cohort effects. In particular, participants from

Innsbruck were predicted to invest more in the risky lottery compared to students from Nijmegen.

As a robustness check, we repeated the main analyses presented in Table 2.2 with the full sample. We show the results in Table 5.6 in the Appendix. The results remained robust and we observed the same qualitative patterns with respect to MLA in all conditions. In addition, we performed another pre-registered robustness check based on three questions we implemented in the experiment to test participants' comprehension of the investment task. Specifically, for the robustness check we excluded participants from the analysis who answered at least two of the three questions incorrectly and those who answered "did not understand at all" (after the decision task; see instructions in OSF repository). We present the results of this robustness check in Table 5.7 in the Appendix. Again, identical qualitative patterns emerged with respect to MLA-compliant behavior. In comparison to our final sample, MLA appears to be a marginally more pronounced characteristic among participants who demonstrated a better understanding of the task.

2.3.3 Multiverse Analysis of Main Results

Typically, researchers enjoy a degree of freedom in choosing study populations, experimental designs, and analytical pathways for a given research question. Existing evidence has demonstrated marked variability in outcomes based on differences in these choices (Holzmeister et al., 2023; Landy et al., 2020; Menkveld et al., forthcoming; Simonsohn et al., 2020; Wicherts et al., 2016). Thus, the integrity of research findings, including those from pre-registered analyses, may still be influenced by the researcher's specific field of expertise or prior experience (Simmons, Nelson, & Simonsohn, 2011). Such researcher degrees of freedom, particularly in the context of analytical heterogeneity, hold high relevance in empirical studies (Menkveld et al., forthcoming). This concept pertains to the discretion afforded to researchers in deciding upon data analysis methods, such as choosing specific statistical models, variables, or methods of interpretation. Such freedom can inadvertently introduce biases or lead to varying conclusions from the same dataset and given the same hypothesis.

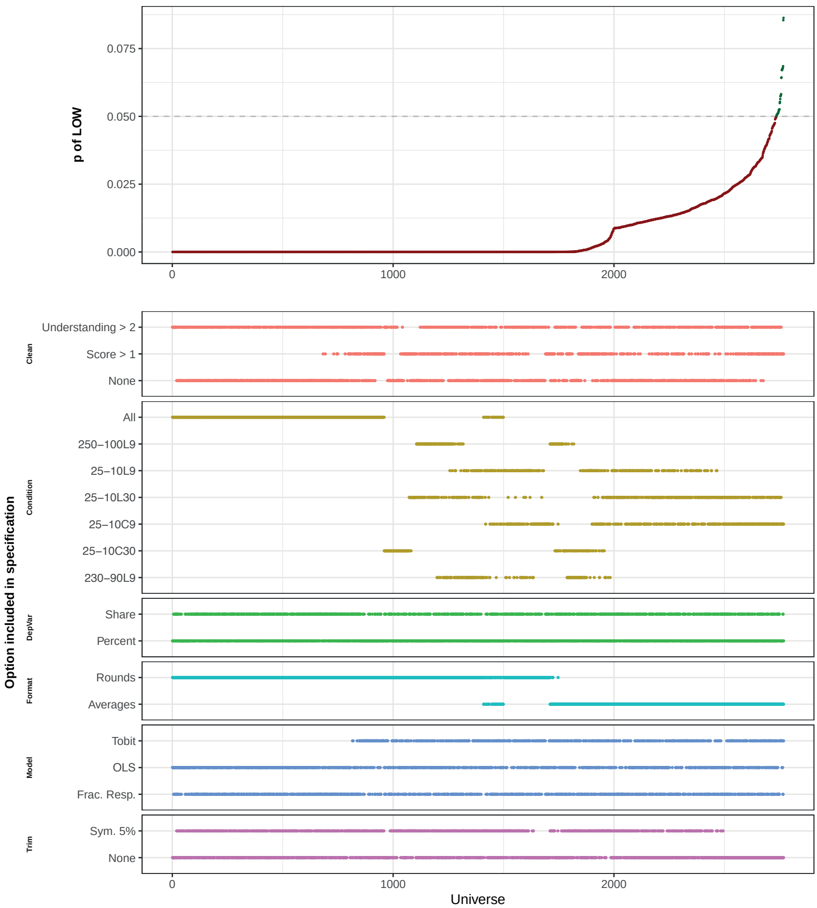

Figure 2.4: Multiverse analysis of main results. The upper panel illustrates the highest and lowest 5% of p-values of the coefficient LOW and a randomly drawn subset of 10% of p-values in between, out of the 13,824 analysis paths. The lower panel features the tested specification. For the purpose of illustration, in- or exclusion of each control variable has been left out in the lower panel.

To counter the challenges posed by analytical heterogeneity, multiverse analysis has emerged as a vital tool. Applying such analysis, researchers systematically explore all reasonable and non-redundant analytical choices for studying the same dataset and the same hypothesis, encompassing different combinations of statistical techniques, variables, and model specifications. By examining the results across these numerous scenarios, researchers can identify how sensitive their findings are to different analytical decisions. This is referred to as "specification curve analysis" (Simonsohn et al., 2020). It effectively limits the flexibility in model selection that might otherwise align closely with a researcher's preconceived hypotheses. The multiverse analysis approach not only bolsters the robustness and credibility of findings but also yields a more comprehensive understanding of the data.

This type of analysis necessitates a definition of multiple branches for both sample selection and model specification. Based on a thorough examination of the literature on MLA, we identified several key dimensions along which we varied our main analysis to ensure a comprehensive and unbiased analytical approach.[15] Next, we outline the various choices adopted in the literature linked to multiple dimensions, which we categorize as distinct branches within our multiverse analysis:

Cleaning: We considered (i) the full sample and (ii) applied exclusion criteria. To enhance data quality, we excluded participants demonstrating a lack of understanding of the task or poor response to straightforward questions about the lottery. In particular, we excluded participants with low self-stated understanding of the experiment ("Did not understand at all" or "I had quite some difficulties") and those who answered two out of three simple test questions incorrectly.[16]

Condition: We analyzed (i) pooled data from all conditions or (ii) tested MLA in each condition separately. In the pooled dataset, we also introduced a branch with dummy control variables for each condition (with 250-100L9 as the reference category).

Dependent Variable: The dependent variable *Investment in the risky asset* was (i) expressed as a portion (between 0 and 1) and (ii) as a percentage (between 0% and 100%) of the endowment. Absolute investment levels were not considered since these differed across conditions for linear versus compound return calculation as well as short versus long investment horizons.

15 Table 5.8 provides an overview of the different analytical paths in the related MLA studies adopting the Gneezy and Potters (1997) paradigm.

16 The associated understanding and test questions are displayed in the instructions on the OSF repository.

Model: We utilized (i) the fractional response regression model when the investment was expressed in shares. Both (ii) Tobit and (iii) OLS regressions were applied for the percentage dependent variable format.

Data Format: We examined (i) individual investments averaged across all periods as well as (ii) panel (period-level) data with nine or thirty observations per participant. In panel data analyses, we additionally control for the period number.

Trimming: We considered (i) no trimming procedure and (ii) a symmetric cutoff below the 5^{th} and above the 95^{th} percentile of the individual time taken to complete the experiment.

Control Variables: All possible combinations of our control variables FEMALE, INVESTOR, RISKTOLERANCE, STAT.KNOWLEDGE, and INNSBRUCK, as well as a version without any control variables, were included in the analysis.

All combinations of these choices yielded a total of 13,824 specifications. To validate the robustness of our results to variations in analytical approaches, we expected at least 95% of all "LOW" coefficients to be statistically significant at the 5% level. Figure 2.4 displays the highest and lowest 5% of p-values among all applied analysis paths as well as an additional 10% of p-values randomly sampled from the remaining set. The upper panel demonstrates that all p-values fall beneath 0.08, encompassing a variety of different branch combinations, as portrayed in the lower panel. Specifically, our multiverse results indicated that in total, 13,793 specifications (99.78%) led to a statistically significant coefficient of LOW.[17] When we based our formal multiverse analysis of MLA on the median of all 13,824 p-values (Simonsohn et al., 2020), we found that increased risk-taking under low decision and feedback frequency (LOW) was highly statistically significant ($p < 0.001$). We thus conclude that behavior consistent with MLA withstands alterations to the sample composition and model specification within the realm of reasonable and non-redundant configurations informed by the existing MLA literature.

[17] At a significance level of 1%, the coefficient of LOW was significant in 95.47% of all cases. Figure 5.3 illustrates the cumulative distribution of p-values for the coefficient LOW.

2.3.4 Determinants of Myopic Loss Aversion

Finally, we addressed the question of which factors determine the magnitude of behavior consistent with MLA, which appeared to be attenuated in most conditions compared to condition 250-100L9. Differences in MLA across conditions can be a result of either higher risk-taking in the HIGH group, lower risk-taking in the LOW group, or both. In non-pre-registered analyses, we explored this further by comparing investment allocations in groups HIGH and LOW in each condition to the behavior of their counterparts in condition 250-100L9—analagous to the original design by Gneezy and Potters (1997). The left panel of Figure 2.5 depicts coefficient plots based on the applied fractional response regressions (see Table 2.2) with treatments HIGH or LOW in condition 250-100L9 as reference groups. Participants in HIGH invested significantly higher amounts in conditions 25-10L9, 25-10C9, and 230-90L9 compared to their counterparts in 250-100L9. Although not statistically significant, in the other two conditions, we observed the opposite pattern (see 25-10L30 and 25-10C30). Investment amounts by participants in group LOW were lower only in condition 25-10L30 but higher in conditions 25-10L9 and 25-10C9 compared to group LOW in condition 250-100L9. Visible in the right panel of Figure 2.5, when benchmarked against the baseline setting by Gneezy and Potters (1997), the difference-in-difference MLA effect between conditions tends to be negative across all but two cases. However, these attenuations of MLA did not reach statistical significance, indicated by the 95% confidence intervals. Thus, our findings suggest that MLA was not statistically significantly less pronounced in settings different from the traditional Gneezy and Potters (1997) experiment. Given the inherent complexity in reliably detecting interaction effects, which typically necessitates a considerably larger sample size compared to detecting equivalent non-interaction effects, it is important to acknowledge that our study may lack sufficient power for small-to-medium difference-in-difference effects, despite our comparatively large sample sizes. Thus, in Figure 2.5 we also depict the results of equivalence tests based on the two one-sided tests (TOST) approach. This procedure provides a nuanced statistical method for establishing similarity of conditions by testing for equivalence with the null hypothesis. For our paper, we adopted a methodological approach that leverages coefficient plots of the difference-in-difference effects with 90% confidence intervals. Specifically, we used these plots to graphically indicate the effects we can rule out with high confidence—that is, any difference-in-difference effect sizes that fall outside the 90% confidence bounds of the effects can be considered statistically implausible based on our data. Across all conditions, we could confidently rule out differences in behavior consistent with MLA to our Gneezy and Potters (1997) replication exceeding a standardized magnitude of approximately $d = 0.25$. However, we cannot confidently reject even smaller, possibly still economically significant, variations in MLA across conditions.

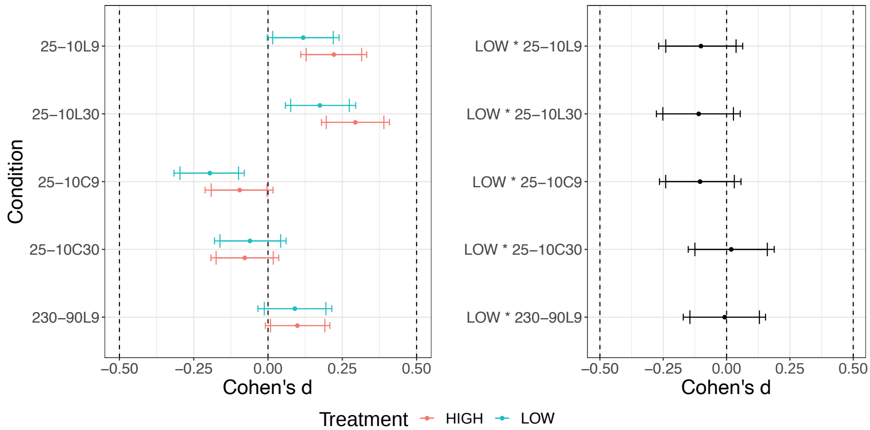

Figure 2.5: Forest plots of fractional response regression coefficients. Left panel: Condition effects separately in the HIGH and LOW treatments with the 250-100L9 condition as the reference category for both. Right panel: Difference-in-difference MLA effect in the full sample with 250-100L9 as the reference category. Bandwidths indicate 90% and 95% confidence intervals of estimated coefficients. The corresponding regression results are displayed in Table 5.9 in the Appendix.

2.4 Discussion

While previous studies have questioned the robustness of myopic loss aversion (MLA) in investment settings closer to reality, they often fell short in statistical power and in systematically exploring the underlying mechanisms that could mitigate behavior consistent with MLA. To bridge this gap, our highly statistically powered study enabled a detailed examination of factors potentially influencing MLA. Contrary to some earlier studies, our research revealed that MLA remains prevalent under more realistic rates of return, compounding, and longer investment horizons.

Introducing rates of return resembling those of annual investment return distributions more closely did not mitigate MLA behavior with or without return compounding. This finding diverges from Beshears et al. (2017) who adopted identical rates of return and return compounding simultaneously. One plausible explanation may be the difference in sample sizes, suggesting that with our sample we were able to capture smaller-sized MLA effects with higher likelihood. In their main study, conducted over the course of a year and involving high stakes, counteracting effects among the four different intervention mechanisms may have further contributed to the absence of support for MLA-consistent behavior. Our findings regarding the robustness of MLA within the framework of Gneezy and Potters (1997), resonate with other MLA research that incorporated realistic rates of return. Thaler et al. (1997) based experimental risky asset returns on value-weighted stock index returns. They found marked increases in risk-taking when participants made decisions over longer horizons. Benartzi and Thaler (1999) demonstrated increased risk-taking of pension plan participants when historical distributions of 30-year stock fund returns were displayed compared to when annual returns were displayed.

Theoretically, return compounding in our setting may shift individuals' focus to final investment outcomes after nine or thirty periods, potentially mitigating the effects of high evaluation and decision frequency. Klos (2013)'s findings, in which MLA tendencies were significantly reduced after eliciting participants' total lottery return expectations, seem to support this hypothesis. Similarly, in Zeisberger, Langer, and Weber (2012), MLA behavior was slightly attenuated when returns were compound. However, under return compounding, MLA persisted in our study, consistent with T. Langer and Weber (2008). Cognitive limitations in individuals' ability to envision long-term aggregates of a geometric series may limit any effect of a focus on final investment outcomes (Stango & Zinman, 2009; Enke, Graeber, & Oprea, 2023). In 25-10C30, expected return aggregation is particularly challenging in LOW compared to HIGH due to the increased investment horizon.

Our analysis also suggested overall lower levels of risk-taking in both HIGH and LOW (see Figure 2.3) under compounding compared to linear return scenarios. The relatively more cautious investment approach in compound return settings might be attributed to the singular initial endowment. Since relative risk—risky asset investment relative to overall wealth—decreases in linear return conditions for later periods but remains the same in compound return conditions (100%), participants in the former might increase their risky asset allocations throughout the experiment more than participants in the latter (Clayton A Looney & Hardin, 2020).

Finally, our results revealed that MLA is resilient to variations in the investment horizon. Longer planning horizons are typically associated with increased investment risk-taking (see, e.g., Anderson & Settle, 1996; Dierkes et al., 2010). In our experiment, additional periods allowed participants to experience the long-term dynamics of the risky asset, enabling better understanding of the underlying return distribution. It was unclear, however, whether this affects participants in HIGH or LOW differently. We did not observe significant differences in MLA behavior for longer investment horizons. Instead, risk-taking seemed to have increased almost proportionally in HIGH and LOW compared to the corresponding conditions with 9 periods (see Figure 2.3. Following the relative risk argument by Clayton A Looney and Hardin (2020), it seems conceivable that risk-taking over longer horizons increases further in linear return conditions, but it does not explain the similar increases in risk-taking in HIGH and LOW over time in the compound return conditions (see Figure 5.2). Instead, such development could potentially be explained by wealth effects.

Our findings imply considerable challenges in designing and communicating the risks of financial assets. Today, individual tendencies to make short-sighted decisions are being reinforced by technological developments around the rapid transmission of information and an overload of stimuli due to the use of technology (see, e.g., Kalda et al., 2021). This is particularly pertinent in decisions regarding the accumulation of retirement or other forms of long-term savings. Management policies fostering broad bracketing of investment outcomes, such as extending minimum return horizon disclosure, as demonstrated by Shaton (2017), or aggregating returns, could help mitigate the negative consequences of myopic financial decision-making. By reducing the focus on short-term fluctuations, investors can be better positioned to make decisions aligned with their long-term financial goals. For mitigating MLA, advanced technological solutions, including software programs, can play a crucial role (Clayton A Looney & Andrew, 2009). Such programs can be designed to dynamically inform investors about risky assets and the long-term outcomes of their investments. By highlighting the consequences of short-term market reactions on long term financial outcomes, these tools can encourage a focus on long-term financial strategies, effectively guiding investors away from reactive decision-making (see, e.g., Kaufmann, Weber, & Haisley, 2013; Hueber & Schwaiger, 2022). Additionally, educational initiatives aimed at increasing financial literacy can play a pivotal role. They can emphasize the importance of long-term planning and the potential pitfalls of reactive decision-making based on short-term market movements. Furthermore, organizational and regulatory frameworks may be structured to incentivize long-term investments for clients. This can be achieved through measures such as an offering of tax benefits for longer holding periods, creating tiered investment products to encourage clients to maintain investments over longer durations for greater benefits, or implementing loyalty bonuses for long-term investments (in a similar fashion as proposed by Bolton & Samama, 2013), which might further reward and motivate sustained investment behavior. Such measures would not only mitigate the impact of myopia on individual investors but also contribute to greater stability in financial markets (Davies, Haldane, Nielsen, & Pezzini, 2014).

2.5 Conclusion

Following the influential work by Benartzi and Thaler (1995) and Gneezy and Potters (1997), the academic community has investigated the applicability of the theory of myopic loss aversion (MLA) across diverse settings. Previous research has extensively discussed the real-world implications of MLA and its importance has been mentioned in many popular media outlets and investing websites. For example, a search within the News on the Web corpus yields 47 entries related to the concept of myopic loss aversion. In contrast, other widely recognized behavioral concepts such as regret aversion yield a comparatively smaller number of results (NOW Corpus, 2024). Recently, however, as the focus on replicability (Camerer et al., 2018; C. Huber et al., 2023) and reproducibility (Menkveld et al., forthcoming) of economic experiments has intensified, there has been a growing discourse on the robustness and generalizability of MLA, notably propelled by the contribution of Beshears et al. (2017)'s work, which suggested that evidence for MLA could be confined to a narrow range of experimental designs. Prior studies attempting to modify experimental design features in this context often encountered challenges related to statistical power or lacked a refined design to clearly dissect the factors influencing MLA-compliant behavior. This left a void in our understanding of MLA's robustness and drivers.

Given both the number of studies and the mentioned practical consequences of MLA, our research endeavored to fill this gap by rigorously examining the resilience of MLA to more conventional investment scenarios. We tackled this by isolating the effects of more realistic rates of return, commonly used investment procedures featuring return compounding, and a longer, more representative investment duration in the established Gneezy and Potters (1997) experimental design across six between-subject conditions. Our results consistently demonstrated the resilience of MLA behavior, even amidst these significant modifications to the original experiment by Gneezy and Potters (1997).

Specifically, MLA persisted in various modified conditions: when the possibility of a total loss was reduced while maintaining similar CPT valuations compared to the original (condition 230-90L9), and when return rates were scaled down to a fraction of the original rates under both compound returns with a dynamic endowment balance (condition 25-10C9) and under linear returns with a period-by-period endowment (condition 25-10L9). The down-scaling of returns did not mitigate MLA under extended investment horizons either, for both compound and linear returns (25-10L30 and 25-10C30). Remarkably, behavior consistent with MLA was most pronounced in condition 25-10C30, the scenario that most closely mirrored real-world investment settings. Here, the effect was close to the one reported in our Gneezy and Potters (1997) replication (condition 250-100L9). Our results were further validated by a multiverse analysis, which confirmed MLA's stability by effectively addressing concerns about analytical researcher degrees of freedom. While MLA appeared somewhat reduced in some conditions that deviated from the original Gneezy and Potters (1997) design, we found no evidence of interaction between these alterations and the magnitude of MLA and could confidently rule out standardized differences in MLA larger than $d = 0.25$ compared to the original design (condition 250-100L9). We conclude that the non-replication of MLA by Beshears et al. (2017) in their second aggregation experiment is likely the result of a false negative. The reason is that despite the substantial costs of the study in terms of monetary incentives, the high number of conditions limited statistical power in the pairwise comparisons.

Our study demonstrates that MLA constitutes a persistent behavioral pattern with significant implications for individual investment decisions, and extends well beyond the confines of the protocol in Gneezy and Potters (1997). This finding is consistent with studies utilizing field data (Larson et al., 2016) and those reevaluating MLA in less abstract lab-in-the-field environments (Iqbal et al., 2021). Considering the demonstrated prevalence of MLA, there is a pressing need for measures that either reduce the frequency of portfolio evaluations or mitigate individuals' sensitivity to frequent assessments, especially in areas requiring long-term consideration, such as retirement planning, healthcare, and environmental stewardship. Techniques such as experience sampling of historical returns (Kaufmann et al., 2013; Hueber & Schwaiger, 2022) and comprehensive performance disclosure (Gerhard et al., 2017) have been suggested. Despite these promising strategies, many platforms currently continue to emphasize short-term perspectives (Borsboom, Janssen, Strucks, & Zeisberger, 2022).

While our study contributes important insights, it also opens new paths for future examination. Our analysis, focusing on modifications to return rates, investment procedures, and time horizons, did not reveal significant differences in MLA-compliant behaviors. We cannot rule out the possibility of very small-sized effects but they are likely less significant economically. Thus, any real-world impact of our alterations, either applied individually or jointly, is likely limited. Future research could investigate whether other variables, such as outcome probabilities of risky assets (see, e.g., Schwaiger & Hueber, 2021), higher moments (see, e.g., Haisley, Mostafa, & Loewenstein, 2008), or longer times delays between investment decisions, play a systematic role in influencing MLA tendencies. Such studies are vital to allow us to fully comprehend the factors driving MLA. Equipped with high statistical power, our research establishes that MLA transcends the synthetic design choices characteristic of earlier path-dependent investigations, proving its applicability in more realistic settings. This furnishes compelling evidence of MLA's relevance, highlighting its potential for broader real-world applicability and impact across various domains.

Chapter 3

History Matters: How Short-Term Price Charts Hurt Investment Performance[1]

Abstract: When making investment decisions, people rely heavily on price charts displaying the past performance of an asset. Price charts can come with any time frame, which the provider might strategically choose. We analyze the impact of the time frame on retail investors' behavior, particularly trading activity and risk-taking, in a controlled experiment with 1,041 retail investors. We find that shorter time frames are associated with more trading activity, resulting in higher transaction fees and investor welfare losses. However, the time frame does not affect average risk-taking.

[1] The study is co-authored with C. Borsboom, D.-J. Janssen, and S. Zeisberger. The appendix is found in chapter 6. Experimental instructions and screenshots are included in the online version of the paper: https://www.sciencedirect.com/science/article/pii/S0378426621003022

3.1 Introduction

Price charts that display the price development of assets are ubiquitous when it comes to investments. Websites like Morningstar or Yahoo! Finance, brokerage platforms, and financial newspapers feature such charts prominently, often as the only graphical element (Glaser, Iliewa, & Weber, 2019; Nolte & Schneider, 2018), thereby attracting investor attention and potentially affecting investment behavior (Barberis, Mukherjee, & Wang, 2016; Goetzmann & Massa, 2002; Jürgen Huber, Kirchler, & Stöckl, 2016). Time frames in price charts have shifted from approximately five years on average in the pre-internet era (Barberis et al., 2016) to short-term defaults of one or a few days. This trend could be due to technological developments and "smart phone investing" (Kalda et al., 2021), or potentially due to strategic choices by brokers. Importantly, various different default time frames are used today, as illustrated in Figure 3.1.

Given the omnipresence of price charts and investors' focus on them and on past price history in general (J. Choi, Laibson, & Madrian, 2010; Glaser et al., 2019; Nolte & Schneider, 2018), the question arises as to whether the displayed time frame in these charts affects investor behavior. Examining the role of graphical time frame displays becomes particularly relevant in an era of online investment platforms, reduced intensity of human financial advice, increased use of cellphones (with limited screen space), and growing pressure to take responsibility for one's own investment decisions.[2] Although the prominence of price charts has increased markedly, very little is known about the impact of the chart time frame on investor trading activity and risk-taking behavior.

With regard to trading activity, we predict that long-term charts stimulate investor understanding of aggregated stock returns, enabling them to make informed decisions over longer investment horizons (Klos, 2013) and to trade less in response to intermediate price developments (Phan, Rieger, & Wang, 2018). In contrast, short time frames lead to more frequent and larger investor belief updating of long-run returns (Gerhard et al., 2017). Additionally, price updates in short-term charts are relatively more salient so that investors attach a larger decision weight to these.

[2] Despite the fact that investors can easily opt out of their assigned default time frame in practice, models of salience and limited attention predict that investors rarely do so (Bolino, Kacmar, Turnley, & Gilstrap, 2008; Bordalo, Gennaioli, & Shleifer, 2013; Hirshleifer & Teoh, 2003).

The visual strength (or extremeness) of these price updates is higher, whereas their actual weight, or credence (Bose, Cordes, Nolte, Schneider, & Camerer, 2022; Griffin & Tversky, 1992), remains identical across different time frames. In turn, this overweighting of new information results in investor overreaction by more frequently adjusting their allocation to risky assets. As a result, short-term stimuli can induce unnecessary overtrading of individual investors. Given trading fees and the typically poor forecasting skills of most investors, overtrading can subsequently lead to investor welfare losses.[3]

Figure 3.1: Price chart time frames in practice. This figure shows the default presented time frames on popular investment platforms, online brokers, and newspaper websites. The indicated horizon corresponds to the default presentation format for single stocks/ETFs.

With regard to risk-taking, literature on myopic loss aversion suggests that shorter time frames discourage investments in risky assets with a positive expected return, either for future potential returns (Benartzi & Thaler, 1999) or for past experienced returns (Gneezy & Potters, 1997), the latter experimental design being replicated multiple times such as in Bellemare et al. (2005), Fellner and Sutter (2009), and Haigh and List (2005). In these experimental studies, investors are informed about a single period (short time frame) or three periods combined (long

[3] Despite a recent development towards diminishing brokerage commission fees, trading costs are implicitly present in (wider) bid-ask spreads (Konana, Menon, & Balasubramanian, 2000).

time frame). Longer time frames are generally associated with higher risk-taking, but the existing studies remain rather simplistic. Despite that, they conclude that less information leads to increased risk-taking in general. Moreover, most studies on myopic loss aversion simultaneously investigate the aggregation of information and the flexibility in investing. For those studies that solely change the information aggregation, as in Benartzi and Thaler (1999), the difference is very noticeable. In a more realistic setting, however, Beshears et al. (2017) are not able to replicate these laboratory experiments findings on myopic loss aversion. They find that the effect of historical return aggregation on equity allocations does not interact with a variable measuring how prone to loss aversion and mental accounting a trader is. Regarding past performance reporting of historical cumulative returns, Shaton (2017) examines a regulatory change for pension funds in Israel. Her results indicate that individual investment propensity increases significantly when a longer minimum reporting time frame is mandated. In this study, we acknowledge the fact that price charts — in contrast to (cumulative or annualized) return charts — do not necessarily aggregate information, but present shorter or longer time frames, which could potentially also induce myopia.

In summary, although previous research on the influence of the time frame of past price information on risk-taking exists, it demonstrates inconclusive findings outside the classical experimental design of Gneezy and Potters (1997), and has hitherto not focused on the role of ubiquitous price charts. The only exception is Diacon and Hasseldine (2007), but they analyze only two sets of static past price charts in a questionnaire. They find no influence of the chart time frame on investors' perceptions of risk and return in this specific setting. Given the thus very limited body of research regarding the effect of the displayed price chart time frame on investor behavior, we aim to address this part of our research question in a much more holistic way. Although our study does not directly address myopic loss aversion in the same way as previous studies, we expect that individuals' myopia induced by shorter time frames influences decision-making in our context.

We address our research questions by conducting an incentivized online experiment in which actual investors make periodic investment decisions while presented with short or long time frames in price charts. While a lot of "real" data are available, using an experiment with simulated price charts allows us to derive results independent of particular price patterns and current market situations.[4] It also gives us control over the chart and asset price process, and we avoid potential problems of identification and investor self-selection. Long-term price trends are hardly controllable with market data and can go in a particular direction, biasing the results. Hence, our research question is ideal for a controlled experimental setting. In order to accommodate our research questions regarding both risk-taking and trading intensity, we make use of dynamic price updates to facilitate repeated decision-making. Specifically, in our experimental setting, participants decide how much of their current wealth to invest in a risky asset that follows a well-communicated, easy-to-understand return process with independent and identically distributed (i.i.d.) returns. After an initial allocation decision, trading is subject to a transaction fee. We contrast a chart displaying only the last period with a 25-period counterpart in a between-subjects design to answer our research questions. In addition, we have introduced a treatment where both charts are displayed to rule out effects stemming from heterogeneous amounts of information across our experimental conditions.

Our results indicate that investors exhibit significantly higher trading volume if they view short-term instead of long-term price charts. Consequently, they pay substantially higher trading fees which results in lower average net returns. In our setting, investors in the short chart frame pay approximately 50% higher transaction fees. These higher average trading costs for investors lead to a significant underperformance compared to a passive investment strategy. Moreover, overtrading persists even if investors are presented with both short- and long-term price charts jointly, suggesting that short time frames dominate behavior. Risk-taking does not cause these differences in trading activity: in contrast to trading volume, we do not find variations in risk-taking when comparing short and long time frames. Numerous studies, beginning with Gneezy et al. (2003) and Fellner and Sutter (2009), have speculated about the real-world consequences of myopic loss aversion and presenting longer-term or aggregated information. Beshears et al. (2017) and Klos (2013) demonstrate some limitations of these effects in related settings. Similar myopic

4 Distinct price path patterns are influential drivers of risk perception, return beliefs and consequently investment decisions (Borsboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018).

behavior might be present for price charts with different display horizons. Yet, we do not detect an influence of the time horizon in price charts on risk-taking behavior, in line with the conclusion of Diacon and Hasseldine (2007).

Our findings are relevant from both a theoretical and practical perspective. We contribute to the current literature by identifying that individuals trade more when presented with short-term information, even if there is a transaction fee in place that should discourage excessive trading. Moreover, we contribute to the theoretical discussion on myopia in different settings. By focusing on the presentation form that is most frequently used in finance, our findings indicate that myopic loss aversion does not play a role in investors' average risk-taking in our setting. However, we recognize that in most studies on myopic loss aversion, myopia was induced by strong restrictions such as limiting the investment flexibility and/or information provision frequency. From a practical perspective, our findings have important implications for financial risk communication, mainly when there is a mismatch between investors' actual and commonly depicted time frames. For instance, regulators could consider requiring minimum default time frames to stimulate less myopia-driven financial decision-making when it comes to essential retirement savings decisions. Short-term presentation formats likely induce considerably more trading. With the substantial evidence on very limited return predictability, this will ultimately reduce the net trading success of many investors. Trading platforms might exploit these findings to induce extra trading, explaining why there has been a shift towards short-term (daily) price charts on many platforms.

3.2 Experimental design

3.2.1 General setup

Investors participate in an investment task consisting of 25 periods. As opposed to a static setting, the dynamic nature of our experiment enables us to mimic real-world contexts and investigate how investors' risk-taking and trading behavior evolve across time. Participants receive (1) extensive information on the underlying return generation process of a risky share and (2) a chart depicting the price development in each period. They then periodically decide how much of their endowment to invest in the risky share, while the remainder is held in cash. In a between-subjects design, we introduce three treatments that distinguish whether subjects receive short- or long-term historical price information (or both). In SHORT, investors view price developments over the last period only, whereas in LONG they see price charts covering the last 25 periods. Investors in COMBINED face both the one-period and the 25-periods price charts. The time frames are chosen to represent both the minimum (one period) and maximum (25 periods) investment period in our experimental setting.

3.2.2 Returns and price chart design

The price charts presented to investors depict the price development of a risky share. In each period, the risky share has a probability of 60% of increasing by either 1%, 3% or 5% (with equal probability) and a 40% probability of decreasing by the same returns[5]. The returns are independent of each other; hence, there is no serial return correlation. By choosing the same absolute returns and similar corresponding probabilities, we reduce the potential effect of return skewness visualized in long-term charts on risk-taking, which allows us to consider the effect of the displayed time frame in isolation. The asset has an expected return of 0.6% per period and 16.13% if held for 25 investment periods. Given the positive expected return of the risky share, approximately 78% of all the price charts initially displayed in LONG contain a positive trend on average, while this is the case for 60% of the price charts in SHORT. Our instructions descriptively and graphically communicate the return process to our participants (we reiterate this in a summary), and we test the participants' comprehension with two questions. Moreover, we display the return process next to the price chart in each single investment period. As a result, all investors receive

[5] We choose these parameters independently of actual market data, to rule out any effects induced by specific time periods. This return process leads to realistically looking price charts that contain only limited skewness, but display an upward-trend in most long-term charts. Our return process does not resemble the median real-life stock which has an expected return of approximately 0% on the daily and monthly level. The first to last price skewness amounts to -0.27 in SHORT and 0.41 in LONG, which would lead to a preference to invest riskily in LONG based on typically found investor preferences.

identical information on the return generating process of the risky share in the instructions and during the investment phase.

The use of a return-generating process with i.i.d. returns offers several advantages over ambiguous future price developments. Subjects have complete information and could calculate that the risky share yields a positive expected return. Furthermore, providing transparency of possible price movements and their associated probabilities ensures a homogeneous amount of relevant information across all treatments and excludes beliefs about possible mean reversion or any other return dependence or predictability. Even though subjects in Long have access to more return realizations than those in Short, it does not provide them with additional information about future price developments.[6] However, it is possible that the information presentation in Long facilitates subjects' understanding of the return generating process, which could consequently lead to dissimilarities in subjects' identification of the positive expected return and decreased loss probability of the risky share after multiple investment periods. To eliminate any possible concerns arising from information contexts, we design the treatment Combined which displays both a short- and a long-term price chart.[7]

In our experimental set-up, a rational investor could neglect the graphical information completely, as past price developments do not affect future returns. Hence, the price charts do not add any meaningful information. However, previous research provides evidence that investors are influenced by graphical representations of past performance in their decision-making process (e.g. Glaser et al., 2019), even if these do not provide additional relevant information. Therefore, we expect that introducing short-term information, even though long-term information was present, is sufficient to provoke trading behavior in line with myopic loss aversion results in our setting. As the short-term price updates alter the price chart in Short entirely,

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6 In real-life investment decisions, distributions of future stock returns are unknown (ambiguous), leading to a variety of potentially confounding influences regarding subjective beliefs affecting investment behavior.

We can rule out the heterogeneity of subjective return beliefs driving our results with a clearly communicated return distribution.

7 We acknowledge that investors in real-life investment decisions face ambiguity. However, without a clearly defined and communicated return process in our experiment, participants in Long would receive more relevant information due to the higher number of periods compared to Short. This would lead to confounding effects, and it is why we opted for a known return distribution.

their visual salience (Jarvenpaa, 1990) is higher than for long-term charts, thereby attracting attention and influencing decisions more than their long-term counterparts, which is relevant for COMBINED.

By generating unique and independent price charts for each participant, any effect of the shape of particular paths (see e.g. Borsboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018) should average out over a sufficiently large number of investors. Furthermore, this process ensures that trends in the price charts are representative with respect to the return process on average, and it allows us to draw conclusions independent of particular price patterns which we would have with "real" data of actual investments.

Figure 3.2 illustrates an example of the price charts displayed in SHORT and LONG. The initial price of the risky share is $100 in period 0. The time frame ranges from period -1 to period 0 in SHORT and from period -24 to period 0 in LONG.[8] For all subsequent periods, the displayed time frame remains fixed at the respective number of periods. We state the last period's return in the top right.

The design of all price charts is identical, except for different time frames and scales, to avoid any design influences. The price scale is adjusted automatically to the price range in the chart. While scaling effects matter, as suggested by Jürgen Huber, Palan, and Zeisberger (2019), fixing the scales between treatments results in nearly non-visible movements in price charts in SHORT. Due to more display periods in LONG, price ranges are naturally wider in LONG while they are narrow in SHORT. As there are no platforms that fix scales across time frames, we refrain from testing the scaling influence separately in our study.

Given research on how price chart elements can affect investors' behavior (e.g. Duxbury & Summers, 2018; Jürgen Huber et al., 2019; Lawrence & O'Conner, 1992), we aim at harmonizing the design between treatments by applying an equal number of price ticks in all charts. The price charts in LONG contain one price tick for each displayed period, leading to a total of 25 price ticks. To avoid any influences arising from the regularity of price patterns or visual differences between LONG and SHORT, we standardize the number of price ticks across treatments by also using 25

8 Due to a small programming mistake, we display 24 instead of 25 past periods in LONG. We have no evidence that this affects our general findings, as also corroborated by our robustness check reported in Section 3.3.3.

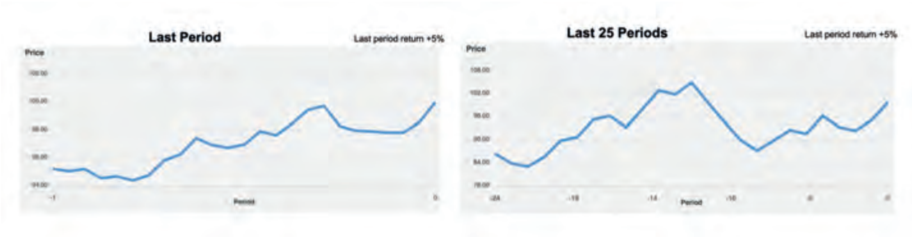

Figure 3.2: Example price charts in treatments Short and Long. This figure illustrates one example of the short- (left) and long-term (right) price charts used in the experiment. In Short, we solely display the last period's development, while the long-term price chart in Long shows the development of the last 25 periods. Both charts display the last period's return in the top right.

price ticks in Short. We do so by implementing 25 intra-period ticks. Creating realistic and irregular price charts is of importance, as Duxbury and Summers (2018) find that regular price patterns are perceived to be significantly less risky than their irregular counterparts, leading to distortions in the investment decision-making process and impeding our main comparison. We construct the intra-period ticks by drawing returns resembling the risk (volatility) characteristics in the main return period, scaled down to 25 intermediate steps. As a result, we harmonize the visual appearance of the charts and the volatility characteristics scale with the displayed period. To ensure understanding of these intermediate steps, the participants are clearly informed that prices contain intra-period fluctuations but that the one-period price change always follows the return lottery process.

Introducing intra-period returns in short-term price charts might raise concerns about additional noise presented to investors. To guarantee that the intra-period ticks do not lead to any confusion in Short, we conduct a robustness check with intra-period ticks in Long. We find that the use of intra-period ticks does not influence our main findings and hence cannot explain the difference in trading behavior we find across treatments. The robustness check is presented in subsection 3.3.3.

3.2.3 Experimental procedure

After consenting to the study's terms and conditions and passing an attention check similar to that in Oppenheimer, Meyvis, and Davidenko (2009), invited investors proceed to the instructions of the experiment. We provide all participants with detailed information on the experimental procedure and the return generating process. To enhance participants' understanding, we use graphical illustrations. Furthermore, we inform participants about the trading transaction fee of 2% of the total transaction amount.[9] Implementing this fee enables us to analyze whether overtrading is prevalent even when it leads to welfare losses. To avoid concerns arising from a possible misunderstanding of the transaction fee, we include a comprehension question to clarify and stress the role of the transaction fee. Additionally, we provide a reading example for the main decision task, including explanations of the numerical information and the price charts. We include multiple comprehension questions that participants have to answer correctly to continue participating in the study. We aim at a medium difficulty to prevent selection bias in our participant pool and to screen out participants with insufficient attention and understanding. If the five comprehension questions are not correctly answered jointly within five attempts, we exclude subjects from further participation. We thus guarantee that participants have a sufficient understanding of the task and that our results are not affected by inattention or misunderstanding. Furthermore, we gain evidence that our instructions were understood well, as subjects' understanding of the questions in the study was rated a 4.40 on average on a scale from 1 (did not understand at all) to 5 (understood very well).

The experiment consists of 25 investment periods. We endow investors with a hypothetical $10,000 in cash to invest in the risky share. Participants decide what proportion of wealth they invest in shares each period using a slider ranging from 0% to 100%. In order to avoid anchoring effects, there is no default position of the slider in the first period (instead, participants have to click on a specific percentage for the slider to appear). In subsequent periods, the slider position is set at the current allocation to the risky share. Therefore, leaving the slider unchanged results in no trading in the respective period. Given that experimental wealth is affected by changes in the asset price, the proportion allocated to shares also depends on price developments and could change even though individuals are not trading.[10] This

[9] The transaction fee is calculated based on the changes in allocation.

[10] For instance, if the risky share price increases from $100 to $101 in one period, and the subject invests 50% of her wealth in the initial period, the wealth allocation to the risky share increases to 50.25% without additional trading.

mechanism is explained in the instructions. Cash and shares are always transferred to the next period; after the last period, all shares are sold at the final share price without incurring trading fees. At the end of the investment task, we inform participants of the total pay-off they accumulated throughout the 25 investment periods. We pay a monetary incentive consisting of the final pay-off divided by 10,000 to every participant, on top of a fixed fee of $1.00. The participants are informed about the monetary incentive scheme in the introduction to the experiment. The average payment is $2.04. The experiment takes on average 17 minutes to complete. Hence, the average hourly wage amounts to $7.20.

After the trading task, we ask individuals to answer general questions, including a question on how confident they are about their decisions in the investment task, an adjusted cognitive reflection test (CRT) and financial literacy test, and two questions related to overconfidence and demographics.[11] We display the survey in the Online Appendix.

3.2.4 Participants

We recruit participants via the online platform CloudResearch[12] restricting participation to current US investors.[13] After exclusions due to inattention or failed comprehension tests, 1,041 participants enter our analyses, 665 for our main study and 376 for our robustness check.[14] Table 6.1 presents the investor characteristics in each of the treatments. We require all participants to be current investors and ask them about the years in which they have been investing. Our sample consists of individuals with extensive investment experience. The investors have on average more than 11 years of investing experience. 63.5% of all participants are male and are around 40 years old,

[11] Including the overconfidence measures in our regression analyses does not change any of our qualitative results.

[12] Participants recruited via CloudResearch (formerly called TurkPrime) show substantially higher answer quality compared to other participant pools such as MTurk itself, still maintaining the same socio-demographic variety (Litman, Robinson, & Abberbock, 2017; Cornil, Hardisty, & Bart, 2019).

[13] We specifically restrict our sample to investors, as Jürgen Huber et al. (2016) indicate that investment experience has a significant impact on investment decisions.

[14] In the main experiment, out of the 844 participants, 74 failed the attention check, and 105 did not pass the test questions; in the robustness check out of the 391 participants, 4 failed the attention check, and 11 did not pass the test questions. When running the robustness check, there was a new option available to block lower quality respondents, which we made use of. In addition, we screened out non-investors immediately.

consistent with the fact that most real-world investors are middle-aged men. Moreover, our subject sample is familiar with economic and financial concepts, as indicated by the average score of at least 4 out of 5 correctly answered financial literacy and numeracy questions. The (adapted) cognitive reflection questions were answered relatively well, with on average more than 2.5 (out of 4) correctly answered questions. Randomly allocating investors over the three treatments in a between-subjects design in our main experiment resulted in 214 subjects in LONG, 231 in SHORT, and 220 in COMBINED.[15]

3.3 Results

3.3.1 Trading behavior and performance

Trading behavior

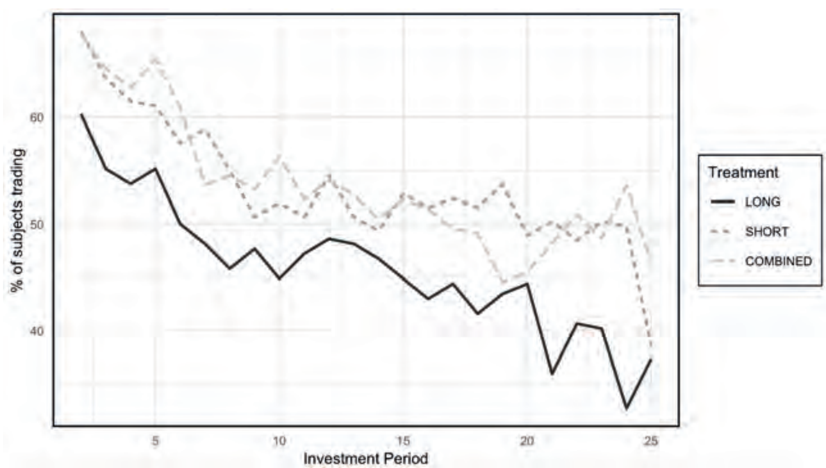

Figure 3.3: Trading activity. The figure illustrates the percentage of active traders during each investment period for each treatment. Trading is defined as a change in the allocation to the risky asset. We do not distinguish the amount traded in this graph; someone who traded at least some part of their wealth in risky shares was defined as an active trader.

[15] Using G* Power (Faul, Erdfelder, Buchner, & Lang, 2009), we conduct a power analysis indicating that a group sample size of 133 is required to detect a small-sized effect (two-tailed; f2 = 0.1) with parameters of Type I error rate $\alpha = 0.05$ and power $1 - \beta = 0.95$. We exceed this number in all of our analyses. Results from a post hoc power analysis show that analysis of our main treatments achieves a power of 0.996 (0.991 for our robustness check).

Figure 3.3 illustrates the percentage of participants changing their allocation to the risky asset in a given period across treatments, which we define as trading activity. Notably, the percentage of subjects trading in LONG is lower than in both SHORT and COMBINED across all investment periods. Furthermore, the overall percentage of traders decreases throughout the investment task by about one-third of its initial value. We hypothesize that this decrease in overall trading activity might result from experiencing the return process and adjusting the allocation to the final exposure to the risky share and learning about the welfare loss imposed by the transaction fee.

To quantify the graphical evidence, we perform a random-effects probit regression in Table 6.2. We find that short-term displays of price information increase a subject's propensity to trade on average by 38.2 percentage points. For COMBINED, we observe a similar result in model (1), which shows that adding a long-term presentation to a short-term one does not help investors reduce trading. However, controlling for other factors (as in models (2) and (3)) we cannot establish an equally statistically significant relationship. The coefficient for COMBINED is only significant at 10% ($p < 0.1$) and the effect size is about two-thirds of that between SHORT and LONG, but it provides some evidence that a result similar to SHORT might be obtained.

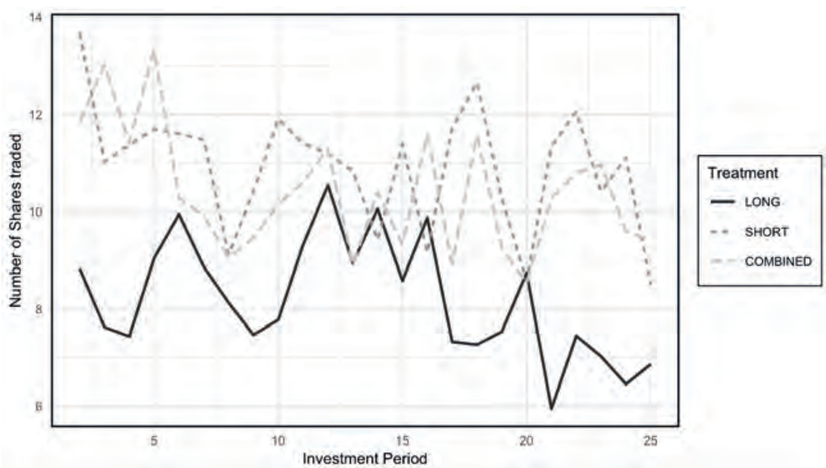

Figure 3.4: Trading volume. The figure shows the absolute change in the average number of shares held by participants in each of the three treatments in each investment period. Fractional share trading is allowed.

Figure 3.4 illustrates the development in mean trading volume, defined as the number of shares traded by participants during the investment task. The number of shares is calculated over the fraction of wealth (starting at $10,000) invested in the risky asset and its price. Hence one share bought corresponds to approximately 1% invested in the risky asset. Results are qualitatively the same for analyzing the number of shares versus the percentage of wealth invested in the risky asset. In the majority of the investment periods, trading volume is considerably lower in LONG compared to both COMBINED and SHORT. The difference is particularly pronounced at the beginning and the end of the investment task. Furthermore, COMBINED and SHORT exhibit higher variability in trading volume between periods.[16]

Descriptive statistics in Table 3.1 corroborate these first insights. The average number of shares traded per period is highest in SHORT with 10.93 shares on average traded per period, closely followed by COMBINED with 10.42 shares, which corresponds to approximately 10% of total wealth traded each period. Participants trade on average at least two shares (approximately 2% of total wealth) less in each investment period in LONG. At the end of 25 investment periods, this difference accumulates to almost 50 shares throughout the entire investment task. This difference is equivalent to almost 100% of the average holding in the risky asset.

Table 3.1: Trading volume. This tables displays the average number of shares traded in each of the 24 periods following the initial allocation decision. Standard deviation in parentheses.

Treatment	Shares traded each period
LONG	8.21 (15.98)
SHORT	10.93 (18.91)
COMBINED	10.42 (18.15)

Table 3.2 presents more detailed results on trading volume. We use a random-effects regression analysis with clustered standard errors on the subject level.[17] When

[16] Subjects have learned about the impact of the trading fee on profits over the course of the experiment. Wilcoxon signed-rank tests comparing the average numbers of shares traded at the beginning five versus the last five trading periods of the experiment show that trading volume is significantly lower at the end of the task ($z = 21.6$, effect size $\frac{z}{\sqrt{N}} = 0.167$). OLS regression results indicate that this proxy for learning however does not differ between treatments.

[17] We get qualitatively equal results when using OLS and when using individual wealth turnover (in %) instead of absolute numbers of traded shares as the dependent variable. To isolate our treatment effect from potentially different learning effects across treatments, we additionally run an OLS regression to analyze the first trading round only. Trading volume remains significantly higher in SHORT ($p = 0.002$) but not in COMBINED ($p = 0.059$).

controlling for both subject characteristics and period fixed-effects, the difference in trading volume between subjects in Long and Short is statistically significant ($p < 0.001$). Hence, subjects assigned to viewing one-period short-term price charts trade on average 2.884 more shares each period during the investment task compared to those who receive 25-period long-term price chart information. Furthermore, displaying a short-term price chart next to a long-term price chart as in Combined is sufficient to provoke higher trading volume. Subjects in Combined trade on average 2.025 more shares in each investment period compared to subjects with similar characteristics in Long ($p < 0.01$).

Result 1: Investor trading activity and volume are significantly higher when presented with short-term compared to long-term price charts. When both short-term and long-term price charts are displayed, trading volume is almost identical to displaying only short-term performance.

Trading performance

The higher trading volume in Short and Combined translates into increased transaction fees and in turn into substantially lower financial performance. Table 3.3 illustrates that investors' average profits in Short and Combined, respectively, are approximately 18.2% and 12.7% lower than in Long. Given the non-predictability in returns and similar risk-taking, this translates into higher fees. The difference in the amount of transaction fees is statistically significant between both Long and Combined (Mann-Whitney U test; $p = 0.02$), and Long and Short ($p = 0.02$).

Despite the random allocation of investors between treatments, higher profits in Long could potentially be explained by superior investment skills/luck, also given that the variance in final outcomes is relatively high after 25 periods. To account for this effect on profits, we run an OLS regression on trading profits at the end of the experiment by including risky share allocation, ending share price and total (cumulative) fees paid as covariates. Table 3.4 displays the results. Fees paid have a statistically significant negative effect on trading profits ($p = 0.000$) and lead to a non-significance of the treatment effects Short and Combined.

Table 3.2: Random-effects regression analysis of trading volume. The table shows the results of a random-effects regression on subject trading volume for periods 2–25. Short and Combined represent the different treatments, while Long acts as reference group. Investment Experience is measured in years. Risk Tolerance has scores ranging from 1 (low) to 10 (high). Financial Literacy is a score from 0 (low) to 5 (high). CRT Score has values ranging from 0 (low) to 4 (high). Female is 0 for males and 1 for females. Age is measured in years. Confidence was elicited after the investment decision on a scale from 1 (low) to 10 (high). Period-fixed effects account for learning effects during the experiment.

	(1) Trading volume	(2) Trading volume	(3) Trading volume
Short	2.722**	2.884***	2.884***
	(3.05)	(3.44)	(3.43)
Combined	2.206**	2.025**	2.025**
	(2.59)	(2.59)	(2.59)
Investment Experience		-0.124*	-0.124*
		(-2.32)	(-2.32)
Risk Tolerance		0.236	0.236
		(1.45)	(1.45)
Financial Literacy		-1.251***	-1.251***
		(-3.37)	(-3.37)
CRT Score		-1.048***	-1.048***
		(-3.33)	(-3.33)
Female		-2.071**	-2.071**
		(-2.75)	(-2.74)
Age		0.109*	0.109*
		(2.46)	(2.45)
Confidence		-0.965***	-0.965***
		(-7.46)	(-7.45)
Constant	8.210***	18.12***	18.23***
	(14.78)	(7.41)	(7.27)
Period-fixed effects	No	No	Yes
Observations	15960	15960	15960
R^2	0.00	0.04	0.05

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.3: Average trading profits and trading fees. This table displays the average profits and average total fees paid by treatment.

Treatment	Profit	Total fees
LONG	432.04 (1509.44)	427.23 (419.57)
SHORT	353.26 (1342.88)	571.72 (562.62)
COMBINED	377.14 (1438.21)	546.86 (519.40)

Standard deviation in parentheses.

Table 3.4: OLS regression of individual trading profits at the end of the experiment. The table shows the results of an OLS regression on individual trading profits at the end of the experiment. LONG acts as reference group. Cumulative Fees is the total amount of fees paid throughout the experiment. Allocation is measured as the proportion of wealth invested in risky shares (between 0 and 1). Ending Price refers to the price of the risky share at the end of the experiment.

	(1) Profit	(2) Profit	(3) Profit
SHORT	-78.78	88.92	105.1
	(-0.58)	(0.72)	(1.45)
COMBINED	-54.90	83.95	72.41
	(-0.39)	(0.64)	(0.92)
Cumulative Fees		-1.161***	-1.138***
		(-11.09)	(-17.16)
Allocation			8.896***
			(10.17)
Ending Price			52.01***
			(22.01)
Constant	432.0***	927.9***	-5722.4***
	(4.19)	(8.03)	(-21.06)
Observations	665	665	665
Adjusted R^2	-0.002	0.165	0.708

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In order to measure the actual welfare loss imposed by excessive trading, we investigate experimental profits more closely by identifying two hypothetical decision scenarios. In the first scenario, we assume that no trading occurred after the initial allocation decision in which fees were absent. Hence, only the initial decision matters, and skills do not influence concurrent developments. We calculate the profit in this alternative scenario as

$$Profit_{No-trading} = Allocation_1 * Wealth_1 * \frac{EndingPrice - FirstPrice}{FirstPrice} \quad (3.1)$$

where $Allocation_1$ is the selected allocation to the risky asset in the first investment period, $Wealth_1$ is the wealth endowed to participants at the start of the experiment, $EndingPrice$ is the asset's price after all periods, and $FirstPrice$ is the initial price of the asset. Under this scenario, subjects would have held the number of shares they initially purchased until the end of the investment task, with no intermediate trading and thus no trading fees.

Because this first scenario imposes strict assumptions of entirely no trading during the investment game, we create a second scenario with eased conditions to allow for trading targeted to a specific purpose. In the second scenario, we calculate profits if trading solely occurred to rebalance to the relative initial allocation. We define the only-rebalancing trading profit as

$$\begin{aligned} Profit_{Only-Rebalancing} = {} & Allocation_1 * Wealth_1 * \frac{EndingPrice - FirstPrice}{FirstPrice} \\ & - \sum_{n=2}^{25} (|Allocation_n - Allocation_1| * Wealth_n * Fee) \end{aligned} \quad (3.2)$$

Under this scenario, subjects only respond to allocation changes caused by price fluctuations. We use the initial decision as a baseline in both scenarios because subjects have had the necessary information to make an informed decision.[18]

Due to the high transaction fee, substantial adjustments in the asset allocation after the initial decision are expected to have a negative effect on profits. Table 3.5 corroborates this expectation. No-trading profits are on average higher by $292.06 in

18 To account for the role of subject learning about the return process throughout the experiment we conduct the same analyses using average instead of initial risky share allocation in Table 6.3. The within- and between-treatments results are qualitatively similar.

Long, \$490.54 in Short and \$460.47 in Combined, while the only-rebalancing profits show an increase of \$257.88 in Long, \$457.74 in Short and \$422.66 in Combined. Figure 3.5 illustrates these substantial deviations in all three treatments.

The deviation of the actual trading strategies of our investors from a passive trading strategy is significantly more pronounced in both Short and Combined compared to Long ($p < 0.001$, Mann Whitney U test). In both passive strategies, random returns in Short are higher by chance compared to the other two treatments. Aggregate differences in initial allocations are insignificant and thus do not explain this substantial difference (see subsection 3.3.2). Hence, the results are even stronger when it comes to trading profits, as investors in Short have been relatively lucky. Overall, our scenario analyses illustrate a substantial deviation from passive trading behavior when short-term charts are displayed to investors, which ultimately impacts their financial performance adversely.

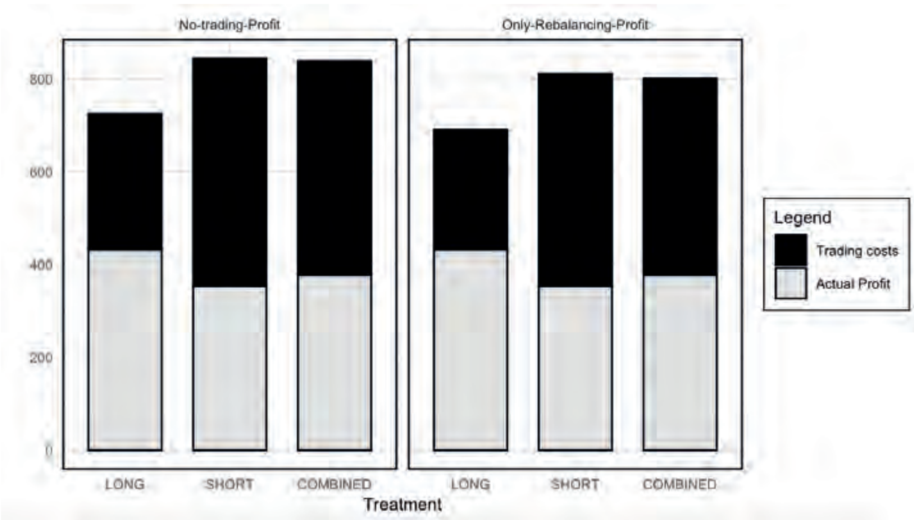

Figure 3.5: Profit scenarios. This figure shows how the profit would have developed if there had been no trading after the initial period (left panel), or if there had been only trading to rebalance to the initial allocation to the risky share (right panel). It illustrates the proportion of the actual profit compared to the trading costs that would have been saved when following one of these mentioned trading strategies. Figure 6.1 displays the percentage reduction in profits for each scenario based on trading costs.

Table 3.5: Alternative profit scenarios. This table displays the potentially achievable profits if there is no additional trading after the initial investment period or trading only occurs to rebalance the initial allocation.

Treatment	Profit	No trading profit	Only-Rebalancing profit
Long	432.04	724.10	689.82
Short	353.26	843.80	811.00
Combined	377.14	837.61	799.80

3.3.2 Risk-taking behavior

Figure 3.6 depicts the development of the subjects' risky asset shareholdings during the investment task. Overall, average allocations do not differ substantially between treatments upon visual inspection. The graphical evidence suggests that subjects in all treatments learn about the expected value of the risky share over the course of the experiment.[19]

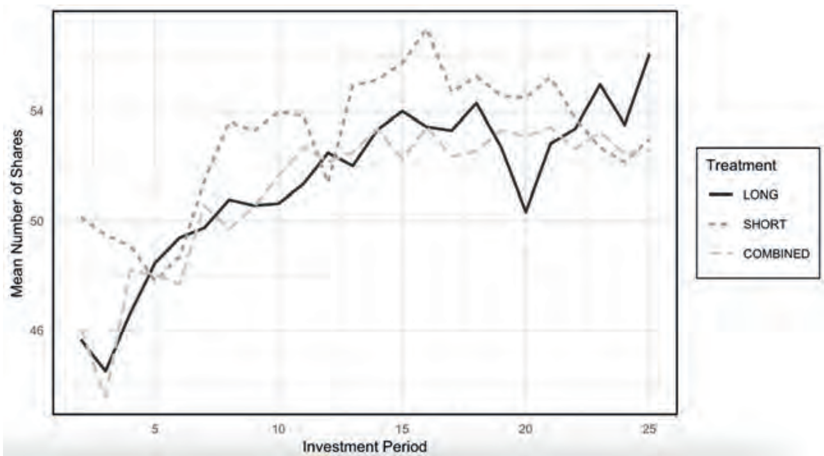

Figure 3.6: Average allocation (number of shares) to the risky share. This figure depicts the development of the mean number of shares investors hold of the risky share for each treatment.

[19] To examine this more closely we compare the average numbers of shares held at the beginning five versus the last five trading periods of the experiment. Shareholdings are significantly higher at the end of the task (Wilcoxon signed-rank test; $z = 32.5$, effect size $\frac{z}{\sqrt{N}} = 0.252$). OLS regression results show that our proxy for learning however does not differ between treatments.

In the initial investment period, the average number of shares held is 45.66 in LONG, 50.14 in SHORT and 46.07 in COMBINED. At the end of the experiment, risky shareholdings increase to 56.12 in LONG, 56.06 in SHORT, and 54.06 in COMBINED. These differences across treatments are not statistically significant.

The displayed time frame in price charts does not affect investors' risk-taking, as evidenced by Tobit regression results in Table 3.6.[20] Equivalence tests using the two one-sided t-tests procedure (TOST) show that the coefficients for SHORT and COMBINED are statistically equivalent to 0 ($p = 0.000$ for both) at $d_L = -0.01$ and $d_U = 0.01$. We therefore reject the presence of even a small-sized effect on risk-taking in longer-term price chart information contexts.

This finding contributes to current literature identifying that myopic loss aversion is not robust to more realistic information presentation formats (for example Beshears et al., 2017). We argue that even though some specific information contexts might provoke individual investors to exhibit behavior within the scope of myopic loss aversion, the concept is not universal to all presentation formats, such as the most prominently used price charts, where no direct return aggregation takes place but more or fewer past returns are displayed.

Result 2: The time frame of the price charts does not affect risky share allocation.

3.3.3 Chart layout and robustness check

Even though periodic price changes of the risky share follow the same process in all treatments, short-term charts in our experiment feature intra-period returns to harmonize the amount of price chart ticks across treatments and provide a more realistically looking short-term chart. A reading example preceding the investment task illustrates that period-to-period price movements always underlie the same return generating process. The smaller intermediate intra-period returns thus should not play

[20] We get qualitatively equal results when using OLS and when using individual percentage allocations of wealth instead of absolute numbers of shares as the dependent variable. For a straightforward comparison with earlier studies on myopic loss aversion, we also tested the same model for decisions solely made in the initial investment period where investment was not subject to fees. We find comparable results with Table 3.6.

Table 3.6: Tobit regression of risk-taking. The table shows the results of a Tobit regression model on the number of risky shares held. Short and Combined represent the different treatments, while Long acts as the reference group. Investment Experience is measured in years. Risk Tolerance has scores ranging from 1 (low) to 10 (high). Financial Literacy is a score from 0 (low) to 5 (high). CRT Score has values ranging from 0 (low) to 4 (high). Female is 0 for males and 1 for females. Age is measured in years. Confidence was elicited after the investment decision on a scale from 1 (low) to 10 (high). Period-fixed effects account for learning effects during the experiment.

	(1) Risky share holdings	(2) Risky share holdings	(3) Risky share holdings
Short	1.359	0.853	0.853
	(0.44)	(0.32)	(0.32)
Combined	-0.413	0.779	0.779
	(-0.14)	(0.28)	(0.28)
Investment Experience		0.339*	0.339*
		(2.18)	(2.18)
Risk Tolerance		2.316***	2.316***
		(4.38)	(4.38)
Financial Literacy		2.916**	2.914**
		(2.61)	(2.61)
CRT Score		3.449***	3.448***
		(3.60)	(3.60)
Female		-5.549*	-5.552*
		(-2.32)	(-2.32)
Age		-0.508***	-0.508***
		(-3.95)	(-3.95)
Confidence		2.921***	2.920***
		(7.14)	(7.14)
Constant	50.577***	16.645*	12.086
	(22.82)	(1.99)	(1.44)
Period-fixed effects	No	No	Yes
Observations	16625	16625	16625
Pseudo R^2	0.000	0.0175	0.018

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

a role in subjects' decisions in Short or Combined. Yet, due to their absence in Long, it could be argued that these additional price ticks confound our previous findings. For instance, it is possible that smaller intra-period returns could account for the increased trading volume in Short and Combined.

To rule out this potentially confounding factor, we design two additional treatments, IntraShort and IntraLong, both containing price charts with intra-period returns. Specifically, charts in the two treatments comprise 625 price ticks, i.e. 625 intermediate (smaller) returns over one period in IntraShort, and 25 intermediate returns over 25 periods in IntraLong. An example chart for each treatment is displayed in Figure 3.7. Importantly, the risky share price in both treatments underlies the same periodic return generating process as described in subsection 3.2.2 as well as the same sampling technique and random return shuffling procedure as for one-period charts in Short and Combined. Hence, the design of our robustness check only differs from our original experiment in the implementation of intra-period price changes in long-term charts, so that both IntraShort and IntraLong have the same layout and characteristics in numbers of ticks, keeping the return process the same.

Similar to the main experiment, we recruited active US retail investors as described above. After excluding those who failed the attention check and comprehension test, 376 investors entered our analysis, 188 in each of the two treatments IntraLong and IntraShort. All other design elements and procedures were kept identical. Investors in this robustness check did not participate in the main experiment.

Figure 3.7: Example price chart in IntraShort and IntraLong

The results for trading behavior and risk-taking are qualitatively the same as our previous findings. Notably, Table 6.4 illustrates that investors in IntraShort trade 3.208 more shares per period than those in IntraLong ($p < 0.001$) after controlling for other factors and potential subject- or period-effects. The effect size is similar to the 2.884 shares we observed in our main experiment. Overall, the results of our robustness check indicate that the existence of intra-period ticks in Short and Combined did not systematically influence investors' risk-taking or trading behavior.[21] As in our main experiment, risky share allocations are not significantly different across treatments (see Table 6.5).

3.4 Discussion

We identify shorter time frames in price charts to induce increased trading intensity and subsequently reduced trading performance among investors. Given the presence of a relatively high transaction fee of 2%, the effect is relatively strong. Our result is in line with Shaton (2017) who finds that aggregating past return information over longer time frames decreases trading volume significantly. Interestingly, the effect in our setting persists when investors see a combined presentation of both short- and long-term price charts. Despite being able to observe long-run price developments, investors in COMBINED are prone to engage in substantially more trading as opposed to investors in LONG. Compared to our study, however, Shaton (2017) uses a natural experiment with clearly defined time periods, while we employ periods without specifically defining the length of them. By not mentioning the length of periods, we remove potentially confounding effects when investors think in specific time frames. However, on the other hand, it also poses limitations on the generalizability of our results. This might be seen in contrast with the related results of Gerhard et al. (2017) who find differences in return belief updating only when investors are forced to stay in their assigned default time frame condition, but not when they are able to view multiple time frames of past performance. Gerhard et al. (2017) state that overtrading as a result of myopia can be explained by a larger magnitude of return belief updating when investors view short-term past performance information. We exclude this belief channel by applying a lottery-like return generating process. However, we acknowledge the variations in our design compared to Gerhard et al. (2017), as investors in our experiment observed both price

[21] In another robustness check, we apply a simple set-up for SHORT, in which we use no intra-period ticks, so that the chart in SHORT consists of only a straight line. Again, we find no significant differences between LONG and this additional treatment with regard to the allocation to the risky asset nor with regard to the trading volume. We find, however, a significant difference in trading volume between SHORT and this additional treatment. We hypothesize that the visual salience of a straight line is lower, thereby triggering no substantial trading reactions. We did not test a straight line setting in LONG. It seems that over-simplifying charts can affect trading behavior and leave this question for further research, see also Duxbury and Summers (2018).

sequences simultaneously, whereas participants in Gerhard et al. (2017) could switch between different time frames.

From a normative perspective, investment decisions in our experiment should be based on the future return distribution rather than past return realizations, as the latter does not predict future returns. Nevertheless, in line with other experimental studies, we find that investors focus excessively on salient information, and adjust their trading behavior (see e.g. Bose et al., 2022; Frydman & Wang, 2020; Nolte & Schneider, 2018), while disregarding information with higher weight or relevance to the trading decision (Griffin & Tversky, 1992). Our finding is particularly relevant under the presence of transaction fees, as investors are aware that trading is costly and can be detrimental to financial performance. In our experimental setting, investors in all treatments could have earned considerably higher profits by following (more) passive investment strategies, such as a no-trading or only-rebalancing approach. The resulting profit gap is most striking in SHORT, followed by COMBINED. We thus conclude that displaying short-term price charts to investors—even when displayed next to long-term charts—promotes excessive trading, which ultimately harms investment performance.

In contrast to other investment presentation contexts, our data do not support a link between chart time frames and investor risk-taking. Identifying risk-taking as being independent of time frames is in line with previous research by Beshears et al. (2017) and Klos (2013). We advocate for a re-evaluation of the effect of time frames in financial information on risk-taking in more realistic settings. We extend previous research to a prominent real-world setting in which dynamic investment behavior is examined in a controlled environment. We do not restrict investors' investment flexibility or their ability to observe their investment performance. Even though earlier studies have found that individuals exhibit myopia when presented with short-term compared to long-term information (for example Benartzi & Thaler, 1999), we do not replicate this effect on risk-taking of frequently used price charts in a setting with less salient information aggregation than previous studies. One possible explanation for these potentially conflicting results is that both short- and long-run price charts contain visible *intermediate past* fluctuations, while other presentation formats, such as return distributions, solely display *aggregate final future* returns. Since individuals are loss averse, observing intermediate fluctuations results in a lower propensity to invest in risky assets, even when the overall historical price trend is positive.

Similarly, in the experiment by Bradbury, Hens, and Zeisberger (2019), which compares showing final outcomes versus wealth paths, mean allocations to a risky asset are slightly lower when wealth paths are shown, compared to the situation when only the terminal wealth distribution is displayed. Similar to their set-up, the difference we observe might be due to individuals' time preferences, i.e., the fact that investors discount long-run future gains much more than potentially imminent losses (Thaler, 1981), decreasing investment attractiveness in long-horizon price chart settings, relative to short-horizon ones. Consequently, intermediate losses in long-term price charts suppress financial risk-taking, thereby yielding no significant differences between short- and long-term asset information. In other words, only showing *final* returns yields a sufficient myopia manipulation with the concerns of, Klos (2013). Also, literature on myopic loss aversion has tended to use quite extreme differences in return framing, e.g. one year vs. 30 years in (Benartzi & Thaler, 1999). In our set-up, investors can evaluate the longer-term development of the risky share in LONG compared to SHORT.

Another possible explanation for the insignificant differences in risk-taking between our treatments could be the dynamic price changes triggering the affective system. Findings in neuroscience suggest a dual-system explanation for risk-taking as the result of competition between affective processes and deliberative cognitive-control processes (Figner, Mackinlay, Wilkening, & Weber, 2009; E. U. Weber, 2010). More impulsive risk-taking behavior can result from the affective system interrupting the more deliberate analytical system. Figner et al. (2009) show that the affective system can be triggered by outcome feedback. In line with this result, Arnold, Pelster, and Subrahmanyam (2021) show that receiving push messages from a brokerage service leads to increased trading and risk-taking on the part of investors. Given these results, we argue that the outcome feedback in our experiment can also serve to interrupt the analytical system, thereby increasing risk-taking. With the salience of the price changes likely being higher in SHORT, this effect could have counteracted a potential myopia effect.

Additionally, in our setting, as in the real world, we present past returns rather than a future potential final return distribution such as in Benartzi and Thaler (1999) Figures 1 and 2, for example. While there is evidence that presenting future final (and thus aggregated) return distributions over long investment horizons or very restricted investment flexibility (Gneezy & Potters, 1997) increases risk-taking, we, in line with Beshears et al. (2017), find that this effect on risk-taking might not translate into more real-world investment settings. Furthermore, prior literature has shown that individuals' attention is substantially attracted by graphical elements in information sets, as their visual salience is high (Jarvenpaa, 1990). Varying graphical presentation formats of the same problem can lead to different revealed preferences (Sun, Li, Bonini, & Liu, 2016). Lastly, preliminary evidence identifies that "placebic" information—information that does not contain any valuable insights for decision-makers (E. J. Langer, Blank, & Chanowitz, 1978)—increases information illusion (Oehler, Horn, & Wendt, 2020).

Consistent with prior literature, we find several demographic factors related to trading behavior and risk-taking. Concerning trading volume, we find that higher financial literacy, higher cognitive abilities, being female, higher confidence, and, to some extent, being younger are associated with lower trading activity. Investment experience (Kaufmann et al., 2013), risk tolerance (Grable, Roszkowski, Joo, O'Neill, & Lytton, 2009), financial literacy (Fernandes, Lynch Jr, & Netemeyer, 2014), cognitive reflection skills (Frederick, 2005) and confidence in the investment decision (Krueger Jr & Dickson, 1994) positively influence risk-taking. Results show a negative relationship of being female (Charness & Gneezy, 2012) and older (due to previously having experienced low stock market returns (Malmendier & Nagel, 2011)) with the allocation towards the risky share.

3.5 Conclusion

Charts that depict the past price development of financial assets are ubiquitous in information sources such as online websites, brokers, or newspapers. They are an important factor influencing investment decisions. However, there is no standardized (default) chart time frame. Typically, displayed time frames range from one day to one year. Even though individual investors are theoretically able to deviate from the current display and view multiple price charts with different time frames, limited attention and cognitive restraints often prevent this. Furthermore, the default time frame has substantially decreased over the last two decades, focusing more on short-term (daily) performance. Brokers might strategically choose the time frame and could affect investor trading activity and risk-taking. Our study examines to what extent investor behavior is influenced by differences in time frames of the ubiquitous price charts. Our findings provide evidence that investors' trading volume is higher when faced with short-term as opposed to long-term price charts. This behavior leads to higher transaction fees and individual investor welfare losses. Such a finding is crucial, as investors prefer to view short-term performance (Fellner & Sutter, 2009) and are even willing to pay for it (Charness & Gneezy, 2010). However, we identify that displayed time frames do not affect financial risk-taking, contrary to what we expected from early literature on myopic loss aversion but in line with more recent findings (e.g. Beshears et al., 2017).

Our findings have several important implications for the practice of financial advice and risk communication. Firstly, when presented with shorter past performance time frames, individuals are inclined to trade at a higher volume. As a consequence, they pay more transaction fees leading to lower investor average net returns. Our study highlights the economic significance of this issue. Therefore, we argue that advisors, online brokers, and information providers should equip their clients with sufficiently extensive information horizons to prevent myopic trading behavior. Secondly, longer time frames possibly facilitate non-professional investors' understanding of the trend underlying a stock asset and simultaneously improve long-term visibility of volatility and downside risk. Regulators could set guidelines regarding the presentation of time frames and presentation formats in general. We recommend mandating minimum reporting time frames in price charts by following the example of Israeli regulators (Shaton, 2017) for highly consequential long-term investments such as retirement savings. As our analysis focuses on actual investors, we emphasize the importance of our results for practical applications.

Research on past performance time frames remains scarce, offering several ways to extend our research. In our experiment, we deliberately choose not to fix the scales across treatments in order to avoid artificially looking charts in Short where price developments are not visible anymore, taking away the very purpose of the chart itself. However, future research can address whether the change in trading propensity can be linked to the scaling or the visibility of a long-term positive trend in longer horizon charts. Given the evidence of a scaling effect on risk perception as in Jürgen Huber et al. (2019), one could expect different effects on trading behavior. Another route is to use real-life price charts of existing financial assets. Although this approach decreases control over the displayed price paths, motivating the choice for a controlled experimental setting, such an approach could increase external validity. Furthermore, we harmonized the number of price ticks between treatments to account for the irregularity of price patterns and their influence on investor risk perception. However, short-term price charts can contain more or fewer price ticks on real-life investment platforms than their long-term counterparts. Future research could concentrate on the effect of these differences on investor behavior.

Chapter 4

Why Do People (Not) Invest? The Role of Return and Risk Expectations[1]

Abstract: We document a substantial gap in the perception of risk of stock investments in the form of loss likelihoods. Online experiment participants, particularly non-investors, overestimate long-run historical loss likelihoods, influencing their experimental investment decisions. Return and volatility estimates do not predict such decisions. An information intervention bridges the perception gap in loss likelihoods, prompting changes in planned allocations. Our findings call for increased transparency on historical stock market risk in order to lower the barriers to stock market participation.

4.1 Introduction

In an era of ageing populations, concerns about the long-term financial welfare of households intensify. Stock investing as an alternative savings vehicle has thus far been neglected by many households due to certain barriers: high perceived

[1] The study is co-authored with S. Zeisberger. The appendix is found in chapter 6. Experimental instructions and screenshots are included in the online version of the paper: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4019188

participation costs, a lack of trust in financial markets, or individual aversion to asset price fluctuation risks (see Gomes, Haliassos, & Ramadorai, 2021, for a detailed overview). Another potential barrier that has not received much attention from scholars is an individual's *perception* of the risks and returns from stock investing. This study explores the importance of risk and return perceptions of stock investing for retail investors and non-investors. Based on recent insights on risk perception (Holzmeister et al., 2020; Zeisberger, 2022), we focus explicitly on the role of loss likelihood expectations as a proxy for perceived stock investing risks.

Traditionally, theoretical models of risky asset allocations have specified intrinsic risk tolerance as the major determinant of stock allocations. Standard portfolio theory asserts that households hold homogeneous, rational expectations (Muth, 1961) and invest at least some part of their wealth in stocks, even when they exhibit low levels of risk tolerance (Merton, 1969). In reality, however, stock market participation is limited and differences in individual investment expectations matter (Greenwood & Shleifer, 2014). In particular, recent work shows a significant impact of investor expectations on stock allocations (e.g., Ameriks, Kézdi, Lee, & Shapiro, 2020; Dominitz & Manski, 2007) and trading behavior (e.g., Hoffmann, Post, & Pennings, 2015; Merkle & Weber, 2014). By assuming that individuals adopt smooth log-normal subjective distributions of asset returns, such studies largely examine the expected risk of stock investing by eliciting the expected likelihood of pre-defined return intervals—e.g., individuals' perceived likelihood of a return between 0 and 10%—in order to calculate the implicit standard deviation σ of individual return expectations. While appealing to embed in existing theoretical models, such designs do not address the lack of predictive validity of models involving symmetric measures of risk. Studies at the extensive margin of stock investing namely tend to conclude economically small effects of return volatility, if any (e.g., Arrondel, Calvo Pardo, & Tas, 2014; Zimpelmann, 2021). Instead, experimental as well as archival studies have found evidence in favor of shortfall measures, while challenging the traditional role of return variance in financial decision making, both on individual level (Holzmeister et al., 2020; Sachse, Jungermann, & Belting, 2012; Veld & Veld-Merkoulova, 2008; Zeisberger, 2023) and in market settings (Jürgen Huber et al., 2019). This indicates that the perceived loss likelihood of investments, rather than both upside and downside dispersion in their perceived returns, drives individual decisions to invest in risky financial assets. Consequently, if households are not able to assess stock market risks (loss frequencies) adequately, they may refrain from investing, not because of their higher risk aversion, but because of a biased perception (i.e., systematic overestimation) of these downside risks. In this way, stock market participation, which has been considered a puzzle (Haliassos & Bertaut, 1995), may be explained by individual differences in (biased) risk perception.

We test our claims by conducting an online experiment with both retail investors and non-investors from the US. We elicit expectations about returns, loss likelihoods and return volatility of an S&P 500 stock index investment. Respondents provide their estimates about the past as well as their expectations for a future investment. Between subjects, we vary the time horizon of investment across two conditions: Respondents either state their expectations and investment choices over a one-year (short-term) or a twenty-year (long-term) horizon. A unique feature of our experimental design is that respondents assume the investment to take place at a random moment of time in the past and the future, which alleviates measurement bias that could potentially distort expectations towards the direction of current or recent economic events. After stating their expectations, respondents face an investment task involving the decision of how much of a hypothetical endowment to allocate to an S&P 500 investment. Our results reveal that expected loss likelihoods drive the propensity to invest in equity on the short and (to some extent) on the long run, while return and volatility expectations do not display such an effect. Risk perception is substantially higher and more biased for non-investors, particularly so for the long run. To close the perceptions gap between investors and non-investors, we introduce a simple information intervention displaying correct historical values next to respondent estimates about the past. Subsequently, we ask respondents to state their expectations for the future again and repeat the investment allocation task. We find that changes in allocations (post-information) for a short-term investment are explained by loss likelihood revisions of non-investors. Updates of long-term investment allocations are however associated with revisions in return expectations. These results show that simple interventions can stimulate more informed decision making especially for the non-investing population that particularly suffers from biased risk expectations. Thereby, such an intervention has the potential to effectively reduce the barriers to stock investing.

Related Literature. Our research bridges two different evolving trends in the literature. The first trend reevaluates traditional asset pricing models that posit a pervasive awareness of equity premia (Merton, 1969). An increasing number of studies models asset prices under the subjective heterogeneous expectations paradigm (Bao, Hommes, & Pei, 2021). Empirically, pessimistic expectations have been shown to explain the existence of high risk premia (Berkman, Jacobsen, & Lee, 2017). In particular, the evidence underscores the role of subjective returns (Giglio et al., 2021; Greenwood & Shleifer, 2014; Hurd, Van Rooij, & Winter, 2011) and experiences (Adam, Matveev, & Nagel, 2021; Malmendier & Nagel, 2011), but does not agree on the role of expected return volatility (see Arrondel et al., 2014; Zimpelmann, 2021). Moreover, a notable gap persists in understanding how long-term expectations are formed and translate into concrete behaviors. Drawing from survey data in the Health and Retirement Study, many models assume a myopic lens with short-term financial planning horizons of up to five years (e.g., Caliendo & Findley, 2013). Yet, especially when it comes to decisions with long-term consequences like saving for retirement and stock market participation, people may project a function of their short-term expectations to the more distant future, even if they struggle to do so. Breunig et al. (2021) for instance shows that households' return expectations are more optimistic on the long run, yet consistently below historical benchmarks. In line with their findings, we find that long-run risk perceptions are remarkably higher than implied by history, which is one of the reasons households refrain from stock investing.

The second trend pivots on how perceived risk is conceptualized. Following Roy (1952) and Slovic (1987), measures signalling the loss potential of an investment have gained increasing traction, particularly in recent years. Unser (2000) tests which lower partial moments risk measures capture the perceived risk of investments best. Among these, an investment's loss likelihood (with a reference point at 0% return) predicts risk perception most, whereas return variance (σ^2) fails to do so. In an international survey, Holzmeister et al. (2020) corroborate this finding in a sample of both professionals and laypersons, highlighting the widespread relevance of these findings. Additionally, Cao et al. (2023) discover that US stocks with higher loss likelihoods reflect a higher premium. Yet, a gap persists: Do perceived loss likelihoods shape investment expectations and subsequent behavior? While J. J. Choi and Robertson (2020) and Giglio et al. (2021) suggest that people's expectations of a rare stock market disaster sway subjective returns, conceptions of such a disaster may vary widely since there is no objective benchmark. Uniquely, we examine whether individual loss expectations align with objective benchmarks and, if misaligned, how any deviations affect investment behavior.

4.2 Hypothesis Development

Assume a decision maker with (Cumulative) Prospect Theory (CPT) preferences (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). For simplicity, we model the stock market as a risky asset with only two possible returns $R_L < 0$ and $R_G > 0$, associated with probabilities p_L and $p_G = 1 - p_L$, respectively. The decision maker invests in the stock market iff:

$$\pi(p_G) * R_G^\alpha - \lambda * \pi(p_L) * (-R_L)^\beta \geq R_f \tag{4.1}$$

where

$$\pi(p_G) = \frac{p_G^\gamma}{(p_G^\gamma + (1 - p_G)^\gamma)^{1/\gamma}}$$

and

$$\pi(p_L) = \frac{p_L^\delta}{(p_L^\delta + (1 - p_L)^\delta)^{1/\delta}}$$

α and β are the value function curvature parameters in the gain and loss domain, respectively, and $\lambda > 1$ indicates loss aversion. R_f is the risk-free interest rate. Depending on the calibration of CPT parameters, rational and homogeneous expectations of individuals would predict that either all households or none invest in the asset, since returns and their associated likelihoods are commonly known. Assuming that returns and likelihoods of a stock market asset are common knowledge, however, is unrealistic. Therefore, models have turned away from homogeneous rational toward heterogeneous subjective expectations. Hommes (2021) highlights the need of such models in light of the historical failure of rational expectations equilibria to explain empirical patterns. Elicited subjective return expectations typically differ from rational ones and explain real-world investment behavior, as various survey studies show. Dominitz and Manski (2007) is one of the first to relate pessimistic return expectations to equity market non-participation of households. In Dominitz and Manski (2011), the authors further characterize similar numbers of individuals adopting persistence versus mean-reversion beliefs, emphasizing the heterogeneity of subjective expectations. Importantly, different studies identify effects of risk and return expectations distinct from the effects of preference-based measures like risk tolerance (Ameriks et al., 2020; Hoffmann et al., 2015; Kézdi & Willis, 2009; Merkle & Weber, 2014). In this regard, Hoffmann et al. (2015) provides a unique step forward by examining not just expectations of return volatility, which underlie several elicitation challenges and therefore lack reliability (Drerup et al., 2017). Instead, the authors evaluate perceived stock market investing risk using Likert scale assessments, and find that these significantly affect investor risk-taking.

In our study, we examine individual risk perceptions more closely by eliciting quantitative loss likelihood expectations, an investment characteristic strongly associated with how risk is perceived (Holzmeister et al., 2020; Zeisberger, 2022). Even among lower partial moments risk metrics, an investment's loss probability explains risk perceptions best, for instance when individuals view asset return distributions (Zeisberger, 2023). It is thus conceivable that loss expectations play a substantial role for financial risk-taking. Recently, Giglio et al. (2021) found that people's perceived likelihood of a large drop in stock prices (rare disaster risk) predicts portfolio risk-taking better than their perceived variability of stock returns. As shown by Cao et al. (2023), higher historical loss probabilities of stocks generate subsequent excess returns, further supporting the relevance of loss probability in asset pricing. From a theoretical perspective, their results support the idea of safety-first utility models, focusing on decision evaluation through minimizing the likelihood of adverse outcomes (Roy, 1952). In line with this intuition, we predict that individual expectations of the loss likelihood of investments explain the propensity to invest in equity:

Hypothesis 1: Loss likelihood expectations are negatively related with investment propensity.

People's expectations about future stock performance vary widely, particularly in the way that past information is used to form expectations (Dominitz & Manski, 2011). Due to informational frictions, inattention, and cognitive limitations, each individual may have a different mental image of the stock market and historical loss likelihoods, in particular. For instance, some may have relatively accurate loss perceptions about stock market developments, whereas others may deviate strongly from the rational benchmark. In simple terms, such deviation can be represented by:

$$\tilde{p}_L = p_L + e \tag{4.2}$$

where $\tilde{p}_L$ is the subjective and p_L the objective (actual) loss likelihood. For a representative CPT decision maker, $\tilde{p}_L$ may be systematically biased upward ($e > 0$) or downward ($e < 0$). Results from surveys eliciting stock market expectations of index returns indicate that individuals are on average pessimistic about future gain likelihoods and returns (e.g., Arrondel et al., 2014). In line with previous research, we predict that $\tilde{p}_L > p_L$. By asking survey respondents about past loss likelihoods, it is possible to test whether estimates differ significantly from realized values.

Hypothesis 2a: On average, individuals overestimate the likelihood of a stock market loss: $\tilde{p}_L > p_L$.

4.2.1 Investment Horizon

Even when investors adopt long investment horizons, they tend to evaluate portfolio performance on the short term (Benartzi & Thaler, 1995). Such myopic perspective requires individuals to accurately aggregate expected short-term outcomes in order to gauge long-term ones. Empirical evidence shows that people struggle to do so, and highlights potential hurdles, including exponential growth bias (Stango & Zinman, 2009), planning fallacy (Buehler, Griffin, & Ross, 1994), cognitive uncertainty (Enke et al., 2023), and time perception (Bradford, Dolan, & Galizzi, 2019), among others. These issues point toward expectations and behavior that systematically differ over short and long time horizons, in contrast to earlier research on the irrelevance of investment horizons for portfolio decisions (Merton, 1969; Samuelson, 1963). Long-horizon investors with CPT preferences may for instance rely on short-term bond investment strategies rather than investing in stocks, although those are more attractive on the long run (Dierkes et al., 2010). A misperception of long-run returns or loss likelihoods may amplify this issue. In a representative sample of German households, Breunig et al. (2021) show that expected long-run stock returns are below the historical benchmark, even after accounting for people's tendency to neglect compounding effects. Similarly, individuals' perceptions of long-run stock market loss likelihoods of 20 years could be substantially biased upward, more so than over the short run of one year:

Hypothesis 2b: Individuals overestimate stock market loss likelihoods more for longer investment horizons: $\tilde{p}_L^{20} - p_L^{20} > \tilde{p}_L^1 - p_L^1$.

4.2.2 Belief Updating

Conventional models of adaptive expectations assume that individuals observe realized outcomes. Explicit historical loss likelihoods however are not readily accessible in commonly used investment information formats (price charts, key information documents, etc.) yet. In our experiment, treatment group participants can view historical investment information next to their own estimate, given horizon. Any belief revisions are exogenously caused by the information, ruling out alternative explanations like (rational) inattention in the acquisition of information. Fuster and Zafar (2023) model the posterior as a function of the prior's deviation from the rational, historical benchmark, which in our framework translates to:

$$\tilde{p}^t_{L,\text{post}}|_{X=1} = \alpha_0 + \theta \left(\tilde{p}^t_{L,\text{prior}} - p^t_L\right) + \epsilon \tag{4.3}$$

where $X = 1$ indicates treatment, α_0 is a constant and ϵ an independent and identically distributed (iid.) error. θ represents the perception gap coefficient, i.e., to what extent estimate errors influence posterior belief formation. Previous studies indicate the promising potential of such interventions in the personal finance domain, describing significant belief revisions and subsequent changes in behaviors. Hanspal, Weber, and Wohlfart (2021) shows that individuals get more optimistic (pessimistic) about their own future wealth when they are presented with shorter (longer) recovery duration of past crises in an experiment during the COVID-19 crisis. Notably, Laudenbach, Weber, and Wohlfart (2021) informs participants about the low serial correlation of stock returns and observes subsequently reduced tendencies of investors to exhibit biased mean reversion beliefs. The larger their perception gap, the more participants in their treatment group update their return beliefs. This may be due to the higher saliency of a larger deviation from the historical benchmark. For any investment horizon, we predict that a larger signed forecast error reduces posteriors.

Hypothesis 3: A positive (negative) loss likelihood bias reduces (increases) posterior loss likelihood beliefs: $\theta < 0$.

4.3 Experimental Design

In contrast to studies matching administrative investment holdings data with surveys (e.g., Giglio et al., 2021), we adopt an experimental approach to be able to study the link between expectations and investing for both investors and non-investors. The first stage of the survey resembles standard elicitation of risk and return expectations, while we go beyond other studies by refraining from a particular point in time. We measure participants' beliefs about both future and past development of a stock index investment for specific investment periods but flexible points in time. In the second stage, subjects receive information on actual past realizations next to their own corresponding estimates from the first stage and are subsequently asked to state their beliefs for future developments of a stock index investment again. We introduce two between-subjects conditions: Subjects either consider a one-year (short-term) index investment, or a twenty-year (long-term) investment. **??** contains screenshots of the experiment.

4.3.1 Elicitation of Risk and Return Expectations

In the introduction of the experiment, subjects are asked to assume a one-year (twenty-year) investment in the S&P 500 stock index. We choose this index due to its popularity, size and representativeness for the US economy. To ensure broad understanding among subjects of what constitutes a stock index investment, we provide explanations in the experimental instructions, and we include a mouse-over explanation during the decision task. Because estimates about stock market developments in the near past/future can bias participants' estimates towards recent economic events, we ask subjects to assume a random moment of time for investment in the last 40 years (1980–2020), and in the next 40 years (2022–2062). Unique to our setting, this allows subjects to think about the past and the future in a more abstract manner and improves the generalizability of our results.[2]

We measure respondents' return expectations by eliciting their expected annual return on a future or past stock index investment. One-year expected returns in the future, for instance, are elicited by asking the following question:

Assume an investment in the S&P 500 index at a random time period between 2022 and 2062. Please estimate: If you invest for one year in the future, what will have been the investment return?

After indicating their expected return, respondents also state their expected lowest and highest possible annual return from an index investment in the given time period (similar to Arrondel et al., 2014). This allows us to compute the perceived range of returns, our symmetric measure of expected stock market risk:

$$ReturnRange_i = HighestReturn_i - LowestReturn_i \tag{4.4}$$

Eliciting the perceived dispersion of returns in this way offers several advantages over conventional approaches computing the standard deviation from point estimates.

2 Laudenbach et al. (2021) use a somewhat similar approach but elicit serial correlation beliefs of past stock returns. Participants in their experiment were asked to think about situations in the past 50 years when the stock market return was within a certain interval.

Firstly, the questions are easy to understand and answer. Asking individuals about their estimated likelihood of different specific returns on the other hand is cognitively demanding and may not yield reliable results. Secondly, we do not assume that individual expectations are defined over (log-)normal subjective return distributions. In contrast to the majority of previous studies on stock market expectations, we adopt a simple and intuitive measure representing the classical definition of asset price risk.

Our symmetric perceived risk measure is contrasted with the expected loss likelihood, an asymmetric proxy of risk expectations. In particular, we ask subjects to indicate the likelihood of the investment resulting in a loss over the given time horizon (one or twenty years). Following Manski (2004), surveys have traditionally elicited gain probabilities. We intentionally deviate from this norm by asking subjects about their perceived *likelihood* of a *loss* out of 100 cases. Past research has shown that frequency presentations facilitate understanding and that probabilistic information may result in cognitive bias potentially leading to measurement bias (Kahneman, Slovic, Slovic, & Tversky, 1982). We ask for subjects' future one-year loss likelihood estimates in the following manner:

Assume an investment in the S&P 500 index at a random time period between 2022 and 2062. Please estimate: If you invest for one year in the future, how likely is it that the investment will have decreased in value?

Recent research has shown that shortfall measures like expected loss amount and likelihood are fundamental drivers of financial decisions (Unser, 2000; Zeisberger, 2022). We hypothesize that previous results on the importance of loss likelihoods extend to the stock market participation decision, in a way that a biased perception of such deters participation. Moreover, we expect the effect to be stronger than for symmetric measures that determine the overall dispersion, such as the range, variance or standard deviation, of individuals' subjective return distributions.

4.3.2 Information Provision

In the second stage of the experiment, all participants observe the actual historical average realizations next to their own expectations of those in the past. We present this information in numerical format in a table. Presenting these numbers directly next to each other makes it easy for participants to see to what extent their estimates approach the correct value, which allows for straightforward computation of estimation errors. The historical averages for one-year (twenty-year) investments are a loss likelihood of 29 out of 100 cases (0 out of 100 cases), an annual return of 10% (8%), a highest return of 53% (14%), and a lowest return of -45% (3%). Figure 4.1 illustrates an example of such a table in our twenty-year condition. For computation, we used daily adjusted closing prices of the S&P 500 between 1980 and 2020 to calculate monthly returns. On the basis of these monthly returns, we compute average terminal loss likelihoods as well as one-year and annualized twenty-year returns:

$$p_L^t = \frac{\sum_{m=1}^{M} R_{m,m+t*12} < 0}{M_t} \tag{4.5}$$

$$R_{annual}^t = \frac{\sum_{m=1}^{M} (1 + R_{m,m+t*12})^{1/t}}{M_t} \tag{4.6}$$

where $t \in \{1, 20\}$ represents the investment horizon in years and $m \in \{1, 2, \ldots, M\}$ is the month index. The information table is displayed on every page of the subsequent expectations and investment task. Such an exogenous information shock allows us to causally identify whether changes in risk and return expectations and subsequent allocations are triggered by their own error in estimating past stock market risk and return characteristics. We expect that non-investors in particular exhibit larger errors in their estimates and subsequently adjust their expectations and allocations more strongly.

	Your estimate	Historical average value (1980 - 2020)
Annual return	7%	8%
Lowest possible annual return	-4%	3%
Highest possible annual return	12%	14%
Likelihood of a loss	30 out of 100 cases	0 out of 100 cases

Figure 4.1: Information table example in twenty-year condition

4.3.3 Experimental Procedure

After reading the instructions and passing an attention check, participants provide their loss and return expectations for a past and future stock index investment in the first stage of the experiment. We randomize the order of past versus future as well as loss versus return expectations. However, once determined, the order is fixed throughout the entire experiment. For instance, if a subject faces past loss expectations questions first, then she will also start with stating her loss expectations first in the block of future expectations. For each question we provide a note explaining the elicited measure to ensure a broad understanding of these. Moreover, respondents state their expectations separately for each measure on a different page, with a timer that allows them to advance only after a minimum of ten seconds. After stating their past and future expectations, respondents indicate their overall confidence in those and face a hypothetical investment task. They answer how much of a \$10,000 endowment they would invest in an S&P 500 stock index investment, with the remainder being held in cash. In the second stage, the information table is displayed and explained. We ask respondents to indicate their expectations about a future index investment again while displaying the information table at the top of each page. Eventually, respondents face the hypothetical investment task again. Figure 4.2 graphically summarizes the procedure of the main part of the experiment. Subsequently, we ask subjects about their confidence in their estimates. Controlling for confidence allows us to disentangle the effect of risk expectations from the influence of individual perceived ambiguity of stock returns (Zimpelmann, 2021). At the end, subjects answer general questions concerning their understanding of financial and probability concepts, risk tolerance, optimism and demographic questions. In particular, we elicit risk tolerance in two different ways to control for different elicitation modes. Risk aversion is measured by subjects' choice for a hypothetical gamble versus a safe payment using the staircase multiple-choice-list elicitation procedure (Falk, Becker, Dohmen, Huffman, & Sunde, 2016), whereas financial risk willingness is based on own (subjective) assessment on a Likert scale ranging from 1 (I am not willing to take financial risks at all) to 10 (I am very willing to take financial risks). Investors additionally answer questions about their investment experience and their investment portfolio share of wealth, whereas non-investors complete questions regarding their agreement to reasons of non-participation in stock markets.

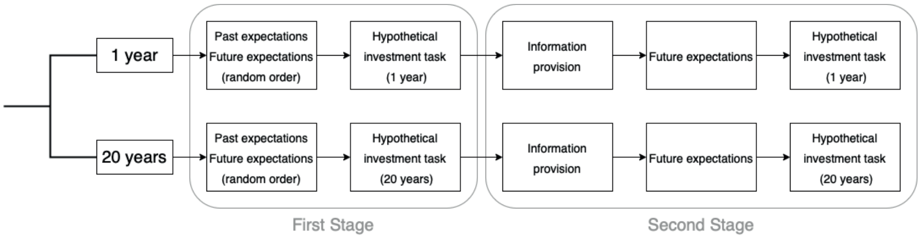

Figure 4.2: Procedure of the main part of the experiment

4.3.4 Sample

For the online experiment, we recruit a total of 793 US investors and non-investors via CloudResearch (Litman et al., 2017).[3] Respondents took on average 9.68 minutes to complete the survey, and they earned a fixed survey completion fee of $1.20, which amounts to an hourly wage of $7.44. We refrained from paying a variable monetary incentive because beliefs about the future with a long flexible time horizon cannot be adequately incentivized. Furthermore, Hackethal, Kirchler, Laudenbach, Razen, and Weber (2023) provide evidence that monetary incentives do not seem to influence these measures. We also ask for respondents' understanding of the survey. Stated

[3] A power test indicates that at least 89 observations are required in each of our analyses to achieve sufficient power to find a medium-sized effect. As some of our analyses are separated by investor/non-investor and by our time horizon conditions, the required sample size is 356 for each sub-group. We initially collect 593 responses. Due to a large number of violations of monotonicity in respondents' return estimates, rendering these observations useless, we collected an additional 200 responses (100 investors and 100 non-investors) precisely four weeks after the initial data collection date.

understanding is generally high in our sample, with a mean of 4.1 on a scale from 1 (did not understand at all) to 5 (everything was clear).[4] In our final sample, we exclude respondents that indicated that they did not understand at all how to answer in the study (9 observations). We also exclude participants that took less than 4 minutes to complete the survey (8 observations). In line with other studies (e.g., Laudenbach et al., 2021), we exclude participants with unrealistically high ($>100\%$ for highest/lowest predictions and $>50\%$ for point expectation) or low ($<-50\%$ for point expectations) return estimates (72 observations). Lastly, we exclude observations where expected returns lie outside the indicated interval of perceived minimum and maximum returns (66 observations). Gaudecker and Wogrolly (2019) show that such monotonicity violations commonly exist for a non-negligible fraction of the sample in probabilistic expectations data. Our final sample is made up of 638 observations, 383 investors and 255 non-investors. An overview of respondent demographics, which will be controlled for in all of our regression analyses, is presented in Table 7.1.

4.4 Results

Are non-investing households more risk-averse when it comes to stock investing, do they overestimate the risks, or both? For a comprehensive analysis of the risk factors driving investment, we distinguish between these elements. After providing an overview of the aggregate differences in risk tolerance and expectations, we examine the partial effects of these on allocations to a hypothetical S&P 500 investment. Subsequently, we analyze how estimates about past stock market risks and returns compare to actual historical values and how they differ between investors and non-investors. Lastly, we analyze whether information provision about historical investment characteristics affects investor and non-investor financial risk-taking. We test our hypotheses along both groups in order to highlight their differences more clearly.

[4] Mean understanding scores differ somewhat between investors ($\mu = 4.3$) and non-investors ($\mu = 3.8$). Our test questions check subject understanding of stock indexes, returns and loss likelihoods in general. Both non-investors and investors answer on average at least two out of these three questions correctly ($\mu = 2.15$ and $\mu = 2.52$, respectively), indicating that both groups understand the necessary key concepts.

4.4.1 Loss expectations and risk tolerance drive investment propensity

In Table 4.1, we present the means of several risk measures in our sample. Both quantitative (risk aversion) and qualitative elicitation (financial risk willingness) of risk tolerance show that non-investors are more risk-averse compared to their investing counterparts. Their self-reported financial risk willingness is lower, while their risk aversion score is higher. Notably, non-investors perceive the long-run loss probabilities on a stock index investment to be higher. The difference of more than 7 percentage points is particularly salient. On average, non-investors thus perceive losses to be around 33% more likely on the long run than investors.

Table 4.1: Overview of Risk Tolerance and Expectations. This table displays the means of selected risk measures and associated two-samples t-test results. Financial risk willingness is measured on a scale from 1–10. Risk aversion is based on scores assigned using a staircase risk elicitation procedure and ranges from 0–15. Perceived loss likelihoods of future S&P 500 investments are measured as percentages.

Group	Financial risk willingness	Risk aversion	Perceived future loss likelihood (1 year)	Perceived future loss likelihood (20 years)
Investors	5.55	9.54	30.96%	21.39%
Non-Investors	3.55	10.91	34.81%	28.86%
t-value (p-value)	11.173 (0.000)	-5.510 (0.000)	-1.756 (0.080)	-3.055 (0.002)

With such aggregate variation in risk perceptions between investing and non-investing subjects, the question arises whether these determine investment behavior after controlling for other relevant factors like individual risk tolerance and financial sophistication. To derive the importance of perceived loss likelihoods and other risk factors in investment decision making, we consider allocations of a $10,000 endowment to the S&P 500 index over short and long time horizons in an investment task of our experiment. Table 4.2 displays the OLS regression results for our investment propensity proxy, the percentage allocated to the stock index investment.[5] Controlling for risk tolerance as well as other individual characteristics we find that the expected loss likelihood matters for short- and long-term investments (Hypothesis 1). For every

[5] Since the inclusion of several risk measures may result in multicollinearity among the covariates, we check Variance Inflation Factors (VIFs) in all of our regression analyses. We do not observe any VIF score above the critical threshold of 5.

10-percentage-point increase in subjects' expected short-run loss likelihood, allocation to a stock index asset reduces by 3.3 percentage points. For long-term investments, this effect is smaller. Strikingly, expected returns and return dispersion do not impact the propensity to invest. Risk aversion, elicited as in several other studies using a version of the Holt and Laury (2002) MPL task, is relevant for long-term investments. Self-stated financial risk willingness, on the other hand, is associated with higher investments for both time horizons. Hence, after controlling for risk expectations, individual risk attitudes remain an important determinant of stock investing. Unsurprisingly, non-investors invest significantly less over both short and long time horizons. For the long run, this difference is particularly salient with around 12.7%, *ceteris paribus*.[6]

We run the regressions in Table 4.2 separately for investors and non-investors and display the results in Table 7.2 and Table 7.3. Surprisingly, short-term loss likelihood expectations fail to explain non-investor allocations, but exhibit a significant impact in the sub-sample of investors. A possible explanation for the absence of an effect in the non-investor sub-sample is that additional frictions play a role that are not captured by our setting. Hence, we analyze non-investor agreement with potential reasons for non-participation based on answers to Likert scale questions. The possibility of small and large losses, high participation costs, a lack of knowledge and insufficient financial wealth emerge as predominant motives for stock market non-participation with medians significantly above the middle category (one-sample Wilcoxon signed-rank tests; $p = 0.000$). This provides suggestive evidence that perceived loss likelihoods play a role, but also that there are additional factors that enter the decision-making process for stock market participation.

4.4.2 Non-investors exhibit higher and more biased loss expectations

The above analysis does not reveal to what extent investor and non-investor expectations are biased. Investors could underestimate loss likelihoods—e.g., due to overconfidence—or non-investors could overestimate them—e.g., due to overweighting the impact of

[6] Using Tobit regressions to account for the clustering of values at the upper and lower bounds of the allocation scale (0% and 100%), we obtain qualitatively the same effects for all variables.

Table 4.2: OLS regression results of investment allocation on return and risk perceptions. The table displays the results of an OLS regression with investment allocation measured in percentage of endowment as dependent variable. Future Loss Likelihood indicates individual expectations of future stock market loss likelihood given horizon. Future Return and Future Return Range represent expectations about average stock market return and return volatility, respectively. Fin. Risk Willingness is based on a self-assessment on a scale from 1 to 7. Risk Aversion is elicited via staricase-method multiple price lists and ranges from 0 to 15. Financial literacy is based on a score from 0 to 5. Optimism indicates the self-reported level of general optimism on a scale from 1 to 10. Female is a dummy variable indicating gender identification. Age is measured in years. Income indicates participant income categories ranging from 1 to 13. Self-rated confidence measures the overall confidence in stated expectations from 1 to 5.

	Dependent variable: Allocation					
	1 year (1)	1 year (2)	1 year (3)	20 years (4)	20 years (5)	20 years (6)
Future Loss Likelihood	−0.434*** (0.085)	−0.397*** (0.079)	−0.333*** (0.083)	−0.326*** (0.076)	−0.233** (0.071)	−0.136* (0.067)
Future Return		−0.101 (0.149)	0.090 (0.167)		−0.189 (0.144)	0.044 (0.155)
Future Return Range		−0.006 (0.035)	−0.0005 (0.031)		−0.070 (0.047)	−0.061 (0.047)
Fin. Risk Willingness		4.488*** (0.614)	3.378*** (0.738)		4.311*** (0.752)	2.619*** (0.774)
Risk Aversion		−1.403** (0.531)	−0.981 (0.520)		−0.860 (0.546)	−1.056* (0.494)
Financial Literacy			2.904* (1.463)			2.721* (1.327)
Non-Investor			−8.807** (3.396)			−12.688*** (3.141)
Optimism			−0.651 (0.585)			−1.024 (0.605)
Female			−0.342 (2.890)			2.500 (2.958)
Age			0.067 (0.107)			0.113 (0.110)
Income			1.167** (0.423)			0.756 (0.422)
Confidence			0.941 (1.401)			5.367*** (1.298)
Constant	57.002*** (3.458)	50.012*** (8.628)	29.955* (13.445)	54.986*** (2.517)	44.169*** (8.473)	20.327 (12.269)
Observations	312	312	312	326	326	326
Adjusted R^2	0.080	0.294	0.355	0.057	0.217	0.336

Robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

negative news. To examine this more closely, we look at respondents' estimates of past loss likelihoods as we can compare these with the actual historical values between 1980 and 2020. On average, respondents overestimate short-run loss likelihoods by 2 percentage points (= 7%), which is not significant ($p = 0.131$), whereas long-run estimates are 22% ($p = 0.000$), which is substantially above the historical benchmark of 0% (Hypothesis 2a). The difference in the signed perception gaps is significant with $p = 0.000$ (Hypothesis 2b). Figure 4.3 illustrates that investors underestimate the likelihood of past one-year losses, whereas non-investors overestimate it (Hypothesis 2a). Interestingly, investors on the aggregate do not seem to predict short-run loss likelihoods better than non-investors. On the long run, however, although both groups severely overestimate loss likelihoods (Hypothesis 2b), investor estimates lie much closer to the historical loss probability of 0%. We hypothesize that this difference is at least in part related to investors' experience with the long-term nature of financial assets.

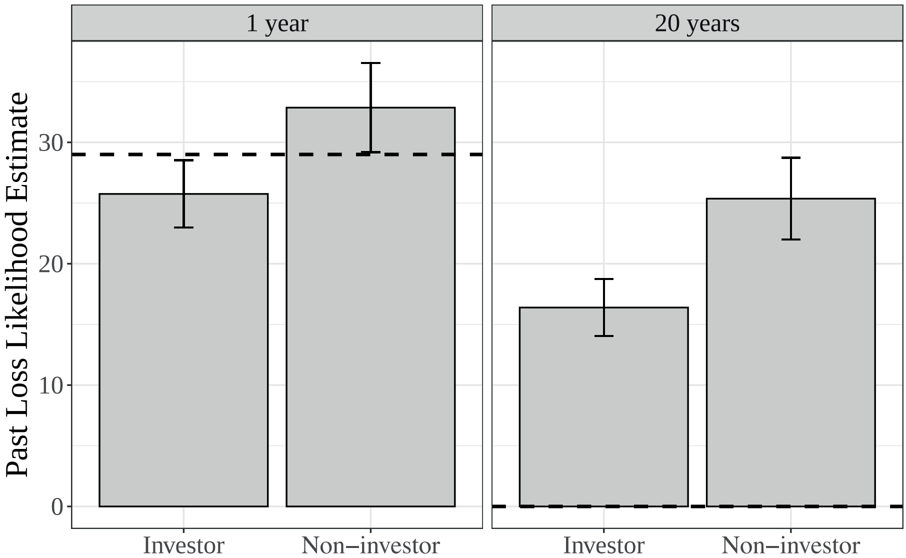

Figure 4.3: Mean past loss likelihood estimates of investors and non-investors. Error bars depict the 95%-confidence interval around the mean.

The substantial difference in perceived loss likelihoods may explain why some households do not invest their wealth in stocks. Neither perceived past return nor return dispersion show such difference between investors and non-investors, as illustrated by Figure 7.1. Estimated returns of a one-year investment are close to the historical average, whereas long-term returns are overestimated by both groups. Similarly, both groups underestimate short-run but overestimate long-run volatility of stock returns. In each case, estimates between groups are close to each other and do not significantly differ. Thus, aggregate differences in return or volatility expectations are not able to account for the stock market participation decision, neither for the case of one-year nor twenty-year stock index investments.[7]

4.4.3 Non-investors update their expectations and allocations more strongly

We have thus far established that non-investors have a particularly strong tendency to exhibit biased perceptions (in the form of overestimation) of the loss likelihood of diversified stock investments. Concurrently, the expected loss likelihood—involving the distorted perception thereof—is a fundamental driver of the propensity to invest. It is thus conceivable that providing correct historical information about past stock market returns and risk closes the perceptions gap between investors and non-investors and increases the propensity to invest in stocks. We test this by displaying subjects' estimates about the past next to correct historical values in our experiment, and subsequently ask subjects to state their expectations about a future S&P 500 investment again. The means and associated 95% confidence intervals of their initial and updated future loss likelihood expectations are illustrated in Panel A of Figure 4.4. Overall, loss expectations in both treatments approach their historical average (29% for one-year, 0% for twenty-year investments), suggesting that subjects adjust their expectations to historical values. Unsurprisingly, since they were already close to the historical average, investors on average do not update their short-run expectations (left) strongly. Investor and non-investor beliefs converge after

[7] Instead of stating nominal investment returns, respondents could base their estimates on real returns. To account for this, we present mean estimates in comparison to inflation-corrected historical values in Figure 7.2. We obtain monthly inflation data from the US Bureau of Labor Statistics to compute real returns and associated loss likelihoods in the past. Inflation-adjusted long-run loss likelihoods are 0 as well so that substantial overestimation of loss probabilities across the sample persists, whereas this is not the case for non-investor estimates about short-run loss likelihoods.

providing historical information. This is also visible for subjects' long-run expectations (right), where initially significantly higher perceived loss likelihoods for non-investors near those of investors. The figure shows that an information intervention can effectively reduce the perceptions gap between investors and non-investors and enable non-investors to make informed decisions. However, it is not just non-investors who benefit from the information intervention: Investors also revise their long-run loss expectations substantially downward. Interestingly, we do not observe full adjustment to the historical long-run loss likelihood of 0 for either group.

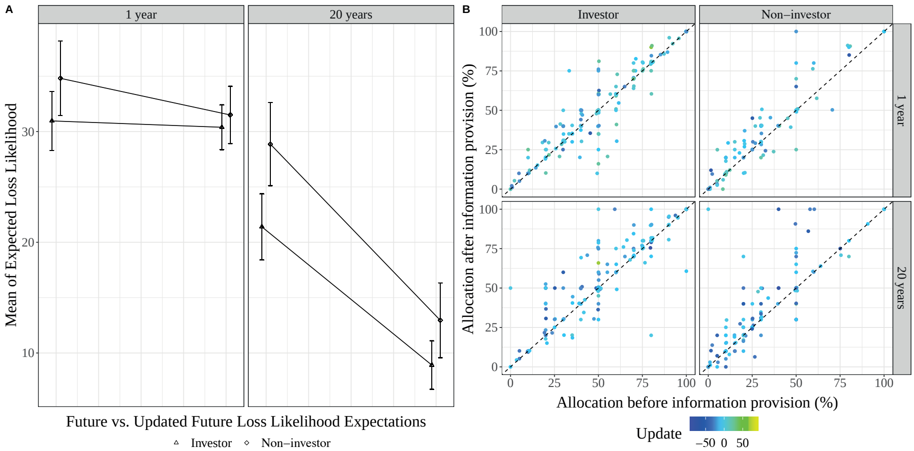

Figure 4.4: Panel A: Loss likelihood updating of investors and non-investors. Error bars depict the 95%-confidence interval around the mean. Panel B: Allocations before and after the information intervention. The color represents the magnitude of loss likelihood updating.

As a next step, we investigate whether belief updates (i.e., revised minus initial future beliefs) affect updates in subjects' allocations to a stock index investment. Average allocations of non-investors increase by 4% (from 30% to 34%), whereas investor allocations increase by 2% (from 55% to 57%) .Panel B maps allocations before and after the information intervention. Points above the dashed line indicate increases in allocations following information. Updates of subjects' loss likelihoods are represented by the color of the points, with a darker blue indicating larger downward loss expectation revisions (i.e., more optimism). It seems that upward revisions of allocations are associated with downward revisions of loss expectations, particularly so for non-investors. In line with this, OLS regression results in Table 4.3 reveal two interesting insights: Firstly, on the short run, changes in expected loss likelihoods affect changes in allocation to an S&P 500 investment (Hypothesis 3). Downward revisions in expected loss likelihoods are associated with upward revisions of investment allocations. Yet, economically speaking the effect is small: For every 10-percentage-point decrease in updated loss likelihoods, individuals invest 0.8 percentage points more in the stock index. Moreover, non-investors update their allocations significantly more compared to investors, by around 3 percentage points. Secondly, in the long run, updating of returns rather than loss likelihoods translates into changes in investment risk-taking. For a 10-percentage-point increase in expected annual return, individuals allocate 1.99 percentage points more to the index asset, controlling for other risk factors and respondent demographics. Likewise, this effect is economically small, given that such an increase in expected annual return is on average rather unlikely. In contrast to the one-year case, the overall difference in allocation updates between investors and non-investors is not significant. Updates of the perceived range of possible returns (i.e., return volatility) do not affect subsequent investment behavior. Together with the regression results in Table 4.2, this indicates that symmetric measures of perceived return dispersion, which are adopted frequently in portfolio theory models, fail to explain the dynamics of individual investment behavior.

We also investigate whether updating affects allocation behavior differently between investors and non-investors. To do so, we run the regressions from Table 4.3 separately for the sample of investors and the sample of non-investors. In Table 7.4, we observe that the short-term effect is driven by the loss likelihood updating of non-investors rather than investors, since the effect is significant in the non-investor sample only. Similarly, Table 7.5 shows that our observed long-term effects are associated with the return updating of non-investors, but not with any updating behavior of investors. Taken together, these results support the notion that information interventions likely benefit non-investors most, and that behavior of investors remains likely unaltered even if they update their expectations about future risk and return potential of stock investments.

Table 4.3: OLS regression of updated allocations following information provision. The table displays the results of an OLS regression with allocation updates (posterior minus prior allocation) measured in percentage points. Loss Likelihood Update indicates revised minus initial expectations of future stock market loss likelihood given horizon. Future Return and Future Return Range represent posterior minus prior expectations in average stock market return and return volatility, respectively. Fin. Risk Willingness is based on a self-assessment on a scale from 1 to 7. Risk Aversion is elicited via staricase-method multiple price lists and ranges from 0 to 15. Financial literacy is based on a score from 0 to 5. Optimism indicates the self-reported level of general optimism on a scale from 1 to 10. Female is a dummy variable indicating gender identification. Age is measured in years. Income indicates participant income categories ranging from 1 to 13. Self-rated confidence measures the overall confidence in stated expectations from 1 to 5.

	Dependent variable: Allocation Update					
	1 year (1)	1 year (2)	1 year (3)	20 years (4)	20 years (5)	20 years (6)
Loss Likelihood Update	−0.077* (0.033)	−0.074* (0.033)	−0.080* (0.034)	−0.058 (0.040)	−0.045 (0.043)	−0.037 (0.040)
Return Update		0.003 (0.096)	−0.012 (0.095)		0.171 (0.092)	0.199* (0.088)
Return Range Update		0.006 (0.017)	0.005 (0.017)		−0.031 (0.034)	−0.025 (0.033)
Fin. Risk Willingness		−0.096 (0.198)	−0.089 (0.253)		0.155 (0.436)	0.271 (0.543)
Risk Aversion		−0.208 (0.168)	−0.284 (0.175)		0.165 (0.281)	0.214 (0.286)
Fin. Literacy			−0.070 (0.570)			0.282 (0.612)
Non-Investor			3.045* (1.471)			0.622 (1.770)
Optimism			0.715** (0.238)			0.607 (0.476)
Female			−1.747 (1.150)			−0.387 (1.932)
Age			0.001 (0.047)			−0.039 (0.049)
Income			−0.003 (0.170)			−0.246 (0.237)
Confidence			−0.703 (0.458)			−1.650* (0.749)
Constant	1.443** (0.515)	3.790 (2.551)	3.719 (4.480)	3.108*** (0.891)	0.719 (4.113)	3.481 (5.616)
Observations	312	312	312	326	326	326
Adjusted R^2	0.015	0.008	0.047	0.004	0.002	0.012

Robust standard errors in parentheses. * $p<0.05$; ** $p<0.01$; *** $p<0.001$

4.4.4 Robustness Check: Student Sample

We investigate whether our results extend beyond the US general population. While such samples are generally broadly representative of the internet population, several challenges with respect to loss of worker naivete, potential self-selection, and limited attention arise (for a comprehensive overview, see e.g., Palan & Schitter, 2018). Therefore, we conduct our online experiment with a sample of second- and third-year undergraduate economics and business administration students at a large Dutch university. As prospective retail investors or financial professionals, it is important to study students' expectations of stock market risks and returns. In particular, one could believe that students, being familiar with financial concepts, exhibit more accurate beliefs about the past and may be more inclined to base their expectations on expected returns and volatility. Moreover, examining differences in risk and return expectations at earlier stages allows us to somewhat control for the effect of (practical) investment experience.[8]

649 students participated in the online experiment, of which 447 (218 investors and 229 non-investors) enter our analysis after applying the same exclusion criteria as in our main sample (see subsection 4.3.4). Figure 4.5 illustrates that estimates about past loss likelihoods are different between investors and non-investors, in line with the findings in our main sample. One-year loss likelihoods are significantly higher than the historical value for non-investors (one-sample t-test; $\mu = 34\%, p = 0.019$), whereas investors' mean estimate is close to 29% ($\mu = 28.7\%, p = 0.869$). On the long run, non-investing students on average expect losses to be twice as likely compared to investing students (28% and 14%, respectively). Again, there are no significant differences in return estimates, neither across groups nor from the historical return averages. Compared to crowdworkers, students' average estimates reach closer to historical realizations.

Our results on the relevance of short-run loss expectations and revisions thereof extend from a sample of US crowdworkers to Dutch students, whereas our results on long-term expectations do not. Table 7.6 shows a significant impact of expected future loss likelihoods on students' propensity to invest on the short run. The effect is of

[8] In our samples, CloudResearch investors have substantially higher investment experience of 12 years on average, compared to 2 years for student investors.

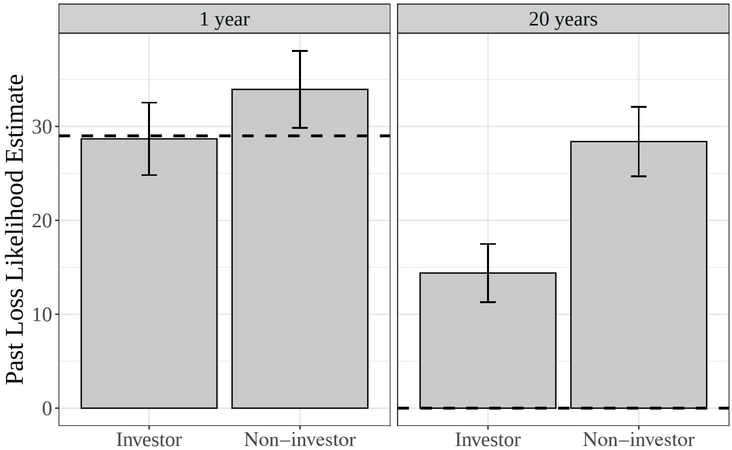

Figure 4.5: Mean past loss likelihood estimates of student investors and non-investors. Error bars depict the 95%-confidence interval around the mean.

slightly lower magnitude than in our main sample. In line with this, downward loss likelihood revisions are associated with higher updates in investment allocations, shown in Table 7.7. Both short-run return expectations and perceived return volatility on the other hand do not affect the propensity to invest in stocks. For the long run, the effect of loss likelihood expectations on investment propensity diminishes after accounting for the influence of risk tolerance. The effect of perceived return updates on investment updates that we initially found in our sample of US retail investors is not robust, given the absence of statistical significance in our student sample.

4.5 Discussion

Expectations about the likelihood of a stock market loss are a fundamental ingredient of investment decision making. We find that in contrast to traditionally adopted symmetric volatility measures, this measure of shortfall potential predicts investment propensity, after accounting for individual attitudes towards risk. Other studies stress the significance of downside expectations as well (Giglio et al., 2021; Malmendier & Nagel, 2011). In Giglio et al. (2021), the authors examine the perceived likelihood to experience a stock market return of less than -30% and use this as a proxy for respondents' perceived likelihood of a rare disaster. They find that larger perceived likelihoods of a stock market disaster are associated with lower expected returns. Our results show that not only extreme events, but also expectations of losses more generally matter for short- and long-run investments in the general population. Practically, the effect of expectations on investment allocations is rather small, in line with the findings of other studies (Ameriks et al., 2020; Giglio et al., 2021; Zimpelmann, 2021). A possible explanation for this is that stated expectations may contain noise due to cognitively demanding numerical tasks (Drerup et al., 2017). Individuals likely adopt simpler heuristics for their real-life financial decisions, resulting in imprecision in their stated (quantitative) expectations. M. Weber, Weber, and Nosić (2013) find strong support for the relevance of qualitative belief measures in hypothetical investment decisions. On the other hand, Merkle and Weber (2014) show that quantitative measures explain actual investment behavior better. In our study, we have aimed to strike a balance by eliciting quantitative measures in ways that are simpler and easier to understand for subjects in order to alleviate measurement error concerning subjects' estimate imprecision. For instance, rather than computing subjective returns and standard deviations from different probability estimates, we elicit expected returns directly (see for instance similar applications in Breunig et al., 2021; Laudenbach et al., 2021) and we adopt an easy-to-understand measure of perceived return dispersion. Yet, these measures may have remained insufficient to capture the heuristics that non-investors use in their decision-making process, which potentially explains the non-significant results in our non-investor sub-sample (see Table 7.2). Merkle and Weber (2014) suggest that the hypothetical nature of investment tasks may lead subjects to rely more on heuristics and automated decision rules, whereas data on actual investments may reveal more deliberate thought processes among subjects. As Merkle and Weber (2014) also indicate, further research is needed to address this argument.

Investors and non-investors differ mainly in their expectations of loss likelihoods, not in their perceived returns or volatility. Non-investors overestimate past stock market loss likelihoods, whereas investors on average underestimate them.[9] Return and volatility estimates on average do not differ substantially between investors and

[9] The latter is in line with widely documented investor overconfidence with respect to their own portfolios (e.g., Statman, Thorley, & Vorkink, 2006) and the market (e.g., Deaves, Lüders, & Schröder, 2010).

non-investors and are therefore not able to account for non-participation. For both groups, return estimates do not significantly differ from their historical values on the short run. This aligns with the findings by Arrondel et al. (2014), who survey both investing and non-investing households and measure past expectations as a proxy for information. They find that most respondents in their sample are well-informed about past stock returns as they are able to identify the correct return bin, while they are pessimistic with respect to the likelihood of a stock market gain. Regarding long-term investments, both investors and non-investors in our sample overestimate returns and loss likelihoods. The former is in stark contrast with the findings by Breunig et al. (2021), who state that respondents underestimate long-run stock returns by more than what could be explained by exponential growth bias. The reason for these contrasting results may be related to the elicitation mode: We ask subjects to estimate *annualized* returns of a twenty-year investment, whereas Breunig et al. (2021) elicit *total* returns of a thirty-year index investment. In our sample, we also find non-investors to exhibit significantly larger errors in their long-run estimates of loss likelihoods. Overall, we find short-term pessimism for non-investors and long-term pessimism for both groups, confirming the widespread findings on stock market pessimism in household surveys (Dominitz & Manski, 2007; Hurd, 2009; Hurd et al., 2011).

Non-investors' systematic overestimation of stock market risks and returns results in a perceptions gap between investors and non-investors, which may account for limited stock market participation. This motivates us to design an information intervention showing historically correct values of loss likelihoods, returns and volatility next to subjects' own estimates. On the basis of the provided information about the *past*, such an intervention effectively closes the perceptions gap since investor and non-investor beliefs about *future* loss likelihoods converge under partial adjustment to the historical value. Non-investors' loss likelihood updates induce higher investment allocations in our hypothetical task, after controlling for perceived returns, risk tolerance and other subject characteristics. This finding is particularly striking given that non-investor loss expectations *ex ante* information provision were not significantly related to investment propensity. We argue that the information on historical stock market characteristics increases subject understanding of the dynamics of returns which in turn leads to less perceived uncertainty and higher propensity to invest in risky assets.[10] In our sample, non-investors in particular benefit from the historical information and react by significantly adjusting their loss expectations, which subsequently leads to higher stock allocations.

Though adjustment to historical values is strongest for long-run loss likelihoods, we do not observe that these influence allocation updates in the second investment task for investors nor non-investors. A potential reason for this finding is that individuals focus excessively on the near future when evaluating the loss potential of investments, i.e. they exhibit myopic loss aversion (Benartzi & Thaler, 1995). This means that historical loss information about twenty-year stock market characteristics receives a comparably low weight in their decisions. However, our results show that expected return updates are to some extent associated with higher investment allocations of non-investors. For long-term investments, it thus seems that the gain potential becomes a driving factor for the propensity to invest, and that providing information of long-run returns can be beneficial to counter limited stock market participation (even when annualized returns are displayed as in our case).

Next to loss expectations, risk tolerance plays a role for short- and long-run investment decisions, confirming the results of earlier studies (Falk et al., 2016). This shows that it is neither risk expectations nor risk tolerance alone which determine risk-taking behavior, but an interplay of these factors. Interestingly, quantitatively elicited risk aversion using multiple choice lists only partially explains investment allocations in our task, whereas self-stated financial risk willingness consistently does, supporting the use of such qualitative measures as valid controls in survey studies (Hoffmann et al., 2015; M. Weber et al., 2013). Our study points at the relevance of both risk tolerance and expectations, but does not attempt to distinguish the relative importance of each. Yet, investigating the relative importance and a potential interaction remains an interesting topic for future research.

[10] In similar contexts, information provision experiments have successfully improved subject forecast accuracy and sparked changes in financial behaviors. Laudenbach et al. (2021) for instance document beliefs about systematic autocorrelation of stock returns among investors and design information charts that visualize the non-predictability of returns based on previous realizations. Following their experiment, investors were less prone to exhibit behavior in line with mean reversion beliefs. Similarly, Hanspal et al. (2021) find that communicating the duration of a past stock market crash influences expectations about the duration of a contemporaneous crash.

4.6 Conclusion

Recent research has highlighted the role of expectations in economic decision-making and concluded that survey evidence is "here to stay" (Giglio et al., 2021, p. 1482) and that it can inform theoretical models on economic decision making (Zimpelmann, 2021). Despite growing evidence around the relevance of loss probabilities in risky decision making, however, no study has addressed individual expectations about stock market loss likelihoods yet. In an effort to shed light on the link between loss perceptions and stock investing, we design a unique survey experiment in which retail investors and non-investors estimate short- or long-run loss likelihood, return and volatility of a stock index investment both for the past and the future, and subsequently make hypothetical allocation decisions. We find that loss expectations predict behavior while being substantially biased compared to actual historical values. Non-investors tend to be much more pessimistic about the potential of stock market losses, whereas the difference regarding expected returns or volatility is not significant, and therefore unlikely to explain differences in participation. Non-investors exhibit larger bias in perceived risk, resulting in a perceptions gap between investors and non-investors. To close this gap, we inform subjects about historical stock market realizations and re-elicit their beliefs and allocations to a stock index investment. Non-investors who lower their estimated loss likelihoods following our information intervention subsequently invest significantly more in the stock index. Updates in return expectations or symmetric measures of perceived risk however do not exhibit such an influence. For long-term investments, we find some evidence in favor of the role of return expectations.

Usually, information acquisition is perceived to be particularly costly and arduous for non-investors due to a lack of experience, financial sophistication, etc. Our results show that a simple and low-cost information intervention using comprehensive measures of stock market risk and return ultimately has the potential to reduce the barriers to stock investing. Our results are important as they demonstrate that willingness to invest and stock market participation is much driven by biased risk perception, not only by typically assumed risk preferences. Besides that, it is the perceived risk in form of loss probability rather than return expectations which drives investment behavior. To some extent, mandating the communication of the loss potential of investments is already covered by financial regulation. The European Union for instance requires issuers of packaged retail investment and insurance-based products (PRIIPs) to issue so-called key information documents (KIDs) that map expected asset returns in different scenarios—e.g., a favorable, moderate, unfavorable or stress scenario (European Union, 2009, 1). Yet, it may be unclear especially for non-investors how likely e.g. an unfavorable scenario is. Augmenting these information documents with information about historical loss likelihoods that can be objectively understood likely leads to less perceived ambiguity and enhanced comprehension of financial asset risks. Ultimately, it seems adequate if people do not invest if this is based on their (robust) risk preferences, but it is desired if they do not invest because of biased risk perceptions.

Chapter 5

Appendix to Chapter 2

Aligned with the methodology of Venkatraman et al. (2006), we conducted a post-investment game survey in Wave 3 (Innsbruck) to explore psychological factors and perceptions related to risk-taking behaviors. While such variables are typically integral to risk-taking analysis, our study specifically aims to understand the dynamics of MLA and how variations in these factors might contribute to different levels of risk-taking between the groups HIGH and LOW across various conditions. We hypothesize that frequent evaluations and decision-making lead to a heightened perception of loss magnitude and likelihood, thus promoting a decrease in risk-taking. Furthermore, this process may also affect individual emotions, potentially increasing worry and diminishing satisfaction with investment choices.

Figure 5.1 displays the average scores for the key variables: risk perception, worry, satisfaction, perceived loss probability, and perceived loss magnitudeâĂŤunder the different experimental conditions. The results of independent-sample t-tests regarding these key variables between HIGH and LOW in each condition are outlined in Table 5.1. Notably, the anticipated disparities were evident primarily in the 230-90L9 condition, where worry and perceived loss probability were significantly higher in the HIGH group compared to the LOW group. Conversely, satisfaction levels were higher in the LOW group. This latter pattern also held for the entire sample, encompassing all conditions. Interestingly, despite higher investments, participants in group LOW perceived greater losses and loss likelihoods than those in HIGH under the 25-10C30 condition. This observation is particularly striking in the context of a long-horizon multiplicative setting, suggesting that participants might feel more confident in overcoming short-term losses due to the potential for cumulative gains over time leading to higher risk-taking.

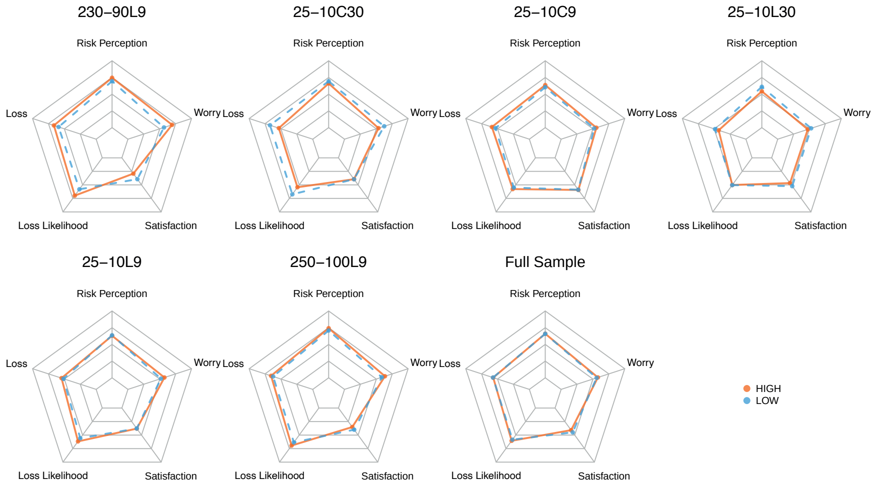

Figure 5.1: Radar charts of mean scores on perception variables. Each variable is measured by means of subject assessment on a seven-item Likert scale. The corresponding t-test results are displayed in Table 5.1.

Table 5.1: T-tests of perception differences between treatments. The table shows mean differences of selected perceptions variables in HIGH- LOW in each condition using independent-samples t-tests.

Condition	N	Risk Perception	Worry	Satisfaction	Loss Probability	Loss
250-100L9	160	0.21	0.30	-0.29	0.35	0.19
230-90L9	166	0.31	0.77**	-0.61*	0.70*	0.44
25-10L9	172	-0.04	0.33	0.01	0.35	0.18
25-10L30	157	-0.40	-0.31	-0.34	-0.01	-0.34
25-10C9	157	0.19	0.21	0.03	0.16	0.34
25-10C30	170	-0.20	-0.54	-0.003	-0.78**	-0.83**
Full Sample	982	0.01	0.12	-0.24**	0.12	-0.02

* p<0.05; ** p<0.01; *** p<0.001

Table 5.2: Final sample randomization checks. FEMALE is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. INVESTOR is a dummy variable that equals 1 if participants have already invested in financial products. RISKTOLERANCE indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. STAT.KNOWLEDGE represents self-assessed statistical knowledge from 1 to 7. INNSBRUCK is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

Condition	Variable	Test	Chi2-Statistic	N
250-100L9	FEMALE	chi2	0.003	347
250-100L9	INVESTOR	chi2	0.566	347
250-100L9	RISKTOLERANCE	Kruskal-Wallis	0.119	347
250-100L9	STAT.KNOWLEDGE	Kruskal-Wallis	6.498*	347
250-100L9	INNSBRUCK	chi2	1.151	347
230-90L9	FEMALE	chi2	0.045	358
230-90L9	INVESTOR	chi2	0.250	358
230-90L9	RISKTOLERANCE	Kruskal-Wallis	0.371	358
230-90L9	STAT.KNOWLEDGE	Kruskal-Wallis	0.051	358
230-90L9	INNSBRUCK	chi2	0.224	358
25-10L9	FEMALE	chi2	2.260	346
25-10L9	INVESTOR	chi2	0.277	346
25-10L9	RISKTOLERANCE	Kruskal-Wallis	0.798	346
25-10L9	STAT.KNOWLEDGE	Kruskal-Wallis	0.430	346
25-10L9	INNSBRUCK	chi2	2.307	346
25-10C9	FEMALE	chi2	0.328	359
25-10C9	INVESTOR	chi2	2.009	359
25-10C9	RISKTOLERANCE	Kruskal-Wallis	0.217	359
25-10C9	STAT.KNOWLEDGE	Kruskal-Wallis	0.169	359
25-10C9	INNSBRUCK	chi2	2.121	359
25-10L30	FEMALE	chi2	0.068	359
25-10L30	INVESTOR	chi2	1.899	359
25-10L30	RISKTOLERANCE	Kruskal-Wallis	2.612	359
25-10L30	STAT.KNOWLEDGE	Kruskal-Wallis	0.879	359
25-10L30	INNSBRUCK	chi2	0.402	359
25-10C30	FEMALE	chi2	0.000	348
25-10C30	INVESTOR	chi2	1.691	348
25-10C30	RISKTOLERANCE	Kruskal-Wallis	0.038	348
25-10C30	STAT.KNOWLEDGE	Kruskal-Wallis	0.041	348
25-10C30	INNSBRUCK	chi2	0.002	348

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table 5.3: Overview of previous MLA studies in chronological order. Selected studies use the between-subjects Gneezy and Potters (1997) investment experiment with a binary-outcome risky asset and the same exogenous manipulation of myopia between HIGH and LOW. Columns 1–4 indicate how the original experiment is modified (blank indicates no modification compared to Gneezy and Potters (1997)). Per-Treatment Sample Size indicates the rounded average number of participants in each condition HIGH/LOW. Total Sample Size refers to the total number of recruited participants in exogenous MLA conditions.

Study	Rates of Return	Probabilities	Earnings	Horizon	Per-Treatment Sample Size	Total Sample Size
Gneezy and Potters (1997)	+250% / -100%	0.33 / 0.67	Linear	9 Periods	42	84
T. Langer and Weber (2005)	+30(15)% / -100%	0.1 / 0.9			17	35
Bellemare, Krause, Kröger, and Zhang (2005)					29	88
Haigh and List (2005)					30	118
T. Langer and Weber (2008)	+7% / -3%	0.4 / 0.6	Compound	30 Periods	27	54
Fellner and Sutter (2009)				18 Periods	30	118[a]
Hardin and Looney (2012)				30 Periods	31	622
Zeisberger, Langer, and Weber (2012)	+230(190)% / -100%	0.4 / 0.6	Compound	36 Periods	48	190
Beshears, Choi, Laibson, and Madrian (2017)	+25% / -10%		Compound		40	320
Durand, Fung, and Limkriangkrai (2019)					64	128
Schwaiger and Hueber (2021)		0.5 / 0.5			234	937
Hueber and Schwaiger (2022)					224	894
This study	+25% / -10%		Compound	30 Periods	187	2,245

[a] Including endogenous-choice treatments, their study comprises a total sample of 444 participants.

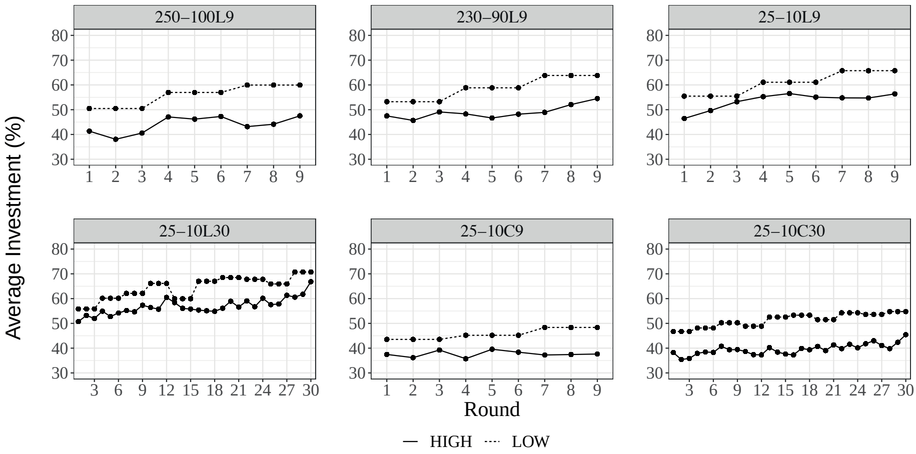

Figure 5.2: Round-level average investment percentages between treatments HIGH and LOW across different conditions. Conditions 250-100L9, 230-90L9, 25-10L9, and 25-10C9 display the development of average investments over nine periods. 25-10L30 and 25-10C30 display thirty-period developments of average investments.

Table 5.4: T-tests of differences between treatments. The table shows mean differences of investment amounts in HIGH and LOW in each condition using independent-samples t-tests. The last column indicates the p-value results of a permutation (asymptotic general independence) test.

Condition	N	Mean diff. (H - L)	lower 95% conf. int.	upper 95% conf. int.	t-stat	Std. Error	p	Perm. p
250-100L9	350	-11.505***	-16.855	-6.156	-4.231	2.719	0.000	0.000
230-90L9	360	-9.913***	-15.615	-4.211	-3.419	2.899	0.001	0.001
25-10L9	359	-7.218*	-12.842	-1.594	-2.525	2.859	0.012	0.012
25-10C9	348	-7.753**	-13.420	-2.085	-2.690	2.882	0.007	0.008
25-10L30	359	-7.640**	-13.105	-2.174	-2.749	2.779	0.006	0.006
25-10C30	355	-12.029***	-17.960	-6.099	-3.990	3.015	0.000	0.000

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table 5.5: Average marginal effects fractional response models with logit links and the amount invested per period in percent of the endowment as dependent variables. The binary dummy variable LOW is coded 0 for participants in the HIGH treatment and 1 for those in the LOW treatment. FEMALE is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. INVESTOR is a dummy variable that equals 1 if participants have already invested in financial products. RISKTOLERANCE indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. STAT.KNOWLEDGE represents participants' self reported statistical knowledge compared to their fellow students on a 7-point scale. INNSBRUCK is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

	Dependent variable: Investment (%)					
	Conditions:					
	250-100L9	230-90L9	25-10L9	25-10C9	25-10L30	25-10C30
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
LOW	0.121***	0.100***	0.070***	0.081***	0.058***	0.117***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.007)	(0.006)
FEMALE	-0.091***	-0.055***	-0.042***	-0.106***	-0.061***	-0.143***
	(0.012)	(0.014)	(0.012)	(0.013)	(0.008)	(0.008)
INVESTOR	-0.014	-0.013	0.016	-0.023	0.070***	-0.025***
	(0.012)	(0.013)	(0.013)	(0.012)	(0.007)	(0.008)
RISKTOLERANCE	0.040***	0.033***	0.019***	0.033***	0.026***	0.031***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
STAT.KNOWLEDGE	0.013**	0.008	0.031***	-0.0004	0.003	0.007**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)
INNSBRUCK	0.081***	0.082***	0.086***	0.050***	0.080***	0.076***
	(0.012)	(0.012)	(0.012)	(0.011)	(0.007)	(0.007)
Observations	3,042	3,159	3,096	3,177	10,680	10,590

Cluster-robust standard errors in parentheses. * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table 5.6: Full Sample average marginal effects fractional response models with logit links and the amount invested in percent of the endowment as dependent variables. The binary dummy variable LOW is coded 0 for participants in the HIGH treatment and 1 for those in the LOW treatment. FEMALE is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. INVESTOR is a dummy variable that equals 1 if participants have already invested in financial products. RISKTOLERANCE indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. STAT.KNOWLEDGE represents participants' self reported statistical knowledge compared to their fellow students on a 7-point scale. INNSBRUCK is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

	Dependent variable: Investment (%)					
	Conditions:					
	250-100L9	230-90L9	25-10L9	25-10C9	25-10L30	25-10C30
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
LOW	0.111***	0.108***	0.072**	0.066*	0.058*	0.117***
	(0.025)	(0.027)	(0.027)	(0.027)	(0.026)	(0.028)
FEMALE	-0.100***	-0.059	-0.023	-0.081*	-0.056	-0.153***
	(0.027)	(0.034)	(0.029)	(0.033)	(0.031)	(0.035)
INVESTOR	-0.014	-0.015	0.005	-0.014	0.068*	-0.025
	(0.027)	(0.033)	(0.031)	(0.032)	(0.030)	(0.033)
RISKTOLERANCE	0.038***	0.033***	0.020*	0.038***	0.027***	0.032***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
STAT.KNOWLEDGE	0.012	0.009	0.031*	-0.002	0.005	0.008
	(0.011)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
INNSBRUCK	0.101***	0.080**	0.093**	0.040	0.077*	0.070*
	(0.027)	(0.030)	(0.030)	(0.029)	(0.030)	(0.030)
Observations	380	370	375	383	369	368

Heteroskedasticity-robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

Table 5.7: Robustness sample average marginal effects fractional response models with logit links and the amount invested in percent of the endowment as dependent variables. The binary dummy variable LOW is coded 0 for participants in the HIGH treatment and 1 for those in the LOW treatment. FEMALE is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. INVESTOR is a dummy variable that equals 1 if participants have already invested in financial products. RISKTOLERANCE indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. STAT.KNOWLEDGE represents participants' self reported statistical knowledge compared to their fellow students on a 7-point scale. INNSBRUCK is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

	Dependent variable: Investment (%)					
	Conditions:					
	250-100L9	230-90L9	25-10L9	25-10C9	25-10L30	25-10C30
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
LOW	0.128***	0.117***	0.102**	0.097**	0.064*	0.117***
	(0.029)	(0.031)	(0.032)	(0.035)	(0.032)	(0.034)
FEMALE	-0.102**	-0.014	-0.069*	-0.122**	-0.055	-0.152***
	(0.034)	(0.039)	(0.034)	(0.044)	(0.038)	(0.042)
INVESTOR	-0.011	-0.012	0.050	-0.041	0.062	-0.058
	(0.030)	(0.036)	(0.037)	(0.040)	(0.035)	(0.039)
RISKTOLERANCE	0.040***	0.039***	0.019*	0.032**	0.029***	0.035***
	(0.009)	(0.008)	(0.009)	(0.010)	(0.009)	(0.009)
STAT.KNOWLEDGE	0.008	0.018	0.029	0.009	0.0003	0.014
	(0.014)	(0.015)	(0.015)	(0.017)	(0.014)	(0.015)
INNSBRUCK	0.095**	0.078*	0.098**	0.020	0.058	0.089*
	(0.032)	(0.035)	(0.034)	(0.040)	(0.037)	(0.038)
Observations	288	286	258	239	281	262

Heteroskedasticity-robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

Table 5.8: Overview of analytical heterogeneity across previous MLA studies in chronological order. Selected studies use the between-subjects Gneezy and Potters (1997) investment experiment with a binary-outcome risky asset and the same exogenous manipulation of myopia between HIGH and LOW. For an overview of the different conditions in the experimental design, see Table 5.3. Blank cells indicate no (additional) deviation from the analytical framework of Gneezy and Potters (1997).

Study	Dependent Variable	Model	Data Format	Cleaning/Trimming	Controls
Gneezy and Potters (1997)	Absolute & relative	Mann-Whitney test	Periods & averages	No	No
T. Langer and Weber (2005)	Relative	Mann-Whitney test	Averages	No	No
Bellemare, Krause, Kröger, and Zhang (2005)	Absolute & relative	Mann-Whitney test	Periods & averages	No	No
Haigh and List (2005)	Absolute	Tobit regression	Periods	No	No
T. Langer and Weber (2008)	Relative	Mann-Whitney test	Averages	No	No
Fellner and Sutter (2009)	Absolute	Tobit Regression	Periods	No	Yes
Hardin and Looney (2012)	Relative	Linear mixed modelling	Averages	No	Yes
Zeisberger, Langer, and Weber (2012)	Absolute	Mann-Whitney test	Periods & averages	No	No
Beshears, Choi, Laibson, and Madrian (2017)	Relative	OLS regression	Averages	No	No
Durand, Fung, and Limkriangkrai (2019)	Absolute	Tobit regression	Periods	No	Yes
Schwaiger and Hueber (2021)	Relative	Tobit regression	Averages	Yes	Yes
Hueber and Schwaiger (2022)	Relative	Tobit regression	Averages	Yes	Yes

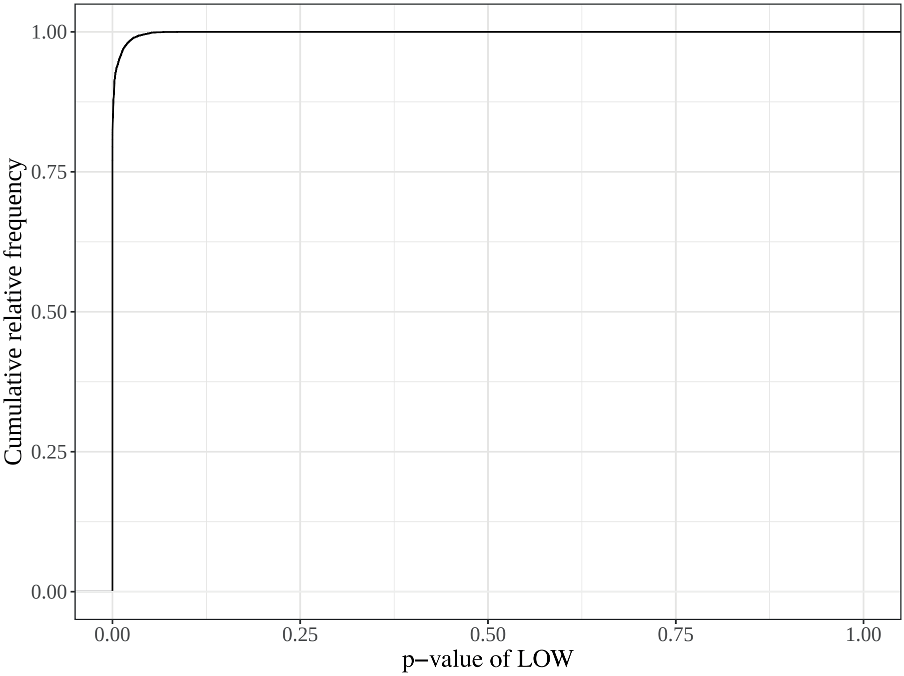

Figure 5.3: Cumulative distribution of p-values in multiverse analysis. The figure displays the cumulative relative frequency of p-values of LOW from all regressions in our multiverse analysis. The multiverse analysis is based on 13,824 regressions featuring different analytical choices as outlined in section 2.3.

Table 5.9: Condition effects fractional response models with logit links and the amount invested in percent of the endowment as dependent variables. The binary dummy variable LOW is coded 0 for participants in the HIGH treatment and 1 for those in the LOW treatment. FEMALE is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. INVESTOR is a dummy variable that equals 1 if participants have already invested in financial products. RISKTOLERANCE indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. STAT.KNOWLEDGE represents participants' self reported statistical knowledge compared to their fellow students on a 7-point scale. INNSBRUCK is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

	Dependent variable: Investment (%)		
	HIGH	LOW	Full
LOW			0.484***
			(0.115)
230-90L9	0.211	0.161	0.207
	(0.110)	(0.119)	(0.114)
25-10L9	0.453***	0.247*	0.447***
	(0.111)	(0.121)	(0.115)
25-10L30	0.542***	0.313**	0.536***
	(0.110)	(0.121)	(0.114)
25-10C9	-0.197	-0.341**	-0.195
	(0.111)	(0.119)	(0.116)
25-10C30	-0.148	-0.115	-0.152
	(0.111)	(0.118)	(0.116)
female	-0.277***	-0.410***	-0.344***
	(0.075)	(0.081)	(0.055)
INVESTOR	-0.022	0.052	0.014
	(0.071)	(0.078)	(0.053)
RISKTOLERANCE	0.113***	0.152***	0.131***
	(0.017)	(0.019)	(0.013)
STAT.KNOWLEDGE	0.068*	0.012	0.043*
	(0.027)	(0.031)	(0.020)
INNSBRUCK	0.190**	0.461***	0.321***
	(0.069)	(0.076)	(0.051)
LOW * 230-90L9			-0.056
			(0.162)
LOW * 25-10L9			-0.208
			(0.163)
LOW * 25-10L30			-0.216
			(0.163)
LOW * 25-10C9			-0.152
			(0.162)
LOW * 25-10C30			0.025
			(0.162)
Observations	1,063	1,068	2,131

Heteroskedasticity-robust standard errors in parentheses. * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Chapter 6

Appendix to Chapter 3

Table 6.1: Subject characteristics. This table provides an overview of characteristics of the participants in each treatment. The presented values are mean values. Age is measured in years. Male indicates the percentage of subjects being male in the sample. Financial literacy is based on a score from 0 (low) to 5 (high). CRT measures the cognitive reflection skills from 0 (low) to 4 (high). Investment experience represents the number of years investors have been investing in financial assets (0 for non-investors).

Treatment	N	Age	Male	Financial Literacy	CRT	Investment experience
Long	214	39.72	69.63%	4.13	2.74	11.07
Short	231	40.00	63.20%	4.03	2.83	11.57
Combined	220	39.81	57.73%	3.95	2.55	10.41
IntraLong	188	39.08	66.49%	4.06	2.82	10.48
IntraShort	188	40.87	60.11%	4.20	2.80	11.58
Total/average	1,041	39.90	63.40%	4.07	2.75	11.03

Table 6.2: Random-effects probit regression of binary trading decision. The table shows the results of a random-effects probit regression model on the subject-period level trading decision: Yes (1) or No (0). The coefficients represent the conditional marginal effects on the probability to trade, at the means of other variables. Short and Combined represent the different treatments, while Long acts as reference group. Investment Experience is measured in years. Risk Tolerance has scores ranging from 1(low) to 10 (high). Financial Literacy is a score from 0 (low) to 5 (high). CRT Score has values ranging from 0(low) to 4 (high). Female is 0 for males and 1 for females. Age is measured in years. Confidence was asked after the investment decision on a scale from 1 (low) to 10 (high). Period-fixed effects account for learning effects during the experiment.

	(1) Traded	(2) Traded	(3) Traded
Short	0.357*	0.373**	0.382**
	(2.30)	(2.84)	(2.82)
Combined	0.362*	0.223	0.229
	(2.44)	(1.69)	(1.69)
Investment Experience		-0.0216**	-0.0224**
		(-2.70)	(-2.70)
Risk Tolerance		-0.00145	-0.00175
		(-0.06)	(-0.07)
Financial Literacy		-0.376***	-0.388***
		(-6.99)	(-6.99)
CRT Score		-0.314***	-0.326***
		(-6.16)	(-6.19)
Female		0.104	0.105
		(0.94)	(0.92)
Age		0.0244***	0.0254***
		(3.70)	(3.71)
Confidence		-0.122***	-0.127***
		(-6.42)	(-6.44)
Constant	-0.255*	2.102***	2.840***
	(-2.30)	(5.77)	(7.43)
Period-fixed effects	No	No	Yes
Observations	15960	15960	15960

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.3: Alternative profit scenarios using average instead of initial decision. This table displays the profits that could have been achieved when either there was no additional trading after the initial investment period (using average allocation decision as initial decision)or if trading only occurred to rebalance to the average allocation.

Treatment	Profit	No trading profit	Only-Rebalancing profit
LONG	432.04	829.40	850.89
SHORT	353.26	909.24	933.84
COMBINED	377.14	890.88	918.03

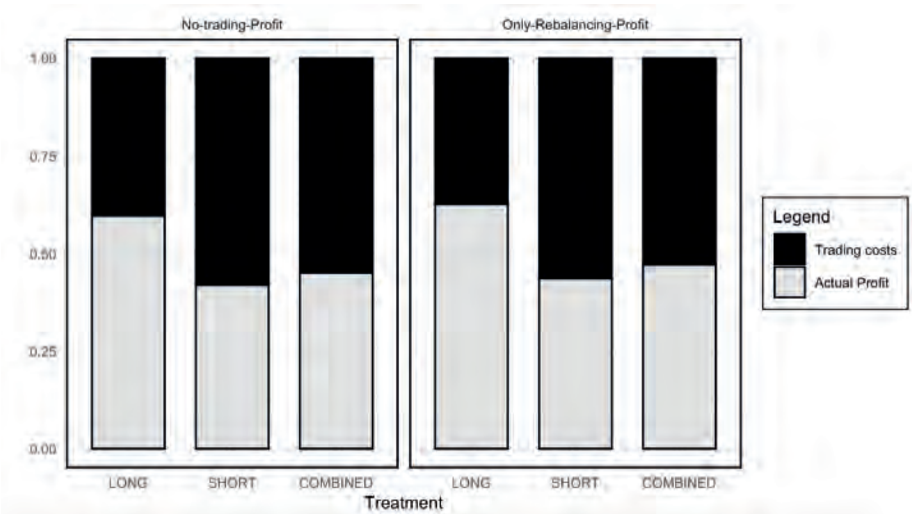

Figure 6.1: Profit scenarios. This figure shows the proportion of actual profits and trading costs from total (hypothetical) profits if there was no trading after the initial period (left panel), or if there was only trading to rebalance to the initial allocation to the risky share (right panel).

Table 6.4: Robustness check: Random-effects regression of trading volume with intra-period returns in Long and Short. The table shows the results of a random-effects regression on subject trading volume. IntraLong acts as reference group. To harmonize the number of price ticks between IntraLong and IntraShort, subjects in IntraShort viewed more and smaller intra-period prices than in Short. Investment Experience is measured in years. Risk Tolerance has scores ranging from 1 (low) to 10 (high). Financial Literacy is a score from 0 (low) to 5 (high). CRT Score has values ranging from 0(low) to 4 (high). Female is 0 for males and 1 for females. Age is measured in years. Confidence was asked after the investment decision on a scale from 1 (low) to 10 (high). Period-fixed effects account for learning effects during the experiment.

	(1) Trading Volume	(2) Trading Volume	(3) Trading Volume
IntraShort	2.653*	3.208***	3.208***
	(2.54)	(3.31)	(3.31)
Investment Experience		0.0897	0.0897
		(1.45)	(1.45)
Risk Tolerance		0.293	0.293
		(1.25)	(1.25)
Financial Literacy		-2.219***	-2.219***
		(-4.29)	(-4.29)
CRT Score		-0.967*	-0.967*
		(-2.36)	(-2.35)
Female		-2.937**	-2.937**
		(-2.99)	(-2.99)
Age		-0.0666	-0.0666
		(-1.28)	(-1.28)
Confidence		-1.008***	-1.008***
		(-5.73)	(-5.72)
Constant	8.668***	26.78***	28.47***
	(13.69)	(8.18)	(8.60)
Period-fixed effects	No	No	Yes
Observations	9024	9024	9024
R^2	0.0049	0.0538	0.0577

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p<0.001$.

Table 6.5: Robustness check: Tobit regression on the allocation to the risky share with intra-period returns in Long and Short. The table shows the results of a Tobit regression on the number of risky shares held. IntraLong acts as reference group. To harmonize the number of price ticks between IntraLong and IntraShort, subjects in IntraShort viewed more and smaller intra-period prices than in Short. Investment Experience is measured in years. Risk Tolerance has scores ranging from 1(low) to 10 (high). Financial Literacy is a score from 0 (low) to 5 (high). CRT Score has values ranging from 0(low) to 4 (high). Female is 0 for males and 1 for females. Age is measured in years. Confidence was asked after the investment decision on a scale from 1 (low) to 10 (high). Period-fixed effects account for learning effects during the experiment.

	(1) Risky share holdings	(2) Risky share holdings	(3) Risky share holdings
IntraShort	2.916	2.798	2.801
	(0.92)	(1.02)	(1.02)
Investment Experience		0.0543	0.0542
		(0.27)	(0.27)
Risk Tolerance		2.467***	2.467***
		(3.70)	(3.70)
Financial Literacy		6.143***	6.139***
		(3.90)	(3.90)
CRT Score		4.945***	4.945***
		(3.91)	(3.91)
Female		-5.415	-5.416
		(-1.87)	(-1.87)
Age		0.0154	0.0156
		(0.10)	(0.10)
Confidence		2.264***	2.263***
		(4.57)	(4.57)
Constant	54.54***	-11.47	-17.63
	(23.95)	(-1.26)	(-1.91)
Period-fixed effects	No	No	Yes
Observations	9400	9400	9400
Pseudo R^2	0.000	0.019	0.020

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Chapter 7

Appendix to Chapter 4

Table 7.1: Overview of Survey Demographics. This table presents the means of demographic variables in our sample. Financial literacy represents the number of correct answers to five questions adapted from Van Rooij, Lusardi, and Alessie, 2011. Optimism is measured on a scale from 1–10. Female depicts the proportion of female participants. Income is based on different categories ranging from 1 (less than $10,000) to 12 (more than $150,000), advancing in increments of $10,000.

	Non-investors	Investors	Full sample
Fin. Literacy	3.549	4.277	3.986
Optimism	5.682	6.674	6.277
Female	64.31%	43.6%	51.88%
Age	42.61	42.03	42.26
Income	5.580	8.018	7.044

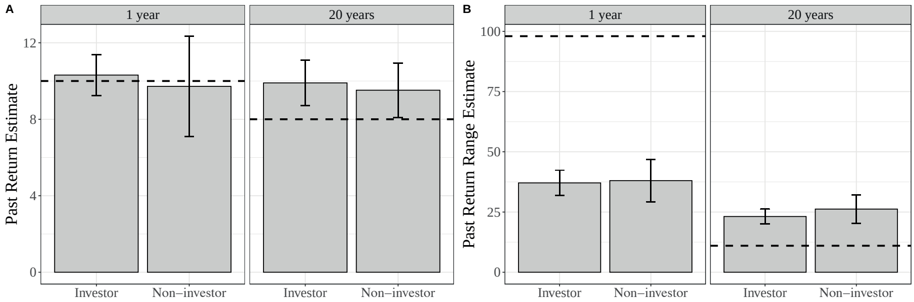

Figure 7.1: Mean estimates about past return (Panel A) and past return range (Panel B) across conditions and investor versus non-investor. Past return estimate is respondents' estimate about the average annual return of a stock index investment between 1980 and 2020. Past return range estimate is based on respondents' estimate about the highest minus the lowest possible annual return in this time range. Error bars represent the 95% confidence interval of mean estimates. The dashed line illustrates the actual (average) historical value of each estimate.

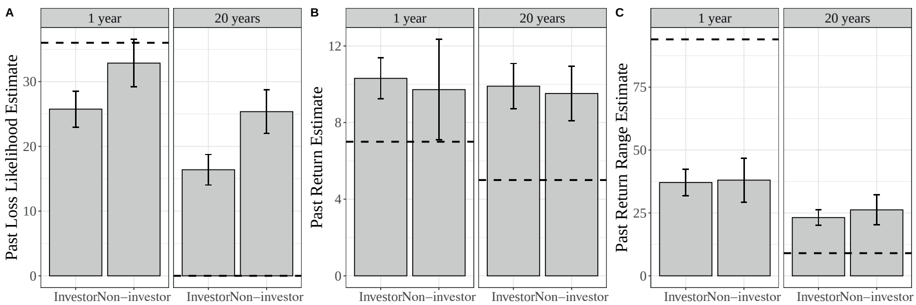

Figure 7.2: Mean estimates about past loss likelihood (Panel A), past return (Panel B) and past return range (Panel C) across conditions and investors versus non-investors. The dashed line represents inflation-adjusted correct historical values.

Table 7.2: OLS regression of one-year allocations separated by investors and non-investors. The table displays the results of an OLS regression with investment allocation measured in percentage of endowment as dependent variable. Future Loss Likelihood indicates individual expectations of future stock market loss likelihood given horizon. Future Return and Future Return Range represent expectations about average stock market return and return volatility, respectively. Fin. Risk Willingness is based on a self-assessment on a scale from 1 to 7. Risk Aversion is elicited via staricase-method multiple price lists and ranges from 0 to 15. Financial literacy is based on a score from 0 to 5. Optimism indicates the self-reported level of general optimism on a scale from 1 to 10. Female is a dummy variable indicating gender identification. Age is measured in years. Income indicates participant income categories ranging from 1 to 13. Self-rated confidence measures the overall confidence in stated expectations from 1 to 5.

	Dependent variable: Allocation					
	Non-Inv. (1)	Non-Inv. (2)	Non-Inv. (3)	Inv. (4)	Inv. (5)	Inv. (6)
Future Loss Likelihood	−0.148	−0.135	−0.121	−0.522***	−0.513***	−0.467***
	(0.138)	(0.122)	(0.136)	(0.095)	(0.095)	(0.094)
Future Return		−0.070	0.021		−0.137	0.181
		(0.176)	(0.200)		(0.241)	(0.301)
Future Return Range		−0.058	−0.053		0.075	0.062
		(0.037)	(0.042)		(0.058)	(0.058)
Fin. Risk Willingness		3.527***	4.218**		3.301***	2.807**
		(1.007)	(1.352)		(0.764)	(0.899)
Risk Aversion		−1.845*	−1.816*		−0.805	−0.767
		(0.738)	(0.734)		(0.671)	(0.696)
Financial Literacy			1.575			4.478
			(1.937)			(2.363)
Optimism			−0.934			−0.632
			(0.924)			(0.792)
Female			2.116			−2.912
			(4.353)			(3.848)
Age			0.203			0.007
			(0.153)			(0.144)
Income			0.518			1.339*
			(0.727)			(0.554)
Confidence			0.521			0.872
			(1.766)			(2.204)
Constant	32.783***	44.420***	24.128	68.861***	56.158***	30.460
	(5.611)	(11.318)	(17.789)	(3.762)	(10.556)	(19.842)
Observations	122	122	122	190	190	190
Adjusted R^2	0.006	0.175	0.166	0.126	0.219	0.256

Robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

Table 7.3: OLS regression of twenty-year allocations separated by investors and non-investors. The table displays the results of an OLS regression with investment allocation measured in percentage of endowment as dependent variable. Future Loss Likelihood indicates individual expectations of future stock market loss likelihood given horizon. Future Return and Future Return Range represent expectations about average stock market return and return volatility, respectively. Fin. Risk Willingness is based on a self-assessment on a scale from 1 to 7. Risk Aversion is elicited via staricase-method multiple price lists and ranges from 0 to 15. Financial literacy is based on a score from 0 to 5. Optimism indicates the self-reported level of general optimism on a scale from 1 to 10. Female is a dummy variable indicating gender identification. Age is measured in years. Income indicates participant income categories ranging from 1 to 13. Self-rated confidence measures the overall confidence in stated expectations from 1 to 5.

	Dependent variable: Allocation					
	Non-Inv.	Non-Inv.	Non-Inv.	Inv.	Inv.	Inv.
	(1)	(2)	(3)	(4)	(5)	(6)
Future Loss Likelihood	−0.085	−0.049	−0.035	−0.355***	−0.267**	−0.166
	(0.100)	(0.095)	(0.097)	(0.098)	(0.096)	(0.097)
Future Return		0.158	0.255		−0.372	−0.143
		(0.179)	(0.211)		(0.219)	(0.233)
Future Return Range		−0.110*	−0.098		−0.048	−0.033
		(0.052)	(0.052)		(0.085)	(0.091)
Fin. Risk Willingness		1.762	1.552		3.690***	2.697*
		(1.012)	(1.132)		(0.979)	(1.103)
Risk Aversion		−1.252	−1.029		−0.655	−1.268
		(0.684)	(0.672)		(0.677)	(0.709)
Financial Literacy			1.052			5.119**
			(1.762)			(1.955)
Optimism			−0.454			−1.061
			(0.856)			(0.914)
Female			1.705			2.797
			(5.287)			(3.783)
Age			0.178			−0.008
			(0.172)			(0.146)
Income			−0.007			1.175*
			(0.668)			(0.560)
Confidence			4.213*			6.346***
			(1.883)			(1.924)
Constant	34.852***	41.525***	15.719	64.671***	53.451***	11.745
	(3.761)	(10.398)	(17.254)	(2.740)	(10.941)	(17.021)
Observations	133	133	133	193	193	193
Adjusted R^2	−0.002	0.093	0.102	0.068	0.168	0.249

Robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

Table 7.4: OLS regression of one-year allocation updates separated by investors and non-investors. The table displays the results of an OLS regression of allocation updates (posterior minus prior allocation) measured in percentage points. Loss Likelihood Update indicates revised minus initial expectations of future stock market loss likelihood given horizon. Future Return and Future Return Range represent posterior minus prior expectations in average stock market return and return volatility, respectively. Fin. Risk Willingness is based on a self-assessment on a scale from 1 to 7. Risk Aversion is elicited via staricase-method multiple price lists and ranges from 0 to 15. Financial literacy is based on a score from 0 to 5. Optimism indicates the self-reported level of general optimism on a scale from 1 to 10. Female is a dummy variable indicating gender identification. Age is measured in years. Income indicates participant income categories ranging from 1 to 13. Self-rated confidence measures the overall confidence in stated expectations from 1 to 5.

	Dependent variable: Allocation Update					
	Non-Inv. (1)	Non-Inv. (2)	Non-Inv. (3)	Inv. (4)	Inv. (5)	Inv. (6)
Loss Likelihood Update	−0.136**	−0.126**	−0.136**	−0.032	−0.031	−0.036
	(0.048)	(0.046)	(0.048)	(0.041)	(0.041)	(0.044)
Return Update		0.096	0.103		−0.082	−0.102
		(0.073)	(0.081)		(0.124)	(0.120)
Return Range Update		−0.011	−0.021		0.028	0.041*
		(0.024)	(0.025)		(0.019)	(0.020)
Fin. Risk Willingness		0.487	0.135		0.027	−0.194
		(0.396)	(0.520)		(0.267)	(0.299)
Risk Aversion		−0.012	−0.020		−0.432	−0.398
		(0.268)	(0.242)		(0.224)	(0.218)
Financial Literacy			0.331			−0.789
			(0.694)			(0.811)
Optimism			0.930*			0.663*
			(0.430)			(0.317)
Female			−0.350			−3.447*
			(1.620)			(1.552)
Age			0.008			0.029
			(0.062)			(0.067)
Income			−0.049			−0.038
			(0.299)			(0.189)
Confidence			−0.690			−0.785
			(0.516)			(0.785)
Constant	2.676***	1.325	−1.368	0.550	3.551	9.298
	(0.777)	(4.297)	(6.381)	(0.663)	(2.907)	(6.344)
Observations	122	122	122	190	190	190
Adjusted R^2	0.049	0.041	0.060	−0.002	0.015	0.032

Robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

Table 7.5: OLS regression of twenty-year allocation updates separated by investors and non-investors. The table displays the results of an OLS regression of allocation updates (posterior minus prior allocation) measured in percentage points. Loss Likelihood Update indicates revised minus initial expectations of future stock market loss likelihood given horizon. Future Return and Future Return Range represent posterior minus prior expectations in average stock market return and return volatility, respectively. Fin. Risk Willingness is based on a self-assessment on a scale from 1 to 7. Risk Aversion is elicited via staricase-method multiple price lists and ranges from 0 to 15. Financial literacy is based on a score from 0 to 5. Optimism indicates the self-reported level of general optimism on a scale from 1 to 10. Female is a dummy variable indicating gender identification. Age is measured in years. Income indicates participant income categories ranging from 1 to 13. Self-rated confidence measures the overall confidence in stated expectations from 1 to 5.

	Dependent variable: Allocation Update					
	Non-Inv. (1)	Non-Inv. (2)	Non-Inv. (3)	Inv. (4)	Inv. (5)	Inv. (6)
Loss Likelihood Update	−0.054	−0.018	−0.047	−0.056	−0.055	−0.027
	(0.061)	(0.068)	(0.064)	(0.051)	(0.056)	(0.050)
Return Update		0.325**	0.303***		0.066	0.122
		(0.101)	(0.090)		(0.152)	(0.153)
Return Range Update		−0.019	−0.015		−0.049	−0.035
		(0.039)	(0.041)		(0.057)	(0.056)
Fin. Risk Willingness		−0.282	−0.544		0.560	0.857
		(0.640)	(0.799)		(0.587)	(0.676)
Risk Aversion		−0.046	−0.037		0.262	0.491
		(0.400)	(0.397)		(0.355)	(0.383)
Financial Literacy			0.498			−0.151
			(0.768)			(0.933)
Optimism			0.468			0.583
			(0.836)			(0.375)
Female			−4.671			1.714
			(3.755)			(2.157)
Age			0.015			−0.047
			(0.073)			(0.068)
Income			−0.086			−0.268
			(0.385)			(0.274)
Confidence			−1.088			−2.225*
			(1.095)			(1.005)
Constant	3.880*	6.021	12.328	2.642*	−3.284	−1.159
	(1.507)	(5.072)	(6.911)	(1.106)	(6.009)	(7.683)
Observations	133	133	133	193	193	193
Adjusted R^2	−0.002	−0.002	−0.019	0.002	−0.006	0.024

Robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

Table 7.6: Student sample: OLS regression results of investment allocation on risk and return perceptions. The table displays the results of an OLS regression with investment allocation measured in percentage of endowment as dependent variable. Future Loss Likelihood indicates individual expectations of future stock market loss likelihood given horizon. Future Return and Future Return Range represent expectations about average stock market return and return volatility, respectively. Fin. Risk Willingness is based on a self-assessment on a scale from 1 to 7. Risk Aversion is elicited via staricase-method multiple price lists and ranges from 0 to 15. Financial literacy is based on a score from 0 to 5. Optimism indicates the self-reported level of general optimism on a scale from 1 to 10. Female is a dummy variable indicating gender identification. Age is measured in years. Income indicates participant income categories ranging from 1 to 13. Self-rated confidence measures the overall confidence in stated expectations from 1 to 5.

	Dependent variable: Allocation					
	1 year (1)	1 year (2)	1 year (3)	20 years (4)	20 years (5)	20 years (6)
Future Loss Likelihood	−0.274**	−0.234*	−0.230*	−0.270**	−0.116	−0.080
	(0.096)	(0.094)	(0.096)	(0.094)	(0.081)	(0.079)
Future Return		−0.075	−0.043		0.096	0.114
		(0.160)	(0.164)		(0.237)	(0.235)
Future Return Range		−0.032	−0.023		−0.074	−0.071
		(0.033)	(0.034)		(0.048)	(0.049)
Fin. Risk Willingness		4.190***	2.593*		5.179***	4.623***
		(0.948)	(1.206)		(0.942)	(1.153)
Risk Aversion		0.142	−0.184		−0.588	−0.618
		(0.639)	(0.676)		(0.581)	(0.605)
Financial Literacy			−0.482			−0.514
			(2.148)			(1.852)
Non-Investor			−4.537			−4.864
			(4.679)			(4.586)
Optimism			0.465			0.415
			(1.269)			(0.995)
Female			−0.175			5.415
			(4.703)			(4.072)
Age			1.285			2.878*
			(0.786)			(1.132)
Confidence			3.866*			1.741
			(1.966)			(1.838)
Constant	57.131***	34.011***	10.851	59.020***	32.105***	−33.465
	(3.819)	(8.606)	(26.473)	(3.061)	(9.269)	(29.393)
Observations	217	217	217	230	230	230
Adjusted R^2	0.030	0.114	0.127	0.037	0.181	0.192

Robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

Table 7.7: Student sample: OLS regression of updated allocations following information provision. The table displays the results of an OLS regression of allocation updates (posterior minus prior allocation) measured in percentage points. Loss Likelihood Update indicates revised minus initial expectations of future stock market loss likelihood given horizon. Future Return and Future Return Range represent posterior minus prior expectations in average stock market return and return volatility, respectively. Fin. Risk Willingness is based on a self-assessment on a scale from 1 to 7. Risk Aversion is elicited via staricase-method multiple price lists and ranges from 0 to 15. Financial literacy is based on a score from 0 to 5. Optimism indicates the self-reported level of general optimism on a scale from 1 to 10. Female is a dummy variable indicating gender identification. Age is measured in years. Income indicates participant income categories ranging from 1 to 13. Self-rated confidence measures the overall confidence in stated expectations from 1 to 5.

	Dependent variable: Allocation Update					
	1 year (1)	1 year (2)	1 year (3)	20 years (4)	20 years (5)	20 years (6)
Loss Likelihood Update	−0.214* (0.085)	−0.223** (0.084)	−0.231** (0.082)	−0.099 (0.063)	−0.073 (0.066)	−0.058 (0.065)
Return Update		−0.175 (0.108)	−0.181 (0.108)		0.284 (0.162)	0.254 (0.171)
Return Range Update		−0.003 (0.020)	−0.003 (0.020)		−0.045 (0.034)	−0.039 (0.036)
Fin. Risk Willingness		−0.937 (0.598)	−0.701 (0.830)		−0.118 (0.559)	−0.046 (0.691)
Risk Aversion		−0.392 (0.330)	−0.330 (0.381)		−0.156 (0.450)	−0.087 (0.483)
Fin. Literacy			2.400 (1.587)			1.103 (1.399)
Non-Investor			2.451 (2.869)			0.049 (2.890)
Optimism			0.786 (0.620)			0.586 (0.557)
Female			−0.265 (3.227)			−1.286 (2.913)
Age			0.049 (0.609)			−0.864 (0.610)
Confidence			−1.228 (0.968)			−1.568 (1.428)
Constant	2.886** (1.111)	11.746* (5.097)	−4.584 (16.851)	7.115*** (1.503)	8.287 (5.570)	22.265 (17.415)
Observations	217	217	217	230	230	230
Adjusted R^2	0.051	0.064	0.060	0.008	0.010	−0.001

Robust standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001

Chapter 8

General Discussion

8.1 Summary

This dissertation revealed the dominance of short-term oriented behavior on financial markets and its consequences for long-run financial well-being. Swayed by the immediate possibility of investment losses, individuals tend to evaluate their investment portfolios often, trade on recent price trends, and pay attention to short-term investment loss likelihoods on stock markets. As a result, they reduce their stock allocations or exit the market. Such myopic tendencies dissuade them from engaging with stock investments, leading to missed opportunities for higher returns compared to traditional, lower-risk savings methods. Myopia thus emerges as a significant barrier to stock market participation and, by extension, to achieving long-term financial security. The ensuing discussion synthesizes the core insights derived from Chapters 2 to 4, elucidating the empirical investigations that underpin these conclusions.

Earlier research by Benartzi and Thaler (1995) proposed myopic loss aversion (MLA) as an explanation for why household stock market exposure has historically remained limited. A prominent experimental investigation by Gneezy and Potters (1997) has faced criticism centered around its external validity, suggesting that features of realistic investment scenarios might diminish MLA propensity by encouraging a long-term perspective. In chapter 2 we addressed these critiques by testing the robustness of MLA along such features in a comprehensive partial-factorial online experiment with 2,245 university students. Lower rates of return, longer investment horizons and return compounding do not attenuate MLA behavior. Across all five modifications, MLA caused significant differences in investment behavior. Our findings addressed issues of analytical heterogeneity commonly encountered in the literature. We concluded that MLA remains a robust feature of financial markets.

chapter 3 explored how the temporal framing of price charts affects trading decisions. Widely used short-term displays of historical asset performance encourage a narrow investment view, signalling short-term fluctuations rather than long-term value. We tested this hypothesis in an online experiment varying the displayed price chart time horizon. Under the presence of a 2% transaction fee, behavior in the short-horizon treatment was characterized by significantly higher trading frequency and volume, ultimately hurting financial performance. Overall levels of financial risk-taking, however, were not affected. In an additional treatment, we displayed both short and long-horizon charts combined and observed similar effects, and we additionally disentangled the time horizon effect from any pure graphical effect arising from the number of line ticks. We concluded that broad framing of historical asset performance can reduce transaction costs due to over-trading.

Furthermore, we discovered that individuals struggle with grappling long-term processes on financial markets. chapter 4 revealed that individuals inherently overestimate the risks associated with long-term stock investments, despite accurately assessing short-term loss probabilities. This misperception extends beyond traditional metrics like expected returns and volatility, underscoring the unique impact of long-run loss likelihood estimations on investment behavior. We demonstrated that disseminating historical long-term risk information aligns the risk perceptions of investors and non-investors, highlighting the potential of long-run risk communication to encourage stock market participation.

8.2 Conclusion

Sound financial decisions require accurate perception, judgment and knowledge. However, cognitive biases and psychological predispositions often cloud our judgment, causing suboptimal financial choices. This dissertation was inspired by one such bias, temporal myopia, which predisposes individuals to overly concentrate on the immediate future, neglecting or underweighting the long-term ramifications of their decisions. In the context of stock investing, where long-term orientation is key to investment success, myopic views can result in inefficient savings allocation, culminating in substantial foregone returns. To examine the significance and economic relevance of individual temporal myopia, we addressed the research question:

To what extent does myopia affect investor risk perception and trading behavior?

A series of decision experiments allowed us to delineate these relationships, holding constant the influence of other factors such as return beliefs or initial wealth endowments. We provided evidence that myopia reduces financial risk-taking, promotes excessive trading, and has the potential to explain biased beliefs about stock investing risks. Consequently, temporal myopia imposes considerable costs on investors, manifesting both as missed opportunities for higher returns and as direct financial losses through elevated trading expenses. Despite the trend toward lower explicit trading costs in passive investment vehicles, excessive trading spurred by myopic behavior can erode returns through unfavorable price quotes (higher bid and lower ask prices), underscoring the critical need for investors to mitigate myopic tendencies in their decision-making processes.

8.3 Policy Implications

Due to continuously ageing populations, households have started to play a more active role when it comes to long-term savings for retirement—a trend that likely continues further. The World Health Organization (WHO) projects the proportion of the world population over 60 years to nearly double between 2015 and 2050 (United Nations, 2017), highlighting the growing importance of long-term personal financial planning. Concurrently, advancements in financial technology (FinTech) have revolutionized the accessibility of stock investing, albeit with mixed consequences. While online brokerage apps have democratized access to financial markets, they have also precipitated less reflective and more impulsive trading behaviors, resulting in trend-chasing behavior, among others (Kalda et al., 2021). As evidenced by events like the GameStop mania in 2021, retail investors have become increasingly vulnerable to market volatility and speculative frenzies. Compared to institutional investors, retail investors face tighter capital constraints, a lack of professional investment experience, and lower financial literacy. Given the various sources of stock return risks in general and people's inclination to focus on short horizons and outcomes in particular, it is essential to implement policies and regulation that facilitate informed long-run decision-making.

To mitigate short-sighted and reactionary financial decisions, policies limiting the frequency or extending the temporal scope of financial reporting can be implemented. Since 2010, Israeli retirement funds have been mandated to disclose at least twelve months of prior performance—rather than the previous one-month horizon mandate—resulting in increased fund contributions (Shaton, 2017). However, as our findings in chapter 3 revealed, merely extending the historical performance horizon might not suffice to encourage informed risk-taking. To reduce investors' excessive focus on intermediate fluctuations and recent developments, regulation could require financial service providers to aggregate historical or projected returns over longer periods. Currently, the European Union requires these providers to issue Key Information Documents (KIDs) for packaged retail and insurance-based investments products (European Union, 2009, 1). KIDs include information about different return performance scenarios—a stress, unfavorable, moderate and favorable scenario—over one year and over the recommended holding period.[1] Longer-horizon risk and return signals are not required to be included in the document.

Beyond simple return metrics, our findings advocate for the explicit communication of long-run investment loss probabilities. Several studies highlight that individuals pay explicit attention to the loss likelihood of an investment (Holzmeister et al., 2020; Borsboom et al., 2022; Zeisberger, 2022). In chapter 4, we went beyond the context of laboratory financial assets and demonstrated that loss likelihood beliefs *ex ante* influence behavior in a planned index investment allocation task. A simple information intervention prompted participants to revise their long-run beliefs toward historical benchmark loss likelihoods. Since individuals struggle to project their short-term perceptions to long-run stock market developments, interventions on long-run loss likelihoods may offer a significant potential to lower the barriers of

[1] In the case of exchange-traded funds, for instance, the recommended holding period is five years.

investing for non-investors. In particular, visual representations of decreasing loss probabilities over extended investment durations could clarify the long-run benefits of stock investing. Since stock market participation is not only a question of risk preference but of risk perception, an effective communication of long-term risks can enable households to make sound savings decisions.

Lastly, initiatives targeted at promoting financial literacy can be supported. Despite global advancements, individual knowledge about basic financial concepts is on average still lacking around the world (Klapper & Lusardi, 2020), let alone the nuanced awareness required for navigating investment risks and opportunities. Educational initiatives could elucidate the distinctions between short and long-term investment risks. This will not only encourage far-sighted financial decisions, but also discourage risky short-term behaviors such as investing in lottery-like stocks (Haisley et al., 2008). Increased knowledge and awareness of long-run developments can spill over to domains beyond personal finance. More prudent financial behaviors could change individual attitudes toward environmental and social issues related to overconsumption. Early educational initiatives could emphasize the benefits of sustainable investment and consumption, addressing environmental, social and governance (ESG) challenges hindering sustainable development in finance and beyond.

8.4 Limitations

This dissertation has shed light on the effect of temporal myopia on individual financial behavior, focusing on personal finance contexts which involve long-term decisions under risk. The results suggest that myopia is an inherent cognitive bias hampering effective financial decision-making. Alternatively, temporal myopia might function as a mental shortcut (heuristic) that helps individuals manage uncertainty and cognitive load by prioritizing immediate, more predictable outcomes. This viewpoint recognizes that in certain contexts, such as financial distress, a short-term focus may be a rational adaptive strategy rather than a flaw (see, e.g., de Almeida et al., 2024).

While we analyzed the implications of myopia in a variety of investment contexts, we did not investigate individual differences and the underlying factors driving such. Related studies focus on myopia implications in business management decisions (e.g., Mizik, 2010), dieting behavior (e.g., Mann & Ward, 2004), pro-environmental behavior (e.g., Arbuthnott, 2010), and academic performance (e.g., Freeney & O'Connell, 2010). The pervasive nature of short-run oriented behavior in influencing a wide array of everyday decisions beckons further research to in particular unravel the multifaceted individual differences of short-termism and their associated causes. For instance, it is worth investigating whether inherent psychological, or environmental/institutional factors promote myopia. Such an inquiry could further clarify the distinction between bias and heuristic: while the former implies irrational decision-making, the latter suggests that myopia could function as an adaptive coping mechanism. For example, regulation mandating frequent performance reporting could lead managers to rationally focus on optimizing short-term key performance indicators.

From a methodological perspective, we relied primarily on between-subjects experimental designs. While these allow for a clear comparison of average or aggregate behavior, they do not capture magnitudes or dynamic patterns in individual behaviors, which is particularly relevant for the design of policy interventions. Repeated measurements post-intervention allow researchers to gauge whether treatment effects within participants extend across longer time periods (Haaland et al., 2023). Mixed designs comparing behavior of multiple groups over time could estimate difference-in-difference treatment effects to address this question. To evaluate the effectiveness of proposed policy interventions, it is esssential that research tests the longevity of their effects.

while our experimental approach allows for a precise identification of investment behavior, it inherently constrains the generalizability of our findings. Successful identification requires fixing parameters of the decision environment. For instance, in chapter 2 and chapter 3, we communicated the distribution of possible investment returns *ex ante* to participants in order to eliminate any effects stemming from the heterogeneity in individual return expectations. This contrasts with real-world scenarios where investors navigate uncertain return environments, adding complexity to financial decision-making that our experiments do not fully capture. Because of this, despite mimicking realistic decision contexts as closely as possible, the experiments presented in this dissertation may not reflect actual decision environments to their full extent. Nevertheless, efforts to bridge the gap between controlled experimental environments and real-world decision contexts, such as in chapter 2, can effectively address concerns about the external validity of studies employing decision experiments.

To close the gap between actual and hypothetical economic behavior, experimental investigations rely on financial compensation of participants for their time and effort spent contributing to them. Compensation relies on a fixed and/or variable (incentivized) monetary component. Incentivization entails linking financial compensation of participants directly to their decisions, in order to align hypothetical with actual behavior outside the laboratory more closely. In two of the three studies presented in this dissertation, participants' earnings were linked to their performance in investment tasks. However, our study in chapter 4 did not incorporate incentivized financial outcomes because it featured investment decisions over twenty-year horizons. A lack of perceived payment uncertainty and experimenter credibility inherent to long-term contexts may influence the decisions of participants (Cohen, Ericson, Laibson, & White, 2020), rendering any comparison with short-run behavior unfeasible. Although this limitation does not affect the internal validity of the findings, given the uniform application of compensation structure across both treatments, it could impact the external validity of our conclusions. Recent literature, such as Hackethal et al. (2023), suggested that non-incentivized decision-making does not markedly deviate from incentivized scenarios, possibly mitigating concerns over the impact of compensation structure. Nonetheless, the potential implications of non-incentivized decisions for investment behaviors under varying time horizons specifically remain unexplored and therefore warrant cautious interpretation.

8.5 Future Research

Because myopia has emerged as a robust cognitive feature impacting financial decisions, it represents an interesting topic for future research. Notably, the variance in short-sighted financial behaviors among individuals, as well as the underlying reasons of such, warrant closer examination. While existing research has delved into cognitive reflection drivers (Mani et al., 2013), the specific determinants of temporal thinking remain less understood. Moreover, Enke and Graeber (2021) suggested a link between hyperbolic discounting and cognitive uncertainty in evaluating long-term decisions, hinting at a complex interplay between myopia and cognitive processes. Future studies implementing within-subjects design could aim to untangle the effects stemming from temporal myopia and the biased processing of information, enriching our understanding of how individuals aggregate intertemporal information. Such endeavors could extend beyond our between-subjects experimental designs and measure varying individual degrees of myopia using within-subjects configurations. Furthermore, mixed designs could address potentially heterogeneous responsiveness to interventions, thereby identifying target groups for policy initiatives.

The foundational work of Benartzi and Thaler (1995) emphasized the significance of decision myopia in household finance, drawing attention to how short-term mental accounting influences investment choices. While chapter 2 confirms the persistence of myopic loss aversion (MLA) under certain conditions, its application to asset classes beyond stocks, such as bonds, remains unexplored. Given that bond portfolios typically present lower loss probabilities, it would be intriguing to consider whether MLA similarly affects risk-taking behaviors in this context. Research by T. Langer and Weber (2001) suggests that aggregate evaluation of bond assets leads to decreased risk-taking, causing a reversal of the MLA effect. Additionally, the relative influence of myopic evaluation versus decision frequency on financial risk-taking remains ambiguous, with literature offering mixed findings (see, e.g., T. Langer & Weber, 2008; Fellner & Sutter, 2009). Future research could clarify these dynamics, offering deeper insights into the triggers of MLA.

chapter 3 shows how external elements in the decision environment can reinforce myopic behaviors. Our study on the effects of short-term price charts could be implemented in the field as well, testing the effect of different default displayed time horizons on actual decisions and investment holding periods of online retail investors. More broadly, future research could test the influence of other short-horizon—or System 1—stimuli on investment behavior. Smart phone push notifications, news reporting of daily index returns, or participation in online investment forums are all examples of factors potentially bolstering the myopic tendencies of individuals. Understanding the potentially adverse impacts of these stimuli could inform the design and testing of interventions like smart default settings or aggregated risk communications in both laboratory and real-world settings.

The findings in chapter 4 open up interesting avenues for future research about the role of long-term expectations in stock investing. Systematic overestimation of long-run risks may have substantial consequences for stock market participation. Future research could address whether other (short-sighted) expectations explain participation in financial markets, or which horizons individuals adopt in their evaluation of stock investing risks. This allows for a more holistic analysis of the role of myopia for stock investing, including, among others, people's difficulty to predict their future utility (projection bias; Loewenstein et al., 2003). Exploring individual differences in myopia, influenced by socio-economic, psychological, or cultural factors, could further enhance our understanding of its determinants and effects. Building upon the theoretical foundation by Gabaix and Laibson (2022), such research could further delineate temporal myopia from simple time preferences, offering valuable insights for both theory and practice.

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Chapter 9

General Appendix

A.1 Author Contributions

The Consequences of Narrow Framing for Risk-Taking: A Stress Test of Myopic Loss Aversion

- Idea: R. Schwaiger, **M. Strucks**, & S. Zeisberger
- Experimental Design: R. Schwaiger, **M. Strucks**, & S. Zeisberger
- Software Programming: **M. Strucks**
- Analysis: **M. Strucks**
- Writing First Draft: R. Schwaiger & **M. Strucks**
- Writing Final Version: R. Schwaiger, **M. Strucks**, & S. Zeisberger

History matters: How Short-Term Price Charts Hurt Investment Performance

- Idea: **M. Strucks** & S. Zeisberger
- Experimental Design: C. Borsboom, D.-J. Janssen, **M. Strucks**, & S. Zeisberger
- Software Programming: C. Borsboom & **M. Strucks**
- Analysis: C. Borsboom & **M. Strucks**
- Writing First Draft: C. Borsboom & **M. Strucks**
- Writing Final Version: C. Borsboom, D.-J. Janssen, **M. Strucks**, & S. Zeisberger

Why Do People (Not) Invest? The Role of Return and Risk Expectations

- Idea: **M. Strucks**, & S. Zeisberger
- Experimental Design: **M. Strucks**, & S. Zeisberger
- Software Programming: **M. Strucks**
- Analysis: **M. Strucks**
- Writing First Draft: **M. Strucks**
- Writing Final Version: **M. Strucks**, & S. Zeisberger

A.2 Research Data Management

Sound management of the data used for academic research ensures scientific integrity and transparency of research methodology. This dissertation features research projects aligning with Radboud University's policy and guidelines on the management of research materials.

Every research chapter contained in this dissertation employs primary data collection through experiments. Responses were collected on the online survey platform Qualtrics. To provide monetary compensation to respondents in our online experiments, we collected uniquely identifiable information, which was deleted upon payment completion. Anonymized data are stored on Radboud University's SurfDrive environment, together with supplementary materials such as experimental screenshots and script files describing the analyses conducted by statistical software programs. Research materials, including non-identifiable data, are also available on the Open Science Framework, for purposes of replication and reproduction of the research findings, exclusively.

The statistical software packages Stata and R were used to clean and analyze the data as well as to report research outcomes. Script files outline each step in this process and include elaboration to enhance clarity. The storage of research materials adheres to the regulation of Radboud University on research data management.

A.3 Nederlandse Samenvatting

De vergrijzing van de bevolking vormt een uitdaging voor huidige pensioenstelsels en vergroot het belang van individuele spaartegoeden op de lange termijn. Maar ondanks de verbeterde toegang tot personal finance tools, versterken technologische ontwikkelingen vaak kortetermijn beleggingsperspectieven. Drie studies in dit proefschrift belichten de individuele gevolgen van kortzichtig, of myopisch, beleggingsgedrag en -percepties door middel van beslissingsexperimenten die realistische scenario's nabootsen. De eerste studie benadrukt de relevantie van myopic loss aversion en laat zien hoe dit het nemen van financiële risico's in verschillende omgevingen beperkt. De tweede studie verbindt de presentatie van kortetermijn prijzen van activa met verhoogde handelsactiviteit en verminderde portfolioprestaties. Tot slot laat de derde studie zien hoe de vooringenomen perceptie van langetermijn risico's op financiële markten de deelname van individuen aan deze markten remt. Gezamenlijk pleiten deze resultaten voor beleidsinitiatieven die de transparantie van en de nadruk op de communicatie over langetermijn risico's en rendementen van financiële activa vergroten, met als doel de financiële zekerheid van huishoudens op de lange termijn te versterken.

A.4 English Summary

Ageing populations challenge current state retirement systems and increase the importance of individual long-term savings accumulation. Yet, despite offering greater access to personal finance tools, technological advancements often reinforce short-term investment perspectives. Three studies in this dissertation elucidate the individual consequences of short-sighted, or myopic, investment behavior and perceptions through decision experiments mimicking real-world scenarios. The first study highlights the relevance of myopic loss aversion, showing how it curtails financial risk-taking in various settings. The second study connects the presentation of short-term asset prices to increased trading activity and reduced portfolio performance. Finally, the third study reveals how individuals' biased perceptions of long-run risk on financial markets inhibit their participation in these markets. Collectively, these results call for policy initiatives enhancing the transparency and emphasis on long-term risk and return communication of financial assets, aiming to bolster the long-term financial security of households.

A.5 Curriculum Vitae

Markus Strucks was born in Kleve (Germany) on December 11, 1993. After completing his German high school diploma (Abitur) in 2013, he pursued a degree in International Economics and Business at Radboud University, Nijmegen, The Netherlands. He graduated with a Bachelor's degree in 2016 and earned a Master of Science in Financial Economics in 2017. Driven by his passion for academia, Markus Strucks embarked on a Ph.D. as a Junior Researcher and Lecturer in the Department of Economics and Business under the supervision of Prof. Dr. Stefan Zeisberger. Throughout his educational trajectory, he participated in exchanges and research visits at institutions in the United States, Sweden, and Austria. He is currently a post-doctoral researcher at Montpellier Business School in France.

In an era of financial democratization and ageing populations, the importance of long-term financial decisions has never been greater. Yet, many individuals remain focused on the short run, neglecting the broader implications of savings choices for their financial well-being. This dissertation presents a series of studies revealing how short-sighted decisions can undermine personal wealth accumulation over time. Collectively, the results underscore the potential of policies improving transparent long-term asset risk and return communication to empower individuals to make future-oriented savings decisions.

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