Cognitive Foundations
of Investor Behavior

The Role of Biased Memory, Imperfect Attention, and Categorical Thinking

in Individual Investment Decisions

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Dissertation

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[1] I remember, we passionatley dicussed about music (of course!).

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[2]Without you and your calmness I would have freaked out with all the paramedics around me!
[3]Even while running, traveling, or partying in the middle of the night.

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Contents

Chapter 1

General Introduction

Some of the most consequential economic decisions we make over our lifetimes are related to investments. Those decisions largely determine our financial situation later in life. Yet, people seem to make systematic investment mistakes – even if these mistakes are associated with large costs. People in the US and Europe generally hold under-diversified portfolios and invest in costly financial instruments; many people trade too actively while others forego substantial equity returns by not participating in the stock market at all (Beshears et al., 2018). Those common mistakes have important consequences, as costly mistakes compound over time in the same way as returns do, only they reduce wealth. Think of investing for retirement. If you invest money each month for 35 years, costs reducing your return from 6% to 5% per year accumulate to substantial wealth reductions at the time of retirement.

How we make decisions is determined by our brain. It pays attention to relevant information, refers back to past experiences, and learns something new with every decision we make. Yet, sometimes our brain tends to trip us up. For example, it manages how we feel about ourselves. The brain can let us ignore particular information or edit our own memories to make ourselves look better; without us even noticing it (Mather and Carstensen, 2005). This can lead us stick to bad decisions despite mounting evidence that they were wrong; like a gambler chasing losses.

This dissertation explores such cognitive processes in investment decisions. I seek to enhance the understanding of people's investment behavior by exploring the cognitive foundations of that behavior. My contention is that a wide range of behavioral phenomena in financial markets, including costly investment mistakes, which seem disparate at first sight, might share a common explanation in terms of cognitive imprecision. Progressing toward a more unified picture of investment behavior is not only important from a theory perspective (Barberis, 2018), but also for designing policy interventions that are targeted to improve household fi-

nancial outcomes (Beshears et al., 2018). However, while economic and finance theory has made great progress in integrating cognitive factors into behavioral models, empirical evidence of the important role of those factors in investor decision-making is scarce. This thesis, thus, aims at enhancing the empirical basis of how cognitive processes influence individual investment decisions. Cognitive psycholpogy put forth evidence for biases in human decision-making being centrally related to cognitive errors. In this vein, my first research question is: *How do cognitive imprecisions influence individual investment decisions?* Therefore, three well-documented cognitive imprecisions from psychology will be examined: (i) biased memory, (ii) imperfect attention and (iii) categorical thinking.

Grounded in finance theory, I explore beliefs as a channel through which cognitive imprecisions shape investment decisions. A central idea in behavioral finance is that people can hold distorted beliefs, which bias their investment decisions. For example, investors are sometimes too optimistic about future outcomes and in turn trade too much (Odean, 1999). Gaining insights into underlying cognitive factors of beliefs promises to provide an organizing structure for why people sometimes hold such wrong beliefs and to advance our understanding of investor behavior. Thus, my second research question is *whether beliefs are the channel through which the investigated cognitive errors influence investment decisions.*

Finally, this dissertation examines whether cognitive factors underlie systematic investment mistakes. This is important for making predictions about whether cognitive imprecisions can actually have consequences for investors' wealth. Hence, this dissertation investigates the question: *Do the investigated cognitive errors cause suboptimal investment decisions?*

My findings from three experimental studies show that cognitive imprecisions play a key role in individual investment decisions. The core chapters document that biased memory, imperfect attention, and categorical thinking systematically distort beliefs and influence investment choices. Notably, these cognitive errors can explain important investment mistakes, such as re-investing in bad performing stocks. Together, my results provide a useful foundation to understand how people attend to and learn from financial information.

The remainder of this introduction outlines theoretical underpinnings of the dissertation and describes important empirical findings from previous literature as the groundwork of my research. I will first present individual beliefs as a basis of investment decisions and then describe the role of cognitive factors in explaining both beliefs and investment decisions. Further, this introduction contains a discussion of my methodological approach, a summary of my core chapters, and illustrates how these chapters contribute to central strands of research

and provide implications for policy.

Individual Beliefs in Investment Decisions

How people form beliefs about future outcomes of a potential investment is key to understanding their decision to invest. Standard theory in finance builds on a model in which people make choices in a way that maximizes their utility, properly incorporating all available information. This is based on two assumptions about the individual decision-maker. First, it is assumed that people form rational beliefs. That is, people update their beliefs about future outcomes when new information arrives, immediately and in a correct manner (according to Bayes' rule). Second, given those correct beliefs, people are assumed to always choose the action with the highest Expected Utility to maximize their utility function.

However, psychology and finance research has put forth rich empirical evidence for people deviating from this standard framework in important ways, which behavioral finance aims at incorporating into theoretical models. An important strand of work formalizes deviations from the standard theory due to non-standard beliefs.[1] These models try to explain systematic deviations of individuals' beliefs from a rational Bayesian account and to describe their consequences for investor behavior as well as phenomena at the aggregate market level. Two of the most important explanations in the current finance literature are extrapolative beliefs and overconfidence (Barberis, 2018).[2]

First, investors tend to form *extrapolative beliefs.* Their expectations of future outcomes of an asset, typically returns, is a positive function of the asset's past returns, with an emphasis on recent past returns (Barberis et al., 2015, 2018; Barberis and Shleifer, 2003). Survey data on investor expectations provide empirical evidence for the extrapolative nature of investor beliefs. Investors' expectations of stock market returns are positively correlated with past market returns (Greenwood and Shleifer, 2014). Consequently, investors' demand for an asset depends on a weighted average of past returns, where recent returns receive more weight (Barberis, 2018). This tendency of return extrapolation can explain important stylized facts about asset prices, such as medium-term momentum, long-term reversal, and the value premium in the cross-section of average returns; excess volatility and time-series predictability in aggregate asset classes; and the formation and collapse of bubbles (Barberis, 2018).

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[1]In general, three major approaches to psychology-based models of investor behavior can be distinguished, namely models formalizing deviations from the standard theory due to non-standard beliefs, non-standard preferences, and bounded rationality (Barberis, 2018).

[2]See (Benjamin, 2018) for an excellent review of biases in beliefs and their integration into economics.

Second, investors are *overconfident.* Overconfidence is a broad concept that relates to different psychological phenomena (Moore and Healy, 2008). People can be overconfident about the precision of their knowledge. This leads investors to value information in an irrational way, i.e., underweight some types of information and overweight others (Odean, 1998). For example, investors can overestimate the precision of their own information and underestimate the precision of other people's information (Daniel et al., 1998). This kind of overconfidence can lead investors to hold quite different beliefs about future outcomes of an asset, generate disagreement, and in turn induce trading between them. Another prominent example is that people have overly good views about their own abilities relative to others, a phenomenon called "overplacement." Gervais and Odean (2001) propose a model in which successful traders become overconfident, because they attribute success disproportionately to their ability rather than luck. Overconfidence-based models provide an explanation of the high trading volume in financial markets. Indeed, empirical findings indicate that overconfidence induces trading (Odean, 1999).

Those concepts of non-standard beliefs offer simple and intuitive explanations of central findings about investment behavior and the aggregate market, such as return predictability, excess volatility, and the equity premium. A key remaining question in this literature, one which will be addressed by this dissertation, is that of the sources of belief distortions (Barberis, 2018). I provide experimental evidence that biased memory of experienced returns (Chapter 2) as well as categorical thinking (Chapter 4) are reasons for non-standard beliefs.

The Role of Cognitive Factors in Investment Decisions

Economics research has begun to take cognitive factors into account when modeling economic behavior. This body of research is motivated by the idea that many well-documented behavioral deviations from standard theory might be rooted in a common explanation related to cognitive imprecision.

So far, finance theory considers cognitive factors by proposing frameworks in which people optimize under limited mental processing capacities (Barberis, 2018). Most prominently, it is argued that investors are not able to immediately attend to every relevant piece of information available. This inattention to some information can explain underreaction to news, such as earnings announcements (DellaVigna and Pollet, 2009; Hirshleifer et al., 2009). *Attention* to an option is a prerequisite for beliefs or preferences to influence financial decisions about that

option. People first select which options to consider and then decide which of those options to choose. For example, how do investors decide which stocks to consider buying? It has been shown that individual investors are more likely to buy rather than sell those stocks that catch their attention through extreme returns, high trading volume, or media coverage (Barber and Odean, 2008).[3]

A second cognitive limitation considered in finance theory is *categorical thinking* (Barberis, 2018). Categorical thinking can be seen as a simplification of Bayesian Updating in which people can hold only a limited set of posteriors rather than every possible posterior (Mullainathan, 2002). That is, when forming beliefs, cognitive constraints can lead people to form overly generalized beliefs based on group-level information, ignoring lower-level information. In this vein, Barberis and Shleifer (2003) propose that some investors put assets into categories and form beliefs about the assets' future returns at the category level (for example for value stocks, growth stocks, or small-cap stocks as a group). The model suggests that, consequently, investors express their demand for assets at the level of those categories. Barberis et al. (2005) provide empirical evidence for such a category-based demand effect.

Economics research has started to integrate another basic cognitive imprecision into the analysis of economic behavior, namely inaccurate *memory*. Two related but distinct strands of work suggest that memory plays an important role in belief formation and economic choice. The first strand is rooted in the idea that the accessibility of information in memory influences subjective beliefs, for instance, how easy the probability of an event can be brought to mind (Tversky and Kahneman, 1974). In this vein, current theory work in economics builds on the concept of representativeness. The representativeness heuristic by Kahneman and Tversky (1972, 1973) suggests that people anticipate outcomes that appear most representative of the evidence, when making probabilistic judgments. A belief formation mechanism based on representativeness is the concept of diagnostic expectations. The key idea of diagnostic expectations is that, when people are judging the probability of an event, the states of the world that are most representative of the event are most likely to "come to mind" (Gennaioli and Shleifer, 2010). People then overestimate the probabilities of these states. Bordalo et al. (2019) find suggestive experimental evidence for selective memory affecting such probability judgments as described by the representativeness heuristic. They show that despite an unbiased experience of information, people systematically overweight representative features because of selective memory. Further, Bordalo et al. (2017) argue that the way previously experienced information

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[3]See Gabaix (2017) for an in-depth review of models of inattention in economics.

is represented in memory should affect subsequent decision-making. They propose a theory in which a decision-maker recalls past experiences in response to a cue of the decision problem. Based on psychological insights (Kahana, 2012), they assume recent and more similar experiences to crowd out other experiences from memory. In addition, the model includes a surprise relative to this memory, which affects the decision-makers subsequent choice.

The second strand of theory builds on the notion that people make decisions based on erroneous subjective perceptions of the decision situation (McFadden and Baron, 1999). In particular, it is argued that people can hold a noisy representation of the decision problem in mind due to neurological constraints. When they rely on this noisy mental representation, suboptimal choice can emerge even if people follow optimal Bayesian inference and decision-making (Gabaix and Laibson, 2017; Khaw et al., 2017; Natenzon, 2019; Steiner and Stewart, 2016; Woodford, 2012). For example, Khaw et al. (2017) propose that decision makers often fail to accurately choose the option with the highest Expected Utility, because their decision is based not on the exact characteristics of the available options, but rather on an imprecise mental representation of the monetary amounts that are offered. One natural mechanism behind such imprecise mental representations is selective storage or retrieval of information from memory (McFadden and Baron, 1999).

Integrating cognitive factors into theory is an important step toward a unifying organization of a wide range of behavioral phenomena, which is crucial to advance the field of behavioral finance (Barberis, 2018). It can help to paint a consistent picture of behavioral biases, their sources, and consequences for market outcomes. In this spirit, my core chapters examine cognitive foundations of investor behavior. I thereby address important, but so far unsolved, issues within this strand of research by providing empirical evidence of cognitive imprecisions influencing investors' belief formation (Chapter 2 and 4) and decision-making (Chapter 2, 3, and 4) as well as offering new insights into potential consequences for investor wealth (Chapter 2, 3, and 4).

Why Lab Experiments?

In order to empirically examine cognitive factors in investment decisions and to isolate their effect on beliefs and choices, this dissertation uses laboratory experiments. Lab experiments are a key source of knowledge in the social sciences (Falk and Heckman, 2009). In this chapter, I briefly outline essential characteristics of lab experiments I take advantage of to address my

research questions.

First, lab experiments allow for a controlled variation of a single variable of interest holding all other things equal, which is the foundation of generating causal knowledge.[4] In my experimental studies, I use controlled variation of time horizons to isolate memory effects (Chapter 2), of attention-grabbing characteristics of returns to isolate attention effects (Chapter 3), and of category-level information to isolate category-learning effects (Chapter 4). In addition, enhanced control of the decision problem enables the implementation of a rational benchmark to which subjects' behavior can be compared to and evaluated. In this dissertation, I use experimental tasks with Bayesian probabilities as a benchmark for objectively correct beliefs and an objectively correct choice based on known expected outcomes.[5] Thereby, I can draw clear conclusions about subjects' deviations from the Bayesian benchmark of objectively correct beliefs and choices throughout my core chapters, which is less viable in non-experimental data.

Second, the lab offers a unique setting to directly measure variables that are not observable in the field. For example, in many available datasets in economics and finance research, beliefs have been unobserved (Benjamin, 2018). Yet, there is now a growing strand of literature concerned with incentive-compatible elicitation of beliefs in the lab (see Schotter and Trevino (2014) for a review). Further, the lab is particularly helpful when one wishes to measure cognitive factors in decision-making. Elicitation methods from cognitive psychology often require a setting with particular technology or a controlled environment. In this dissertation I take advantage of the lab setting to use a reliable elicitation method for subjects' beliefs (Chapter 2 and 4) and to directly measure cognitive factors, such as memory (Chapter 2) and attention (Chapter 3).

A more general argument is that tight control of the decision problem enhances the ability to replicate results. The replicability of empirical findings is crucial for the trust in scientific knowledge. Yet, studies show that in economics and finance, statistical findings from non-experimental data are not always replicable, even when the data and code are easily accessible (Anderson and Kichkha, 2017; Dewald et al., 1986; Hubbard and Vetter, 1991). By contrast, Camerer et al. (2016) document a relatively high replication success for laboratory experiments in economics and finance. They argue that especially two methodological research practices

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[4]For an in-depth discussion of advantages and limitations of lab experiments in social sciences and a comparison of this methodological approach to research based on non-experimental data and field experiments see Falk and Heckman (2009).

[5]The benchmarks in my chapters are based on the assumption of risk neutrality, but the findings hold for a wide range of reasonable risk attitudes. See Chapter 2 and 4 for a detailed discussion.

contribute to this: (i) strong norms about the use of financial incentives and the avoidance of deception, and (ii) norms of transparency with respect to experimental instructions, procedures, and original data. These practices are assumed to make subjects more responsive during the experimental tasks and may reduce variability in how experiments are performed across different research teams. Throughout the studies of this dissertation, I follow those norms strictly.

Outline of Core Chapters

This dissertation explores cognitive foundations of investment behavior. In line with my research questions, my core chapters investigate how (i) biased memory, (ii) imperfect attention, and (iii) categorical thinking influence people's beliefs and investment decisions. I use experimental methods to examine these cognitive factors and isolate their effect on beliefs and choices. The studies focus on how people attend to and learn from returns, a key form of financial information. In particular, I test how subjects attend to and learn either from available information about returns or from past experiences of returns.

The first study of this dissertation (Chapter 2) investigates how *memory* shapes investment decisions. While we all learn from experiences, our memories of those experiences can be both selective and distorted. Memory is not a neutral, accurate account of past events, but is subject to errors and biases (Schacter, 1999). An important finding from psychology is that memory tends to be biased in ways that maintain and enhance one's own positive self-image: People are more likely to remember personal successes than failures and to remember features of past options that are supportive of the choices they made (Mather and Johnson, 2000). My co-authors and I formalize a model in which people's memory of investment outcomes can be systematically biased in a self-serving way and thereby distorts beliefs. The memory bias stems from quasi-Bayesian belief updating with a probability of under-remembering specific previously observed signals. In the model, the agent observes outcomes of an asset in order to update her belief about the quality of the asset. She relatively under-remembers outcomes that are inconsistent with her positive self-image, and thus underweights them. If the agent invested in the asset, she under-remembers negative outcomes relative to positive ones and becomes over-optimistic about the quality of the asset. We use an experimental setting to test for the self-serving memory bias as well as its effect on beliefs and investment decisions. In the experiment, subjects choose to invest either in a risky stock or a risk-free asset (Kuhnen, 2015).

To identify subjects' memory bias, we let subjects observe a series of investment outcomes, i.e., stock returns, and elicit their memory of those outcomes either immediately following or one week after the observation. To relate subjects' memory bias to their beliefs and future investment behavior, we further elicit their beliefs about the stock's future outcomes and ask them to make another investment decision.

We find experimental evidence of a systematic memory bias for gains and losses and show that this memory bias distorts beliefs and impacts investment choices. The memory bias is self-serving. Our results show that subjects over-remember investment gains and under-remember investment losses, if they actively invested in the asset. In contrast, subjects who decided not to invest in the asset do not display this memory bias. Thus, a key characteristic of the self-serving memory bias is the distinction between memory of events with different levels of self-relevance (active experience versus passive observation). Further, we show that the memory bias predicts subjective beliefs and affects future investment decisions. We find that subjects who invested in the asset put more weight on positive outcomes relative to negative outcomes from memory and thus form overly optimistic beliefs about the asset. Those subjects are also more likely to re-invest in the stock, even when doing so reduces their expected return. Hence, subjects do not adjust their behavior to account for the fallibility of their memory, which leads to investment mistakes. The memory bias we document changes the understanding of how people form beliefs based on experiences in financial markets and is relevant for understanding household financial decision-making.

The second study (Chapter 3) examines investor *attention*. Previous research documents that individual investors are more likely to buy rather than sell those stocks that catch their attention (Barber and Odean, 2008). In cases when attention-attracting qualities of a stock indirectly detract from its utility, the tendency to buy attention-grabbing stocks can lead to suboptimal investment decisions. Indeed, empirical studies find that stocks underperform after private investors buy those stocks due to an attention shock. My co-author and I study the causal effect of extreme returns – as an important attention-attracting quality – on subjects' attention and subsequent stock buying behavior at the individual level. In an experimental setting, we manipulate the magnitude of price changes and investigate both situations in which these attention-grabbing characteristics are positively correlated with stock performance and situations in which these two are negatively correlated. Further, we employ a direct measure of visual attention by recording subjects' eye movements during the experimental tasks using eye-tracking devices.

We find that attention-grabbing returns affect people's stock purchase patterns. However, this finding hides part of the mechanisms behind investor attention. Our findings show that the attention-driven purchase behavior is asymmetric. Shares of stocks with recent extreme negative returns are more likely to be purchased than shares of stocks with recent less extreme negative returns. Yet, comparable patterns are not observed for stocks with positive returns. The directly measured individual visual attention mediates this effect. Extreme returns increase subjects' stock purchase volume through channeling their visual focus on the respective stock. Importantly, the results show that attention-driven purchase behavior occurs even in situations in which it reduces subjects' expected return. Moreover, we observe that the demand for attention-grabbing stocks increases at the expense of the demand for non-attention-grabbing stocks, further supporting the finding of an attention-driven investment bias. The attention effect we document is important, because it can influence trading, liquidity, returns, and investor wealth.

The third study (Chapter 4) focuses on a fundamental mechanism of human thought: *categorization*. One of the most important functions of categorization is its role in learning (Bransford et al., 2000). Categorization allows the prediction of unseen features; people classify objects into categories and make predictions about object features at the level of its category (Anderson, 1991). A classification of objects into categories is also pervasive in financial markets. It has been argued that investors seem to first categorize assets into broad classes based on common characteristics, such as into value stocks, growth stocks, or small-cap stocks, and then move funds across those classes, which is called "style investing" (Barberis and Shleifer, 2003). Style investing has important implications for asset prices, as styles become popular and unpopular and drive excessive return comovement of firms within specific classes (Barberis et al., 2005; Green and Hwang, 2009). Theory suggests that style-level demand for those assets emerges from the fact that investors form beliefs about the future performance of assets at the category level (Barberis and Shleifer, 2003). Yet, empirical insight into how investors form category-based beliefs is scarce. This study examines the role of coarse categories in individuals' learning from financial information in an experimental setting. Based on a theoretical model of categorical thinking in economic decision-making (Mullainathan, 2002), this study tests implications of coarse categories for individulas' belief formation and investment decisions. Similar to Chapter 2, the experimental setting consists of investment tasks. Subjects choose to invest either in a risky stock or a risk-free asset (Kuhnen, 2015). To identify category-based beliefs, we provide subjects with coarse category-level information

about the potential stock, i.e., industry information, and let them observe a series of stock returns before we elicit their beliefs about the stock's future outcomes. The key idea of the experimental design is a manipulation of the categories' level of coarseness. Thus, we compare subjects' beliefs in this treatment to beliefs stated in a condition in which subjects see more disaggregated information based on finer categories, but still face the identical learning environment. The treatments are implemented within-subjects across four experimental blocks. To relate subjects' category-based beliefs to their future investment behavior, we ask them to make investment decisions after observing the stock's outcome.

The study's results show that, when coarse categories are present, subjects form on average more pessimistic beliefs about the stock investment. Yet, as proposed by the theoretical model by Mullainathan (2002), we find evidence for overreaction to new information in case the new information is suggestive of a "category change". That is, when an observed outcome of the stock should objectively change the belief about the stock's industry belongig, subjects updated their beliefs too strongly and formed overly optimistic beliefs about the stock's future outcomes. This overreaction varies across different category types and is associated with higher stock investments afterwards. Interestingly, this tendency correlates with fewer suboptimal investment decisions in our experimental setting. The findings enhance the understanding of how people learn from financial information when information aggregation along prominent categories in financial markets, such as industries, is present.

Together, my results provide a useful foundation of how people attend to and learn from both available financial information as well as related past experiences. The explored cognitive imprecisions distort beliefs and influence investment choices. In the next two chapters, I evaluate my results' contribution to current research and discuss implications for policy.

Contribution to Central Strands of Research

This dissertation provides empirical evidence for cognitive imprecisions being an important driver of investment behavior and thereby contributes to central strands of research. In this section, I structure the contributions to these research areas along my three research questions.

My first research question is: How do cognitive imprecisions influence individual investment decisions? By answering this question, I provide *empirical evidence of cognitive errors* influencing people's belief formation and investment decisions. Thereby, my findings add to current research that incorporates cognitive factors into the analysis of economic decision-

making. Economic and finance theory has made great progress in integrating cognitive factors into behavioral models. However, empirical evidence for the importance of those cognitive factors in investor decision-making is limited. The core chapters of my thesis address this by providing empirical evidence for biased memory (Chapter 2), imperfect attention (Chapter 3), and categorical thinking (Chapter 4) affecting investment decisions.

Further, Chapter 2 sheds light on the role of "motivated cognition" in investor behavior. Motivated cognition refers to the influence of motives on cognitive processes. A growing body of literature in economics proposes that motivation is a central theme underlying individual beliefs and reasoning (Bénabou and Tirole, 2002, 2016; Kőszegi, 2006). Chapter 2 supports this notion and relates it to memory. I provide evidence for a memory-based mechanism that helps people end up with the beliefs that are favorable to them. My results thereby offer a new perspective on how biased memory impacts economic decision-making by linking the two strands of research on motivated beliefs (Bénabou and Tirole, 2002, 2016; Kőszegi, 2006) and memory (Bordalo et al., 2017; Bordalo et al., 2019) in economic choice.

Further, my dissertation is concerned with the question whether beliefs are the channel through which the investigated cognitive errors influence investment decisions. In line with this second research question, my results show that biased memory (Chapter 2) as well as categorical thinking (Chapter 4) alter beliefs about future returns. The dissertation thereby contributes to behavioral finance research by isolating cognitive factors as *sources of non-standard beliefs*, which is a key question in current literature. Chapter 2 investigates biased memory as a source of distorted beliefs. The study shows that positive and negative outcomes, such as returns, are remembered differently dependent on whether people invested in a stock or not. Subjects relatively under-remember negative compared to positive outcomes. This self-serving memory bias has important consequences. After investing, subjects in our study form overly optimistic beliefs. This changes the current understanding of how people form beliefs based on experiences in financial markets. The key implication of the "experience hypothesis" from prior literature is that experiencing high returns should be correlated with higher financial risk taking and experiencing low returns should be correlated with lower financial risk taking (Malmendier and Nagel, 2011). Yet, we add to this strand of research by showing that this depends on whether people invested or not. People who invested can show high levels of risk taking despite experiencing low returns, if they form overly optimistic beliefs based on their biased memory – compared to those who did not invest.

Moreover, Chapter 2 provides experimental results that are in line with the idea that

traders learn to be overconfident. Gervais and Odean (2001) present a model in which biased learning leads successful investors to become overconfident, because they attribute success disproportionately to their ability rather than luck. However, the memory bias documented in Chapter 2 can even explain why unsuccessful traders become overconfident and persist trading (Barber et al., 2017). Forgetting own losses can lead to the overweighting of successes despite an extensive experience of losses. Overconfidence is also related to overoptimism, a bias toward beliefs that are too favorable to oneself (Windschitl and Stuart, 2015). Chapter 2 isolates memory as a foundation of such overoptimistic beliefs and helps explain why overoptimistic beliefs are maintained in the face of contradictory evidence. A biased representation of experienced returns in memory leads people to hold overly optimistic beliefs about their asset.

Chapter 4 sheds light on categorical thinking as a source of non-standard beliefs. More precisely, I provide empirical insights into when people form category-based beliefs. The results document that subjects form distorted beliefs based on financial information when the observed data suggests a category change. Subjects then update their beliefs too strongly and form overly optimistic beliefs about the stock's future outcomes. Yet, this overreaction varies across different category types. It is observed for "good" stock categories associated with gains. However an opposite belief pattern emerges for "bad" stock categories associated with losses. This finding provides a cognitive explanation for differences in how people form beliefs in financial markets.

Finally, I investigate the question: Do the investigated cognitive errors cause suboptimal investment decisions? Addressing my third research question offers new insights into potential *consequences for investors' wealth.* The experimental findings of my core chapters show that cognitive factors are an underlying reason for systematic investment mistakes, which so far has been difficult to identify in previous studies based on non-experimental data. In the stock market, individual investors are more likely to buy rather than sell those stocks that catch their attention (Barber and Odean, 2008). This can lead to suboptimal choices when attention-attracting qualities of a stock may indirectly detract from its utility. In this vein, Chapter 3 shows that attention-grabbing characteristics of stock returns can lead people to make suboptimal choices. The study considers both situations in which these attention-grabbing characteristics are positively correlated with stock performance and situations in which these two are negatively correlated. The findings show that subjects' tendency to focus on stocks with extreme returns makes them decide suboptimally and systematically lose money in the experiment. In addition, Chapter 2 provides evidence of memory-based invest-

ment mistakes. Subjects do not adjust their behavior to account for the fallibility of their memory. After investing, they form overly optimistic beliefs and re-invest in the stock even when doing so reduces their expected return.

Implications for Policy

Politics promote initiatives to overcome common investment mistakes of private households. However, interventions to improve household financial outcomes that are inspired by behavioral theories, such as financial education, disclosure, social norms, or choice architecture, differ strongly in their impact (Beshears et al., 2018). I argue that cognitive factors might offer an underlying explanation for why some interventions are powerful while others are not, opening avenues for the improvement of intervention designs.

Debiasing strategies typically follow three main forms. They either modify the presentation of the decision problem to induce the appropriate mental procedure, train people to correctly approach the decision problem, or undertake the actual problem solving for people (Roy and Lerch, 1996). If investors have information processing constraints, theoretical models suggest that especially the first category, modifying the presentation format of information, can effectively change investment decision-making (Hirshleifer and Teoh, 2003). Hence, a successful approach to reduce private households' investment biases could be to modify the presentation of financial information based on insights into cognitive imprecisions.

This dissertation's findings reveal that the way stock returns, a key form of financial information, are communicated, is an important starting point. Chapter 2 and Chapter 3 indicate that people can erroneously react differently to positive and negative return information, when people rely on their memory or when returns are extreme. Presentation formats, which balance time horizons or the extremity of price changes might, thus, have the potential to alleviate such investment mistakes. Further, Chapter 4 shows that people deviate much stronger from rational beliefs when return information is aggregated along categories, such as industries in financial markets. Disaggregating information when communicating returns might therefore improve people's belief formation and subsequent investment choice.

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Chapter 2

Investor Memory

with Peiran Jiao and Paul Smeets

How does memory shape individuals' financial decisions? We find experimental evidence of a self-serving memory bias, which distorts beliefs and drives investment choices. Subjects who previously invested in a risky stock are more likely to remember positive investment outcomes and less likely to remember negative outcomes. In contrast, subjects who did not invest but merely observed the investment outcomes do not have this memory bias. Importantly, subjects do not adjust their behavior to account for the fallibility of their memory. After investing, they form overly optimistic beliefs and re-invest in the stock even when doing so reduces their expected return. The memory bias we document is relevant for understanding how people form expectations from experiences in financial markets and, more generally, for understanding household financial decision-making.

2.1 Introduction

How does memory shape individuals' financial decisions? While we all learn from experiences, our memories of those experiences can be both selective and distorted. Furthermore, the memories of personal experiences may be over-weighted relative to less subjective information. If you had a great time with friends at Dave's birthday party in the fancy fish restaurant, you may forget that the food wasn't that good. Such memory limitations are largely ignored in economic and finance research. While economic theory has recently integrated psychology-based facts about memory formation and retrieval into behavioral models, we are the first to provide empirical evidence for a systematic memory bias in financial decisions. We document a self-serving memory bias for gains and losses, which changes the understanding of how people learn from experiences in financial markets.

Personally experienced events are generally stored in episodic memory (Kahana, 2012; Tulving, 1972; Tulving and Murray, 1985).[1] Memory is not a neutral, accurate account of past events, but is subject to errors and biases (Schacter, 1999). Episodic memory, in particular, tends to be biased in ways that maintain and enhance one's own positive self-image: People are more likely to remember personal successes than failures and to remember features of past options that are supportive of the choices they made (Mather and Johnson, 2000).

We formalize a model in which people's memory of investment outcomes can be systematically biased in a self-serving way and thereby distorts beliefs. The memory bias stems from quasi-Bayesian belief updating with a probability of under-remembering specific previously observed signals. The probability of under-remembering particular signals depends on whether they are consistent with the decision maker's positive self-image. In the model, the agent observes outcomes of an asset in order to update her belief about the quality of the asset. She relatively under-remembers outcomes that are inconsistent with her positive self-image, and thus underweights them. If the agent invested in the asset, she under-remembers negative outcomes relative to positive ones and becomes over-optimistic about the quality of the asset. Our approach extends recent theoretical work by introducing a systematic memory bias, which is self-serving. In contrast to previously considered mechanisms of memory formation and retrieval based on representativeness, similarity, or recency (Bordalo et al., 2017; Bordalo et al.,

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[1]Literature contrasts episodic memory of events to semantic memory of abstract knowledge. As an illustration for the different use of episodic and semantic memory in decision-making, consider people's judgements about the likelihood of future events. Applying Bayesian updating to base rate information needs the application of semantic knowledge. Yet, when frequencies of experienced events are incorporated into people's predictions, episodic memory leaks into their judgements.

2019; Gennaioli and Shleifer, 2010; Mullainathan, 2002; Nagel and Xu, 2018), this allows us to differentiate between memory of events with different levels of self-relevance (active experience versus passive observation).

We use an experimental setting to test for a self-serving memory bias as well as its effect on beliefs and investment decisions. Subjects choose to invest either in a risky asset or a risk-free asset (cf. Kuhnen, 2015). The risky asset is either a "good stock" or a "bad stock". A good stock is more likely to generate positive outcomes and a bad stock is more likely to generate negative outcomes. Subjects do not initially know whether their stock is good or bad. To identify subjects' memory bias, we let subjects observe a series of investment outcomes (i.e., stock returns) and elicit their memory of these outcomes either immediately following or one week after the observation. To relate subjects' memory bias to their beliefs and future investment behavior, we elicit their beliefs about the stock's chance of being the good stock and ask them to make another investment decision. An important feature of our experiment is that we can measure what people actually remember and can draw clear conclusions about subjects' deviations from the Bayesian benchmark of objectively correct beliefs and choices.

We have two main findings. First, subjects remember investment outcomes in a self-serving way. They relatively under-remember investment losses compared to gains, if they invested in the stock. In contrast, subjects who decided not to invest in the stock (i.e., chose the risk-free asset) do not display this memory bias. Second, the self-serving memory bias is correlated with subjects' belief formation and future investment choices. One week after the observation, subjects who invested in the stock form overly optimistic beliefs about the stock based on their memory and are likely to re-invest in the stock even when doing so reduces their expected return. For example, 54% of the subjects kept investing in the stock, although from a Bayesian perspective the risk-free asset was optimal. The results are consistent with our model in which image-concerns form the basis for how information is remembered and robust to different measures of memory bias.

How past returns affect individual financial beliefs and decisions has been the focus of a rich strand of literature. There is extensive theoretical work (Barberis et al., 2015, 2018, 1998; De Long et al., 1990; Hong and Stein, 1999) as well as empirical evidence (De Bondt, 1993; Greenwood and Shleifer, 2014; Koijen et al., 2015) suggesting that investors' expectations of future stock market returns are positively correlated with recent past returns. Yet, survey data documents over-extrapolation of returns as investors' expectations are negatively correlated with subsequently realized returns (Koijen et al., 2015). Furthermore, personal experiences

of returns play an important role in financial behavior. Malmendier and Nagel (2011) show that individuals' level of risk taking in financial markets is related to the returns they have experienced during their lifetime. Households with higher experienced stock market returns subsequently invest more of their liquid assets in stocks. Other studies show that investors over-extrapolate from their personal experiences when making savings decisions (Choi et al., 2009), IPO subscriptions (Kaustia and Knüpfer, 2008), or stock repurchasing decisions (Strahilevitz et al., 2011). They tend to repeat actions that have generated favorable investment outcomes in the past.

The novel contribution of this paper is that we isolate memory as a channel through which past returns affect financial beliefs and behavior. We find that positive and negative outcomes, such as returns, are remembered differently dependent on whether people invested or not. This changes the understanding of how people learn from experiences in financial markets. The key implication of the experience hypothesis from prior literature is that experiencing high returns should be correlated with higher financial risk taking and experiencing low returns should be correlated with lower financial risk taking (Malmendier and Nagel, 2011). Yet, we find that this depends on whether people invested or not. People who invested can show high levels of risk taking despite experiencing low returns, if they form overly optimistic beliefs based on their biased memory – compared to those who did not invest. For example, our results are in line with the idea that traders learn to be overconfident. Gervais and Odean (2001) present a model in which biased learning leads successful investors to become overconfident, because they attribute success disproportionately to their ability rather than luck. However, our memory bias can even explain why unsuccessful traders become overconfident and persist trading (Barber et al., 2017): forgetting own losses can lead to the overweighting of successes despite an extensive experience of losses.

Our paper also contributes to the economic literature on self-serving beliefs. This line of work argues that people form those beliefs in order to maintain a positive self-view (Bénabou and Tirole, 2002; Köszegi, 2006). Recent work provides evidence for self-serving belief formation and updating in ego-relevant tasks related to intelligence (Zimmermann, 2018), beauty (Eil and Rao, 2011), and generosity (Di Tella et al., 2015; Saucet and Villeval, 2018). A key question in the literature on self-serving beliefs remains how such belief distortion relates to future behavior. In this paper, we investigate memory as a microfoundation of self-serving beliefs and the impact on future financial decisions. The latter relates to people's naiveté about the fallibility of their own memory. We look at whether people take their memories as

accurate and use them to make decisions or whether they adjust their behavior for limitations of their memory (see Mullainathan (2002) for a naive model where people do not adjust for limitations of memory).

At the aggregate market level, the memory bias may help to explain why short-term momentum is dependent on the state of the market, i.e., is stronger following up markets than down markets (Cooper et al., 2004).[2] We show that the memory of past outcomes, such as returns, is biased in a self-serving way. Thus, in a market with mainly positive returns, investors over-remember their positive returns, overreact to those and generate positive return momentum. However, in a market with mainly negative returns, investors under-remember their negative returns, underreact to those thus dampening or even preventing negative return momentum.

More generally, this paper adds to the field of household finance. The memory bias we document enhances the understanding of why households tend to make costly mistakes regarding key themes in household financial decision-making: asset allocation and risk-taking (Barberis et al., 2006; Campbell, 2009).

2.2   A Model of Memory-Based Belief Distortion

In this section, we present a simple behavioral mechanism for the self-serving memory bias and its effect on beliefs. In the model, the agent uses observed signals to update beliefs about an underlying state in a quasi-Bayesian way (e.g. Rabin, 2002). She behaves as a Bayesian updater, but places wrong weights on signals (e.g. Mobius et al., 2011; Rabin and Schrag, 1999). In our setting, the biased signal weighting happens when the agent retrieves historical data, such as earnings surprises, returns, or dividends, from memory. The weights are biased in a self-serving way (e.g. Köszegi, 2006):[3] the agent relatively under-remembers signals that are inconsistent with her positive self-image, and becomes over-optimistic about more preferred states.

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[2]Cooper et al. (2004) show that the mean monthly momentum profit following positive market returns is 0.93%, whereas it is -0.37% following negative market returns. They find that macroeconomic factors are unable to explain these patterns and suggest microeconomic reasons, such as overconfidence (Daniel et al., 1998; Gervais and Odean, 2001).

[3]See Bénabou and Tirole, 2016 for a review of this literature.

2.2.1 The Model

Suppose in each period t, a stock generates an outcome $d_t \in \mathcal{D}$, where $\mathcal{D}$ is a finite ordered set of outcomes. Outcomes in all periods are *i.i.d.* In a financial market, these outcomes can be thought of as earnings surprises, returns, or dividends. Which outcome is generated in each period is determined by the stock's underlying type. The agent's task is to observe the outcomes and to make inference about the stock's type. For simplicity and for the convenience in our subsequent experimental testing, we use binary outcomes and a binary type space. The outcomes are either positive or negative: $d_t \in \{-1, 1\}$, where -1 represents a negative outcome and 1 represents a positive outcome.[4] The stock is of one of 2 different types good or bad, represented by G and B respectively. Each type corresponds to an underlying distribution from which outcomes are drawn. The probability of a positive outcome is θ_G for a good stock, and θ_B for a bad stock, with $0 < \theta_B < \theta_G < 1$. In other words, the good type has an outcome distribution that first-order stochastically dominates the bad type. Additionally, suppose the two types are equally likely. Let μ_0 represent the agent's prior belief about the stock's type, and we have $\mu_0^G = \mu_0^B = 0.5$.

The true history of outcomes up to period t is represented by $h_t = (d_1, ..., d_t)$. The agent observes the history of outcomes h_t, stores the outcomes in memory as the history of remembered outcomes $h_t^R = (d_1^R, ..., d_t^R)$, and forms beliefs about the stock's type and future outcomes based on h_t^R. Up to period t, the total number of positive outcomes occurred is n_t^+, the total number of negative outcomes occurred is n_t^-. The total number of positive and negative outcomes sum up to t. Let the number of remembered positive and negative outcomes be denoted as $n_t^{+,R}$ and $n_t^{-,R}$, respectively.

Assume that the agent always remembers the total number of periods correctly, thus $t^R = t$.[5] However, $n_t^{+,R}$ and $n_t^{-,R}$ may not be correct representations of n_t^+ and n_t^-. If the agent invests in the stock, she may relatively under-remember negative outcomes compared to positive outcomes.[6] This memory bias could emerge because obtaining negative outcomes might suggest that the initial investment decision was wrong and positive outcomes might justify the initial investment decision. In other words, negative outcomes might be inconsistent with the agent's positive self-image and positive outcomes might align with the agent's posi-

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[4]This is without loss of generality, as long as the set of outcomes is ordered.

[5]This means if the agent relatively over-remembers positive outcomes, she must relatively under-remember negative outcomes. Of course the agent could also under-remember all outcomes in general, but that is not the type of memory bias we would like to capture.

[6]Relative mis-remembering a kind of outcome relative to the other is the phenomenon of interest here. Uniform mis-remembering of both positive and negative outcomes is not explored here.

tive self-image. In a similar vein, if the agent does not invest in the stock, she may relatively under-remember positive outcomes compared to negative outcomes. However, the effect does not have to be symmetric. For instance, the decision to invest could be of higher importance for the agent's self-image compared to the decision not to invest. Many studies document the power of action to alter self-views and provide evidence for an asymmetry between the influence of action and non-action on self-perception (Allison and Messick, 1988; Cioffi and Garner, 1996; Fazio et al., 1982).

Suppose R_t represents the memory bias in period t, given the agent's initial choice to invest in the stock and dependent on whether the outcome is positive or negative:

$$R_t = I_t q^- + (1 - I_t)q^+, \tag{2.1}$$

where I_t is an indicator function that is equal to 1 if the agent invests in the stock in period t, and 0 otherwise. Additionally, $q^- \in [0, 1]$ is the probability of under-remembering a negative outcome and $q^+ \in [0, 1]$ is the probability of under-remembering a positive outcome. The assumption here is that if the agent invests, she faces a probability q^- of forgetting each negative outcome, but she does not mis-remember positive outcomes. Thus, she relatively under-remembers negative compared to positive outcomes. In case the agent invests (does not invest), if $q^- = 0$ ($q^+ = 0$) there is no memory bias, and if $q^- = 1$ ($q^+ = 1$) the memory bias is extreme, i.e., the outcomes are forgotten completely. It is possible that $q^- = q^+$, or $q^- \neq q^+$. That is, the agent may or may not have the same bias if she invests or if she does not. Further, it is possible that either q^- or q^+ is 0, which means the agent has a memory bias only if she invests in the stock, or only if she does not invest in the stock. When $q^- = q^+ = 0$, the model reverts to rational Bayesian updating.

If the agent invests in the stock in period 1 to t, then in period t, the remembered number of negative outcomes will be $n_t^{-,R} = (1 - q^-)n_t^- \leq n_t^-$, and the remembered number of positive outcomes will be $n_t^{+,R} = t^R - n_t^{-,R} \geq n_t^+$. If the agent does not invest in the stock, then in period t, the remembered number of positive outcomes will be $n_t^{+,R} = (1 - q^+)n_t^+ \leq n_t^+$, and the remembered number of negative outcomes will be $n_t^{-,R} = t^R - n_t^{+,R} \geq n_t^-$. Note that equality holds if there is no outcome that contradicts with the agent's positive self-image. This is the case when $n_t^- = 0$ if the agent invests, and $n_t^+ = 0$ if the agent does not invest.

An unbiased agent uses the true history h_t to update her belief about the stock's type. The posterior belief that the stock's type is G of an unbiased agent is represented by:

$$\mu_t^{G,Bayesian}(h_t) = \frac{P(h_t|\theta_G)\mu_0^G}{\sum_{j=G,B} P(h_t|\theta_j)\mu_0^j}.$$

The likelihood ratio of type G relative to type B is given by:

$$\Lambda^{Bayesian}(h_t) = \frac{\theta_G^{n_t^+}(1-\theta_G)^{n_t^-}\mu_0^G}{\theta_B^{n_t^+}(1-\theta_B)^{n_t^-}\mu_0^B}. \tag{2.2}$$

A biased agent uses the history of remembered outcomes h_t^R to update her belief about the stock. The posterior belief that the stock's type is G of a biased agent is represented by:

$$\mu_t^{G,Biased}(h_t) = \frac{P(h_t^R|\theta_G)\mu_0^G}{\sum_{j=G,B} P(h_t^R|\theta_j)\mu_0^j}.$$

The likelihood ratio of type G relative to type B for a biased agent is

$$\Lambda^{Biased}(h_t) = \frac{\theta_G^{n_t^{+,R}}(1-\theta_G)^{n_t^{-,R}}\mu_0^G}{\theta_B^{n_t^{+,R}}(1-\theta_B)^{n_t^{-,R}}\mu_0^B}, \tag{2.3}$$

If the agent invests in the stock $n_t^{+,R} \geq n_t^+$, and thus $\Lambda_{ij}^B(h_t) \geq \Lambda_{ij}^U(h_t)$: the biased agent overestimates the good type relative to the bad type compared to a Bayesian agent. Conversely, if the agent does not invest in the stock $n_t^{+,R} \leq n_t^+$, and thus $\Lambda_{ij}^B(h_t) \leq \Lambda_{ij}^U(h_t)$. Again, the biased agent updates her beliefs like a Bayesian agent if there is actually no outcome that contradicts with her positive self-image.

In general, after a biased agent invests in the stock, her memory of observed outcomes will be biased. She relatively under-remembers less preferred outcomes, and thus when updating beliefs, she becomes overly optimistic about the underlying type of the stock. The opposite might happen if the biased agent does not invest in the stock. However, as stated before, the memory bias might not be symmetric for the cases in which the agent invests and does not invest. Note that when the probability of under-remembering (q^- or q^+) is zero, Equation (2.3) and Equation (2.2) coincide.

The agent with a self-serving memory bias can also be seen as placing biased weights on past outcomes when retrieving them from memory. If she invests in the stock, she relatively overweights positive outcomes, and overestimates the probability that the stock is of the good type. By contrast, if she does not invest in the stock, she relatively overweights negative outcomes, and overestimates the probability that the stock is of the bad type.

Without loss of generality, suppose that $\theta_G = \theta$, and $\theta_B = 1 - \theta$, where $\theta \in (0.5, 1)$.

Additionally, the two types are equally likely, $\mu_0^G = \mu_0^B = \mu_0$.[7] This further simplifies matters and helps us to derive simple representations of biased signal weightings, which are testable in our experiment.

Rewriting Equation (2.2), an unbiased agent's posterior likelihood ratio of G relative to B is

$$\Lambda^{Bayesian}(h_t) = \frac{\theta^{n_t^+}(1-\theta)^{n_t^-}}{\theta^{n_t^-}(1-\theta)^{n_t^+}}$$

For a biased agent, if she invests in the stock, the posterior likelihood ratio of G relative to B is

$$\Lambda^{Biased,INV}(h_t) = \frac{\theta^{t-(1-q^-)n_t^-}(1-\theta)^{(1-q^-)n_t^-}}{\theta^{(1-q^-)n_t^-}(1-\theta)^{t-(1-q^-)n_t^-}} \geq \Lambda^{Bayesian}(h_t)$$

If the biased agent does not invest in the stock, the posterior likelihood ratio of G relative to B is

$$\Lambda^{Biased,NOT}(h_t) = \frac{\theta^{(1-q^+)n_t^+}(1-\theta)^{t-(1-q^+)n_t^+}}{\theta^{t-(1-q^+)n_t^+}(1-\theta)^{(1-q^+)n_t^+}} \leq \Lambda^{Bayesian}(h_t)$$

A Bayesian agent uses the correct number of occurred positive and negative outcomes to update her beliefs, placing equal weight on positive and negative outcomes. As in Equation (2.4), the weight should be exactly equal to $\ln(\frac{\theta}{1-\theta})$, which represents the informativeness of positive relative to negative signals.

$$\ln \Lambda^{Bayesian}(h_t) = \ln(\frac{\theta}{1-\theta})n_t^+ - \ln(\frac{\theta}{1-\theta})n_t^- . \tag{2.4}$$

However, the agent with a self-serving memory bias has the following log likelihood ratios

$$\ln \Lambda^{Biased,INV}(h_t) = \ln(\frac{\theta}{1-\theta})(n_t^+ + q^- n_t^-) - \ln(\frac{\theta}{1-\theta})(1-q^-)n_t^- ;$$

$$\ln \Lambda^{Biased,NOT}(h_t) = \ln(\frac{\theta}{1-\theta})(1-q^+)n_t^+ - \ln(\frac{\theta}{1-\theta})(n_t^- + q^+ n_t^+).$$

It can be shown that the following equations characterize the difference between the log

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[7]In the experiment, we also have binary signals generated from the underlying distribution, either positive or negative outcomes. We used three positive and three negative outcomes, respectively, that are equally likely. However, this is irrelevant for a Bayesian updater when forming beliefs. Beliefs should be solely formed based on whether the signal is positive or negative.

likelihood ratios of a biased agent and a Bayesian agent.

$$\ln \Lambda^{Biased,INV}(h_t) - \ln \Lambda^{Bayesian}(h_t) = \ln(\frac{\theta}{1-\theta})2q^- n_t^-, \qquad (2.5)$$

$$\ln \Lambda^{Biased,NOT}(h_t) - \ln \Lambda^{Bayesian}(h_t) = -\ln(\frac{\theta}{1-\theta})2q^+ n_t^+. \qquad (2.6)$$

Hence, the belief distortion, measured as the log-likelihood deviation from the Bayesian belief, is positively correlated with θ, q^- (or q^+), and n_t^- (or n_t^+). The magnitude of the belief distortion is non-zero, when $q^- n_t^- \neq 0$ (or $q^+ n_t^+ \neq 0$), as $\theta \in (0.5, 1)$.

2.2.2 Model Propositions

Equations (2.5) and (2.6) yield the following propositions.

Proposition 1 *Given $q^- n_t^- \neq 0$ (or $q^+ n_t^+ \neq 0$), the magnitude of the belief distortion is positively correlated with the contrast between the underlying processes (θ).*

Proposition 2 *Given $q^- \neq 0$ (or $q^+ \neq 0$), the magnitude of the belief distortion is positively correlated with the number of signals inconsistent with one's self-image (n^- or n^+).*

Proposition 3 *Given $n_t^- \neq 0$ (or $n_t^+ \neq 0$), the magnitude of the belief distortion is positively correlated with the magnitude of the memory bias (q^- and q^+).*

The model serves two important purposes for our subsequent experimental testing. In the experiment, we fix θ but vary n_t^- and n_t^+. First, our model proposes interesting comparative statics. The model predicts that holding θ, q^- and q^+ constant, the belief distortion compared to the Bayesian posterior is larger if there are more true outcomes that are contradictory to the biased agent's self-image (Proposition 2). These are the negative outcomes if the agent invests and the positive outcomes when the agent does not invest. We will provide experimental evidence for this proposition.[8] Further, the model predicts that holding θ, n^- and n^+ constant,

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[8]Note that in our experiment, memory elicitation was a surprise task so we could not vary parameters within-subjects.

the belief distortion relative to the Bayesian posterior is larger for agents with a larger memory bias (Proposition 3). We will also provide evidence for this proposition.

Second, Equations (2.5) and (2.6) provide the foundation for our regression analysis with regard to memory-based belief distortion. With subjects' belief distortion as the dependent variable, $\ln(\frac{\theta}{1-\theta})2n_t^-$ or $-\ln(\frac{\theta}{1-\theta})2n_t^+$ as the independent variable, we can directly estimate the value of q^- and q^+, i.e., the memory bias, on average across subjects.

2.3 Experiment

2.3.1 Experimental Design

A setup to investigate a self-serving memory bias for investment outcomes and its effect on beliefs and choices requires (i) a meaningful investment decision that generates self-relevant outcomes, (ii) exogenous variation in investment outcomes (positive and negative outcomes), (iii) direct memory elicitation, and (iv) an experimental manipulation of the time span between observation of outcomes and tasks to isolate memory effects. In this section, we outline how our experimental setting meets these requirements (Table 2.1 summarizes our treatment conditions).[9]

Table 2.1: Experimental Conditions

Treatment	First investment choice, observation of outcomes	Memory elicitation	Belief elicitation, second investment choice
Delay	Week t	Week t+1	Week t+1
Immediate1	Week t	Week t	Week t
Immediate2	Week t+1	Week t+1	Week t+1
NoRecall	Week t	No	Week t+1

Notes: This table provides an overview of the treatment and control conditions of the experiment with different time spans between tasks.

First, subjects make an investment decision. They choose to invest either in a stock with risky outcomes (positive and negative outcomes) or in a bond with known safe outcomes (cf. Kuhnen, 2015). After that decision, investment outcomes are observed over the course of 12 periods. With equal probability, the stock may be good or bad. That is, the stock is either more likely to generate positive outcomes or more likely to generate negative outcomes. We choose $\theta = 0.6$. Good stocks have positive outcomes with a 60% probability and negative outcomes

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[9]The experiment instructions are provided in Appendix 2.A.

with a 40% probability each period. Bad stocks have positive outcomes with a 40% probability and negative outcomes with a 60% probability.[10] The positive outcomes of the stock are either 11, 13, or 15 EUR and the negative outcomes are either -5, -3, or -1 EUR. More precisely, given that the outcome in a period is positive, it is randomly drawn from {11, 13, 15} with equal probability. Given that the outcome in a period is negative, it is randomly drawn from {-5, -3, -1} with equal probability. The determination of the outcomes is independent across periods. The bond has a certain outcome of 3.10 EUR each period. Subjects start with an initial endowment of 60 EUR.[11] See Table 2.2 for an overview of subjects' investment options.

To measure subjects' memory bias, we let subjects observe the generated stock outcomes and then elicit their memory of these outcomes. Subjects see the outcomes of the stock, irrespective of whether they chose to invest in the stock or bond. The outcome of each of the 12 periods is sequentially presented on a screen for 2 seconds. After subjects observe the outcomes, we ask them to recall how many positive and negative outcomes they observed and, more specifically, how often the stock paid 11, 13, 15, -5, -3, and -1 EUR. This memory task is not announced beforehand.[12]

Importantly, to clearly identify the effect memory has on subjects' recollection, we manipulate the time span between the observation phase and the memory elicitation, following a between-subject design. We randomly assign subjects to one of three experimental conditions for the whole experiment. In the *Delay* condition, subjects perform the memory task one week after the observation and in the *Immediate* condition, subjects perform the memory task immediately after they observed the investment outcomes (Table 2.1). Comparisons between the *Delay* and *Immediate* treatment allow us to isolate memory effects from other factors such as attention (Barber and Odean, 2008; DellaVigna and Pollet, 2009) or salience (Bordalo et al., 2012, 2013), which might influence subjects' recollection of outcomes, but are related to subjects' information acquisition and processing. Differences between the *Delay* and the *Immediate* condition cannot be caused by subjects' information acquisition or processing, but solely by the fact that subjects have to remember the stock's outcomes from last week.

A *NoRecall* condition, in which subjects do not perform a memory elicitation task, serves as a control condition. This treatment allows us to identify potential effects of simply asking subjects to recall investment outcomes. Note that we do not find a significant difference in

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[10]To make sure that subjects understand the distributions, we included a phase of experience sampling (for both the distribution of the good stock's and the bad stock's outcomes) which did not influence subjects payout.

[11]The incentive structure is described in detail in Section 2.3.2.

[12]The instructions for the memory elicitation are provided in Appendix 2.A.

Table 2.2: Overview of subjects' investment options

	Investment Option	Risk about Asset Type	Asset Type	Possible Outcome(s)	Probability of Outcome(s)	Expected Outcome
First Choice (Before Observation)		50% probability	Good Stock	11, 13, 15 EUR	60%	6.60 EUR
	Stock			-5, -3, -1 EUR	40%	
		50% probability	Bad Stock	11, 13, 15 EUR	40%	3.40 EUR
				-5, -3, -1 EUR	60%	
	Bond	No	-	3.10 EUR	100%	3.10 EUR
Second Choice (After Observation)		Based on Subjective posterior	Good Stock	11, 13, 15 EUR	60%	6.60 EUR
	Stock			-5, -3, -1 EUR	40%	
		Based on Subjective posterior	Bad Stock	-5, -3, -1 EUR	60%	3.40 EUR
				11, 13, 15 EUR	40%	
	Bond	No	-	5.10 EUR	100%	5.10 EUR

Notes: This table provides an overview of subjescts' investment options during the experiment.

subjects' beliefs or investment decisions between the *Delay* and *NoRecall* condition (*T*-test, $p = 0.714$ and $p = 0.343$, respectively), suggesting that simply asking subjects to recall the stock's outcomes does not drive our results. Please refer to Appendix 2.A for a detailed description of the analyses.

Subjects in the *Delay* treatment observe investment outcomes in week t and perform the memory elicitation task in week $t+1$. In contrast, subjects in the *Immediate* condition perform all experimental tasks in the course of one session. This could happen either in week t or in week $t + 1$. To rule out timing effects, we vary whether subjects perform the tasks in week t (*Immediate1* condition) or in week $t + 1$ (*Immediate2* condition). In half of the experimental sessions, subjects perform the tasks in week t and in the other half of the sessions in week $t + 1$ (Table 2.1). In our main analyses, we pool the data of the *Immediate1* condition and the *Immediate2* condition and control for the session the subject participated in. Further, subjects had to sign up for and participated in two experimental sessions, with one week in between, before they were randomly assigned to *Delay* or *Immediate* treatments to avoid selection effects.

To relate subjects' memory bias to their beliefs, we elicit subjects' beliefs about the stock's chance of paying a positive outcome after they observed the investment outcomes. Initially, subjects do not know the quality of the stock. They start with a prior that the stock is either good or bad with equal probability. After observing the outcomes, subjects make informed inferences about the stock's probability of paying from the good distribution of outcomes. A

fully rational (Bayesian) subject counts the number of positive outcomes (11, 13, or 15 EUR) in the course of the 12 periods. The value of the objective Bayesian posterior can be calculated as:

$$\mu_t^G(h_t) = \frac{1}{1 + \frac{1-\mu_0^G}{\mu_0^G} * (\frac{\theta}{1-\theta})^{t-2n_t^+}} \tag{2.7}$$

where μ_0^G is 50% and indicates the prior that the stock is good; θ is 60%, the probability that a good stock generates the positive outcome in each period; t is the total number of observations; h_t represents the history of outcomes for t observations; n_t^+ represents the number of positive outcomes. This posterior serves as benchmark for objectively correct beliefs in our experimental setting.

To further investigate the consequence of a memory bias for subsequent investment behavior, we ask subjects to make a second investment decision after observing the outcomes. They choose to invest in the stock they have observed or another bond for further 12 periods (Table 2.2). Risk-neutral subjects should invest in the stock if it has a higher expected outcome than the bond. Note that for the post observation round of investment decisions, the bond pays 5.10 EUR per period. If the stock is good, the expected outcome of the stock is higher (6.60 EUR per period) than the expected outcome of the bond. Yet, if the stock is bad, the expected outcome is lower (3.40 EUR per period). Given these expected outcomes in our experimental setup, a risk-neutral Bayesian subject should always invest in the stock if there were more than 6 positive outcomes, which leads to a Bayesian posterior about the stock being good of 69.2% or greater.[13] Risk-averse subjects should require a higher posterior belief about the stock being a good stock in order to choose the stock. Since we are particularly interested in subjects' decision to invest in the stock despite an objectively low Bayesian posterior probability (Section 2.4.3), our results should hold for a range of reasonable risk attitude parameters.[14]

In the *Delay* condition, we elicit subjects' beliefs and second investment choice one week after the observation phase and in the *Immediate* condition immediately after the observation phase. Further, to avoid spill-over effects, the order in which subjects perform these tasks, i.e., the memory elicitation, belief elicitation, and the second investment task, is random.

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[13]In general, a risk-neutral subject should invest in the stock if the observed outcomes lead to a posterior belief of the stock being good above 53.1% and otherwise invest in the bond.

[14]Typically, people are risk-averse even at low payoff levels (Holt and Laury, 2002, 2005). However, note that the small stakes in the laboratory setting might lead subjects to behave in a risk-neutral manner (Rabin, 2000).

2.3.2 Incentives and Procedures

The experimental sessions were organized in two parts. Subjects first made their decision to invest in the stock or bond, and observed the stock's outcomes, and afterwards participated in a memory elicitation, belief elicitation, and a second investment task.

Subjects were paid a show-up fee of 8 EUR for participating in the study.[15] Further, we randomly drew three participants from each session (with maximum 30 participants per session) who were paid based on their performance in one of the tasks. For each drawn subject, the computer randomly decided which task determined his or her payment.[16] In the first investment choice, subjects could earn an initial endowment of 60 EUR plus either 37.20 EUR from investing in the bond or accumulated outcomes over 12 periods from investing in the stock. In the belief elicitation task, subjects were paid according to the accuracy of their probability estimates. We paid them 120 EUR for a probability estimate within 5 percent of the objective Bayesian value. In the memory elicitation task, subjects could earn 12 EUR for each correct answer provided, which could add up to 120 EUR if they answered all memory questions correctly. In the second investment choice, subjects could earn an initial endowment of 60 EUR plus either 61.20 EUR from investing in the bond or accumulated outcomes over 12 periods from investing in the stock.

The experiment was followed by a questionnaire with background and control questions. We elicited subjects' general risk preferences (Dohmen et al., 2011), financial literacy (Van Rooij et al., 2011), stock market participation, as well as subjects' understanding of the risk-return relationship of investments. Further, subjects were asked to indicate their age, gender, and highest level of education. In addition, subjects were asked to solve three Raven matrices and we elicited their mood (Watson et al., 1988).

A total of 229 subjects participated in the laboratory experiment, mostly business and economics students from one of the authors' universities.[17] On average, subjects earned 16.90 EUR. For each subject, both sessions took about 45 minutes each. The experiment is programmed and conducted with z-Tree (Fischbacher, 2007) and the experimental sessions were organized and administrated with the software hroot (Bock et al., 2014).

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[15]In the first two sessions, subjects were paid 5 EUR for participating in the study. We increased this amount to 8 EUR after the first two sessions because the average duration of the experimental sessions was longer than expected.

[16]It has been shown that paying a subset of participants is an effective payment scheme for economic experiments (Charness et al., 2016) and that random incentive systems do not bias risk-taking behavior in experiments (Cubitt et al., 1998; Hey and Lee, 2005; Starmer and Sugden, 1991).

[17]The experiment and its procedure were ethically approved by the University Experimental Laboratory Committee. We obtained subjects' consent orally before participating in the experiment.

2.4 Results

The results from our experiment document that subjects exhibit a self-serving memory bias for investment outcomes, which distorts their beliefs and drives subsequent investment decisions. The findings are consistent with our model in which image-concerns form the basis for how information is remembered and are robust to different measures of memory bias.

2.4.1 Memory Bias

We find that (i) subjects' memory of investment outcomes is systematically inaccurate; (ii) subjects' memory bias differs for positive and negative outcomes; and (iii) subjects' memory bias depends on whether they invested or not. Together, these results provide evidence for a self-serving memory bias for own investment gains and losses.

Based on our direct memory elicitation, memory bias is estimated at the individual level by taking the difference between each subject's recalled number of positive and negative outcomes in the memory elicitation task and the actual observed number of outcomes. If subjects had perfect memory, their memory bias would be zero. A memory bias above zero means that subjects recollect a higher number of outcomes than actually observed and a memory bias below zero means that subjects remember a lower number of outcomes than observed. Importantly, to isolate memory effects from other factors related to subjects' information acquisition or processing, we compare subjects' recollection in our two treatment conditions, *Immediate* and *Delay.*

Table 2.3 provides an overview of subjects' memory bias and reports results from T-tests against the null hypothesis that the memory bias is zero (column 2, column 4, column 6, and column 8). We first focus on the *Delay* condition, in which people had time to form inaccurate memory in the week between observing the stock's outcomes and recollecting them. Column 1 illustrates that subjects have inaccurate memory of the stock's outcomes in the *Delay* condition, as implied by a self-serving memory bias: If they invested in the stock, they remember significantly more positive outcomes (T-test, $p < 0.001$) and significantly less negative outcomes (T-test, $p < 0.001$) than actually observed. On average, subjects over-remember the number of gains by 0.9 and under-remember the number of losses by 0.7. This corresponds to a deviation from the average number of observed outcomes of $+15.3\%$ and -11.4%, respectively. Moreover, the first columns (columns 1-4) illustrate that while subjects who invested in the stock show a significant memory bias for investment outcomes, subjects

Table 2.3: Subjective Memory Bias

Observed outcomes	Delay				Immediate				Difference (if invested)
	Invested (N = 74)	T-test	Not invested (N = 18)	T-test	Invested (N = 78)	T-test	Not invested (N = 18)	T-test	T-test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Positive outcomes	0.89	p = 0.001	-0.06	p = 0.918	0.27	p = 0.058	-0.11	p = 0.668	p = 0.018
Negative outcomes	-0.73	p = 0.000	-0.22	p = 0.664	-0.28	p = 0.037	-0.06	p = 0.875	p = 0.038

Notes: This table displays subjects' memory bias in the *Delay* and *Immediate* condition, seperately for subjects who invested in the stock and subjects who did not invest in the stock, i.e., invested in the bond. Memory bias is estimated at the individual level by subtracting the actual individually observed number of positive (negative) outcomes from subject's recalled number of the stock's positive (negative) outcomes. The table reports mean values and T-test results against the null hypothesis that the memory bias is zero (columns 1-8) and T-test results of the difference in means between our conditions *Delay* and *Immediate* for subjects who invested in the stock (column 9).

who did not invest do not display a memory bias. This is in line with studies suggesting that the decision to do something is of higher importance for one's self-image compared to the decision not to do something (Allison and Messick, 1988; Cioffi and Garner, 1996; Fazio et al., 1982).

Further, our results suggest a memory effect on subjects' recollection beyond factors that might be related to subjects' information acquisition or processing capacities. The comparison of subjects' recollection between the *Immediate* and *Delay* condition isolates the effect of memory from these alternative explanations. We indeed find that the self-serving memory bias is significantly larger in the *Delay* treatment than in the *Immediate* treatment, both for positive and for negative outcomes (*T*-test, $p < 0.05$).

These results provide supportive evidence for the essential notion of our model, a self-serving memory bias for investment outcomes. Our findings are robust to different estimations of memory bias. Please refer to Appendix 2.A for robustness of these findings to using estimations based on the relative fraction of the recalled number of positive and negative outcomes as well as the difference between the number of recalled positive and negative outcomes.

2.4.2 Memory-Based Beliefs

In this section, we show that the memory bias is associated with overly optimistic subjective beliefs. First, our results document that subjects' elicited memory bias is significantly correlated with too optimistic beliefs about the stock. Second, in accordance with our model, we

test for subjects' memory bias based on how they weight observed outcomes when forming beliefs about the stock. In line with the model propositions, we find that subjects who invested in the stock relatively underweight negative compared to positive outcomes, resulting in overly optimistic beliefs. This supports our finding of a memory bias without relying on a specific memory elicitation method. Moreover, we show that the belief distortion of subjects who invested in the stock is larger if more negative outcomes occurred, which is consistent with the self-serving mechanism we propose.

First, Figure 2.1 gives a graphical presentation of subjects' beliefs in our experiment if they chose to invest. The figure displays subjects' beliefs relative to the objective Bayesian probabilities. The x-axis indicates the value of each possible objective Bayesian posterior belief, i.e., the objective probability that the stock is good, and the y-axis represents the average belief indicated by the subject, i.e., the subjective probability that the stock is good. If subjects indicated the objectively correct probability, their subjective posteriors would line up along the 45° reference line. The figure suggests that subjective beliefs deviate from the objective posteriors in a systematic way and are associated with subjects' memory. In the *Delay* condition (left panel) subjective beliefs are overly optimistic regarding the likelihood that the stock is good. Moreover, the belief of subjects with an above average memory bias (solid line) is further away from Bayesian objective posteriors relative to the belief of subjects with a below average memory bias (dashed line).

In accordance with this graphical display, we find that subjects' elicited memory bias predicts subjective beliefs. We focus our analysis on subjects in the *Delay* treatment. The regression models in Table 2.4 indicate that subjects' memory bias for positive and negative outcomes is significantly correlated with their beliefs. We use subjects' belief that the stock is the good stock (columns 1 and 2) and their belief distortion compared to the Bayesian posterior (columns 3 and 4) as dependent variables. Subjects' belief distortion is the difference between the posterior log-likelihood ratios of subjects' elicited probabilities and the objective Bayesian probabilities. The elicited memory bias for positive and negative outcomes serve as independent variables. In our first two models, we control for the correct Bayesian probability that the stock is good, given the information seen by the subject. In all models we control for session fixed effects. Column 1 shows that subjects' beliefs are on average 4.89% higher for each positive outcome they over-remember ($p < 0.001$). That is, subjects who recollect a higher number of positive outcomes than observed form more optimistic beliefs about the stock. We find the opposite direction for negative investment outcomes (column 2). Subjects' beliefs

Figure 2.1: Subjective Beliefs

This figure displays the average subjective posterior that the stock is the good stock, as a function of the correct objective Bayesian probability. The sample is limited to subjects who invested in the stock (first choice). If subjective estimates were Bayesian, they would line up on the 45° line. The left panel presents subjective beliefs from the *Delay* condition and the right panel presents subjective beliefs from the *Immediate* condition. Subjects' probability estimates for each level of the objectively correct Bayesian posterior are shown on solid lines for subjects with a high memory bias, and on dashed lines for subjects with a low memory bias. *High Memory Bias* is a dummy variable equal to 1 if the subject has a memory bias that is larger than the mean memory bias in its treatment condition. *Low Memory Bias* is a dummy variable equal to 1 if the subject has a memory bias that is smaller than the mean memory bias in its treatment condition.
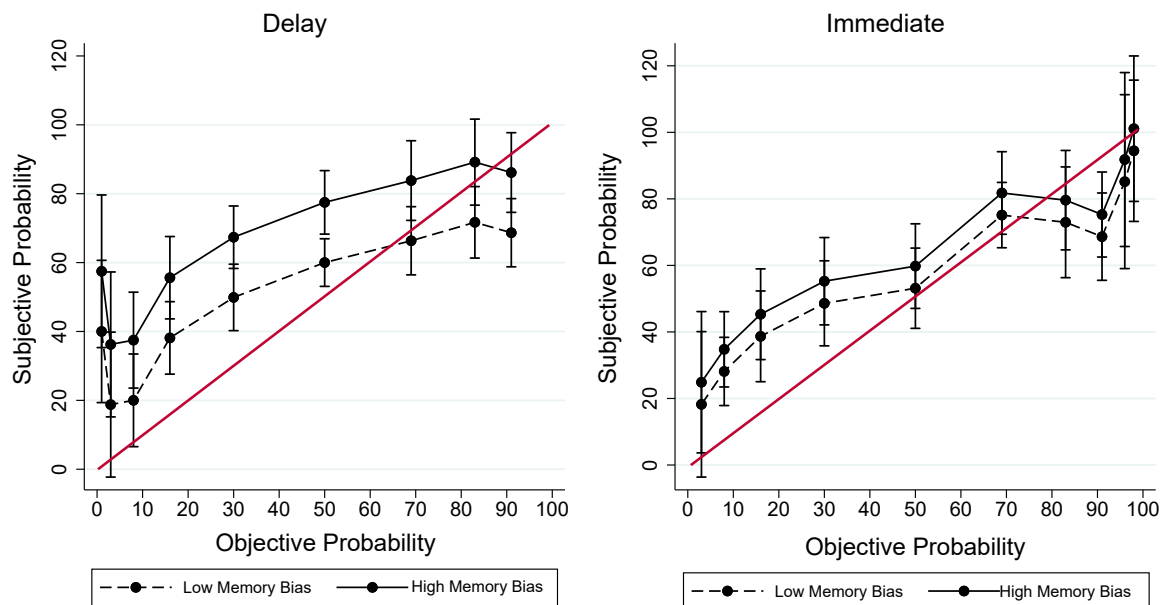
are on average 6.94% lower for every loss they over-remember ($p < 0.001$). This also means that subjects who remember a lower number of losses than observed form also more optimistic beliefs about the stock.[18] Similarly, results in column 3 and 4 document that subjects' elicited memory bias is significantly correlated with their actual deviation from the objective Bayesian probability. Subjects who remember a higher number of positive outcomes (or a lower number of negative outcomes) than observed, form overly optimistic beliefs compared to the Bayesian benchmark.

Second, we show that subjects' weighting of observed outcomes when forming beliefs is consistent with our model and supports our finding of a self-serving memory bias without relying on a specific memory elicitation method. To begin with, we find that subjects' belief distortion is positively correlated with the number of observed signals that might be inconsistent with

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[18]Note that the magnitude of the regression coefficients for the objective probability as well as the constant are similar to previous results reported by Kuhnen (2015).

Table 2.4: Memory-Based Beliefs

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the subjective posterior belief that the stock is the good stock (from 1 to 100), *Subjective Probability*, or subjects' belief distortion measured by the difference between the posterior log-likelihood ratios of subjects' elicited probabilities and the objective Bayesian probabilities, *Belief Distortion*. The sample is limited to subjects in the *Delay* treatment. *Memory Bias (Pos. Out.)* represents subject's memory bias for observed positive outcomes. This variable is estimated at the individual level by subtracting the actual individually observed number of positive stock outcomes from subject's recalled number of the stock's positive outcomes. *Memory Bias (Neg. Out.)* represents subject's memory bias for observed negative outcomes. This variable is estimated at the individual level by subtracting the actual individually observed number of negative stock outcomes from subject's recalled number of the stock's negative outcomes. *Objective Probability* is the value of the objective Bayesian probability that the stock is the good stock (from 1 to 100). *Session* is a dummy variable representing the different sessions of the experiment. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Subjective Probability	(2) Subjective Probability	(3) Belief Distortion	(4) Belief Distortion
Memory Bias (Pos. Out.)	4.891***		0.343***	
	(4.47)		(5.32)	
Memory Bias (Neg. Out.)		-6.939***		-0.466***
		(-5.21)		(-5.88)
Objective Probability	0.612***	0.637***		
	(7.91)	(8.45)		
Constant	12.090	11.341	-0.847**	-0.786**
	(1.55)	(1.51)	(-2.27)	(-2.16)
Session	Yes	Yes	Yes	Yes
N	92	92	91	91
R^2	0.48	0.51	0.38	0.42

their self-image, as indicated in Proposition 2. Figure 2.2 displays this finding for subjects who invested in the stock. The bars represent the mean value of subjects' belief distortion for different numbers of observed negative outcomes (n^-). The red line indicates the prediction for a linear regression. The figure illustrates a significant positive trend ($p < 0.001$), in line with our Proposition 2. The magnitude of the belief distortion of subjects who invested in the stock is positive as soon as subjects observed more than four negative outcomes. Further, the belief distortion increases significantly with a growing number of observed negative outcomes.

Moreover, we are interested in subjects' memory bias parameters from our model, q^- and q^+. In the model, q^- is the probability of under-remembering a negative outcome of invested in the stock and q^+ is the probability of under-remembering a positive outcome if not invested. If q^- or q^+ equals zero, the probability of under-remembering an outcome is zero and if it equals one, the probability of under-remembering an outcome is 100%. Regressions in Table 2.5 estimate q^- and q^+. The table reports results from regressions with subject's belief distortion as dependent variable. As independent variable, we use a combination of the informativeness of evidence (the log likelihood ratio $\ln \frac{\theta}{1-\theta}$) and the strength of evidence (n^- or n^+) in our

Figure 2.2: Belief Distortion and Observed Outcomes

This figure displays mean values of subjects' belief distortion measured by the difference between the posterior log-likelihood ratios of subjects' elicited probabilities and the objective Bayesian probabilities (*Belief Distortion*). The sample is limited to subjects who invested in the stock (first choice). The bars represent the mean values for different numbers of individually observed negative outcomes by subjects (n^-). Error bars indicate 95% confidence intervals. The red line represents the prediction for a linear regression of *Belief Distortion* on a Dummy variable for different numbers of n^-.
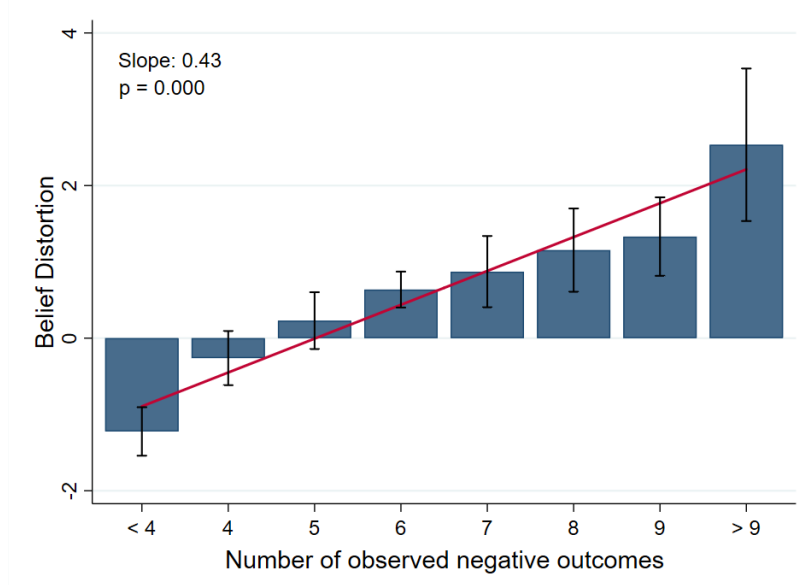
experimental situation, according to Equations (2.5) and (2.6) and control for session fixed effects. Thus, the regression coefficients represent our estimations for q^- and q^+ from our model based on subjects' relative underweighting of negative and positive outcomes n^- and n^+ when forming beliefs about the stock. The regressions are reported separately for subjects who invested and for those who did not invest as well as across our two treatments *Delay* and *Immediate*. Our results show that subjects who invested in the stock (columns 1 and 3) are likely to underweight negative relative to positive outcomes when forming beliefs ($p > 0.001$), while subjects who did not invest in the stock (columns 2 and 4), do not display a significant probability to underweight outcomes in a systematic way. This is consistent with the proposed behavioral mechanism in our model as well as our previous results based on subjects' directly elicited memory bias (Table 2.3). Here, q^- can be interpreted as the magnitude of subjects' memory bias when updating beliefs. We find that subjects who invested in the stock show a higher belief distortion when their memory bias (q^-) is higher. After observing a negative outcome in the *Delay* condition, subjects who invested in the stock forget this outcome with a probability of 59.9% ($p < 0.001$). Moreover, this probability is larger for subjects in the

Delay condition than for subjects in the *Immediate* condition (47.3%, $p < 0.001$). Thus, we find that subjects' belief distortion stems from relatively underweighting negative outcomes when forming beliefs about the stock. This finding is consistent with our proposed self-serving memory bias and does not rely on a specific memory elicitation method. This finding and the observation that subjects' elicited memory bias is significantly correlated with their belief distortion (Table 2.4) is supportive of our Proposition 3.

Table 2.5: Estimated Memory Bias Based on Relative Weighting of Observed Outcomes

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is subjects' belief distortion, *Belief Distortion* (*Belief Dist.*), measured by the difference between the posterior log-likelihood ratios of subjects' elicited probabilities and the objective Bayesian probabilities. As independent variables, we use the combination of the informativeness of evidence (the log likelihood ratio $\ln \frac{\theta}{1-\theta}$) and the strength of evidence (n^- or n^+) in our experimental situation, according to Equations (2.5) and (2.6). *Session* is a dummy variable representing the different sessions of the experiment. Regression coefficients represent parameters q^- and q^+. We present the regression models for our treatments *Delay* (*Del.*) and *Immediate* (*Imm.*) as well as for subjects who invested and who did not invest separately. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Belief Dist. (*Del.*, inv.)	(2) Belief Dist. (*Del.*, not inv.)	(3) Belief Dist. (*Imm.*, inv.)	(4) Belief Dist. (*Imm.*, not inv.)
$ln(\frac{\theta}{1-\theta})2n_t{}^-$	0.599***		0.473***	
	(8.10)		(6.64)	
$-ln(\frac{\theta}{1-\theta})2n_t{}^+$		0.341		0.147
		(1.26)		(0.41)
Constant	-3.189***	0.686	-1.880***	1.830
	(-5.93)	(0.38)	(-3.73)	(0.91)
Session	Yes	Yes	Yes	Yes
N	73	18	73	19
R^2	0.55	0.58	0.46	0.40

2.4.3 Consequences for Investment Decisions

The evidence so far shows that subjects relatively under-remember negative outcomes compared to positive outcomes if they invested in the stock. This self-serving memory bias is associated with overly optimistic beliefs about the investment. In this section, we show that subjects' memory affects future investment choices. We find that subjects in the *Delay* condition invest significantly more in the observed stock compared to subjects in the *Immediate* condition, even in cases when this is objectively a mistake. This investment mistake is strongly related to subjects' elicited memory bias.

Table 2.6 shows the proportion of subjects who chose to invest in the stock after observing the investment outcomes and *T*-tests for differences in means across our treatments. In the

Immediate condition, subjects were asked to decide immediately after the observation and in the *Delay* condition with a one week delay. Comparing the results in columns 1 and 2 illustrates that subjects decide differently in the two conditions, although they show the same preferences for investing in the risky stock before the treatment (first choice in the experiment). An important question is whether this effect is associated with the quality of subjects' choices. Therefore, column 3 reports results for subjects who made a suboptimal choice from a Bayesian perspective, assuming risk neutrality. Given the individual outcomes subjects observed, they invested in the stock, although the stock's expected outcome was lower than the bond's outcome. The results show that more than half of the subjects in the *Delay* condition (54.39%) invest in the stock despite its lower expected outcome, while in the *Immediate* condition only 29.82% of the subjects invest in such a manner. The difference between the two treatments is significant at the 1% level. Thus, subjects seem to be more likely to avoid suboptimal decisions when immediately deciding whether to invest or not (*Immediate* condition), whereas subjects who have to rely on their memory from last week (*Delay* condition) are likely to invest, although the decision is suboptimal. Note that we assume risk-neutral subjects. If instead some subjects were risk averse, the fraction of subjects investing suboptimally would be even larger. Hence, our estimates are rather conservative.

Table 2.6: Memory-Based Investment Decisions

	First choice		Second choice			
	Investment in stock	N	Investment in stock	N	Investment in stock (suboptimal)	N
	(1)		(2)		(3)	
Immediate	80.41	97	40.21	97	29.82	75
Delay	80.43	92	56.52	92	54.39	69
Difference (T-test)	p = 0.997		p = 0.025		p = 0.008	

Notes: This table displays subjects' investment decisions before (first choice) and after (second choice) observing the stock's outcomes in the *Delay* and *Immediate* condition. *Investment in stock* is a dummy variable equal to one if the subjects chose to invest in the stock. The table reports mean values and T-tests for differences in group means between our conditions *Delay* and *Immediate*. *Investment in stock (suboptimal)* is a dummy variable equal to one if the subject invested in the stock with a lower expected outcome than the bond after the observation phase (second choice).

Furthermore, regression analyses in Table 2.7 show that subjects' suboptimal investment decisions are correlated with their elicited individual memory bias. The table reports results from Probit regressions with a dummy variable equal to one for subjects who chose to invest

in the stock with a lower expected outcome than the bond after observing the outcomes as dependent variable (second choice). We use subjects' memory bias for positive and negative outcomes as independent variables and control for session fixed effects. Column 1 indicates that subjects' probability to invest in the stock with a lower expected outcome than the bond increases by 25.8% with each positive outcome they over-remember ($p < 0.001$). In other words, subjects who recollect a higher number of positive outcomes than actually observed have a significantly higher probability to invest in the stock with a lower expected outcome. We find the opposite direction for negative investment outcomes (column 2). Subjects' probability to invest in the stock with the lower expected outcome is on average 23.3% lower for every loss they over-remember ($p < 0.01$). Note that the average subject remembers a lower number of negative outcomes than actually occurred (Table 2.3). In this regard, our results indicate that subjects who remember a lower number of losses than actually observed have a higher probability to invest in the stock with a lower expected outcome. Together, these findings document that subjects' memory bias predicts suboptimal investment choices.

Table 2.7: Subjective Memory Bias and Suboptimal Investment Decisions

This table contains the coefficients and t-statistics (in parentheses) of Probit regressions in which the dependent variable is a dummy variable which is equal to one if the subject invested in the stock with a lower expected outcome than the bond after the observation phase (second choice). *Memory Bias (for Pos. Outcomes)* represents subject's memory bias for observed positive outcomes. This variable is estimated at the individual level by subtracting the actual individually observed number of positive stock outcomes from subject's recalled number of the stock's positive outcomes. *Memory Bias (for Neg. Outcomes)* represents subject's memory bias for observed negative outcomes. This variable is estimated at the individual level by subtracting the actual individually observed number of negative stock outcomes from subject's recalled number of the stock's negative outcomes. *Session* is a dummy variable representing the different sessions of the experiment. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Investment in Stock (Suboptimal)	(2) Investment in Stock (Suboptimal)
Memory Bias (for Pos. Outcomes)	0.258***	
	(3.78)	
Memory Bias (for Neg. Outcomes)		-0.233***
		(-3.19)
Constant	-1.701***	-1.732***
	(-3.44)	(-3.50)
Session	Yes	Yes
N	188	188
Pseudo R^2	0.12	0.10

2.5 Conclusion

This paper investigates how memory shapes individuals' financial decisions. We find a self-serving memory bias for investment gains and losses. A key characteristic of the self-serving memory bias is the distinction between memory of events with different levels of self-relevance (active experience versus passive observation). Our results show that subjects relatively under-remember investment losses compared to gains, if they actively invested in the stock. By contrast, subjects who decided not to invest in the stock do not display this memory bias.

The self-serving memory bias predicts subjective beliefs and affects future investment decisions. We find that subjects who invested in the stock relatively underweight negative compared to positive outcomes from memory, resulting in overly optimistic beliefs. This belief distortion increases with the number of observed negative outcomes. These findings are consistent with our model in which image-concerns form the basis for how information is remembered and robust to different measures of memory bias. We further show that those subjects do not adjust their behavior to account for the fallibility of their memory when making investment choices, which leads to investment mistakes. They are likely to re-invest in the stock even when doing so reduces their expected return. More than half of the subjects in our treatment condition (54.39%) – one week after the observation of investment outcomes – invest in the asset despite its lower expected outcome.

Our study provides empirical evidence of a systematic memory bias in financial decision-making and thereby complements important theoretical work that formalizes consequences of memory limitations for economic choices (Bordalo et al., 2017; Mullainathan, 2002). Further, our findings enhance the understanding of how people learn from experiences when they rely on their memory. Theoretical work proposes that people's beliefs can be distorted by biased retrieval of what has been stored in memory (Bordalo et al., 2018; Gennaioli and Shleifer, 2010) or by imprecise mental representations of the decision problem (e.g. Khaw et al., 2018). We explicitly designed an experiment in which subjects have to rely on their recollection of financial information and we directly elicit subjects' memory of this information at different points in time. This allows us to isolate biased memory as a foundation of subjective beliefs and choices, which can have important implications for financial decision-making. People often rely on their experience when making financial decisions (Malmendier and Nagel, 2011). This might, for instance, happen when information is costly (e.g. due to search costs) or people overestimate their memory accuracy (e.g. due to overconfidence). In such cases, relying on

biased memory is likely to result in suboptimal decisions.

The memory bias documented in this paper opens several avenues for further research. First, our results indicate that levels of self-relevance are crucial for the formation of biased memory in economic decision-making. In addition, Bordalo et al. (2019) find experimental evidence for selective memory based on representativeness. Future empirical work could investigate the role of other kinds of memory bias in financial and economic decision-making that have been modeled based on stylized facts from psychology research, such as similarity, rehearsal, or associativeness (Bordalo et al., 2017; Mullainathan, 2002). Second, our experiment studied the effect of biased memory one week after the initial investment decision. Future work can explore the degree and dynamics of biased memory over longer time horizons. Third, we decided to conduct a laboratory experiment that provides tight identification of biased memory and an objectively correct benchmark for subjects' beliefs and choices. A promising avenue for future research is validating our findings in the field.

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2.A   Appendix

2.A.1   Experimental Instructions

(translated from German)

Introduction

Welcome to our financial decision making study

For the duration of the study, we ask you to follow a few rules. Should there be questions, please raise your hand and an experimenter will answer your question privately. We ask you not to communicate with each other or use a calculator during the study.

We also ask you to turn off your cell phones and other devices, or at least to put them on silent, and to pack them away with your bag or belongings. We do not want you or other participants to be disturbed or distracted. If you do not adhere to these rules, this will lead to an automatic exclusion from the study and from payment.

The study consists of 3 stages and will last approximately 1.5 hours. You will perform different tasks of the study at different points in time, which last about 45 min today and 45 min next week.

After the study, you will receive a payout for your participation. The actual amount will depend on your decisions in the experiment and luck.

Everyone will earn 8 EUR for participating in this study. In addition, the computer will randomly pick three out of the present participants who get paid his or her earnings from one of the study's tasks.

Please press 'proceed' to continue with the general instructions.

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General Instructions

In this study you complete investment tasks, related to two securities: a risky security (i.e., a stock with risky payoffs) and a riskless security (i.e., a bond with a known payoff), and will provide estimates as to how good an investment in the risky security is.

Please click 'proceed' to continue with the detailed instructions for the tasks. Take your time to read the instructions carefully. Note that you cannot go back to previous pages. Please let us know if you have any questions.

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Stage 1 of the Study

Investment task 1

First, you will decide to invest in one of two securities for 12 periods: a risky security (i.e., a stock with risky payoffs) and a riskless security (i.e., a bond with a known payoff).

Either way, you start with an endowment of 60 EUR. In addition to this endowment, you will get payoffs from investing.

If you choose to invest in the bond, you get a payoff of 3.10 EUR for sure in each period.

If you choose to invest in the stock, you will receive a dividend in every period, which can be either positive or negative. A positive dividend is either 11, 13, or 15 EUR with equal probability. A negative dividend is either -1, -3, or -5 EUR with equal probability.

The stock can either be good or bad, and this will determine the likelihood of its dividend being positive or negative. If the stock is good then the probability of receiving a positive dividend is 60% and the probability of receiving a negative dividend is 40%. If the stock is bad then the probability of receiving a positive dividend is 40% and the probability of receiving a negative dividend is 60%.

If you decide to invest in the stock, you will have the possibility to choose between two stocks,

Stock BLUE and Stock YELLOW. One of the stocks is good and one is bad. You will not know which type of stock you chose. You may be facing the good stock, or the bad stock, with equal probability.

The dividends of the stock are independent from period to period, but come from the same distribution. In other words, once you decided for a stock (BLUE or YELLOW) and it is a good stock, then in each period the odds of the dividend being positive are 60%, and the odds of it being negative are 40%. If the chosen stock is a bad stock then the probability of receiving the positive dividend is 40% and the probability of receiving the negative dividend is 60% in each period.

If you decide to invest in a stock you accumulate the dividends paid by the stock over 12 periods and if you invest in the riskless security you accumulate the known payoff over 12 periods, i.e. you earn 37.20 EUR for sure.

At the end of the task, you will be told how much you have accumulated. Your task earnings will be your accumulated payoffs plus your initial endowment of 60 EUR.

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Stock evaluation task

You will then see the dividends of the stock, no matter if you chose to invest in the stock or the bond. You will see either the dividends paid by the stock you chose, or - if you decided to invest in the bond - by one of the stocks randomly picked by the computer.

After that, we will ask you to tell us two things:

(1) what you think is the probability that the stock is the good one (the answer must be a number between 0 and 100);

(2) how much you trust your ability to come up with the correct probability estimate that the stock is good. In other words, we want to know how confident you are that the probability you estimated is correct.

There is always an objective, correct, probability that the stock is good, which depends on the history of dividends paid by the stock already. For instance, at the beginning of the task, the probability that the stock is good is exactly 50%, and there is no doubt about this value.

As you observe the dividends of the stock, you will update your belief whether or not the stock is good. It may be that after a series of good dividends, you think the probability of the stock being good is 75%. However, how much you trust your ability to calculate this probability could vary. Sometimes you may not be too confident in the probability estimate you calculated and sometimes you may be highly confident in this estimate. For instance, at the very beginning of the task, the probability of the stock being good is 50% and you should be highly confident in this number because nothing else has happened since then.

If you provide us with a probability estimate that is within 5% of the correct value (e.g., correct probability is 80% and you say 84%, or 75%) you will earn 120 EUR in this task.

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Investment task 2
Further, you will again decide to invest in the stock you observed (Stock BLUE/Stock YEL-LOW) or in another bond for the next 12 periods.

Either way, you start with an endowment of 60 EUR. In addition to this endowment, you will get payoffs from investing.

If you choose to invest in the bond, you get a payoff of 5.10 EUR for sure in each period.

Again, if you choose to invest in the stock, you will receive a dividend in every period, which can be either positive or negative. A positive dividend is either 11, 13, or 15 EUR with equal probability. A negative dividend is either -1, -3, or -5 EUR with equal probability.

The dividends of the stock are independent from period to period, but **come from the same distribution as in Investment Task 1**. In other words, once you decided for a stock (BLUE

or YELLOW) and it is a good stock, then in each period the odds of the dividend being positive are 60%, and the odds of it being negative are 40%. If the chosen stock is a bad stock then the probability of receiving the positive dividend is 40% and the probability of receiving the negative dividend is 60% in each period.

As in the Investment Task 1, if you decide to invest in the stock you accumulate the dividends of the stock over 12 periods and if you invest in the riskless security you accumulate the known payoff over 12 periods, i.e. you earn 61.20 EUR for sure.

At the end of the task, you will be told how much you have accumulated. Your task earnings will be your accumulated payoffs plus your initial endowment of 60 EUR.

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Stage 2 of the study

We will then ask you to complete three IQ test questions. The more questions you answer correctly, the more you earn in this task. For each correct answer you earn 40 EUR. For example, if you answer all three questions correctly, you earn 3 x 40 EUR i.e., 120 EUR. If you don't answer any question correctly, you will earn nothing.

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Your final payment at the end of the study
Your final payment will be:

You will get paid 8 EUR for participating in our study regardless of your task earnings.

In addition, your earnings in one of the experimental tasks can determine your payment. We will randomly draw three participants out of each session (with maximum 30 participants) who will get paid one of her or his task earnings. The computer will randomly decide which of the above-described tasks will determine the participants' payment. Remember, your task earnings depend on your decisions and answers:

Investment Task 1: Your initial endowment of 60 EUR and either 37.20 EUR from investing in the bond or accumulated dividends over 12 periods from investing the stock.

Stock Evaluation Task: Either 120 EUR if you provide us with a probability estimate that is within 5% of the correct value or nothing.

Investment Task 2: Your initial endowment of 60 EUR and either 61.20 EUR from investing in the bond or accumulated dividends over 12 periods from investing the stock.

IQ Test: Between 120 EUR and nothing; dependent on how many questions you answer correctly (40 EUR for each correct answer).

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Stage 3: Post-questionnaire

At the end of the experiment, we will ask you some personal questions. Note that all answers will be treated confidentially and will be analyzed anonymously.

2.A.2 Memory Elicitation

The memory elicitation task was not announced beforehand. We randomized the order of the specific recall questions, i.e. whether we first asked to recall positive or negative outcomes.

Instructions

Before we proceed to the next part, we ask you to complete a Recall Task, related to information you observed [last week]. Similar to the other experimental tasks, your answers can determine your final payment. This Recall Task can as well be selected by the computer for additional payment, which three of you will receive.

We will ask you 10 questions. The more questions you answer correctly, the more you earn in this task. For each correct answer, you earn 12 EUR. For example, if you answer all ten questions correctly, you earn 10 x 12 EUR i.e., 120 EUR. If you don't answer any question correctly, you will earn nothing.

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Questions for positive and negative outcomes

First, your task consists of recalling the stock dividends from last week. You observed 12 dividends of the stock.

How many positive dividends (11, 13, or 15) did you observe? ☐

... and how many negative dividends (-1, -3, or -5) did you observe? ☐

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Questions for specific outcomes

How often did the stock pay a dividend of -1 EUR? ☐

How often did the stock pay a dividend of -3 EUR? ☐

How often did the stock pay a dividend of -5 EUR? ☐

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How often did the stock pay a dividend of 11 EUR? ☐
How often did the stock pay a dividend of 13 EUR? ☐
How often did the stock pay a dividend of 15 EUR? ☐

2.A.3   Subjective Beliefs and Choices in Control Condition *NoRecall*

This table shows differences in subjective beliefs and investment decisions after observing the stock's outcomes (second choice) between subjects in the Delay and in the NoRecall condition. The results indicate no significant differences. Thus, simply asking subjects to recall investment outcomes seems to have no effect on their subjective beliefs or choices afterwards.

Table 2.8: Comparison of Subjective Beliefs and Choices between *Delay* and *NoRecall*

	Delay		*NoRecall*		Differences
	Mean	N	Mean	N	T-test
	(1)		(2)		(3)
Subjective Probability	58.011	92	59.725	40	p = 0.714
Investment in stock (second choice)	0.565	92	0.475	40	p = 0.343
Investment in stock (second choice, suboptimal)	0.544	92	0.435	40	p = 0.383

Notes: This table displays subjective beliefs as well as subjects' investment choice after the observation phase (second choice) in the *Delay* and *NoRecall* condition. Subjective beliefs are subject's indicated probability that the observed stock is the good stock (1 to 100). Investment in stock is a dummy variable which is equal to one if the subject invested in the stock after the observation phase (second choice); Investment in stock (suboptimal) is a dummy variable which is equal to one if the subject invested in the stock with a lower expected outcome than the bond after the observation phase (second choice). The table reports mean values and T-tests for differences in group means between our conditions *Delay* and *NoRecall* (column 3).

2.A.4 Robustness to Different Measures of Memory Bias

This section presents the robustness of our findings in Table 2.3 to different measures of subjects' memory bias. Table 2.9 uses a memory bias measure based on the fraction of recalled positive and negative outcomes relative to all observed outcomes and Table 2.10 shows results for a bias in the recalled absolute difference between observed positive and negative outcomes. Our results are qualitatively unchanged.

Table 2.9: Subjective Memory Bias based on a the Recalled Fraction of Gains and Losses

	Delay				Immediate				Difference (if invested)
	Invested (N = 74)	T-test	Not invested (N = 18)	T-test	Invested (N = 78)	T-test	Not invested (N = 18)	T-test	T-test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Positive outcomes	0.07	p = 0.000	0.01	p = 0.846	0.02	p = 0.042	-0.00	p = 0.953	p = 0.015
Negative outcomes	-0.07	p = 0.000	-0.01	p = 0.846	-0.02	p = 0.042	0.00	p = 0.953	p = 0.015

Notes: This table displays subjects' memory bias in the *Delay* and *Immediate* condition, seperately for subjects who invested in the stock and subjects who did not invest in the stock, i.e., invested in the bond. Memory bias is estimated at the individual level by subtracting the actual individually observed fraction of positive (negative) outcomes relative to the 12 observed outcomes from subject's recalled fraction of the stock's positive (negative) outcomes relative to the 12 observed outcomes. The table reports mean values and T-tests against the null hypothesis that the memory bias is zero (columns 1-8) and of differences in group means between our conditions *Delay* and *Immediate* (column 9).

Table 2.9 reports a self-serving memory bias of gains and losses for subjects who invested in the stock. They significantly over-remember the fraction of gains and under-remember the fraction of losses (column 1, column 2, column 5, and column 6). Similar to our main results, there is no significant memory bias for subjects who did not invest in the stock (column 3, column 4, column 7, and column 8). In line with our previous results, Table 2.9 indicates a significant difference in subjects' memory bias, if they are invested, between our *Delay* and *Immediate* condition, suggesting a memory effect.

Table 2.10 reports similar patterns and significance levels for subjects' memory bias for the difference between the observed number of gains and number of losses.

Table 2.10: Subjective Memory Bias based on a the Recalled Absolute Difference between the Number of Recalled Gains and Losses

	Delay				Immediate				Difference (if invested)
	Invested (N = 74)	T-test	Not invested (N = 18)	T-test	Invested (N = 78)	T-test	Not invested (N = 18)	T-test	T-test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Difference between positive and negative outcomes	1.62	p = 0.000	0.16	p = 0.871	0.55	p = 0.045	-0.06	p = 0.927	p = 0.013

Notes: This table displays subjects' memory bias in the *Delay* and *Immediate* condition, seperately for subjects who invested in the stock and subjects who did not invest in the stock, i.e., invested in the bond. Memory bias is estimated at the individual level by subtracting the actual difference between observed positive and negative outcomes from subject's recalled difference between the stock's positive and negative outcomes. The table reports mean values and T-tests for differences in group means between our conditions *Delay* and *Immediate* (column 9).

Chapter 3

Attention to Extreme Returns

with Moritz Lukas

It has been shown that individual investors are more likely to buy rather than sell stocks that catch their attention. This can lead to suboptimal choices when attention-attracting qualities of a stock may detract from its utility. This paper tests the causal effect of extreme returns on stock purchase behavior at the individual level by means of a controlled laboratory experiment. We find a strong asymmetry, as shares of stocks with recent extreme negative returns are more likely to be purchased than shares of stocks with recent less extreme negative returns. Yet, comparable patterns are not observed for stocks with positive returns. We further track subjects' eye movements and show that individual visual attention mediates our treatment effect. Interestingly, the results show that attention-driven purchase behavior occurs even in situations in which it reduces subjects' expected return.

3.1 Introduction

It is part of human nature that some features of the environment attract our attention. Most of the time this is helpful. For example, responding to changes in the environment or the appearance of new stimuli can have survival value. Shifting attention to a car approaching a cross-walk too fast might save us from colliding. In the context of the stock market, returns might be attention-grabbing as they are frequently reported and subject to continuous change. Such changes in returns are most likely to catch our attention if they are extreme: as an example, returns can be substantially different from returns in previous periods. However, stock returns' attention-grabbing characteristics do not necessarily coincide with the respective stocks' attractiveness as investment. Theory suggests that how individuals allocate attention impacts their economic choice (Bordalo et al., 2012; Schwartzstein, 2014). Indeed, it has been shown that the attention to salient features is an important factor in explaining riky choice (Frydman and Mormann, 2018). This paper investigates whether attention-grabbing characteristics of stock returns guide individuals' attention and thus influence their subsequent investment choice. We investigate both situations in which these attention-grabbing characteristics are positively correlated with stock performance and situations in which these two are negatively correlated.

Building on the notion that investors who want to purchase stocks are likely to focus on stocks that catch their attention, there is robust evidence of a general attention effect in financial markets (Barber and Odean, 2008; Gervais et al., 2001; Odean, 1999). High levels of investor attention seem to induce buy-sell imbalances as well as abrupt price reactions (Barber and Odean, 2008; Da et al., 2011), whereas limited investor attention appears to cause underreaction to new information (DellaVigna and Pollet, 2009; Huberman and Regev, 2001).

Previous research on investor attention is usually based on empirical analyses of stock market data. The key challenge of this type of analysis is that competing explanations of observed trading behavior are difficult or impossible to disentangle. Imagine a stock with an extreme positive return in the previous period – a proxy for attention that is frequently used (e.g., Barber and Odean (2008)). The observation that investors are net buyers of this stock could be either driven by a belief in stock price momentum, by a preference for stocks with volatile prices, or by the fact that this return pattern catches investors' attention. Now imagine a stock with an extreme negative return in the previous period. The observation that

investors are net buyers of this stock might either be related to a belief in the mean reversion of stock prices, by a preference for stocks with high volatility, or to the attention-grabbing characteristics of extreme negative returns. In both examples, investors might rationally trade on their beliefs regarding the future stock price development and risk preferences. Thus, in real-world stock market data, the effects of trading on beliefs, trading on preferences, and trading on attention can hardly be disentangled. As a remedy, some empirical studies resort to an ex-post rationalization of preferences or beliefs, but such measures are unlikely to fully mirror investors' ex-ante preferences and beliefs. In addition, the causal interpretation is ambiguous; as an example, extreme returns could both induce and follow excessive investor attention. Lastly, in many instances, a clear conclusion whether attention-driven investing has the potential to adversely effect individuals' financial position cannot be drawn.

Using natural experiments or settings with information events varying only in media coverage, more recent studies establish a causal relation between attention-catching events and investment behavior. They show the causal effect of media coverage on local trading, of being positioned at the front page of the Bloomberg terminal news screen on the security's market dynamics, such as trading volume, and of being mentioned in a prominent ranking list on flows into mutual funds (Engelberg and Parsons, 2011; Fedyk, 2018; Kaniel and Parham, 2017). Yet, these studies use events attracting attention in the cross-section, which makes conclusions about the nature and underlying mechanisms of individual attention-driven investment behavior difficult.

This paper enhances the understanding of investor attention by means of an incentivized laboratory experiment. We study the causal effect of extreme stock returns on investors' purchase behavior at the individual level.[1] By providing subjects with lottery-like investment opportunities, we are able to examine risky decision-making in an abstract stock market setting. Importantly, we include a direct measure of visual attention at the individual level by recording subjects' eye movements during their investment tasks using eye tracking devices. In contrast to stock market data, our experimental design allows us to observe individual attention and to separate rational trading on investor preferences and beliefs from attention-driven purchase behavior. While beliefs in momentum or mean reversion and risk preferences might correctly drive attention-like trading patterns observed in stock market data, they can constitute a bias in our experiment by design. Subjects make 10 independent investment decisions

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[1]Our experiment focuses on purchase decisions only, since investor attention has been shown to matter most on the buy side where the whole universe of stocks needs to be considered while selling decisions should only consider the assets currently held in a portfolio (Barber and Odean, 2008).

based on information about past asset price changes. We manipulate the magnitude of the price change of one given stock in order to vary the attention-grabbing characteristic of this stock's return. In line with Barber and Odean (2008), we vary the stock's return in the period preceding the investment decision by implementing two return conditions: an extreme return as treatment condition and a normal return condition as control. Importantly, the presented stocks differ in their quality, which can be observed by our subjects when following the concept of Bayesian optimization. As a critical element of our experiment design, the stock quality is constant across the two return conditions (i.e., treatment and control).

We find that attention-grabbing returns affect stock purchase patterns: stocks with extreme prior returns have higher purchase volumes subsequently. However, this finding hides part of the mechanisms behind investor attention. Analyzing our results in more detail, we find evidence for asymmetry in investor attention. While stocks with positive extreme returns do not seem to channel subjects' purchase decisions, stocks with negative extreme returns experience a significantly higher purchase volume compared to the control treatment. Moreover, our analysis of eye tracking data reveals that subjects' visual attention to the respective stock mediates our treatment effect. Extreme returns increase subjects' stock purchase volume through channeling subjects' visual focus on the respective stock. Further, we find that in our experiment, attention-driven purchase behavior occurs even in situations in which it reduces investors' wealth. Subjects show attention-driven stock buying behavior even for stocks with negative *expected* returns. This suggests that attention-driven purchase behavior has the potential to lead to wealth reductions for investors in the stock market. This conclusion is supported by the observation that the demand for stocks with attention-grabbing returns increases at the expense of the demand for stocks with non-attention-grabbing returns, leaving investors' total amount invested in stocks unchanged.

This paper makes several contributions to the existing literature. First, we provide causal evidence on attention-grabbing returns affecting investment patterns in the stock market. The controlled lab environment allows for a clear identification of causal effects – disentangled from alternative determinants such as institutional differences that might affect individuals' investment decisions in the field. Our experimental design provides an environment where the attention-grabbing characteristic of returns is exogenously varied and uncorrelated to stocks' fundamentals. Second, this study enhances our understanding of the nature of investor attention by employing eye tracking devices in the laboratory, allowing us to observe visual attention effects on the individual level. Our results uncover an important attention mechanism, namely

asymmetric attention patterns with regard to positive and negative extreme returns. Third, in contrast to archival studies, we are able to identify the true quality of stocks. This allows us to judge whether attention-driven investment behavior increases or decreases investors' return in our experiment.

The remainder of this paper proceeds as follows: In Section 3.2, we review the related literature. The experiment design is presented in Section 3.3, along with our hypotheses. The results are presented in Section 3.4. In Section 3.5, we discuss alternative explanations which might potentially drive our results. Potential implications of attention-driven investment behavior in the stock market are investigated in Section 3.6. Section 3.7 discusses our results and concludes.

3.2 Review of Related Literature

Our paper is related to the empirical literature examining the role of investor attention in the stock market. A first strand of this research focuses on the cross-sectional effects of specific attention-grabbing events or salient stock features. Gervais et al. (2001) report that the higher visibility of a stock caused by high trading volume influences the demand and price for that stock. Li and Yu (2012) find that nearness to the 52-week high of the Dow Jones positively predicts future aggregate market returns and that nearness to the historical high negatively predicts market returns. Further, Koester et al. (2016) find that extreme positive earnings surprises attract investor attention by increasing the subsequent number of institutional owners, the number of analysts, and trading volume. More generally, Yuan (2015) reports that market-wide attention events raise the level of attention investors pay to their portfolios, causing them to become more active in processing information and making trading decisions. This is supported by the finding that there is attention co-movement, i.e., investor's firm-specific attention in the stock market correlates with attention to the industry of a firm and the market (Drake et al., 2017). Most closely related to ours is the study by Barber and Odean (2008), who find that investors have a high propensity to purchase attention-grabbing stocks with abnormal trading volume, extreme returns, and high press coverage prior to the investment decision. Disentangling the causal impact of media reporting from the impact of the reported events, Engelberg and Parsons (2011) find a positive impact of local media coverage on local trading.[2]

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[2]Testing the investor recognition hypothesis (Merton, 1987), Fang and Peress (2009) document a related long-term media impact. They show that stocks without media coverage have higher returns than stocks with

Building on these findings, a second strand of literature makes use of stock listings and published rankings to identify investor attention. Jacobs and Hillert (2016) find that US stocks near the top of alphabetical listings have higher trading activity and liquidity than stocks near the bottom. Using natural experiments, Fedyk (2018) shows that being positioned at the front page of the Bloomberg terminal news screen affects the security's market dynamics, such as trading volume, and Kaniel and Parham (2017) finds a causal effect of being mentioned in a prominent ranking list on flows into mutual funds. Related to these attention effects, Hartzmark (2015) shows that the so-called rank effect – investors' tendency to sell extreme winning and losing positions in their portfolio – determines trading behavior.

A third strand of literature measures investors' attentiveness more directly in the cross-section. Da et al. (2011) measure investor attention with Google search frequency and show that attention is related to stock price increases and subsequent reversals as well as to the typical patterns of IPO stocks. Other studies use a company's Wikipedia page views to measure investor attention. Based on this measure, Focke et al. (2016) document that advertising positively affects investor attention and Ungeheuer (2017) finds that stocks classified as daily winners or losers are likely to receive higher attention by investors, while no such effect is observed for stocks with extreme returns but without such classification. So far, only few studies use direct measures of investor attention at the individual level. Using panel data on daily investor online account logins, Karlsson et al. (2009) and Sicherman et al. (2016) find that investors pay more attention to their portfolios in rising than in flat or falling markets. Investors' logins decrease substantially after market declines and are remarkably low during high volatility periods. Additionally observing what information investors browse and how much time they spend doing it by measuring web-activity, Gargano and Rossi (2017) find that investors pay more attention to large companies that are risky but have high growth potentials.

Our paper is also related to the literature investigating the relation between investor attention and investment performance. Attention-driven investing may affect equilibrium market outcomes as well as individual performance. It is typically argued that attention effects negatively impact stock market performance. Barber and Odean (2008) suggest that if attention and investors' utility are orthogonal or at least negatively correlated, attention-attracting characteristics of an alternative may indirectly detract from its utility. Consequently, attention-based purchase behavior by many investors could temporarily inflate a stock's price, leading to lower subsequent returns. Seasholes and Wu (2007) find that attention-grabbing events co-

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more media coverage and argue that these results are consistent with limited investor attention.

incide with statistically significant mean reversion in prices. Moreover, retail investors' market returns appear to decrease on days following attention-grabbing events (Yuan, 2015).[3] Further, Kumar et al. (2018) find a significant underperformance of attention-catching stocks – daily winners and losers – after they are bought by retail investors. On the other hand, Gargano and Rossi (2017) provide evidence that investors are more attentive to their brokerage account if it shows better investment performance, both at the portfolio return level and the individual trades level.

We further relate to theoretical work on investor attention explaining investors' attentional patterns as well as the resulting effects on decision outcomes. Theoretical work by Bordalo et al. (2012) models context-dependent choice under risk, which integrates the concept of salience. Salience refers to the disproportionate weighting of information that exhibits higher levels of attention relative to other pieces of information. In an asset market context, the key implication of salience theory is that extreme payoffs receive disproportionate weight in the valuation of assets (Bordalo et al., 2013). Thus, salient returns are overweighted, i.e. exhibit a higher decision weight, compared to non-salient returns. In particular, salient positive features should receive a disproportionate positive decision weight, whereas salient negative features should receive a disproportionate negative decision weight. In contrast, Barber and Odean (2008) argue that assets that attract investors' attention are more likely to be considered and chosen, while assets that do not attract attention might be ignored, i.e. preferences determine choices after attention has determined the choice set.

3.3 Experimental Design

In this section, we first describe our experimental setup (Section 3.3.1) along with the treatment (Section 3.3.2) and then derive our hypotheses (Section 3.3.3).

3.3.1 Experimental Setup

Our experimental setting builds on Weber and Camerer (1998). Subjects make individual investment decisions based on information about past asset prices.[4] They have the possibility to purchase shares of risky stocks with different price trends; in contrast to the Weber and Camerer (1998) design, subjects make 10 independent one-shot investment decisions since we

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[3]A comprehensive overview on the role of investor attention for trading behavior and economic outcomes is provided by Jacobs (2015).

[4]The experiment instructions are provided in Appendix 3.A.

do not focus on investment dynamics.[5] Each of the 10 decisions consists of two phases. In the first phase, subjects receive 1,000 experimental currency units (*Taler*) and have the possibility to purchase shares of six stocks with different price trends or alternatively to hold their initial endowment (which does not earn interest).[6] In the following phase, their positions are sold automatically and returns from the investment activities are calculated.

The six risky stocks in each decision task have different predefined chances of rising and falling in price. The probability of a price to increase is 65% for one stock type labeled $++$, 55% for one stock type labeled $+$, 50% for two stock types labeled 0, 45% for one stock type labeled $-$, and 35% for one stock type labeled $--$. Notably, prices never remain constant; thus, the chance of a price fall is one minus the chance of rising. The size of the experienced price change is randomly assigned and varies between 1, 3, 5, and 10 Taler. Rises and falls in price are independent across stocks and the probability of a stock's price increase is uncorrelated with the size of the price change; in other words, subjects cannot infer the quality of a stock from the size of the price change.[7] Subjects know the probabilities of price increases and decreases for the different stock types, but do not know which of the stocks offered in each decision task has which chance, since they are neutrally labeled. For each decision, subjects are confronted with completely new stocks, i.e., there is no relation to the stocks from past decisions. To ensure that subjects understand this aspect of the experiment, the labels of the six stocks vary between the decision tasks and no label is used more than once.[8]

Before the experiment, 10 different choice sets with price sequences of six risky stocks each were drawn based on the defined chances of a price increase.[9] In each decision task, subjects are provided with a table containing information about stocks' current prices (Period 0) as

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[5]Using independent one-shot decisions has the advantage that path dependencies are unlikely to influence subjects' purchase behavior. As an example, in an experimental setup with interdependent decisions, a subject carrying forward a portfolio from the previous period with high risk might be more likely to invest in stocks with seemingly lower risk.

[6]Offering a risk-free alternative which does not pay any interest is meant to increase the overall level of stock investments and is consistent with Weber and Camerer (1998). Since our main interest lies in the composition of investors' stock portfolios and not in the split between risky and risk-free assets, this design choice does not influence our conclusions.

[7]We use exactly the same probabilities as in Weber and Camerer (1998). Compared to their setup where the magnitude of price changes is either 1, 3, or 5, we added a more extreme price change of 10. While this choice of parameters does not necessarily imply a positive risk-return relation as assumed by the Capital Asset Pricing Model (CAPM) (Lintner, 1965; Mossin, 1966; Sharpe, 1964), it allows us to separate attention effects generated by extreme returns from alternative purchase motives such as investor preferences or beliefs and fundamental asset values. To ensure that subjects understood the randomness of the magnitude of price changes, i.e., that the magnitude of price changes is unrelated to the stock quality, all subjects had to correctly answer two comprehension questions regarding the magnitude of price changes and the quality of stocks. The questions are provided in Appendix 3.A.

[8]Table 3.7 in Appendix 3.A displays the labels of the stocks used in the 10 decision tasks.

[9]The 10 choice sets are depicted in Appendix 3.A.

Table 3.1: Experimental Design: Control and Treatment

This table displays an exemplary decision task as seen by the control group (left-hand side) and the treated group (right-hand side).

	Control							Treatment						
Period	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**
Price Change	40	45 (+5)	48 (+3)	53 (+5)	56 (+3)	46 (-10)	*47 (+1)*	40	45 (+5)	48 (+3)	53 (+5)	56 (+3)	46 (-10)	*56 (+10)*
Price Change	45	40 (-5)	45 (+5)	46 (+1)	41 (-5)	46 (+5)	41 (-5)	45	40 (-5)	45 (+5)	46 (+1)	41 (-5)	46 (+5)	41 (-5)
Price Change	50	49 (-1)	46 (-3)	45 (-1)	35 (-10)	34 (-1)	35 (+1)	50	49 (-1)	46 (-3)	45 (-1)	35 (-10)	34 (-1)	35 (+1)
Price Change	55	50 (-5)	53 (+3)	63 (+10)	58 (-5)	53 (-5)	52 (-1)	55	50 (-5)	53 (+3)	63 (+10)	58 (-5)	53 (-5)	52 (-1)
Price Change	60	61 (+1)	62 (+1)	63 (+1)	73 (+10)	78 (+5)	77 (-1)	60	61 (+1)	62 (+1)	63 (+1)	73 (+10)	78 (+5)	77 (-1)
Price Change	65	75 (+10)	65 (-10)	68 (+3)	73 (+5)	72 (-1)	62 (-10)	65	75 (+10)	65 (-10)	68 (+3)	73 (+5)	72 (-1)	62 (-10)

well as past prices from six given previous periods (Periods -6 to -1); the left-hand panel of Table 3.1 shows an example of a decision task (a screenshot of a decision task is displayed in Appendix 3.A). The six stocks have different starting prices. All sessions have the same choice sets.

Using the provided stock information, a fully rational (Bayesian) subject should count the number of times that a stock experienced a price increase in the course of the given periods to infer the stock's chance of a price increase in the next period.[10] Specifically, the stock that has increased most frequently is most likely to be the $++$ stock type with the highest chance of a price increase in the next period and subjects should be most likely to buy shares of this stock. With the same logic, the stock with the highest number of price decreases is most likely to be the $--$ stock type and subjects should be least likely to buy shares of this stock. In addition, the $-$ and $--$ stock types have a negative expected return (we refer to them as *negative stocks*), thus buying shares of these stock types reduces subjects' profits on average. Rational investment decisions would only include $+$ and $++$ stock types with a positive expected return (we label them *positive stocks*) and potentially 0-drift stocks with an expected return of zero (*neutral stocks*) for reasons of diversification.[11]

Our experiment is incentivized, and subjects' investment decisions during the experiment

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[10]Since subjects see the full history of stock prices from Period -6 to Period 0 displayed at once, estimates of stock quality are not updated in the proper sense of the word. However, in the following, we refer to Bayesian subjects when subjects behave consistently with Bayesian updating in that they are most likely to purchase shares of stocks with the highest number of price increases.

[11]Diversification is possible since price movements are uncorrelated across stocks in our design.

determine their payout. At the end of each experimental session, one of the 10 decision tasks of each subject is randomly chosen for payout in order to avoid path-dependent decisions. Subjects' Taler holdings are then converted into € based on a known exchange rate of 100 Taler to €1. However, the realized returns of the stocks subjects invested in, namely the difference between buy price and sale price, is doubled.[12] Thus, the payout is computed as shown in Equation (3.1):

$$T_f = T_s + \sum_{i=1}^{6} 2 \cdot (p_{i,1} \cdot n_{i,1} - p_{i,0} \cdot n_{i,0}) \tag{3.1}$$

T_f denotes the final amount of Taler, T_s denotes the amount of Taler when a decision task starts (i.e., the initial endowment), $p_{i,t}$ is the price of Stock i in Period t, and $n_{i,t}$ represents the number of shares of Stock i purchased and (automatically) sold in Period t. Subjects' cash holdings are not carried over from one decision to the next. No interest is paid on Taler holdings and subjects do not face any transaction costs. Short selling and borrowing are not possible.

Subjects have 15 minutes to read the instructions on their own and questions are answered privately. In order to ensure that subjects understand the experimental design, we use introductory comprehension questions that have to be answered correctly before proceeding with the experiment. The investment tasks are followed by a questionnaire with demographic and control questions. Similarly to Dohmen et al. (2011), subjects are asked to self-assess their risk tolerance in general matters on a scale from 0 (lowest) to 10 (highest); moreover, in order to obtain an objective measure of risk aversion, subjects are asked to complete a lottery task in a multiple price list setting (Holt and Laury, 2002). We also ask for subjects' knowledge in statistics and econometrics.

The experiment was conducted with 117 subjects, mostly business and economics students (about one third of the subjects have no economics or business background), from the experimental laboratory's subject pool. Table 3.2 displays the summary statistics. Subjects are 24 years old on average; 42% are male. The average self-assessed risk tolerance equals about 5; the average switching point in the multiple price list is almost 6. On average, subjects earned €9.98. For each subject, the experimental session took about 1 hour. Our visual attention analyses are based on a sample of 114 subjects, as the eye-tracking devices of three subjects could not be calibrated sufficiently. The experiment is programmed and conducted with z-Tree

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[12]The range of potential payoffs equals €2 to €18.

Table 3.2: Summary Statistics of Subjects

This table contains the summary statistics of the experimental subjects. *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Business/economics as main field of study* is a dummy variable which is equal to one if a subject studies a major related to business and/or economics; *Advanced statistics knowledge* is a dummy variable which is equal to one if subjects assess their statistics knowledge as advanced (e.g., having completed a statistics class at university); *Risk tolerance* is subjects' self-assessment of their risk tolerance in general matters, measured on a scale from 0 (lowest) to 10 (highest); *HL switching point* is the switching point from the Holt and Laury (2002) lottery task.

	Mean	Median	SD	Min	Max
Age	24.14	24.00	4.80	18.00	53.00
Male	0.42	0.00	0.50	0.00	1.00
Business/economics as main field of study	0.72	1.00	0.45	0.00	1.00
Advanced statistics knowledge	0.57	1.00	0.50	0.00	1.00
Risk tolerance	5.03	5.00	2.27	0.00	10.00
HL switching point	5.76	5.00	1.86	2.00	10.00
N	117				

(Fischbacher, 2007) and the experimental sessions were organized and administrated with the software hroot (Bock et al., 2014).[13]

3.3.2 Treatment

To study the nature and implications of investor attention, we manipulate the attention-grabbing characteristic of one of the available stocks in each of the 10 decision tasks. In line with Barber and Odean (2008), we vary the stock's return information in the period preceding the investment decision (Period 0) by implementing two return conditions, an extreme return as treatment condition and a normal return condition as control.[14] In our design, we implement price changes by 10 Taler as extreme returns and price changes by 1 Taler as normal returns in the choice sets. As we vary the type of the manipulated stock across the decision tasks, we test choice environments with positive as well as negative stock returns.[15]

For each choice set, we manipulate the magnitude of the price change of *one* given stock. Table 3.1 displays an example of the manipulation of a positive stock. In the normal return

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[13]As is common practice in laboratory experiments, our subjects are students. On the one hand, compared to the general population our subjects might make smarter investment decisions since many of them study a subject related to business or economics. On the other hand, since all subjects are students they might have lower experience with stock investments and therefore make less appropriate decisions. The net effect of these two drivers is not clear ex-ante.

[14]Previous research has identified further characteristics that coincide with catching investors' attention. As an example, Barber and Odean (2008) additionally investigate news coverage and abnormal trading volume. The latter is also examined by Gervais et al. (2001). Hartzmark (2015) identifies the so-called rank effect as a further driver of trading behavior: traders are more likely to sell extreme winners and extreme losers in their portfolio. As for our experiment, we implement extreme returns.

[15]Refer to Appendix 3.A for a detailed illustration.

condition (left-hand panel), this stock has a last period return of $+1$ Taler; in the extreme return condition (right-hand panel), the stock's last period return is $+10$ Taler. However, we do not manipulate whether the stock experiences a price increase or decrease, which would change the informative value of the price sequence. Importantly, the sequences are chosen such that positive stocks have last-period returns of $+1$ Taler or $+10$ Taler in the control and the treatment condition, respectively, and negative stocks have returns of -1 Taler or -10 Taler. As for neutral stocks, one stock has last-period returns of either $+1$ Taler or $+10$ Taler while the other has returns of either -1 Taler or -10 Taler. This mechanism implies that manipulated positive stocks have positive normal and extreme returns in the control and the treatment condition, respectively, and manipulated negative stocks have negative normal and extreme returns; it is a critical feature of the experiment design since attention to extreme positive returns can increase utility while attention to extreme negative returns can decrease utility in this setting. One of the positive stocks is manipulated in choice sets 1 to 4, one of the neutral stocks in choice sets 5 and 6, and one of the negative stocks in choice sets 7 to 10. Since the absolute magnitude of a price change (1, 3, 5, or 10 Taler) is randomly assigned to the different stock types, the two conditions do not differ in their informative value for subjects. The quality of the manipulated stocks is constant across the treatment and control condition.

This setup allows for a distinction between trading on attention and trading on preferences or beliefs. Since extreme last-period returns are unrelated to stock quality and subjects know this mechanism, trading on extreme last-period returns cannot be explained with investors' beliefs. Moreover, as extreme last-period returns do not change the expected volatility of a stock and subjects know this mechanism, trading on extreme last-period returns cannot be explained with investors' risk preferences.

The experiment follows a between-subjects design. We randomly assign subjects to one of the two return conditions for every decision task; i.e., a given subject might see the control condition of a choice set in one of the 10 decision tasks and the treatment condition of another choice set in another task. In addition, we vary the order of the predefined choice sets between the subjects to prevent order effects. Across the 10 decisions, we also vary the order of the presented stock types and the stocks' initial starting prices (40, 45, 50, 55, 60, and 65 Taler).

In all ten choice sets the information on past stock prices is sufficient to clearly identify the quality of the manipulated stock by counting the number of past price increases and ranking the six stocks accordingly. Consequently, it can be ruled out that a significant treatment

effect is caused by subjects not having the possibility to correctly infer the true quality of the manipulated stock.

3.3.3 Hypotheses

Based on the insights described in Section 3.2, we expect extreme return patterns in the period preceding the purchase decision – as an attention-grabbing characteristic – to significantly influence subjects' purchase volume of the respective manipulated stock.

Hypothesis 1   *Subjects treated with the extreme return information show a higher purchase volume of the manipulated stock compared to the control group.*

The null hypothesis to Hypothesis 1 is that the purchase volume of manipulated stocks does not differ between the treatment and the control group or that the purchase volume of the manipulated stock is higher for the control group.

Moreover, we are interested in investors' visual focus while making their purchase decisions. As discussed above, eliciting subjects' visual fixations allows us to measure visual attention. Thus, we expect that subjects' visual focus to a stock significantly influences their purchase volume of the respective stock.

Hypothesis 2   *Subjects with higher visual fixation to the information of a stock show a higher purchase volume of the respective stock.*

The null hypothesis to Hypothesis 2 is that subjects' visual fixation is not reflected in subjects' purchase volume of the respective stock or that subjects with higher visual fixation to the information of a stock show a lower purchase volume of the respective stock.

3.4   Results

This section reports our main results. We first describe subjects' stock buying and portfolio decisions in response to extreme returns implemented in our experiment (Section 3.4.1). In Section 3.4.2, we test whether subjects' visual fixations are associated with their stock buying behavior in the experiment.

3.4.1 Extreme Returns

To investigate Hypothesis H1, we first examine subjects' purchase decisions in response to extreme returns implemented in our experiment.

Attention Effects in Stock Buying Behavior

For the following analyses, we define purchase volume as the number of stock shares purchased.[16] We pool the data from all subjects since all subjects are presented the same price sequences (except for the Period 0 return of the treated stock for a given decision).

On average, subjects invest about 525 of their 1,000 Taler in stocks. I.e., on average, subjects invest slightly more than half of their initial endowment in each decision task in risky stocks and keep slightly less than half of the endowment in the (non-interest paying) risk-free asset. This number is relatively constant across all 10 choice sets of the experiment. The average number of shares purchased equals 10, and subjects purchase 3 different stocks in each decision situation on average.

Figure 3.1 displays the average number of shares of the manipulated stock purchased for each category of stock that is manipulated (positive, neutral, and negative), grouped by whether the treated stock exhibits a normal or an extreme return in the period preceding the purchase decision (Period 0). As an example, across all choice sets, the average number of shares purchased of the respective manipulated stock equals about 1.7 when the stock exhibits a normal return in Period 0; with an extreme return in Period 0, the number increases to about 2.2, which is an increase by almost 30%. As indicated by the higher average purchase volumes in Choice Sets 1 to 4 compared to Choice Sets 7 to 10, subjects purchase more positive than negative manipulated stocks. With respect to positive stocks, extreme returns of +10 instead of normal returns of +1 have virtually no impact on the number of shares purchased. For negative stocks however, the purchase volume increases from 0.6 to 1.8 when the last-period return of a given stock equals the extreme −10 instead of the normal −1.

In line with our hypothesis H1, nonparametric tests show that the increase in purchase volume across all choice sets as well as for negative stocks is significant at the 1% level. The changes in purchase volume between the normal and the extreme condition are insignificant as far as positive and neutral stocks are concerned.

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[16]In our robustness tests reported in Appendix 3.A, we show that our results are not substantially changed when volume is computed as the product of the number of stock shares purchased and the corresponding stock prices.

Figure 3.1: Extreme Returns and Number of Shares Purchased

This figure displays the number of manipulated shares purchased in the choice sets of the experiment for each category of stock that is manipulated and the corresponding confidence intervals (95%). *Normal* represents the control condition for a given choice set; *Extreme* represents the treatment condition for a given choice set. The data of all subjects is pooled. The total number of observations equals 1,170 for all stocks (468 for positive and negative stocks, respectively, and 234 for neutral stocks).

Table 3.3 displays the results of an OLS regression in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased in a given decision situation. The main explanatory variable is a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision is extremely high or low (i.e., equal to $+10$ instead of $+1$ for positive stocks and -10 instead of -1 for negative stocks). Since we include 10 observations for each subject, standard errors are clustered at the subject level.

The coefficient of the treatment dummy is significantly positive, indicating that about 0.5 additional shares are purchased when the respective stock exhibits extreme returns in the preceding period, which is in line with our hypothesis H1. Importantly, we find that this effect is mainly driven by investors' buying of extreme negative stocks. The treatment dummy

Table 3.3: Extreme Returns and Number of Shares Purchased

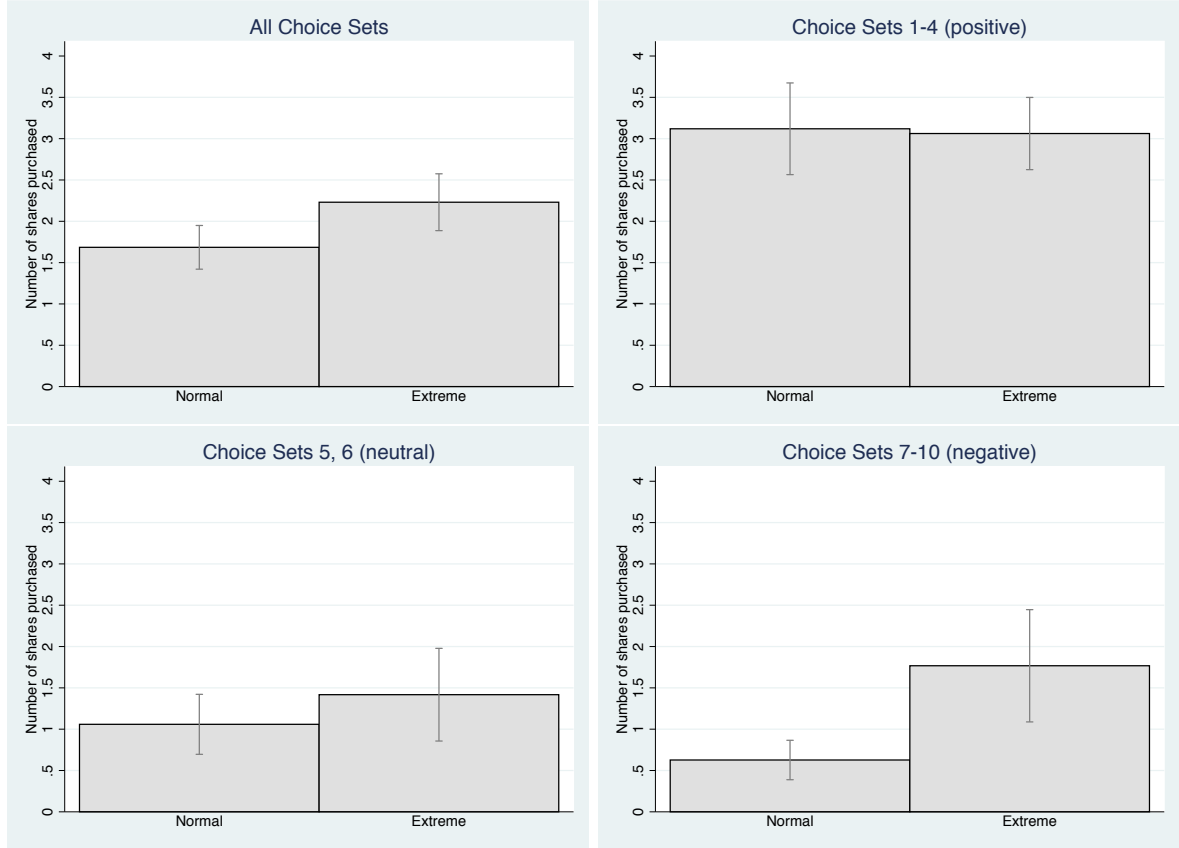This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	0.455**	-0.173	0.443	0.956***
	(1.98)	(-0.53)	(1.11)	(2.73)
Risk tolerance	0.235***	0.208**	0.146**	0.306
	(2.63)	(2.38)	(2.41)	(1.45)
Age	-0.056***	-0.132***	-0.060**	0.024
	(-2.73)	(-2.90)	(-2.09)	(0.63)
Male	0.652*	1.461***	0.392	-0.057
	(1.85)	(2.87)	(1.27)	(-0.07)
Earnings in preceding decision	0.000	0.001	0.001	-0.000
	(0.48)	(1.58)	(1.10)	(-0.13)
Number of decision	0.029	-0.001	-0.079	0.076
	(0.64)	(-0.02)	(-1.45)	(0.93)
Constant	1.690*	4.965***	2.512**	-1.467
	(1.83)	(3.45)	(2.31)	(-0.84)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
R^2	0.07	0.14	0.14	0.10

is insignificant as far as positive and neutral stocks are concerned; regarding negative stocks however, the coefficient is significantly positive. Observing an extreme low return in the period preceding the purchase decision increases the number of negative stock shares purchased by about 1. Compared to the baseline number of shares of negative stocks purchased of about 0.6, this is an increase by more than 150%. Note that we control for whether the extreme prior return of the treated stock represents a unique maximum or minimum among all prior returns (e.g., if there is no further stock with a return of +10 in Period 0 in the case of positive manipulated stocks; this is the case in some choice sets of our experiment); in so doing, we ensure that the rank effect (Hartzmark, 2015) does not confound our results.

Higher self-assessed risk tolerance increases the number of shares of the manipulated stock

purchased as far as positive and neutral stocks are concerned. Moreover, older subjects buy significantly fewer manipulated stocks (except for negative stocks) and male subjects purchase significantly more shares of positive manipulated stocks. Although the decisions of each subject are independent, we also control for subjects' earnings in the decision task preceding the respective task; as expected, we find no significant effect.[17]

Additional analyses provided in Appendix 3.A (Table 3.14) reveal that subjects that are likely to base their decisions on Bayesian updating show no attention-driven purchase patterns, which seems plausible. In other words, subjects not following Bayesian updating are most likely to exhibit attention-driven purchase behavior. In addition, the effect of attention on purchase behavior is observed for individuals with lower stock investments and who take less time to make their investment decisions primarily. These findings strengthen the interpretation of our results as evidence of investor attention: individuals with lower stock investments might have lower stock market experience (either in reality and/or in our experiment) and are thus looking for cues where to invest their money; for these individuals, attention-grabbing stock characteristics might represent such cues. Subjects with lower decision time might strive to make quick and intuitive decisions; for these individuals, extreme prior returns are a quick and easy way to determine where to invest.

Attention Effects in Portfolio Composition

The analyses presented above focus on the purchasing patterns with respect to the manipulated stocks in the respective choice sets (i.e., they focus on one of the six stocks in each choice set). In this section, we investigate whether attention-driven purchase behavior affects subjects' overall portfolio composition.

As stated above, the average investment amount across all subjects and all choice sets equals about 525 Taler. Column 1 of Table 3.4 displays the results of an OLS regression in which the dependent variable is the total amount of Taler invested in stocks in a given decision situation. The coefficient on the variable indicating an extreme prior return is insignificant, indicating

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[17]Using the switching point from the Holt and Laury (2002) lottery task instead of self-assessed risk tolerance leaves our main results qualitatively unchanged. To rule out the possibility that our results are influenced by the definition of purchase volume, we repeat our main analysis in Table 3.12 in Appendix 3.A but substitute the volume of shares purchased, defined as the product of quantity and price, for the mere number of shares purchased as the dependent variable. We find that our main results are qualitatively unchanged. To rule out that our results depend on the specific regression model used, Table 3.13 in Appendix 3.A repeats our main analysis but uses a Tobit specification instead of the OLS model. As before, we observe that our main results are almost unchanged. In addition, we find that subjects do not react differently to the treatment in earlier or later decisions; while subjects' learning could improve later decisions, their exhaustion might have the opposite effect. Our results suggest that neither effect is relevant or that both effects cancel each other out.

Table 3.4: Extreme Returns and Investment in Stocks

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions; the dependent variable in Column 1 is the total amount of Taler invested in stocks in a decision situation; the dependent variable in Column 2 is the total number of stocks purchased in a decision situation; the dependent variable in Column 3 is the number of different stocks purchased in a decision situation. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Field of study* represents subjects' main field of study; *Degree* is the degree with which a subject expects to graduate; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Amount in Stocks	(2) Number of stocks	(3) Number of stock types
Extreme prior return	1.475	-0.087	0.062
	(0.09)	(-0.29)	(0.77)
Risk tolerance	33.277***	0.723***	0.026
	(2.70)	(2.84)	(0.47)
Age	-14.625***	-0.202**	-0.024
	(-3.31)	(-2.40)	(-1.31)
Male	140.412**	2.494**	-0.392
	(2.55)	(2.17)	(-1.64)
Earnings in preceding decision	-0.022	-0.001*	-0.000
	(-1.37)	(-1.95)	(-0.37)
Number of decision	-5.571**	-0.131**	-0.056***
	(-2.17)	(-2.32)	(-3.25)
Constant	696.534***	10.846***	3.554***
	(3.45)	(2.68)	(3.90)
Session	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes
Degree	Yes	Yes	Yes
Field of study	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes
N	1,170	1,170	1,170
R^2	0.23	0.22	0.16

that our treatment did not make subjects invest more or less in stocks. We further observe that more risk-tolerant subjects (as measured with the self-assessment), younger subjects, and men invest more in stocks. Column 2 shows that the total number of stocks purchased in a given decision situation is unaffected, too. Finally, Column 3 suggests that extreme prior returns do not affect the number of different stock types subjects invest in (ranging from 0 to 6) for a given decision situation.[18]

In sum, these observations imply that extreme prior returns do not induce subjects to change the split between risky stocks and the risk-free asset, nor to change the total number

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[18]In unreported regressions (available from the authors upon request), we use a Tobit specification instead of an OLS regression and find that our results are qualitatively unchanged.

of shares they purchase or how much they diversify by investing in different types of stocks. Instead, subjects change the allocation of the amount invested in risky assets across the six stocks, purchasing more attention-grabbing stocks in the treatment and fewer non-attention-grabbing stocks. In other words, the presence of attention-grabbing stocks does not increase stock buying. These findings suggest that the demand for attention-grabbing stocks increases at the expense of the demand for non-attention-grabbing stocks. To the extent that attention-grabbing stocks are less profitable than non-attention-grabbing stocks, such behavior is likely to reduce investors' wealth. We resume this debate in Section 3.6.

3.4.2 Visual Fixations

With respect to Hypothesis H2, we use eye tracking devices to measure subjects' visual attention and test whether subjects' visual fixations are associated with their stock buying behavior.

Measurement

Visual attention plays a crucial role in decision-making (for a review see Orquin and Mueller Loose (2013)). Empirical evidence suggests that visual attention determines the perception as well as processing of stimuli (Droll et al., 2005; Triesch et al., 2003). Based on these insights, Orquin and Mueller Loose (2013) argue that visual attention influences individual decision-making by limiting the decision to the fixated stimuli and enhancing the influence of the fixated information.

We measure visual attention patterns by tracking subjects' eye movements, which is in line with studies reporting strong links between eye movements and visual attention (Deubel and Schneider, 1996; Hoffman and Subramaniam, 1995; Kowler et al., 1995). Eye movements were recorded with remote binocular Tobii Pro X2-60 eye trackers using a screen with a resolution of 1920×1200 pixels and size of 20.3×12.8 inches. The tracking distance was 50 cm to 80 cm. Data was gathered at a sampling rate of 60 Hz (about 16.67 ms) with an accuracy of 0.4 degrees and a precision of 0.34 degrees; a standard five-point calibration was applied and a maximum of two recalibrations were conducted.[19] No chin rest was used. Fixation durations exceeding 60 ms were included in the analyses (Komogortsev et al., 2010; Salojarvi et al., 2005). To analyze the length of the fixation duration on a specific stimulus, non-overlapping areas of interest (AOIs) were defined. In particular, we use AOIs with respect to different pieces of information provided in the table displayed on the experimental screen in each of

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[19]The background color of the calibration screen was white.

the ten decision situations.[20] We defined AOIs for each stock (rows) of 807×116 pixels in size. Subjects with corneal irregularity or other eye disease as well as with diopter strength exceeding +/- 2.8 were excluded from participating.

Attention Effects in Stock Buying Behavior

In our analyses, we resort to *fixation duration*, the most widely used measure in eye-tracking research (Holmqvist et al., 2011). Figure 3.2 displays the heatmap of absolute fixation durations as an average of all subjects for one of the ten decisions of the experiment. Yellow and red areas indicate locations of relatively longer fixation duration. The main finding is that fixation durations generally increase from left to right, implying that fixation durations are higher for more recent periods and shorter for periods that are further in the past. Independent of the specific decision task, the heatmaps provide a first indication for subjects' strong visual attention to the period prior to the purchase decision (Period 0), i.e., the period manipulated with attention-grabbing stock characteristics in the treatment condition. Assuming that counting consistent with Bayesian updating should result in gaze patterns with equally distributed attention to all periods displayed in the table (i.e., Periods -6 to 0), this observation implies biased visual attention with a strong focus on stock price information of the very period preceding the purchase decision. A further observation is that fixation durations are higher in upper rows than in lower rows; this is consistent with the empirical observation that stocks appearing at the top of a list have higher trading activity and liquidity than stocks appearing at the bottom (Jacobs and Hillert, 2016). Since – as described above – we varied the position of the stock types across choice sets, our results should not be affected.[21]

For the following analyses, we define relative fixation duration as subjects' fixation duration on the manipulated stock AOI relative to the fixation duration on all stock AOIs for each choice set, measured in percent. Again, we pool the data from all subjects. The average number of stocks fixated in each decision situation equals 5.5. On average, subjects allocate 19% of their fixation duration on the manipulated stock AOIs across the different choice sets. Subjects' relative fixation duration on the manipulated stock AOI is substantially higher in the treatment (20.9%) than in the control (17.2%) condition. Nonparametric tests show that subjects' relative fixation duration on the manipulated stock in the treatment condition is significantly higher (1% level) than in the control treatment as well as compared to equally

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[20]An example table is provided in Appendix 3.A. The font size was 18pt.

[21]The other nine heatmaps show virtually identical patterns of visual attention.

Figure 3.2: Heatmap of Absolute Fixation Durations

This figure displays the heatmap of absolute fixation durations of one of the ten decisions in the experiment, averaged over all subjects.
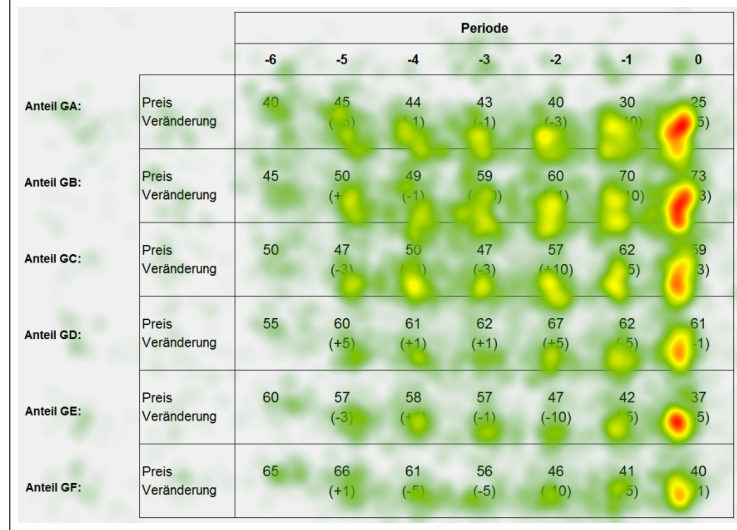
Figure 3.3: The Effect of Extreme Returns on Purchase Volume Through Visual Attention

This figure displays unstandardized regression coefficients from mediation analysis obtained through bootstrapping. The range in brackets represents the bias-corrected CI of the natural indirect effect.
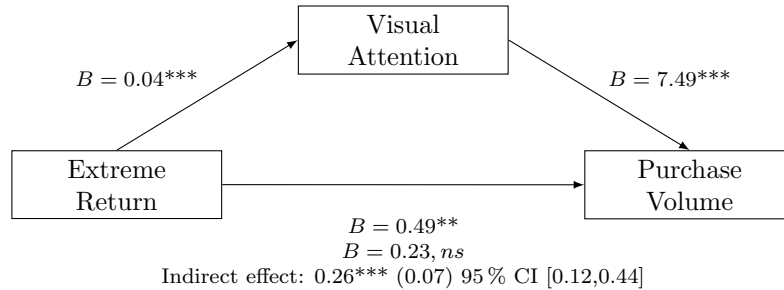
distributed attention.

We also predicted that the effects of our treatment on stock purchase volume would be mediated by subjects' visual attention. To investigate this channel of attention, we conduct a mediation analysis, which is displayed in Figure 3.3.[22] Subjects show a higher purchase volume of manipulated stocks after experiencing extreme returns, $B = 0.49$, $SE = 0.24$, $P = 0.039$, 95% CI (0.02, 0.96)[23], and significantly higher visual attention to those stocks after experienc-

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[22]We control for risk tolerance, age, gender, subjects' earnings in the preceding decision, the number of the decision, and the ranking of the extreme return.

[23]For our mediation analyses we used a slightly different set of control variables compared to our regression

ing extreme returns: $B = 0.04$, $SE = 0.01$, $P = 0.000$, 95% CI $(0.02, 0.05)$. After controlling for visual attention, the treatment is no longer a significant predictor of stock purchase volume: $B = 0.23$, $SE = 0.21$, $P = 0.280$, 95% CI $(-0.19, 0.65)$. Testing the significance of the natural indirect effect using bootstrap estimation results in a significant indirect coefficient: $B = 0.26$, $SE = 0.07$, $P = 0.000$, 95% CI $(0.12, 0.44)$. That is, extreme returns increase subjects' stock purchase volume through channeling subjects' visual focus on the respective stock. In sum, our mediation analysis shows that the relationship between exposure to extreme returns and stock purchase behavior is indeed explained by visual attention to the manipulated stocks.

Table 3.5 displays the results of an OLS regression in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased in a given decision situation.[24] The main explanatory variable is subjects' relative fixation duration on the manipulated stock AOI. Thus, we replace the treatment dummy from our previous analyses (attention-grabbing characteristic) by the alternative measure of attention reflecting visual fixation. Standard errors are clustered at the subject level. As before, we control for risk tolerance, age, gender, subjects' earnings in the preceding decision, the number of the decision, the experimental session, the rank effect, as well as subjects' educational degree, field of study, and statistical knowledge.

As shown in the mediation analyses and in line with our Hypothesis H2, the coefficient of the relative fixation duration variable is significantly positive. A higher allocation of fixation duration on the manipulated stock is positively correlated with subjects' purchase volume of the respective stock. In detail, the results indicate that an increase in the relative fixation duration by 10 percentage points increases the number of purchased shares of the manipulated stock by about 0.75. This is an increase by almost 40% compared to the average number of 1.9 purchased shares of the manipulated stock across all choice sets. Furthermore, we find that the attention effect is largest for negative stocks, which is in line with the observed asymmetry in Table 3.3: the effect is almost three times as large as for positive stocks and more than five times as large as for neutral stocks. In other words, the asymmetric effect of investor attention is reflected in these patterns of visual attention.

In a robustness test reported in Appendix 3.A (Table 3.15), we further show that our asymmetric treatment effect is not driven by different general attention levels to positive

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analyses in Section 3.4.1 (without multicategorical independent variables), which explains the small deviations in results.

[24]The total number of observations in Table 3.5 equals 114 (subjects)·1 (manipulated stock)·10 (decisions) = $1,140$.

Table 3.5: Relative Fixation Duration and Number of Shares Purchased

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Relative fixation duration* represents subjects' relative fixation duration on the manipulated stock AOI relative to the fixation duration on all stock AOIs for each choice set in percent; *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Relative fixation duration	7.488***	4.877***	2.239**	12.595**
	(4.58)	(3.81)	(2.37)	(2.35)
Risk tolerance	0.236***	0.216**	0.134**	0.277
	(2.88)	(2.42)	(2.30)	(1.62)
Age	-0.071***	-0.129***	-0.067**	0.005
	(-3.40)	(-3.03)	(-2.57)	(0.19)
Male	0.612*	1.543***	0.270	-0.068
	(1.80)	(3.15)	(0.86)	(-0.10)
Earnings in preceding decision	0.000	0.000	-0.001	-0.000
	(0.14)	(0.71)	(-1.27)	(-0.58)
Number of decision	0.062	0.035	-0.074	0.079
	(1.28)	(0.60)	(-1.35)	(1.01)
Constant	0.632	3.389**	4.018***	-2.703
	(0.56)	(2.24)	(3.03)	(-1.17)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,140	456	228	456
R^2	0.15	0.19	0.15	0.21

and negative stocks because they have been shown in different rows of the information table provided to subjects. The analyses are restricted to choice sets with positive and negative manipulated stocks in the same row (second row) of the information table provided to the subjects. The results show that although positive and negative manipulated stocks are shown in the same row, extreme returns significantly increase visual attention to negative stocks, but not to positive stocks.

3.5 Alternative Explanations

This section discusses potential alternative drivers of our results. These potential drivers are unrelated to investor attention but might lead to similar trading patterns. In the following,

we argue that none of these explanations is able to explain our results.

Diversification Motives Since the six stocks are uncorrelated with each other, adding stocks to subjects' portfolios might add value in terms of diversification (Markowitz, 1952). There are three reasons why diversification motives cannot explain our findings.

First, adding stocks with negative expected returns which systematically lose in value cannot be made for reasons related to diversification. In other words, investors should never invest in negative stocks in our experiment (i.e., $-$ stocks and $--$ stocks). If subjects want to diversify their portfolios, they should purchase positive and neutral stocks only. In fact, Weber and Camerer (1998) and Weber and Camerer (1992) demonstrate that Bayesian utility optimizing investors should never hold $-$ and $--$ stocks in the context of the experimental setting on which our analysis is based.

Second, the asymmetric purchase patterns documented above might arise if subjects exhibit a two-step search process in each choice set: they might start by buying positive stocks (not driven by extreme returns) and then search for additional stocks in order to diversify. In this second search step, subjects might see no use in purchasing additional positive stocks but shares of stocks with a lower correlation with those already selected (such as neutral and negative stocks). It is possible that stocks with extreme returns are most salient and therefore more likely to be chosen in this second search step. However, as described above, investors should never invest in negative stocks in our experiment. In addition, it is unlikely that purchase behavior in the first step of this hypothetical search process is not driven by extreme returns while extreme returns drive purchases in the second step. These conclusions are further supported by the observation that extreme returns do not significantly increase the purchase volume of neutral stocks (see Table 3.3).

Third, assuming subjects have the tendency to buy negative stocks in order to diversify their portfolio, price decreases by -10 Taler and by -1 Taler for a given negative stock should have the same effect on subjects' purchase behavior. Yet, we do only observe an increased purchase volume for negative stocks with extreme returns in the last period. This pattern cannot be explained by diversification motives.

Investor Beliefs A further challenge to our results is the possibility that our finding is rather driven by investors' beliefs instead of their attention. The tendency to purchase shares of stocks which have previously lost in value could be driven by the expectation of mean-reverting stock

prices. Following this reasoning, shares of stocks with negative returns in the previous period (i.e., -1 Taler or -10 Taler) should be more likely to be purchased than shares of stocks with positive returns. In addition, shares of stocks with extreme negative returns in the previous period (i.e., -10 Taler) might be more likely to be purchased than shares of stocks with less extreme negative returns. This could lead to the observed patterns of purchases of shares with previous negative extreme returns. Although the belief in mean reversion is incorrect in our design, we cannot fully rule out that subjects formed such beliefs. However, if this explanation were valid, we should observe that shares of positive stocks should be bought less compared to negative stocks, most notably if the increase in the preceding period is as high as 10 Taler. We do not observe such patterns; positive stocks exhibit substantially higher purchase volumes than negative stocks on average.

Further, it could be the case that a particular subset of our subjects believe in mean reversion and drive our results. We therefore conduct additional regressions to those in Section 3.4.1 and our mediation analyses in Section 3.4.2 with a control variable capturing whether subjects follow a buying strategy in line with a belief in mean reversion. We use a dummy variable which is equal to one if a given subject invests in a stock (other than the manipulated stock) with a prior negative return in the respective decision situation. Table 3.6 shows that the coefficient of the treatment variable is significantly positive in the cross-section, insignificant as far as positive and neutral stocks are concerned, and significantly positive for negative stocks. The size of the coefficients and the significance levels are similar when including the control variable for a potential belief in mean reversion. Our dummy variable for a belief in mean reversion shows no significant correlation with the number of negative stock shares purchased. In Appendix 3.A (Figure 3.5) we report the results for mediation analyses with control for beliefs in mean reversion. The results are qualitatively unchanged. In addition, we run these regression analyses with an alternative control variable capturing whether subjects follow a buying strategy in line with a belief in mean reversion across all ten decisions. The results for our treatment effect remain qualitatively unchanged (Appendix 3.A, Table 3.16).

Alternatively, subjects might believe in momentum. In this case, shares of stocks with extreme negative (positive) returns in the previous period might be deemed more likely to exhibit negative (positive) returns in the next period. As with mean reversion, this belief is incorrect in our experimemtal design. Yet, if subjects still believed in momentum, we should observe a significantly negative effect of negative (extreme) returns and a significantly positive effect of positive (extreme) returns on stock purchases. However, neither of these patterns is

Table 3.6: Extreme Returns and Number of Shares Purchased with Control for Beliefs in Mean Reversion

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Invest in other neg. return stock* is the control variable for beliefs in mean reversion, a dummy variable which is equal to one if the subject invested in a stock (other than the manipulated stock) with a prior negative return in the respective decision situation; *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	0.464**	-0.108	0.463	0.957***
	(2.00)	(-0.33)	(1.13)	(2.79)
Risk tolerance	0.241**	0.248**	0.127**	0.307
	(2.55)	(2.60)	(2.24)	(1.43)
Age	-0.057***	-0.133***	-0.062**	0.024
	(-2.73)	(-2.94)	(-2.43)	(0.60)
Male	0.641*	1.421***	0.351	-0.065
	(1.77)	(2.82)	(1.20)	(-0.08)
Earnings in preceding decision	0.000	0.000	-0.001	-0.000
	(0.20)	(0.52)	(-1.01)	(-0.19)
Number of decision	0.028	0.006	-0.068	0.077
	(0.62)	(0.11)	(-1.17)	(0.94)
Invest in other neg. return stock	-0.334	-1.264***	0.655	-0.095
	(-1.13)	(-3.51)	(1.49)	(-0.16)
Constant	2.014**	5.710***	3.182**	-1.395
	(2.11)	(3.92)	(2.27)	(-0.82)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
R^2	0.07	0.16	0.16	0.10

observed in our data.

Budget Constraints A potential strategy of subjects is allocating a fixed budget (in Taler) to each stock. Following this reasoning, price decreases by -10 Taler instead of -1 Taler allow for a higher number of share purchases for a given negative stock, which might lead to a comparable behavior of purchasing shares of stocks which have experienced extreme negative returns previously.

However, by the same argument, price increases by $+10$ Taler instead of $+1$ Taler for

positive stocks should decrease the number of shares purchased for a given stock. Yet we do not observe such behavior and therefore conclude that it is unlikely to drive our results.

3.6 Implications for Investor Wealth

Barber and Odean (2008) find that retail investors are net buyers of stocks that catch their attention. They concede that investors' utility might increase in cases in which attention-grabbing features of a stock match features which increase investors' utility. Importantly, they argue that if the opposite is true, i.e., attention-grabbing features coincide with negative utility, investors' utility might actually decrease. Some empirical evidence suggests that investors indeed buy attention-grabbing stocks with features that coincide with negative wealth implications. Da et al. (2011) find that stocks with search frequency spikes exhibit higher prices in the next two weeks and price reversals within the year. Given the empirical evidence for retail buying pressure for attention-grabbing stocks (Barber and Odean, 2008), this could indicate that attention-induced stock purchases are followed by a price reversal (i.e., negative returns); leading to potential wealth losses. Further, Kumar et al. (2018) find a significant underperformance of attention-catching stocks – daily winners and losers – after they are bought by retail investors. On the other hand, Gargano and Rossi, 2017 show that attentive investors achieve higher risk-adjusted returns and portfolio Sharpe ratios.

However, whether attention-attracting features of a stock and investor wealth are positively or negatively correlated is hardly discernible in real-world trading data. Our experimental design allows for a clear deduction of implications with respect to investors' financial position at the individual level: First, stock quality can be observed based on past stock prices. Subjects can infer stock quality from the sign of returns only but not from the absolute amount of price changes. Thus, in theory, we should observe no treatment effect: extreme returns are irrelevant for decision-making as they are not correlated with fundamentals of a stock (which is clear from the instructions). Second, attention-driven purchase behavior regarding stocks with negative extreme prior returns (as observed by Barber and Odean, 2008) reduces investors' financial positions in situations in which such prior returns are associated with stocks with negative expected returns.

Thus, based on our findings, we contend that subjects' tendency to focus on stocks with extreme returns makes them systematically lose money in our experiment. While negative extreme prior returns are not necessarily associated with stocks with negative expected returns

outside our laboratory setting, our results indicate that attention-driven purchase behavior even occurs in situations in which stocks with negative expected returns are easy to identify and in which attention-driven purchases behavior reduces investors' wealth. While we do not claim that attention-driven purchase behavior always reduces investors' wealth in real-world financial markets, our results imply that return patterns catching investors' attention have the potential to dominate decision criteria related to expected returns and Bayesian updating.

3.7   Discussion and Conclusion

This paper establishes a causal link between investor attention and stock purchase behavior at the individual level. Based on an incentivized laboratory experiment, we find that extreme returns affect purchase patterns of stocks. In contrast to empirical analyses of stock market data, investor preferences or beliefs cannot explain these trading patterns. In particular, we uncover an asymmetric attention effect as shares of stocks with recent extreme negative returns are more likely to be purchased than shares of stocks with recent less extreme negative returns. Comparable patterns are not observed for stocks with extreme positive returns. At the portfolio level, we observe that the demand for attention-grabbing stocks increases at the expense of the demand for non-attention-grabbing stocks. Moreover, we provide evidence for subjects' visual attention to the respective stock's information mediating our treatment effect. Extreme returns increase subjects' stock purchase volume through channeling subjects' visual focus on the respective stock. Importantly, purchase patterns driven by attention-grabbing characteristics even occur if it is a mistake in our experiment and reduce subjects' return.

Our finding of an asymmetric effect on investors' purchase behavior is in line with previous research showing that individuals behave differently in the face of positive and negative information or events in stock markets. Empirical research finds evidence of the *negativity effect* hypothesis showing that announcement effects of consumer sentiment news on stock markets can only be observed for the release of bad sentiment news (Akhtar et al., 2013). Remarkably, this effect seems to be more pronounced for salient stocks. With respect to investor attention, an indication of asymmetric effects is also present in previous empirical findings. In particular, Barber and Odean (2008) investigate three types of retail investors representing individual investors (customers at a large discount brokerage, a large retail brokerage, and a small discount brokerage) as opposed to professional money managers. While professional managers do not exhibit purchase patterns driven by attention, they report the tendency of investors to be

net buyers of previous extreme losers and *not* to be net buyers of previous extreme winners for two of the three retail investor groups. Similar tendencies can be found with respect to investors' stock evaluations, as studies suggest that extreme returns play a significant role in the cross-sectional pricing of stocks (*MAX effect*) (Bali et al., 2011; Zhong and Gray, 2016).

But why do subjects buy shares of extreme negative stocks which harms their financial performance in the experiment and in turn considerably minimizes their payment? This result is in line with the tendency of retail investors to be net buyers of previous extreme losers found by Barber and Odean (2008). We can exclude rational beliefs in mean reversion as a potential alternative explanation for purchases of shares with extreme negative returns. Thus, in our setup, attention-driven purchase behavior in fact constitutes a bias. We relate the asymmetry in subjects' actual purchase patterns to the general insight that negative outcomes are experienced more strongly than positive outcomes when making decisions under risk (such as in prospect theory described in Kahneman and Tversky (1979)). Our results suggest that the asymmetric mechanisms underlying investor's attention in the stock market are associated with subjects' visual attention patterns. Thus, we argue that our findings are likely to arise from an attention-driven bias, where extreme negative returns seem to influence individuals' decision-making more strongly than extreme positive returns. In fact, psychological research supports this notion; several studies indicate that losses lead to more attention than equivalent gains. People tend to narrow and focus their attention on events or information that elicit a negative state to a greater degree than to positive or neutral objects (see Peeters and Czapinski (1990) for a review). Yechiam and Hochman (2013) actually describe losses as "modulators of attention" and show that even in the absence of loss aversion, losses have distinct effects on attention and subsequent behavior.[25]

Our results offer various avenues for future research. As an example, while this experiment focuses on purchase decisions, future experimental studies might additionally include selling decisions to test whether attention is in fact of minor importance on the sell side, as suggested by previous work Barber and Odean (2008). Moreover, it might be interesting to investigate whether the asymmetric effects of attention exist in markets other than the stock market. Moreover, the channels via which the asymmetry in investors' purchase behavior arises might be further investigated.

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[25]Yechiam and Hochman (2013) show that, as predicted by their attentional model, asymmetric effects of losses on behavior emerge where gains and losses are presented separately but not concurrently. This seems to contradict our findings, as we confront participants with positive, neutral, and negative stocks concurrently. However, in each decision task, we only vary one return (normal and extreme condition).

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3.A Appendix

3.A.1 Experiment Instructions

(translated from German)

Introduction

You will be taking part in an economics related experiment. The experiment will last approximately 1 hour. For the duration of the experiment, we ask that you observe a few rules: starting now we ask that you refrain from any sort of communication. If at any point you have a question, please notify us by raising your hand to be visible outside of the cubicle. We will then come to you to answer any questions. If you do not adhere to this rule, this will lead to an automatic exclusion from the experiment and from payment.

We also ask you to turn off your cell phones and other devices, or at least to put them on silent, and to pack them away with your bag or belongings. We do not want you or other subjects to be disturbed or distracted.

General Explanation of Eye-Tracking

We would like to provide you with some general information on the eye-tracking technology that is used in this experiment. The eye tracking technology is used to capture movements of your eyes. Eye-tracking adds a new dimension to data gathering by allowing us to measure where you are looking on your monitor. The eye-tracking data, as well as all other data collected during the experiment, are recorded anonymously. Only data needed to calculate the direction of your eye movements are recorded. Neither your face nor any other features that could provide information about you are recorded.

The measurements are made by the black bar found at the bottom edge of your monitor. With this, your eyes are illuminated with an infrared light. This is the faint red light you will occasionally see flashing in the black bar. The illumination of your eyes to measure your viewing direction is harmless to your health. You can review this again in the consent form that we have given you

Please read and sign the consent form for the eye-tracking experiment. If you have any questions, please notify us from your cabin and we will come to you. Once you have signed your consent form, please hand this to us as we walk by your cubicle to collect the forms.

Introduction to the Experiment

You are taking part in an experiment on investment decisions. Decision-making situations will be simulated in which you can decide on how to invest in company shares. Depending on your investment decisions, you will be rewarded at the end of the experiment.

To start the experiment, detailed introductions will be displayed on your screen – these extend over several pages. Please read the instructions carefully. They will not be available to you during the experiment. You have enough time to read through the instructions and therefore do not need to hurry. If you have any questions, please ask. Please note that all the instructions for the experiment will be displayed before the experiment starts.

Once you have read the instructions, we will ask you two questions about the rules of the experiment. We want to make sure you understand the design. If you have questions or problems at this point specifically (or to the general experiment), please do not hesitate to contact us. The experiment is anonymous, for that reason you will receive a questionnaire at the end of the experiment that will ask for some sociodemographic information, but not your name. This is then followed by the experiment payout. For the payout, we will call you individually by your cubical number. Only one of the experiment supervisors and you will see what you earned.

Alignment and Calibration of the Eye-Tracker

Now we will start with the alignment and calibration of your eye-tracker. For the alignment, you will see a window on your monitor in a few moments. This window shows your eyes as white dots. The goal of this step is to position your eyes in the middle of the window. To do so, the bar at the right edge of the window, which indicates your distance, should be at 0.5. If you are at a suitable distance from the monitor, this bar will turn green. To properly align yourself, you can move your chair and monitor. Please make sure that you can still comfortably reach your keyboard and mouse. Once alignment is complete, please wait until all other subjects are also aligned. If you require assistance, please notify a supervisor from your cubicle.

Now we will start the calibration. For this, we ask you to look in the middle of the yellow dot. The yellow dot appears on your monitor and then jumps to four more points on the monitor. We will show you all the calibration points for the test run on your screen now.

Investment Task

The experiment consists of 2 independent parts.

The purpose of this experiment is to study individual economic decisions. Decision-making situations will be simulated in which you have the opportunity to invest in company shares. The currency in this experiment is *Taler* with an exchange rate of

$$100 \text{ Taler} = €\,1$$

The experiment lasts approximately 60 minutes. If you leave the experiment prematurely, you cannot receive a payment.

After the experiment, you will receive a payout for your participation. The actual amount will depend on your decisions in the experiment. The average payout is around €\,10. Your actual remuneration may be above or below this.

There is no time limit in any part of this experiment.

Part 1. Investment Decisions

This part of the experiment is relevant for your payout.

In this part of the experiment, you will be given a total of 10 independent situations, in which you can invest in different company shares. This means that in each respective situation you can buy different shares, which will then be resold in the following period. At the end of each decision situation, you will receive a notification of your monetary balance. The final balance after each situation will be relevant for your payout.

The process is the same in every situation:

1) Buy

In every situation, you have a choice of 6 possible shares which you can buy any quantity of. In each decision-making situation, you will receive an initial amount of 1,000 Taler to use as you wish.

You do not have to use the full amount of money to purchase shares. The portion not invested in shares will go directly into your final balance unchanged i.e. with no interest earned. You may buy different shares simultaneously. You may also choose to not buy any shares.

In every situation, you will first receive an overview of the price development of all 6 shares over the previous 6 periods.

To purchase shares, please enter the desired amount. The amount can be adjusted with the 2 circular buttons in the row of the respective share. If you would like to increase the amount, click the right circle ("increase"). If you would like to correct the amount you entered and would like to reduce the amount, then click on the left circle ("reduce"). Once you have reached your desired quantity of shares to purchase, click "buy". Only then will your purchase be made. Please be aware that in every situation you only have 1,000 Taler available to you. You cannot borrow money. There are no additional costs when purchasing shares.

You make your purchase decision in Period 0. In the following period, Period 1, any shares you purchased are automatically sold.

2) Automatic Selling of Shares

At the end of every situation (i.e. in Period 1) all of your shares will be sold. Your final balance at the end of every situation is composed of the sum of the Taler you did not invest in shares and the value of your shares after Period 1.

On the next screen you will be shown the results of your investment. Click "next" to move on to the next decision situation.

Price development of company shares:

The price of a share can rise or fall from one period to the next. The 6 shares to choose from each contain different types of shares that have different probabilities to rise or fall per period:

Stock Type	Probability to Rise	Probability to Fall
++	65%	35%
+	55%	45%
0	50%	50%
0	50%	50%
−	45%	55%
−−	35%	65%

However, it is not disclosed which shares correspond to which share type. In each situation, the shares are arranged based on the initial price in the first period (in ascending order). Thus, the order of the shares given provides no information about the type of share price.

When a share increases in price, the price change per share is either +1 Taler, +3 Taler, +5 Taler, or +10 Taler. Each of these values is equally likely when there is an increase.

When a share decreases in price, the price change per share is either −1 Taler, −3 Taler,

−5 Taler, or −10 Taler. Each of these values is equally likely when there is a decrease.

Be aware that the 10 decision situations are independent from each other. The share in each situation has no connection to the shares in the other situations. At the beginning of each situation, you will receive 1,000 Taler regardless of your results in the other situations.

On the next page you can get an idea of how to make your investment decision and which information will be made available to you.

Part 2. Final Questions

This part of the experiment is not relevant for your payout.

After the investment decisions have been made, you will be asked a few final questions. Please answer the questions. Please click "next" to confirm your answers and go to the next page.

Please stay in your seat until the experiment supervisor calls you forward for your payout for the experiment.

Determining Your Payment

Your payment depends on your decisions during the experiment. It is based on your final balance in Taler after you made your investments. In other words, it is the sum of your money not spent on buying shares from the initial 1,000 Taler plus the value of your shares after playing Period 1. However, your win or loss from investing activities (difference between buy price and sale price, if you invested) is doubled. Thus, the following calculations are made for each decision situation:

$$\text{Final Balance in Taler} = \text{Initial Balance in Taler} + 2 \times (\text{sell-price in Period 1} -$$
$$\text{buy-price in Period 0 of the purchased shares in Taler})$$

One of your 10 decision situations from Part 1 will be chosen at random, the final balance of this situation will be paid to you (converted to €). So, you should try to maximize your balance in every decision-making situation.

The fixed conversion rate of 100 Taler to €1 will be used to convert your balance. This conversion rate is the same for every subject. If you earned more Taler compared to other subjects, then you will also receive more € in comparison.

Sample Calculation per Period

Imagine that in Period 1 you invested in a company share that cost 50 Taler. You bought 20 shares. In Period 1 you discover that the value of the share increased at $+3$ Taler per share. This results in the following calculation:

$$\text{Final Balance} = 1,000 \text{ Taler} + 2 \times ((53 \times 20) - (50 \times 20)) = 1,120 \text{ Taler}$$

If the value had decreased, for example, -3 Taler per share, the following calculation would be made:

$$\text{Final Balance} = 1,000 \text{ Taler} + 2 \times ((47 \times 20) - (50 \times 20)) = 880 \text{ Taler}$$

Questionnaire

Please answer each of the following questions as accurately as possible. Of course your responses will be treated completely confidentially. Your answers will be of immense value for our scientific investigation. If you have any questions, do not hesitate to contact the experimenter. Thank you in advance for your cooperation.

Sociodemographics

1. What is your gender?

   ☐ Male

   ☐ Female

2. How old are you in years?

   Age in years: ☐☐☐☐☐

3. If you are a student, what is you major?

   ☐ Business Administration

   ☐ Economics

   ☐ Socioeconomics

   ☐ Other

4. What is the level of the highest degree you are currently studying?

   ☐ Qualification for university entrance

   ☐ Bachelor

   ☐ Master

   ☐ Doctor/PhD

   ☐ Other

5. How do you rate your your statistical knowledge?

   ☐ Basic knowledge (from school)

   ☐ Advanced knowledge (basic courses at the University)

   ☐ Deeper knowledge (specialized courses at the University)

   ☐ Other

Risk Preferences: Lottery Task

18. Here you see two lotteries each (option A and option B) with different outcomes and probabilities. Please indicate which of the both options you would prefer for *each* row.

Option A	Option B
1/10 of € 2.00, and 9/10 of € 1.60	1/10 of € 3.85, and 9/10 of € 0.10
2/10 of € 2.00, and 8/10 of € 1.60	2/10 of € 3.85, and 8/10 of € 0.10
3/10 of € 2.00, and 7/10 of € 1.60	3/10 of € 3.85, and 7/10 of € 0.10
4/10 of € 2.00, and 6/10 of € 1.60	4/10 of € 3.85, and 6/10 of € 0.10
5/10 of € 2.00, and 5/10 of € 1.60	5/10 of € 3.85, and 5/10 of € 0.10
6/10 of € 2.00, and 4/10 of € 1.60	6/10 of € 3.85, and 4/10 of € 0.10
7/10 of € 2.00, and 3/10 of € 1.60	7/10 of € 3.85, and 3/10 of € 0.10
8/10 of € 2.00, and 2/10 of € 1.60	8/10 of € 3.85, and 2/10 of € 0.10
9/10 of € 2.00, and 1/10 of € 1.60	9/10 of € 3.85, and 1/10 of € 0.10
10/10 of € 2.00, and 0/10 of € 1.60	10/10 of € 3.85, and 0/10 of € 0.10

Risk Preferences: Self-Assessment

19. How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

    ☐ 0 (avoid taking risks)

    ☐ 1

    ☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10 (take risks)

☐ Refusal

Problems and Comments

20. Did you ever make a mistake during the investment task?

    If so, please tell us exactly what went wrong and in what period: ☐

21. Did you find the instructions of the experiment clear and understandable?

    What if anything was unclear? ☐

3.A.2 Comprehension Questions

Question 1

From the instructions you could see that the price of the shares can rise or fall from one period to the next. With an equal probability, the price change per share assumes the values +/- 1, +/- 3, +/- 5 or +/- ☐ ?

Question 2

Please state which answer you believe is correct. The probability of a price increase for a company's share depends on:

☐ chance

☐ the type of share

☐ the investment decision in the previous decision-making situation

3.A.3 Experimental Design

Table 3.7 shows the labels of the six stocks in each of the 10 choice sets of the experiment. Since subjects make 10 independent one-shot decisions, the labels change in each decision task.

Table 3.7: Experimental Design: Labels

This table displays the labels of the stocks used in the 10 choice sets of the experiment.

1	2	3	4	5	6	7	8	9	10
AA	BA	CA	DA	EA	FA	GA	HA	IA	JA
AB	BB	CB	DB	EB	FB	GB	HB	IB	JB
AC	BC	CC	DC	EC	FC	GC	HC	IC	JC
AD	BD	CD	DD	ED	FD	GD	HD	ID	JD
AE	BE	CE	DE	EE	FE	GE	HE	IE	JE
AF	BF	CF	DF	EF	FF	GF	HF	IF	JF

Table 3.8 summarizes the manipulations in each of the 10 choice sets. As an example, in the first choice set, Stock ++ is manipulated. While some subjects (control) observe this stock having a return of +1 in Period 0, others (treatment) observe the same sequence with the exception that the return of the stock in Period 0 is equal to +10. Note that with respect to the neutral stocks, one stock exhibits Period 0 returns comparable to the positive stocks while the other stock has Period 0 returns comparable to the negative stocks.

Table 3.8: Experimental Design: Magnitude of Price Changes

This table displays the stock which is manipulated in each of the 10 choice sets of the experiment as well as the magnitude of normal and extreme price changes in the period prior to the purchase decision.

Choice set	Manipulated stock	Normal	Extreme
1	++	+1	+10
2	++	+1	+10
3	+	+1	+10
4	+	+1	+10
6	0	+1	+10
5	0	-1	-10
7	−	-1	-10
8	−	-1	-10
9	−−	-1	-10
10	−−	-1	-10

3.A.4 Choice Sets

Table 3.9: Experimental Design: Choice Sets 1–4

Choice Set 1

			Control									Treatment					
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	45 (+5)	48 (+3)	53 (+5)	56 (+3)	46 (-10)	47 (+1)	48 (+1)	40	45 (+5)	48 (+3)	53 (+5)	56 (+3)	46 (-10)	56 (+10)	57 (+1)
Price Change	45	40 (-5)	45 (+5)	46 (+1)	41 (-5)	46 (+5)	41 (-5)	40 (-1)	45	40 (-5)	45 (+5)	46 (+1)	41 (-5)	46 (+5)	41 (-5)	40 (-1)
Price Change	50	49 (-1)	46 (-3)	45 (-1)	35 (-10)	34 (-1)	35 (+1)	40 (+5)	50	49 (-1)	46 (-3)	45 (-1)	35 (-10)	34 (-1)	35 (+1)	40 (+5)
Price Change	55	50 (-5)	53 (+3)	63 (+10)	58 (-5)	53 (-5)	52 (-1)	42 (-10)	55	50 (-5)	53 (+3)	63 (+10)	58 (-5)	53 (-5)	52 (-1)	42 (-10)
Price Change	60	61 (+1)	62 (+1)	63 (+1)	73 (+10)	78 (+5)	77 (-1)	74 (-3)	60	61 (+1)	62 (+1)	63 (+1)	73 (+10)	78 (+5)	77 (-1)	74 (-3)
Price Change	65	75 (+10)	65 (-10)	68 (+3)	73 (+5)	72 (-1)	62 (-10)	61 (-1)	65	75 (+10)	65 (-10)	68 (+3)	73 (+5)	72 (-1)	62 (-10)	61 (-1)

Choice Set 2

			Control									Treatment					
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	35 (-5)	45 (+10)	50 (+5)	53 (+3)	58 (+5)	59 (+1)	58 (-1)	40	35 (-5)	45 (+10)	50 (+5)	53 (+3)	58 (+5)	68 (+10)	67 (-1)
Price Change	45	42 (-3)	45 (+3)	40 (-5)	37 (-3)	32 (-5)	42 (+10)	43 (+1)	45	42 (-3)	45 (+3)	40 (-5)	37 (-3)	32 (-5)	42 (+10)	43 (+1)
Price Change	50	40 (-10)	45 (+5)	48 (+3)	38 (-10)	39 (+1)	36 (-3)	46 (+10)	50	40 (-10)	45 (+5)	48 (+3)	38 (-10)	39 (+1)	36 (-3)	46 (+10)
Price Change	55	52 (-3)	49 (-3)	48 (-1)	38 (-10)	33 (-5)	32 (-1)	33 (+1)	55	52 (-3)	49 (-3)	48 (-1)	38 (-10)	33 (-5)	32 (-1)	33 (+1)
Price Change	60	57 (-3)	52 (-5)	42 (-10)	52 (+10)	55 (+3)	60 (+5)	50 (-10)	60	57 (-3)	52 (-5)	42 (-10)	52 (+10)	55 (+3)	60 (+5)	50 (-10)
Price Change	65	55 (-10)	54 (-1)	55 (+1)	54 (-1)	53 (-1)	48 (-5)	47 (-1)	65	55 (-10)	54 (-1)	55 (+1)	54 (-1)	53 (-1)	48 (-5)	47 (-1)

Choice Set 3

			Control									Treatment					
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	45 (+5)	42 (-3)	41 (-1)	51 (+10)	46 (-5)	41 (-5)	38 (-3)	40	45 (+5)	42 (-3)	41 (-1)	51 (+10)	46 (-5)	41 (-5)	38 (-3)
Price Change	45	50 (+5)	60 (+10)	59 (-1)	49 (-10)	46 (-3)	47 (+1)	48 (+1)	45	50 (+5)	60 (+10)	59 (-1)	49 (-10)	46 (-3)	56 (+10)	57 (+1)
Price Change	50	49 (-1)	54 (+5)	51 (-3)	52 (+1)	53 (+1)	52 (-1)	62 (+10)	50	49 (-1)	54 (+5)	51 (-3)	52 (+1)	53 (+1)	52 (-1)	62 (+10)
Price Change	55	52 (-3)	49 (-3)	50 (+1)	45 (-5)	42 (-3)	37 (-5)	27 (-10)	55	52 (-3)	49 (-3)	50 (+1)	45 (-5)	42 (-3)	37 (-5)	27 (-10)
Price Change	60	57 (-3)	56 (-1)	46 (-10)	45 (-1)	35 (-10)	30 (-5)	27 (-3)	60	57 (-3)	56 (-1)	46 (-10)	45 (-1)	35 (-10)	30 (-5)	27 (-3)
Price Change	65	62 (-3)	65 (+3)	75 (+10)	70 (-5)	75 (+5)	78 (+3)	68 (-10)	65	62 (-3)	65 (+3)	75 (+10)	70 (-5)	75 (+5)	78 (+3)	68 (-10)

Choice Set 4

			Control									Treatment					
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	43 (+3)	44 (+1)	34 (-10)	29 (-5)	24 (-5)	25 (+1)	24 (-1)	40	43 (+3)	44 (+1)	34 (-10)	29 (-5)	24 (-5)	25 (+1)	24 (-1)
Price Change	45	55 (+10)	60 (+5)	61 (+1)	60 (-1)	61 (+1)	62 (+1)	59 (-3)	45	55 (+10)	60 (+5)	61 (+1)	60 (-1)	61 (+1)	71 (+10)	68 (-3)
Price Change	50	47 (-3)	37 (-10)	32 (-5)	42 (+10)	39 (-3)	34 (-5)	39 (+5)	50	47 (-3)	37 (-10)	32 (-5)	42 (+10)	39 (-3)	34 (-5)	39 (+5)
Price Change	55	60 (+5)	61 (+1)	60 (-1)	57 (-3)	47 (-10)	52 (+5)	53 (+1)	55	60 (+5)	61 (+1)	60 (-1)	57 (-3)	47 (-10)	52 (+5)	53 (+1)
Price Change	60	50 (-10)	55 (+5)	56 (+1)	61 (+5)	64 (+3)	69 (+5)	79 (+10)	60	50 (-10)	55 (+5)	56 (+1)	61 (+5)	64 (+3)	69 (+5)	79 (+10)
Price Change	65	68 (+3)	63 (-5)	60 (-3)	55 (-5)	56 (+1)	59 (+3)	60 (+1)	65	68 (+3)	63 (-5)	60 (-3)	55 (-5)	56 (+1)	59 (+3)	60 (+1)

Table 3.10: Experimental Design: Choice Sets 5–8

Choice Set 5

	Control								Treatment							
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	39 (-1)	36 (-3)	39 (+3)	44 (+5)	54 (+10)	53 (-1)	48 (-5)	40	39 (-1)	36 (-3)	39 (+3)	44 (+5)	54 (+10)	44 (-10)	39 (-5)
Price Change	45	46 (+1)	56 (+10)	46 (-10)	47 (+1)	57 (+10)	60 (+3)	65 (+5)	45	46 (+1)	56 (+10)	46 (-10)	47 (+1)	57 (+10)	60 (+3)	65 (+5)
Price Change	50	60 (+10)	70 (+10)	73 (+3)	63 (-10)	53 (-10)	58 (+5)	59 (+1)	50	60 (+10)	70 (+10)	73 (+3)	63 (-10)	53 (-10)	58 (+5)	59 (+1)
Price Change	55	45 (-10)	48 (+3)	53 (+5)	52 (-1)	42 (-10)	41 (-1)	36 (-5)	55	45 (-10)	48 (+3)	53 (+5)	52 (-1)	42 (-10)	41 (-1)	36 (-5)
Price Change	60	70 (+10)	65 (-5)	64 (-1)	63 (-1)	58 (-5)	48 (-10)	43 (-5)	60	70 (+10)	65 (-5)	64 (-1)	63 (-1)	58 (-5)	48 (-10)	43 (-5)
Price Change	65	66 (+1)	65 (-1)	60 (-5)	63 (+3)	58 (-5)	48 (-10)	45 (-3)	65	66 (+1)	65 (-1)	60 (-5)	63 (+3)	58 (-5)	48 (-10)	45 (-3)

Choice Set 6

	Control								Treatment							
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	45 (+5)	50 (+5)	47 (-3)	50 (+3)	60 (+10)	63 (+3)	53 (-10)	40	45 (+5)	50 (+5)	47 (-3)	50 (+3)	60 (+10)	63 (+3)	53 (-10)
Price Change	45	40 (-5)	35 (-5)	38 (+3)	37 (-1)	34 (-3)	31 (-3)	30 (-1)	45	40 (-5)	35 (-5)	38 (+3)	37 (-1)	34 (-3)	31 (-3)	30 (-1)
Price Change	50	51 (+1)	52 (+1)	51 (-1)	46 (-5)	41 (-5)	42 (+1)	37 (-5)	50	51 (+1)	52 (+1)	51 (-1)	46 (-5)	41 (-5)	51 (+10)	46 (-5)
Price Change	55	45 (-10)	50 (+5)	55 (+5)	54 (-1)	55 (+1)	56 (+1)	59 (+3)	55	45 (-10)	50 (+5)	55 (+5)	54 (-1)	55 (+1)	56 (+1)	59 (+3)
Price Change	60	55 (-5)	60 (+5)	50 (-10)	49 (-1)	46 (-3)	45 (-1)	44 (-1)	60	55 (-5)	60 (+5)	50 (-10)	49 (-1)	46 (-3)	45 (-1)	44 (-1)
Price Change	65	70 (+5)	75 (+5)	80 (+5)	79 (-1)	84 (+5)	89 (+5)	99 (+10)	65	70 (+5)	75 (+5)	80 (+5)	79 (-1)	84 (+5)	89 (+5)	99 (+10)

Choice Set 7

	Control								Treatment							
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	43 (+3)	42 (-1)	52 (+10)	42 (-10)	41 (-1)	46 (+5)	47 (+1)	40	43 (+3)	42 (-1)	52 (+10)	42 (-10)	41 (-1)	46 (+5)	47 (+1)
Price Change	45	55 (+10)	45 (-10)	50 (+5)	40 (-10)	39 (-1)	38 (-1)	28 (-10)	45	55 (+10)	45 (-10)	50 (+5)	40 (-10)	39 (-1)	29 (-10)	19 (-10)
Price Change	50	51 (+1)	41 (-10)	38 (-3)	43 (+5)	53 (+10)	50 (-3)	45 (-5)	50	51 (+1)	41 (-10)	38 (-3)	43 (+5)	53 (+10)	50 (-3)	45 (-5)
Price Change	55	52 (-3)	47 (-5)	46 (-1)	51 (+5)	41 (-10)	38 (-3)	35 (-3)	55	52 (-3)	47 (-5)	46 (-1)	51 (+5)	41 (-10)	38 (-3)	35 (-3)
Price Change	60	63 (+3)	68 (+5)	69 (+1)	72 (+3)	62 (-10)	67 (+5)	62 (-5)	60	63 (+3)	68 (+5)	69 (+1)	72 (+3)	62 (-10)	67 (+5)	62 (-5)
Price Change	65	64 (-1)	74 (+10)	84 (+10)	87 (+3)	90 (+3)	80 (-10)	77 (-3)	65	64 (-1)	74 (+10)	84 (+10)	87 (+3)	90 (+3)	80 (-10)	77 (-3)

Choice Set 8

	Control								Treatment							
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	45 (+5)	55 (+10)	56 (+1)	66 (+10)	71 (+5)	72 (+1)	75 (+3)	40	45 (+5)	55 (+10)	56 (+1)	66 (+10)	71 (+5)	72 (+1)	75 (+3)
Price Change	45	42 (-3)	32 (-10)	29 (-3)	34 (+5)	35 (+1)	45 (+10)	55 (+10)	45	42 (-3)	32 (-10)	29 (-3)	34 (+5)	35 (+1)	45 (+10)	55 (+10)
Price Change	50	47 (-3)	42 (-5)	45 (+3)	48 (+3)	43 (-5)	44 (+1)	41 (-3)	50	47 (-3)	42 (-5)	45 (+3)	48 (+3)	43 (-5)	44 (+1)	41 (-3)
Price Change	55	56 (+1)	66 (+10)	67 (+1)	68 (+1)	67 (-1)	77 (+10)	87 (+10)	55	56 (+1)	66 (+10)	67 (+1)	68 (+1)	67 (-1)	77 (+10)	87 (+10)
Price Change	60	57 (-3)	58 (+1)	68 (+10)	58 (-10)	48 (-10)	47 (-1)	42 (-5)	60	57 (-3)	58 (+1)	68 (+10)	58 (-10)	48 (-10)	38 (-10)	33 (-5)
Price Change	65	62 (-3)	57 (-5)	58 (+1)	57 (-1)	56 (-1)	53 (-3)	52 (-1)	65	62 (-3)	57 (-5)	58 (+1)	57 (-1)	56 (-1)	53 (-3)	52 (-1)

Table 3.11: Experimental Design: Choice Sets 9–10

Choice Set 9

	Control								Treatment							
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	45 (+5)	44 (-1)	43 (-1)	40 (-3)	30 (-10)	25 (-5)	30 (+5)	40	45 (+5)	44 (-1)	43 (-1)	40 (-3)	30 (-10)	25 (-5)	30 (+5)
Price Change	45	50 (+5)	49 (-1)	59 (+10)	60 (+1)	70 (+10)	73 (+3)	74 (+1)	45	50 (+5)	49 (-1)	59 (+10)	60 (+1)	70 (+10)	73 (+3)	74 (+1)
Price Change	50	47 (-3)	50 (+3)	47 (-3)	57 (+10)	62 (+5)	59 (-3)	49 (-10)	50	47 (-3)	50 (+3)	47 (-3)	57 (+10)	62 (+5)	59 (-3)	49 (-10)
Price Change	55	60 (+5)	61 (+1)	62 (+1)	67 (+5)	62 (-5)	61 (-1)	56 (-5)	55	60 (+5)	61 (+1)	62 (+1)	67 (+5)	62 (-5)	61 (-1)	56 (-5)
Price Change	60	57 (-3)	58 (+1)	57 (-1)	47 (-10)	42 (-5)	37 (-5)	36 (-1)	60	57 (-3)	58 (+1)	57 (-1)	47 (-10)	42 (-5)	37 (-5)	36 (-1)
Price Change	65	66 (+1)	61 (-5)	56 (-5)	46 (-10)	41 (-5)	40 (-1)	39 (-1)	65	66 (+1)	61 (-5)	56 (-5)	46 (-10)	41 (-5)	31 (-10)	30 (-1)

Choice Set 10

	Control								Treatment							
Period	-6	-5	-4	-3	-2	-1	0	1	-6	-5	-4	-3	-2	-1	0	1
Price Change	40	39 (-1)	38 (-1)	35 (-3)	45 (+10)	50 (+5)	47 (-3)	57 (+10)	40	39 (-1)	38 (-1)	35 (-3)	45 (+10)	50 (+5)	47 (-3)	57 (+10)
Price Change	45	42 (-3)	32 (-10)	42 (+10)	52 (+10)	49 (-3)	54 (+5)	59 (+5)	45	42 (-3)	32 (-10)	42 (+10)	52 (+10)	49 (-3)	54 (+5)	59 (+5)
Price Change	50	47 (-3)	52 (+5)	62 (+10)	63 (+1)	62 (-1)	67 (+5)	68 (+1)	50	47 (-3)	52 (+5)	62 (+10)	63 (+1)	62 (-1)	67 (+5)	68 (+1)
Price Change	55	58 (+3)	63 (+5)	73 (+10)	83 (+10)	86 (+3)	89 (+3)	99 (+10)	55	58 (+3)	63 (+5)	73 (+10)	83 (+10)	86 (+3)	89 (+3)	99 (+10)
Price Change	60	50 (-10)	55 (+5)	52 (-3)	42 (-10)	41 (-1)	40 (-1)	30 (-10)	60	50 (-10)	55 (+5)	52 (-3)	42 (-10)	41 (-1)	31 (-10)	21 (-10)
Price Change	65	66 (+1)	56 (-10)	51 (-5)	61 (+10)	60 (-1)	57 (-3)	56 (-1)	65	66 (+1)	56 (-10)	51 (-5)	61 (+10)	60 (-1)	57 (-3)	56 (-1)

3.A.5   Screenshots of Experimental Screen

Figure 3.4: Experimental Screen

This figure displays the experimental screen. The explanations provided in this screenshot were also available to subjects before the experiment was started.

3.A.6 Tests of Robustness and Extensions

This section presents alternative specifications of our main regression displayed in Table 3.3.

Table 3.12 uses an alternative definition of the volume of shares purchased. Instead of using the number of stocks purchased as the dependent variable, the product of quantity and price is chosen. Our main results are qualitatively unchanged: significantly positive coefficients of extreme prior returns are observed in the cross-section and for the subset of negative manipulated stocks. As expected, the coefficients are larger in size since the product of stock quantity and price is chosen as the dependent variable.

Table 3.12: Extreme Returns and Volume of Shares Purchased

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the volume of shares purchased, defined as the product of quantity and price. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	22.779**	16.451	20.979	23.564**
	(2.13)	(0.86)	(1.03)	(2.35)
Risk tolerance	10.267***	11.897**	6.490**	10.268
	(2.86)	(2.27)	(2.34)	(1.42)
Age	-3.358***	-7.730***	-2.784**	0.903
	(-3.09)	(-2.77)	(-2.18)	(0.68)
Male	36.242**	86.144***	16.226	-5.678
	(2.38)	(2.81)	(1.12)	(-0.21)
Earnings in preceding decision	0.009	0.008	-0.040	-0.005
	(0.56)	(0.21)	(-1.16)	(-0.43)
Number of decision	0.421	-1.195	-4.155	2.234
	(0.21)	(-0.34)	(-1.51)	(0.91)
Constant	119.152***	335.659***	173.027***	-46.891
	(2.76)	(3.73)	(2.68)	(-0.73)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
R^2	0.07	0.15	0.14	0.09

Table 3.13 shows the results of a Tobit regression in which the dependent variable is equal to the number of shares purchased. The dependent variable is left-censored at zero. Compared

to our main specification, the results are qualitatively unchanged. Note that the coefficients of extreme prior returns are significant at the 1% level both in the cross-section and for negative stocks.

Table 3.13: Extreme Returns and Number of Shares Purchased (Tobit Specification)

This table contains the coefficients and t-statistics (in parentheses) of Tobit regressions in which the dependent variable is the number of shares purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	1.250***	0.070	1.308	3.593***
	(2.60)	(0.16)	(1.52)	(2.65)
Risk tolerance	0.343**	0.211*	0.246	0.752
	(2.24)	(1.65)	(1.45)	(1.40)
Age	-0.119***	-0.172***	-0.144	0.056
	(-2.80)	(-2.69)	(-1.58)	(0.31)
Male	0.362	1.392**	0.235	-2.130
	(0.58)	(2.09)	(0.30)	(-0.95)
Earnings in preceding decision	0.000	0.000	-0.002	-0.000
	(0.32)	(0.53)	(-1.50)	(-0.10)
Number of decision	0.021	0.007	-0.173	0.105
	(0.27)	(0.10)	(-1.26)	(0.51)
Constant	-0.412	4.918**	3.872	-12.080
	(-0.21)	(2.25)	(1.17)	(-1.56)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
Pseudo R^2	0.02	0.03	0.05	0.04

Since the concept of Bayesian updating is key to separate rational from non-rational subjects in our experimental design, we next examine whether subjects not following the notion of Bayesian updating are indeed influenced by attention to a greater extent than subjects adhering to Bayesian updating. Of the 117 subjects, 31 subjects (i.e., about one fourth) never purchase shares of negative stocks. These subjects are most likely to use the optimal Bayesian approach and identify positive and neutral stocks by counting the number of price increases from Period −6 to Period 0. Columns 1 and 2 of Table 3.14 split the sample between these

Table 3.14: Extreme Returns and Number of Shares Purchased: Investor Heterogeneity

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Field of study* represents subjects' main field of study; *Degree* is the degree with which a subject expects to graduate; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	Bayesian		Amount in Stocks		Time Needed	
	(1) Yes	(2) No	(3) $\leq$ p50	(4) $>$ p50	(5) $\leq$ p50	(6) $>$ p50
Extreme prior return	-0.114	0.697**	0.296**	0.686	0.805**	0.179
	(-0.32)	(2.39)	(2.25)	(1.49)	(2.21)	(0.57)
Risk tolerance	0.230***	0.247*	0.012	0.373**	0.292**	0.176**
	(4.61)	(1.90)	(0.46)	(2.60)	(2.00)	(2.25)
Age	-0.071*	-0.053*	-0.023**	-0.011	-0.046	-0.076***
	(-1.88)	(-1.91)	(-2.23)	(-0.26)	(-1.28)	(-3.07)
Male	0.937**	0.442	0.203	0.220	0.658	0.577*
	(2.70)	(0.89)	(1.20)	(0.40)	(1.35)	(1.78)
Earnings in preceding decision	0.000	0.000	-0.000	0.000	0.000	0.000
	(0.09)	(0.32)	(-0.22)	(0.43)	(0.26)	(0.17)
Number of decision	-0.014	0.043	-0.001	0.086	0.039	0.088
	(-0.19)	(0.77)	(-0.03)	(0.95)	(0.61)	(1.59)
Constant	1.359	2.244*	1.456***	0.868	0.222	3.158***
	(1.30)	(1.83)	(2.80)	(0.53)	(0.15)	(3.13)
Session	Yes	Yes	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes	Yes	Yes
N	310	860	586	584	594	576
R^2	0.13	0.08	0.08	0.07	0.09	0.07

two groups of subjects and repeat our regression. As expected, the coefficient on the dummy variable indicating extreme prior returns is insignificant for Bayesian subjects and significantly positive for all other subjects.[26] This result is consistent with attention-driven purchase behavior that violates Bayesian updating.

In Columns 3 and 4 of Table 3.14, we implement a split by the median amount of Taler invested in stocks in a decision situation (487 Taler). The significantly positive coefficient on extreme prior returns is observed for decision situations with below-median investment

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[26]In principle, the coefficient might be significantly positive for Bayesian subjects if these subjects purchase positive and neutral stocks based on extreme returns in the preceding period.

amounts only.[27] This might indicate that subjects that are generally less willing to invest in stocks (and potentially less experienced with stock investments) are more likely to exhibit attention-driven purchase behavior while more experienced subjects do not make purchases based on attention-grabbing stock characteristics.

In Columns 5 and 6 of Table 3.14 reveal that attention-driven purchase behavior is observed for subjects that take less time to make their decisions: the significantly positive coefficient is only observed in situations in which subjects need to not take more time than the median time of 31 seconds to make their investment decisions.[28] It is possible that extreme prior returns facilitate fast decisions in that subjects quickly decide to purchase the attention-grabbing stocks. Alternatively, for subjects that want to make a quick decision, it might be easiest to simply pick stocks that catch their attention. Both mechanisms support the interpretation as attention-driven purchase behavior.

The next analyses are restricted to choice sets with positive and negative manipulated stocks in the second row of the information table provided to the subjects. Table 3.15 shows the results of an OLS regression in which the dependent variable is subjects' relative fixation duration on the manipulated stock AOI. The main explanatory variable is our treatment dummy variable. The results show that although positive and negative mannipulated stocks are shown in the same row, extreme returns significantly increase visual attention to negative stocks, but not to positive stocks. We control for subjects' risk tolerance, age, gender, earnings in the preceding decision, number of decision, education, field of study, statistics knowledge, as well as the experimental session and whether the extreme prior return of the treated stock represents a unique maximum or minimum among all prior returns.

Table 3.16 shows results of additional regression analyses to those in Section 3.4.1. We ran the regression analyses with an alternative control variable capturing whether subjects follow a buying strategy in line with a belief in mean reversion across all ten decisions.

Figure 3.5 displays the results of our mediation analyses in Section 3.4.2 with a control variable capturing whether subjects follow a buying strategy in line with a belief in mean reversion. We use a dummy variable which is equal to one if the subject invested in a stock (other than the manipulated stock) with a prior negative return in the respective decision situation.

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[27]The same qualitative results are obtained when the median amount is computed on the subject level instead of the choice set level.

[28]The same qualitative results are obtained when the median time is computed on the subject level instead of the choice set level.

Table 3.15: Extreme Returns and Relative Fixation Durations for Same Row Stocks

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is subjects' relative fixation duration on the manipulated stock AOI relative to the fixation duration on all stock AOIs for each choice set in percent. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) CS 3,4,7 (all)	(2) CS 3,4 (positive)	(3) CS 7 (negative)
Extreme prior return	0.026*	0.016	0.053*
	(1.79)	(0.89)	(1.89)
Risk tolerance	0.001	0.002	0.002
	(0.44)	(0.62)	(0.30)
Age	-0.002	-0.002	-0.001
	(-1.34)	(-1.14)	(-0.15)
Male	0.003	0.010	-0.004
	(0.20)	(0.58)	(-0.15)
Earnings in preceding decision	-0.000	-0.000	0.000
	(-0.15)	(-1.40)	(1.14)
Number of decision	0.004	0.005	0.005
	(1.34)	(1.40)	(1.01)
Constant	0.314***	0.392***	0.141
	(5.99)	(5.41)	(1.05)
Session	Yes	Yes	Yes
Rank of extreme prior return	No	No	No
Degree	Yes	Yes	Yes
Field of study	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes
N	342	228	114
R^2	0.09	0.15	0.11

Figure 3.5: The Effect of Extreme Returns on Purchase Volume Through Visual Attention

This figure displays unstandardized regression coefficients from mediation analysis obtained through bootstrapping. The range in brackets represents the bias-corrected CI of the natural indirect effect. We control for risk tolerance, age, gender, subjects' earnings in the preceding decision, the number of the decision, and the ranking of the extreme return, and subjects' belief in mean reversion.
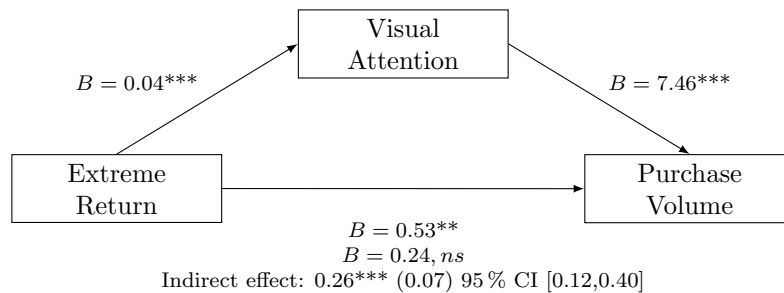

$B = 0.04^{***}$ $B = 7.46^{***}$

$B = 0.53^{**}$
$B = 0.24, ns$
Indirect effect: 0.26^{***} (0.07) 95 % CI [0.12,0.40]

Table 3.16: Extreme Returns and Number of Shares Purchased with Control for Beliefs in Mean Reversion across Decisions

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is the number of shares of the manipulated stock (treatment or control) purchased. *Extreme prior return* represents a dummy variable which is equal to one if the return of the treated stock in the period preceding the purchase decision (Period 0) is extremely high or low (i.e., equal to 10 in absolute size); *Risk tolerance* is subjects' self-assessed risk tolerance in the general domain, measured on a scale from 0 (lowest) to 10 (highest); *Age* is subjects' age, measured in years; *Male* is a dummy variable which is equal to one if a subject is male; *Earnings in preceding decision* denotes the amount of Taler a subject earned in the preceding decision situation; *Number of decision* denotes the number of the respective decision for a subject (ranging from 1 to 10); *Number invests in other neg. return stock* is the control variable for beliefs in mean reversion, denoting the number of subject's investments in a stock (other than the manipulated stock) with a prior negative return across all decisions; *Session* is a dummy variable representing the different sessions of the experiment; *Rank of extreme prior return* is a dummy variable indicating whether the extreme prior return of the treated stock is a unique maximum or minimum; *Degree* is the degree with which a subject expects to graduate; *Field of study* represents subjects' main field of study; *Statistics knowledge* is subjects' self-assessed knowledge in statistics. Standard errors are clustered at the subject level. *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) All Choice Sets	(2) CS 1-4 (positive)	(3) CS 5&6 (neutral)	(4) CS 7-10 (negative)
Extreme prior return	0.445*	-0.083	0.469	0.913***
	(1.95)	(-0.25)	(1.15)	(2.65)
Risk tolerance	0.221**	0.238**	0.105*	0.255
	(2.55)	(2.52)	(1.78)	(1.27)
Age	-0.053**	-0.135***	-0.050*	0.034
	(-2.56)	(-3.06)	(-1.94)	(0.95)
Male	0.681**	1.402***	0.417	0.049
	(1.99)	(2.82)	(1.53)	(0.06)
Earnings in preceding decision	0.000	0.000	-0.001	0.000
	(0.22)	(0.34)	(-1.00)	(0.01)
Number of decision	0.029	-0.002	-0.073	0.065
	(0.63)	(-0.03)	(-1.30)	(0.79)
Number invests in other neg. return stock	0.073	-0.180**	0.159***	0.278***
	(1.63)	(-2.19)	(2.71)	(4.23)
Constant	1.418	6.281***	2.480*	-2.994
	(1.34)	(4.01)	(1.67)	(-1.41)
Session	Yes	Yes	Yes	Yes
Rank of extreme prior return	Yes	Yes	Yes	Yes
Degree	Yes	Yes	Yes	Yes
Field of study	Yes	Yes	Yes	Yes
Statistics knowledge	Yes	Yes	Yes	Yes
N	1,170	468	234	468
R^2	0.07	0.15	0.17	0.13

Chapter 4

Categorization and Learning from Financial Information

single-authored

This paper examines the role of coarse categories in individuals' learning from financial information. In particular, we (i) test theoretical predictions about categorical over- and underreaction to information by Mullainathan (2002) in an investment context, (ii) explore differences in category-based belief formation and (iii) link category-based beliefs to investment behavior. Our findings document that information aggregation along prominent categories in financial markets, such as industries, can affect people's beliefs and investment decision-making. Interestingly, we find differences across category types. Subjects form category-based beliefs when the observed stock belongs to "good" stock categories associated with gains. People then overreact to category changes, form overly optimistic beliefs, and invest significantly more in the stock. Yet, we find the opposite pattern if the stock belongs to "bad" stock categories associated with losses. People then seem to be generally sensitive to the stock's outcomes. Category changes do not distort their beliefs.

4.1 Introduction

It has been argued that investors first categorize assets into broad classes based on common characteristics, such as into value stocks, growth stocks, or small-cap stocks, and then move funds across these classes, called "style investing" (Barberis and Shleifer, 2003). Style investing has important implications for asset prices, as styles become popular and unpopular and thus drive excessive return comovement of firms within specific classes (Barberis et al., 2005; Green and Hwang, 2009). Theory suggests that style-level demand for these assets emerges from the fact that investors form beliefs about the future performance of assets at the category level (Barberis and Shleifer, 2003). An important empirical question remains how people form category-based beliefs about investments and whether they are linked to suboptimal investment decisions.

This study examines the role of coarse categories in individuals' learning from financial information. In particular, we test theoretical predictions by Mullainathan (2002) about individuals' under- and overreaction to new information when forming beliefs applied to an investment context. Importantly, we investigate differences in individuals' category-based belief formation and relate their beliefs to investment decisions. Our experimental results document a categroy-based belief distortion, which affects investment decisions. Yet, this depends on the type of category and the type of information associated with it. The findings enhance the understanding of how people learn from financial information when information aggregation along prominent categories in financial markets, such as industries, is present.

People often rely on categories when they interpret information. In general, this tendency can be very useful, as it allows individuals to assess large amounts of information by focusing on a specific level of detail and ignoring specialization of lower levels. One of the most important functions of categorization is its role in learning (Anderson, 1991). Categorization allows the prediction of unseen features of an object by relating to features of an object's category. In this vein, a Bayesian account suggests that people consider all the categories an object could belong to when they make inferences about that object. However, the crux is that psychology literature shows that people use a simple heuristic in which they consider only the most likely category and ignore alternative categories, which distorts their inferences (Malt et al., 1995; Murphy and Ross, 1994).

This insight from psychology is used in economic theory to study belief formation in economic choice. A failure to account for alternative categories can create over-generalized beliefs,

for example stereotypical beliefs (Bordalo et al., 2016). Closest to this study is theoretical work by Mullainathan (2002). He formalizes human categorical thinking as a simplification of Bayesian updating in which people use coarse categories to make inferences. A category corresponds to a specific probability distribution over single units. Assuming people can only hold a finite subset of beliefs for making predictions, Mullainathan (2002) suggests that individulas use that probability distribution associated with the category to make predictions for particular units. He introduces a mechanism which can explain under- and overreaction to new information: People update the assigned category only when they see enough information to suggest that an alternative category better fits the observed information. Applying this framework to financial markets, the model can explain investor under- and overreaction to news.

This study uses an experimental approach to examine the role of coarse categories in individuals' learning from financial information and subsequent investment decisions. The experiment is designed to (i) test the theoretical predictions by Mullainathan (2002) in an investment context as well as to (ii) explore differences in category-based belief formation and (iii) to link category-based beliefs to investment behavior. Our design thereby exploits advantages of laboratory experiments to directly elicit subjective beliefs and compare subjects' beliefs and choices to a Bayesian benchmark. This allows us to draw clear conclusions about subjects' deviations from objectively correct beliefs and choices.

In the main task, subjects choose to invest either in a risky asset or a risk-free asset Kuhnen (2015). The risky asset is a stock that generates positive and negative outcomes, i.e., stock returns, with a specific probability. Subjects do not initially know the likelihood of the stock to generate a positive or negative outcome, but can make inferences about the probability from observing outcomes. The stock belongs to one of several different stock categories (industries in our experiment) that determines how likely the stock generates a positive rather than a negative outcome. The subjects do not know to which category the stock belongs to before they see any outcomes. To identify whether subjects ignore alternative categories and form biased category-based beliefs, we provide subjects with category-level information, i.e., the probability distributions of the categories, and let them observe the stock's return before eliciting their beliefs about the stock's future outcome. The key idea of the experimental design is a manipulation of the categories' level of coarseness. We compare subjects' beliefs in this treatment to beliefs stated in a condition in which subjects see more disaggregated information based on finer categories, but still face the identical learning environment. To

relate subjects' category-based beliefs to their future investment behavior, we ask them to make investment decisions after observing each stock outcome.

We have three main findings. First, when coarse categories are present, subjects form more *pessimistic* beliefs about the stock investment on average. Yet, as proposed by the theoretical model by Mullainathan (2002), we find evidence for overreaction to new information in case the new information is suggestive of a "category change." That is, if an observed outcome of the stock should objectively change the belief about the stock's industry belongig, subjects updated their beliefs too strongly and formed overly *optimistic* beliefs about the stock's future outcomes. Second, this overreaction varies across different category types. Category-based belief formation in accordance with the model predictions by Mullainathan (2002) is observed for "good" stock categories associated with gains. However an opposite belief pattern emerges for "bad" stock categories associated with losses. Third, subjects' overreaction to category changes is associated with higher stock investments. Interestingly, this tendency correlates with fewer suboptimal investment decisions in our experimental setting.

There is a rich strand of finance literature on return comovement. Several studies examine common factors in asset returns and whether the sensitivity to these factors can explain average rates of return. For example, characteristics such as firm size and book-to-market ratio appear to explain cross-sectional variation in stock returns in excess of the covariance structure of returns (Daniel and Titman, 1997). Motivated by strong common factors in the returns of specific asset categories, Barberis et al. (2005) ask the question why patterns of comovement in asset returns arise. Beyond traditional theory stating that comovement in returns reflect only correlation in fundamentals, they reveal the importance of market frictions and investor sentiment for common return movement. Examining leading and lagged returns of S&P 500 and non-S&P 500 stocks, Barberis et al. (2005) make the first attempt to disentangle different friction- and sentiment-based explanations of comovement and determining the importance of behavioral explanations. One of the most prominent behavioral explanations is investor category-learning (Barberis and Shleifer, 2003). This is supported by empirical evidence on investor reactions to mere category changes with no fundamental linkage. Cooper et al. (2001) document a remarkably high stock price reaction for firms' change to dotcom names during the Internet bubble period and Rashes, 2001 finds excessive comovement between stocks with similar ticker symbols.

Our study contributes to this strand of research by (i) isolating category-based beliefs as a source of such behavioral patterns observed in financial markets as well as (ii) uncovering

differences in the formation of category-based beliefs, which helps explain different reactions to categorical information. We find that subjects form category-based beliefs as predicted by Mullainathan (2002) when the observed stock belongs to "good" stock categories associated with gains. People then overreact to category changes, form overly optimistic beliefs, and invest significantly more in the stock compared to a situation with no category change, but the same quality of the stock. Yet, our results indicate that this depends on the type of category and the type of information associated with it. We find the opposite result if the stock belongs to "bad" stock categories associated with losses. People then seem to be sensitive to the stock's outcome and even overreact to negative information with too pessimistic beliefs if there is no category change. This can explain the overreaction to firms' change to dotcom names during the Internet bubble period with high returns Cooper et al. (2001), but suggests that, in contrast, this pattern could be weaker or even diminshed for stock categories associated with negative returns.

This paper also contributes to specific work on investor category learning. Previous literature links category learning to investors' attentional constraints. Peng and Xiong (2006) present a model in which investors allocate attention across fundamental factors and show that an attention-constrained investor tends to pay more attention to market- and sector-level factors than to firm-specific factors, leading to category-learning. Indeed, Drake et al. (2017) empirically show that investors focus on market and sector-wide information which is then associated with excess return comovement. In addition, Yuan (2015) reports that market-wide events raising the attention level investors pay to their portfolios, cause them to become more active in information processing and trading. However, our experimental results show that category learning in an investment context even occurs in settings in which subjects do not face attention constraints. We thus provide evidence for categorical thinking by itself being a cognitive limitation beside pure attentional constraints. This is important for the understanding of the underlying mechanism of category learning in financial markets.

Finally, our results contribute to literature on the effect of information aggregation on risk taking. For example, in a financial market context, it has been found that individuals take more investment risk if they observe more aggregated return information, i.e., less frequent return information, long-horizon return information, or return information at the portfolio- rather than at the asset-level (Anagol and Gamble, 2013; Benartzi and Thaler, 1999; Gneezy and Potters, 1997; Haigh and List, 2005; Thaler et al., 1997). These findings are typically explained by myopic loss aversion. We add to this strand of literature by showing evidence

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for another form of information aggregation affecting risky investment decisions: information aggregation along stock categories, which is very common in financial market media.

4.2   Theory and Hypotheses

This study is based on a model of human inference in which people rely on coarse categories when forming beliefs (Mullainathan, 2002). Categorical thinking is defined as a simplification of Bayesian updating in which people use coarse categories to make inferences. The model introduces two key features of coarseness into human inference: (i) people tend to group together several different types of objects into one large category and (ii) people do not consider all available categories, when making inferences. Together, these two features are formalized into a simple assumption: people can only hold a finite subset of beliefs for making predictions. Consequently, they choose the most likely category given the observed data and make forecasts solely by using the probability distribution associated with the chosen category, ignoring all other possible categories. They update the assigned category only when they see enough data suggesting that an alternative category better fits the data. As a result, categorical thinking reduces the set of posteriors people can hold compared to Bayesian thinking.

This idea can be applied to the stock market. Suppose an investor aims at evaluating a stock which generates an outcome each period. This outcome is stochastic and can be either good or bad. Imagine the stock can belong either to a good, mediocre, or bad industry. The industry determines the stock's probability to generate a good or bad outcome. A stock of the good industry pays a good outcome with probability $g > 50\%$, a stock of the mediocre industry with probability $m = 50\%$, and a stock of the bad industry with probability $b = 1 - g < 50\%$. The investor observes the stock's outcome each period and wants to forecast the outcome next period. A Bayesian updater counts how many good outcomes are already realized and updates the probability over all possible industries. That is, a Bayesian infers the probability of generating a good outcome for each industry, multiplies by the up dated probabilities, and then adds them together. According to the model by Mullainathan (2002), categorical thinking, in contrast, means choosing the most likely industry based on the observed outcomes and then using that industry's probability of generating a good outcome to make forecasts.

The model generates three predictions about people's beliefs in the face of coarse categories. First, the model suggests that when categories are fine enough, the categorical thinker will approximate the Bayesian probability when making inferences. That is, as the number

of available categories increases, the individual's belief approximates the objectively correct Bayesian posterior. Thus, individuals' belief error, measured by the deviation of their subjective beliefs from the objectively correct Bayesian posterior, decreases with an increasing number of categories. Imagine, for example, the extreme case in which the number of categories equals the number of objects that can be assigned to categories. In this case, the beliefs would be identical to the Bayesian posteriors. This notion is captured in our first hypothesis:

Hypothesis 1 (Approximation)   A higher number of available categories is positively correlated with a lower belief error.

Further, the model predicts that indviduals change their beliefs rarely, because they are not sensitive enough to small changes in probability. More precisely, they do not respond to new information if it does not lead to a change of category, because it is small enough. In other words, if the observed signals do not suggest a change of category, for example from the mediocre category to the good categroy, people do not update their beliefs. This creates underreaction to new information. In this vein, our second hypothesis is as follows:

Hypothesis 2 (Underreaction)   Individuals do not update their beliefs in response to single information signals.

By contrast, the model proposes that in case of new information that is large enough to suggest a category change, individuals will respond too strongly, because of an immediate category switch. This creates overreaction to new information. Thus, our third hypothesis is:

Hypothesis 3 (Overreaction)   Individuals update their beliefs too strongly in response to information signals consistent with a category change.

In an experimental setting, we will test these three hypotheses about how coarse categories are associated with individuals' learning from financial information. We will further analyse differences in subjects' belief formation based on category characteristics and relate potential belief biases to subsequent investment decisions.

4.3   Experiment

A setup to investigate the role of coarse categories in individuals' learning from financial information and its effect on their investment decisions requires (i) categories relevant for inference, (ii) exogenous variation of the coarseness of categories to isolate the category effect, and (iii) an incentive-compatible measure of beliefs and decisions. This section outlines how the experimental setting meets these requirements (Table 4.1 summarizes our experimental conditions).

4.3.1   Experimental Design

The experimental setting is based on the learning problem subjects face in the study by Kuhnen, 2015.[1] Subjects perform a task consisting of investment choices and belief estimation exercises. In all treatments, subjects repeatedly choose to invest either in a stock with risky outcomes (positive and negative outcomes) or in a bond with known safe outcomes. After each decision, irrespective of whether they chose to invest in the stock or bond, subjects observe the stock's outcome and are asked to provide estimations regarding the stock's probability of paying a positive outcome. Subjects do not initially know the likelihood of the stock to generate a positive or negative outcome, but can make inferences about the probability from its realized outcomes. After that, subjects can again decide to invest in either the stock or bond each period. In total, subjects take part in four learning blocks consisting of six decisions each. Within each learning block, they face the same stock, so that they can learn from its realized outcomes. In all learning blocks, the positive outcome of the stock is 20 EUR and the negative outcome is -5 EUR. The bond has a certain outcome of 6 EUR each period.

In each block, the stock belongs to one of several different stock categories that determines how likely the stock generates a positive rather than a negative outcome. Importantly, the stock categories differ in quality. Comparing the expected outcomes in each category yields to a clear ranking of categories in the sense of first-order stochastic dominance. The coarseness of available categories varies between treatments to isolate category effects. The experimental treatments are implemented across the four learning blocks, i.e., within-subjects, in random order. The categories are implemented as industries. It has been shown that industries are important categories in financial markets (Drake et al., 2017).

In the *Category* treatment, the stock belongs to one of three industries with equal probabil-

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[1]The experiment instructions are provided in Appendix 4.A.

ity, either to the "good industry," the "mediocre industry," or the "bad industry." If the stock comes from the good industry, it generates a positive outcome with a 70% probability and a negative outcome with a 30% probability each period. A stock that belongs to the mediocre industry generates positive and negative outcomes with equal probability, i.e., 50%. If the stock belongs to the bad industry, it generates a positive outcome with a 30% probability and a negative outcome with a 70% probability.

Subjects' beliefs and decisions in the *Category* treatment are compared to a condition in which subjects are provided with more disaggregated category information, but still face the identical learning problem. Specifically, the number of available categories increases. In the *Disaggregated* treatment, the stock belongs to one of six industries with equal probability (Table 4.1). This allows to isolate the category effect on subjects' beliefs.

Additionally, we manipulate the symmetry of category sizes by varying the probability that the stock belongs to the good category. Again, the stock can belong to one of three industries, as in the *Category* treatment. Yet, in the *Broad* treatment, the stock has a very high probability to belong to the good industry (80%) and in the *Narrow* treatment it has a very high probability (80%) to belong to the bad industry, i.e., a low probability to belong to the good industry. These variations allow us to isolate relative size effects in subjects' failure to account for alternative categories. This can be of importance in financial markets. Stock categories sometimes group together stocks based on specific characteristics, such as "automobile industry stocks," and sometimes based on general characteristics, such as "value stocks."

Table 4.1: Experimental Conditions

Treatment	Number of categories	Size of categories	Comparison to *Category*
Category	3	Symmetric	-
Disaggregated	6	Symmetric	Isolation of category effect
Broad	3	Asymmetric (high probability of good industry)	Isolation of relative size effect
Narrow	3	Asymmetric (low probability of good industry)	Isolation of relative size effect

Notes: This table provides an overview of the experimental conditions of the experiment with different numbers and sizes of categories. The last column reports the effects isolated by a comparison to the baseline condistion *Category*.

4.3.2 Belief Elicitation and Behavioral Outcome Measure

In order to investigate category-based beliefs, we elicit subjects' beliefs about the stock's chance of paying a positive outcome, which will serve as one of the key outcome measures of this study. Subjects had to provide an estimate in percent as an integer from 0 to 100 after each new outcome they observe. Initially, subjects do not know this probability. They start with a prior based on information about the possible underlying processes. That is, in the *Category* and the *Disaggregated* treatment, they start with a prior that the stock pays either a positive or negative outcome with equal probability. Because of the asymmetric category sizes in the *Broad* and *Narrow* conditions, the prior increases to 64% in the *Broad* treatment and descreases to 36% in the *Narrow* condition. After observing the realized outcomes, subjects make informed inferences about the stock's probability of paying a positive outcome. A fully rational (Bayesian) subject counts the number of positive outcomes in the course of the periods and updates the probability over all possible industries. That is, a Bayesian infers the probability of generating a good outcome for each industry, multiplies by the updated probabilities, and then adds them together. For example, the value of the objective Bayesian posterior for the stock paying a positive outcome in the *Category* condition can be calculated as:

$$P(P) = P(G) * P(P|G) + P(M) * P(P|M) + P(B) * P(P|B) \qquad (4.1)$$

where $P(P)$ is the probability that the stock pays the positive outcome. $P(G)$, $P(M)$, $P(B)$ denote the probability that the stock belongs to the good, mediocre, and bad industry, respectively. Before observing any outcomes, these are 33%. $P(P|G)$, $P(P|M)$, $P(P|B)$ represent the probability that the stock pays a positive outcome conditional on belonging to the good (70%), mediocre (50%), and bad industry (30%), respectively. Further, the probabilities that the stock belongs to each category after observing stock ouctomes can be calculated as:

$$P(G) = \frac{(1 - P(P|G)^{n-t} * P(P|G)^t * P(G)}{P(T)} \qquad (4.2)$$

$$P(M) = \frac{(1 - P(P|M)^{n-t} * P(P|M)^t * P(M)}{P(T)} \qquad (4.3)$$

$$P(B) = \frac{(1 - P(P|M)^{n-t} * P(P|B)^t * P(B)}{P(T)} \qquad (4.4)$$

where n represents the number of periods so far and t the number of observed positive ouctomes so far. The total probability $P(T)$ is the same in each of the denominators and is the sum of the three numerators of Equations (2) to (4).

In an additional step, subjects are asked to rate their confidence regarding the belief estimates after indicating them. After each probability estimate they provide a confidence number from one to nine, with one meaning not confident at all and nine meaning very confident.

To relate subjects' category-based beliefs to their investment behavior, we ask them to repeat their investment decision after observing the stock's outcome each period. These decisions will serve as the second key outcome measure of this study. Subjects again choose to invest in either the stock they have observed or the bond. Risk-neutral subjects should compare the expected outcomes of the two assets and invest in the asset with a higher expected value. In our main treatment conditions *Category* and *Disaggregated*, a risk-neutral Bayesian subject should always invest in the stock if the number of realized positive outcomes leads to a Bayesian posterior about the stock paying a positive outcome of 50% or greater.[2] In the result section we will discuss our results with regard to a range of reasonable risk attitude parameters of subjects.

4.3.3 Incentives and Procedures

This study uses two key outcome measures, namely subjects' beliefs and investment decisions. Both measures are incentivized. Subjects are paid a show-up fee of 15 EUR for participating in the study. Further, we randomly draw 1 out of 10 participants each session (with maximum 30 participants per session) who are paid based on their performance in one of the experimental tasks. They can earn more than 100 EUR in each task. For each drawn subject, the computer randomly decides which task determines his or her payment. It has been shown that paying a subset of participants is an effective payment scheme for economic experiments (Charness et al., 2016; Cubitt et al., 1998; Hey and Lee, 2005; Starmer and Sugden, 1991). In the belief elicitation task, subjects' earnings are determined by the accuracy of their probability estimates. They can earn 20 EUR for a probability estimate within 5 percent of the correct objective Bayesian value each period, in total up to 120 EUR. With respect to subjects' investment decisions, they can earn an initial endowment of 35 EUR plus their accumulated investment outcomes over a horizon of 6 periods. The investment outcome can be 6 EUR from

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[2]In the *Broad* and *Narrow* treatment, these values deviate slightly with the necessary Bayesian posterior being 53% in the *Broad* condition and 47% in the *Narrow* condition.

investing in the bond or either 20 EUR or -5 EUR from investing in the stock each period.

The experiment was conducted with 129 subjects, mostly business and economics students, from the University of Hamburg. On average, subjects earned 27.98 EUR. For each subject, the experimental session took about 1.5 hours. In order to ensure that subjects understand the experimental design, we use four introductory comprehension questions that have to be answered correctly before proceeding with the experiment (Appendix 4.A). At the end of the four learning blocks, subjects are informed about their accuracy of estimates, their investment outcomes, and their resulting task earnings. The experiment is followed by a questionnaire with background and control questions. We elicited subjects' general risk preferences (Dohmen et al., 2011), financial literacy, and stock market participation. Further, subjects were asked to indicate their age, gender, and highest level of education. The experiment is programmed and conducted with z-Tree (Fischbacher, 2007) and the experimental sessions were organized and administrated with the software hroot (Bock et al., 2014). Ethical approval for the experiment was obtained from the University of Hamburg Experimental Laboratory Committee.

4.4   Results

The results from this experiment document that coarse categories affect subjects' learning from financial information and subsequent investment decisions. When coarse categories are present, subjects form in general more pessimistic beliefs about the stock investment. Yet, in accordance with the theoretical model by Mullainathan (2002), we find evidence for overreaction to new information in case that information is suggestive of a category change. In that case, subjects update their beliefs too strongly and form overly optimistic beliefs about the stock's future outcomes. This overreaction varies across different category types and impacts subsequent decisions to invest in the stock.

4.4.1   Category-Based Beliefs

We find that (i) subjects' beliefs are systematically distorted when coarse categories are present, (ii) the belief distortion decreases with finer categories, and (iii) the predicted overreaction to information after a category change varies across category types. Together these results provide experimental support for the model propositions by Mullainathan (2002), but uncover variation across different category types.

Based on our belief elicitation in the experiment, subjects' belief distortion is estimated by

taking the difference between subject's indicated subjective probability that the stock pays a positive outcome and the actual, objectively correct, Bayesian probability in each period. If subjects were perfectly correct about the probability, their subjective belief would equal the Bayesian posterior and their belief distortion would be zero. A positive belief distortion means that the subject is too optimistic about the probability and indicated a subjective probability that is higher then the actual Bayesian probability; a negative belief distortion means that the subject is too pessimistic about the probability and indicated a lower probability than the actual Bayesian probability. In this section, we compare subjects' belief distortion across our treatment conditions as well as different category states.

To start, we compare subjects' belief distortion in the *Category* treatment to their belief distortion in the *Disaggregated* treatment. This allows us to isolate the effect of coarse categories on subjects' beliefs compared to a situation with more finer categories present. Table 4.2 presents subjects' beliefs and deviations from the Bayesian probabilities separately for our two treatments. The table further reports *T*-tests for the difference between subjective probabilities and objective Bayesian probabilities. The results show that in our *Category* treatment, subjects have distorted beliefs about the stock paying a positive outcome in the next period. On average, they have too pessimistic beliefs compared to the actual Bayesian probability (T-test, $p < 0.1$). In the *Disaggregated* condition, in contrast, subjects' belief distortion decreases and gets insignificant. This is in line with our first hypothesis (approximation). In case of a higher number of available categories, subjects' beliefs approximate to the objective Bayesian posterior. Moreover, to test the relative size effects in subjects' failure to account for alternative categories, the table displays subjects' belief distortion in the *Broad* and *Narrow* condition. Table 4.2 illustrates that in the *Broad* condition, in which the probability of the good industry is in general higher, subjects exhibit overly pessimistic beliefs (T-test, $p < 0.001$). By contrast, subjects do not show distorted beliefs in the *Narrow* condition, in which the probability of the good industry is in general lower. Thus, the results suggest that the category effect is even stronger in case of asymmetric category sizes, when the "good" industry is broad, i.e., has a high probability. Please refer to Section 4.4.2 for an analysis considering category characteristics in more detail.

Next, we are interested in whether subjects' belief distortions are actually related to category-level probabilities, i.e. whether subjects form beliefs at the level of the industry rather than on the individual stock level. Table 4.3 indicates that subjects rely more on category-level probabilities in case of coarse categories compared to more finer categories being present. We

Table 4.2: Belief Distortion by Treatment

Treatment	Subjective belief	Bayesian posterior	Belief distortion	Difference (T-test)
Category	49.49	50.30	-0.82	p = 0.085
Disaggregated	48.34	48.97	-0.62	p = 0.190
Broad	61.16	64.08	-2.92	p = 0.000
Narrow	36.75	36.31	0.44	p = 0.399

Notes: This table displays subjects' beliefs and deviations from the Bayesian posteriors in the different experimental conditions in percent (from 1 to 100). Subjects' belief distortion is estimated each period at the individual level by subtracting the objectively correct Bayesian probability from subject's indicated probability that the stock pays a positive outcome. The table reports mean values and and T-test results of the difference in means between the two probabilities.

use subjects' belief distortion as dependent variable. The category-level probability serves as independent variable. The category-level probability is the general probability that the stock pays a positive outcome based solely on the characteristics of the industry suggested by the observed outcomes, ignoring that the stock can belong to alternative industries. For example, if the suggested industry was the good industry, the category-level probability is always 70%, irrespective of how likely the stock might belong to alternative industries. We control for subject fixed effects. Column 1 shows that on average subjects' belief distortion is correlated with the category-level probability. This correlation is stronger in our treatments with coarse categories (column 2) and diminishes in our treatment with disaggregated information (column 3).

Further, we test whether subjects' belief distortions are related to category changes, in our experimental setting a change of industry classification. Mullainathan (2002) proposes that subjects first underreact to single signal information that do not lead to any change of category and then overreact in case there is a consistent series of information signals suggesting a category change. First, the regression models in Table 4.4 show subjects' belief distortion seperately for suggested category changes and no suggested category changes by the observed outcomes. We use subjects' belief distortion as dependent variable. A treatment dummy serves as independent variable. The dummy variable is equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. We control for subject fixed effects. The two regression models present results seperately for the case of a suggested category change (column 1) and no suggested category change (column 2) by the observed outcomes. The results indicate that subjects in the *Category* condition have

Table 4.3: Category-Based Belief Distortion

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is subject's belief distortion estimated each period by subtracting the objectively correct Bayesian probability from subject's indicated probability that the stock pays a positive outcome in percent (from 1 to 100), *Belief Distortion*. *Category Probability* is the general probability that the stock pays a positive outcome based solely on the characteristics of the industry suggested by the observed outcomes, ignoring that the stock can belong to alternative industries. *Subject* is a dummy variable controlling for subject fixed effects. The models report results for the full sample (column 1), the category conditions, i.e., the *Category*, *Broad*, and *Narrow* conditions (column 2), and the *Disaggregated* condition (column 3). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Belief Distortion	(2) Belief Distortion (Category Cond.)	(3) Belief Distortion (Disaggregated)
Category Probability	-0.043*	-0.054**	-0.026
	(-1.71)	(-2.16)	(-0.42)
Constant	2.441*	3.896***	-1.507
	(1.77)	(3.12)	(-0.36)
Subject	Yes	Yes	Yes
N	3,086	2,312	774
R^2	0.20	0.30	0.46

a significantly higher belief distortion compared to subjects in the *Disaggregated* condition when the observed outcomes suggest a category change. The belief distortion increases by 3.3 percentage points ($p < 0.01$). In case of no category change, there is no significant difference in belief distortion between the conditions. The coefficients of the two models are significantly different (Wald test, $p < 0.05$). Thus, subjects show a significantly higher belief distortion in the *Category* condition than in the *Disaggregated* condition after a category change compared to the case of no category change. This result is in line with our hypothesis 3 (overreaction), but not supportive of our hypothesis 2 (underreaction).

These experimental results provide supportive evidence for some of the key model predictions by Mullainathan (2002). The next section focuses on differences in the observed overreaction to category changes to take a closer look at situations in which the model predictions hold.

4.4.2 Differences in Belief Formation: The Role of Category Types

In this section we show that the observed overreaction to new information after a category change is related to the respective category type. Table 4.5 provides an overview of subjects' belief distortion for different category types. The table reports subjects' beliefs and deviations from the Bayesian probabilities separately for different category types suggested by the observed outcomes. C* represents the suggested category type by the observed information, i.e.,

Table 4.4: Belief Distortion and Category Changes

This table contains the coefficients and t-statistics (in parentheses) of OLS regressions in which the dependent variable is subject's belief distortion estimated each period by subtracting the objectively correct Bayesian probability from subject's indicated probability that the stock pays a positive outcome in percent (from 1 to 100), *Belief Distortion*. *Category Treatment* is a dummy variable equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. *Subject* is a dummy variable controlling for subject fixed effects. The models report results for observations with stock outcomes that suggest a category change (column 1) and for observations with stock outcomes that do not suggest a category change (column 2). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Belief Distortion (Cat. Change)	(2) Belief Distortion (No Cat. Change)
Category Treatment	3.322***	0.063
	(2.67)	(0.08)
Constant	-2.600	-1.291
	(-0.59)	(-0.25)
Subject	Yes	Yes
N	580	968
R^2	0.33	0.35

the good, mediocre, or bad industry.

The results indicate that if the suggested category C* is the good industry, subjects form distorted beliefs after a category change. Subjects' then form overly optimistic beliefs about the stock paying a positive outcome in the future. By contrast, in case of no category change, subjects do not deviate significantly from the Bayesian probability. This result is again in line with our hypothesis 3 (overreaction), but not supportive of our hypothesis 2 (underreaction). That is, subjects tend to overreact to a change to the good industry with too optimistic beliefs that are 3.7% higher than the Bayesian probability (*T*-test, $p < 0.05$). Yet, they do form correct beliefs without a category change. However, the opposite pattern is observed for subjects' belief if the suggested category C* is the bad industry. Subjects' form their beliefs correctly in case of a change to the bad industry, but overreact to information consistently suggesting that C* is the bad industry. That is, in case of no category change subjects form overly pessimistic beliefs about the stock paying a positive outcome, on average 2.6% lower than the Bayesian probability (*T*-test, $p < 0.01$). If the suggested category C* is the mediocre industry, subjects form correct beliefs in both cases with and without category change.

Our findings indicate that subjects' overreaction to new information after a category change is associated with the type of category. This could be related to the type of new information subjects observe. Note that in case of C* being the good industry, the new information is always a positive outcome and in case of C* being the bad industry, the new information is always a negative outcome.

Table 4.5: Belief Distortion by Category Type

Category	Subjective belief	Bayesian posterior	Belief distortion	Difference (T-test)
Category change				
C* = good	59.98	56.33	3.65	p = 0.025
C* = mediocre	51.12	49.96	1.16	p = 0.205
C* = bad	41.55	43.21	-1.67	p = 0.498
No category change				
C* = good	58.45	59.77	-1.32	p = 0.122
C* = mediocre	49.74	49.57	0.18	p = 0.877
C* = bad	38.42	41.04	-2.62	p = 0.009

Notes: This table displays subjects' beliefs and deviations from the Bayesian posteriors in the *Category* condition in percent (from 1 to 100). Subjects' belief distortion is estimated each period at the individual level by subtracting the objectively correct Bayesian probability from subject's indicated probability that the stock pays a positive outcome. The table reports mean values and and T-test results of the difference in means between the two probabilities, seperately for observations with stock outcomes that suggest a category change and observations with stock outcomes that do not suggest a category change. Further, the table displays the results seperateley for the different category types, the good industry, the mediocre industry, and the bad industry.

4.4.3 Consequences for Investment Decisions

So far, the results show that subjects tend to form distorted beliefs based on category-level information. In this section, we link these category effects to behavior. We show that the presence of coarse categories affects investment decisions. We find that in the *Category* condition, subjects' probability to invest in the risky stock is significantly higher than in the *Disaggregated* condition, although the expected outcomes (as well as risk) are identical. Importantly, this increase in probability to invest in the stock is strongest after a category change.

Table 4.6 presents Probit regression models with an investment dummy variable, which is equal to one if the subject invested in the stock and zero otherwise, as dependent variable. A treatment dummy serves as independent variable. The treatment dummy variable is equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. We control for subject fixed effects. The regression models display results for all observations (column 1) and seperately for cases of a suggested category change (column 2) and no suggested category change (column 3) by the observed outcomes. On average, the probability to invest in the stock increases by 6.7% in the *Category* condition compared to the *Disaggregated* condition ($p < 0.01$). Yet, subjects' investment behavior is associated with changes in categories. In case of a category change this increase is 17.9% ($p < 0.01$) and in

case of no category change the increase is 4.6% ($p < 0.1$). The coefficients of the two models are significantly different (Wald test, $p < 0.01$). Thus, subjects invest significantly more in the risky stock in the *Category* condition than in the *Disaggregated* condition after a category change compared to the case of no category change.

Table 4.6: Category-Based Investment Decisions

This table contains the coefficients and t-statistics (in parentheses) of Probit regressions in which the dependent variable is a dummy variable which is equal to one if the subject invested in the stock. *Category Treatment* is a dummy variable equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. *Subject* is a dummy variable controlling for subject fixed effects. The models report results for all observations (column 1), for observations with stock outcomes that suggest a category change (column 2) and for observations with stock outcomes that do not suggest a category change (column 3). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Stock Invest	(2) Stock Invest (Cat. Change)	(3) Stock Invest (No Cat. Change)
Category Treatment	0.329***	1.079***	0.262**
	(3.78)	(4.98)	(2.12)
Constant	1.204**	4.883	0.673
	(2.34)	(0.04)	(1.06)
Subject	Yes	Yes	Yes
N	1,056	317	577
Pseudo R^2	0.18	0.25	0.18

Category changes, i.e. observed outcome series with the latest information changing the suggested industry belonging, lead to an increase of stock investings. This investment behavior is in line with our finding of more optimistic beliefs in the *Category* condition after a category change (Table 4.4) and Mullainathan's (2002) idea that people over-respond to a series of outcomes suggesting a category change. Table 4.7 provides further evidence for biased beliefs driving this investment behavior. The table displays the results of Probit regressions models with the investment dummy variable as dependent variable. Subjects' beliefs, i.e., indicated probability estimates during the experiment, serve as independent variable. We control for the objectively correct Bayesian probability and subject fixed effects. The regression models report results for all observations (column 1) and seperately for cases of a suggested category change (column 2) and no suggested category change (column 3) by the observed outcomes. The regression results show that subjects' decision to invest in the stock is positively correlated with their subjective beliefs ($p < 0.01$). This effect is stronger after a category change, but is insignificant for cases with no category change.

A key question is whether this observed investment behavior is associated with actual mistakes. Table 4.8 shows that this is not the case. The table reports results from Probit re-

Table 4.7: Subjective Beliefs and Investment Decisions

This table contains the coefficients and t-statistics (in parentheses) of Probit regressions in which the dependent variable is a dummy variable which is equal to one if the subject invested in the stock. *Bayesian Posterior* is the value of the objective Bayesian probability that the stock pays a positive outcome in percent (from 1 to 100). *Subjective Belief* is the subject's indicated posterior belief that the stock is the good stock in percent (from 1 to 100). *Subject* is a dummy variable controlling for subject fixed effects. The models report results for all observations (column 1), for observations with stock outcomes that suggest a category change (column 2) and for observations with stock outcomes that do not suggest a category change (column 3). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Stock Invest	(2) Stock Invest (Cat. Change)	(3) Stock Invest (No Cat. Change)
Bayesian Posterior	0.022	-0.003	0.052*
	(0.90)	(-0.04)	(1.65)
Subjective Belief	0.020***	0.063***	0.008
	(2.76)	(2.61)	(0.89)
Constant	-1.114	2.311	-2.435
	(-0.90)	(0.00)	(-1.62)
Subject	Yes	Yes	Yes
N	336	43	216
Pseudo R^2	0.22	0.29	0.19

gressions for subjects' suboptimal investment decisions from a Bayesian perspective, assuming risk neutrality. We use two suboptimal choice variables as dependent variables. First, we use a dummy variable for a suboptimal choice to invest in the stock, which is equal to one if the subject chose to invest in the stock, although the stock's expected outcome was lower than the bond's outcome (column 1 and 2). Second, we include regression models with a dummy variable for a suboptimal choice to invest in the bond as a dependent variable. The dummy variable is equal to one if the subject invested in the bond, although the bond's outcome was lower than the stock's expected outcome (column 3 and 4). Results are reportet separately for all observations (column 1 and 3) and observations after a category change (column 2 and 4). As independent variable we use the category treatment dummy variable. Note that we implemented our treatments within-subjects. Although individual risk preferences can explain deviations from this Bayesian benchmark, they cannot explain differences between our treatments. We control for subject fixed effects. The results show that subjects make significantly fewer investment mistakes in the *Category* condition compared to the *Disaggregated* condition, both regarding stock investments (column 1) as well as bond investments (column 3). After a category change this effect is even stronger in case of bond investments (column 4), but diminishes in case of stock investments (column 3). Thus, subjects seem to be more likely to avoid suboptimal investment decisions in the *Category* condition compared to the *Disaggre-*

gated condition, especially they are more likely to avoid suboptimal investments in the bond after a category change.

This findings is based on a comparison to a Bayesian benchmark assuming that subjects behave in a risk neutral manner. As these results imply an increase in risk taking, the finding might change for subjects with strong risk aversion. However, this would only affect the classification of the decision as a mistake, not the treatment effect per se. Note that we compare behavior within-subjects and changes in risk taking across treatments are more likely to be driven by the decision problem compared to personal preferences.

Table 4.8: Suboptimal Investment Decisions

This table contains the coefficients and t-statistics (in parentheses) of Probit regressions in which the dependent variable is a dummy variable which is equal to one if the subject invested in the stock with a lower expected outcome than the bond, *Suboptimal Stock Invest* or a dummy variable which is equal to one if the subject invested in the bond with a lower expected outcome than the stock, *Suboptimal Bond Invest*. *Category Treatment* is a dummy variable equal to one for observations from the *Category* condition and zero for observations from the *Disaggregated* condition. *Subject* is a dummy variable controlling for subject fixed effects. The models report results for all observations (column 1 and 3) and for observations with stock outcomes that suggest a category change (column 2 and 4). *, **, and *** denote significance at the 10%, the 5%, and the 1% level, respectively.

	(1) Sub. Stock Invest	(2) Sub. Stock Invest (Cat. Ch.)	(3) Sub. Bond Invest	(4) Sub. Bond Invest (Cat. Ch.)
Category Treatment	-0.173*	0.262	-0.185*	-0.792***
	(-1.73)	(0.99)	(-1.92)	(-3.72)
Constant	-4.917	-5.350	-1.279**	-5.123
	(-0.05)	(-0.02)	(-2.47)	(-0.02)
Subject	Yes	Yes	Yes	Yes
N	936	203	876	292
Pseudo R^2	0.16	0.08	0.16	0.20

4.5 Conclusion

This study uses an experimental approach to examine the role of coarse categories in individuals' learning from financial information and subsequent investment decisions. In particular, we (i) test the theoretical predictions by Mullainathan (2002) in an investment context, (ii) explore differences in category-based belief formation and (iii) link category-based beliefs to investment behavior.

We document that subjects form category-based beliefs as predicted by Mullainathan (2002) when the observed stock belongs to "good" stock categories associated with gains. People then overreact to category changes, form overly optimistic beliefs, and invest signif-

icantly more in the stock compared to a situation with no category change, but the same quality of the stock. Yet, we find the opposite result if the stock belongs to bad stock categories associated with losses. People then seem to be sensitive to the stock's outcome and even overreact to negative information with too pessimistic beliefs if there is no category change. Moreover, we observe a stronger category effect in case of asymmetric category sizes. If the "good" stock category is larger relative to other categories, the category-based belief distortion is higher. We further show that subjects' overreaction to category changes is associated with higher stock investments. Interestingly, this tendency correlates with fewer suboptimal investment decisions in our experimental setting.

The study's results enhance the understanding of how people learn from financial information when aggregated category information, such as industry information, is present. This kind of information aggregation along stock categories is very common in financial market media. Further, our study provides experimental evidence of category-based belief distortion in investment decision-making and thereby (i) complements theoretical work on how categorical thinking affects economic choice (Mullainathan, 2002; Mullainathan et al., 2008) and (ii) shows that categorical thinking by itself is a cognitive limitation that influences investor learning beside pure attentional constraints.

The findings documented in this paper open interesting avenues for further research. First, future work could investigate whether our observed effect on investment decisions is robust to making the experimental environment closer to the typical investment environment. For example, it would be interesting to look at whether the results hold for modifying the risky asset's return distribution or the delay between investment choice and return realization as done in the field experimental study by Beshears et al. (2017) with respect to return information aggregation effects. Further, we show differences in subjects' belief formation based on category types. Future research could explore how different market states, i.e., up or down markets, influence category learning. This might uncover important insights into how individuals form expectations and decide to participate in the stock market during different states in financial markets.

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4.A Appendix

4.A.1 Experimental Instructions

(translated from German)

Introduction

Welcome to our financial decision making study

For the duration of the study, we ask you to follow a few rules. Should there be questions, please raise your hand and an experimenter will answer your question privately. We ask you not to communicate with each other or use a calculator during the study.

We also ask you to turn off your cell phones and other devices, or at least to put them on silent, and to pack them away with your bag or belongings. We do not want you or other participants to be disturbed or distracted. If you do not adhere to these rules, this will lead to an automatic exclusion from the study and from payment.

The study will last approximately 1.5 hours.

After the study, you will receive a payout for your participation. The actual amount will depend on your decisions in the experiment and luck.

Everyone will earn 15 EUR for participating in this study. In addition, the computer will randomly pick three out of the present participants who get paid his or her earnings from one of the study's tasks.

Please press 'proceed' to continue with the general instructions.

-Next Page-

General Instructions

In this study you complete investment tasks, related to two securities: a risky security (i.e., a stock with risky payoffs) and a riskless security (i.e., a bond with a known payoff), and will

provide estimates as to how good an investment in the risky security is.

Please click 'proceed' to continue with the detailed instructions for the tasks. Take your time to read the instructions carefully. Note that you cannot go back to previous pages. Please let us know if you have any questions.

-Next Page-

Detailed Instructions

Stages of the Study

The experiment consists of **five stages**.

In each stage, you will decide to invest in one of two securities: a risky security (i.e., a stock with risky payoffs) and a riskless security (i.e., a bond with a known payoff).

Either way, you start with an endowment of 35 EUR. In addition to this endowment, you will get payoffs from investing.

Each stage consists of 7 investment periods. For each period you can decide wether to invest in the stock or bond, thus you will make 7 decisions. After each period you will earn a payoff from your investment.

Before each block you will be provided with extra information about the stock and the bond. This information can influence your willingness to invest in the stock or bond. **Thus, please read this information carefully – the information is different for each stage.**

If you choose to invest in the bond, you get a payoff of 6 EUR for sure in each period.

If you choose to invest in the stock, you will receive a dividend in every period, which can be either positive or negative. A positive dividend is 20 EUR and a negative dividend is -5 EUR.

At the end of each stage you will have earned your accumulated payoffs from the investment plus your initial endowment of 35 EUR.

-Next Page-

Stock evaluation task

You will then see the dividends of the stock, no matter if you chose to invest in the stock or the bond.

After that, we will ask you to tell us two things:

(1) what you think is the probability that the stock pays a positive outcome (the answer must be a number between 0 and 100);

(2) how much you trust your ability to come up with the correct probability estimate that the stock pays a positive outcome. In other words, we want to know how confident you are that the probability you estimated is correct.

There is always an objective, correct, probability that the stock pays a positive outcome, which depends on the history of dividends paid by the stock already.

If you provide us with a probability estimate that is within 5% of the correct value (e.g., correct probability is 80% and you say 84%, or 75%) you will earn 20 EUR for each correct estimate. In total you can earn up to 120 EUR in this task.

-Next Page-

Your final payment at the end of the study

Your final payment will be:

You will get paid 15 EUR for participating in our study regardless of your task earnings.

In addition, your earnings in one of the experimental tasks can determine your payment. We will randomly draw one of 10 participants out of each session (with maximum 30 participants) who will get paid one of her or his task earnings. The computer will randomly decide which

of the above-described tasks will determine the participants' payment. Remember, your task earnings depend on your decisions and answers:

Investment decision in each stage: Your initial endowment of 35 EUR and in each period either 6 EUR from investing in the bond or either 20 EUR or -5 EUR from investing in the stock.

Stock evaluation task in each stage: 20 EUR for each probability estimate that is within 5% of the correct value.

Information Provision

[*Category* condition]

You will soon have the probability to decide to invest either in the stock or bond.

If you decide to invest in a stock you earn the dividend paid by the stock, which can be positive or negative. The positive dividend is 20 EUR and the negative dividend is -5 EUR. The stock belongs to an industry, that determines how likely it is that the stock pays a positive dividend. The stock can belong either to the good, mediocre, or bad industry. A stock from the good industry pays a positive dividend of 20 EUR with a probability of 70% and a negative dividend of -5 EUR with a probability of 30%. A stock from the mediocre industry pays a positive and negative dividend with equal probability, i.e., 50%. If the stock belongs to the bad industry, the stock pays a positive dividend of 20 EUR with a probability of 30% and a negative dividend of -5 EUR with a probability of 70%.

Initially, you won't know to which industry the stock belongs. The probability to belong to the good, mediocre, or bad industry is equal, i.e. 33%.

Please see the overview table below.

Importantly, in each stage, you will observe the same stock during the whole stage. The dividends of the stock are independent from period to period, but come from the same distribution.

Asset	Probability of industry	Industry	Possible outcomes per period	Probabilities for outcomes
Stock	1/3 (33%)	Good industry	20 EUR - 5 EUR	70% 30%
	1/3 (33%)	Mediocre industry	20 EUR - 5 EUR	50% 50%
	1/3 (33%)	Bad industry	20 EUR - 5 EUR	30% 70%
Bond	-	-	6 EUR	100%

That is, the industry of the stock is the same during the whole stage.

If you decide to invest in the bond, each period you will earn 6 EUR for sure.

During each stage, you accumulate your investment outcomes from investing in the stock or bond. These will be added to your initial endowment of 35 EUR.

The stock evaluation depends on what kind of stock outcomes you have already observed. Please refer to the overview table: The initial probability of the stock to pay a positive outcome is 50%, without any doubt. After observing a series of positive outcomes, you might believe that the probability increased to 65%. Yet, how much you trust your ability to come up with the correct probability estimate that the stock pays a positive outcome might vary.

[*Information provision in the other treatments varied according to the number and size of categories. In the next section you find the overview tables with the relevant information.*]

Post-questionnaire

At the end of the experiment, we will ask you some personal questions. Note that all answers will be treated confidentially and will be analyzed anonymously.

4.A.2 Information Provision Across Treatments

Figure 4.1: Overview Disaggregated condition

Asset	Probability of industry	Industry	Possible outcomes per period	Probabilities for outcomes
Stock	1/6 (17%)	Very good industry	20 EUR - 5 EUR	75% 25%
	1/6 (17%)	Good industry	20 EUR - 5 EUR	65% 35%
	1/6 (17%)	Good - mediocre industry	20 EUR - 5 EUR	55% 45%
	1/6 (17%)	Mediocre - bad industry	20 EUR - 5 EUR	45% 55%
	1/6 (17%)	Bad industry	20 EUR - 5 EUR	35% 65%
	1/6 (17%)	Very bad industry	20 EUR - 5 EUR	25% 75%
Bond	-	-	6 EUR	100%

Figure 4.2: Overview Broad condition

Asset	Probability of industry	Industry	Possible outcomes per period	Probabilities for outcomes
Stock	80%	Good industry	20 EUR - 5 EUR	70% 30%
	10%	Mediocre industry	20 EUR - 5 EUR	50% 50%
	10%	Bad industry	20 EUR - 5 EUR	30% 70%
Bond	-	-	6 EUR	100%

Figure 4.3: Overview Narrow condition

Asset	Probability of industry	Industry	Possible outcomes per period	Probabilities for outcomes
Stock	10%	Good industry	20 EUR - 5 EUR	70% 30%
	10%	Mediocre industry	20 EUR - 5 EUR	50% 50%
	80%	Bad industry	20 EUR - 5 EUR	30% 70%
Bond	-	-	6 EUR	100%

Chapter 5

General Conclusion

This dissertation provides empirical evidence for a cognitive foundation of behavioral biases in financial markets. I use experimental methods to examine central cognitive errors and isolate their effect on beliefs and investment decisions. In line with my research questions, I show that three central cognitive imprecisions, namely (i) biased memory, (ii) imperfect attention, and (iii) categorical thinking, systematically distort beliefs and influence investment choices. Importantly, my core chapters document that these cognitive factors can explain costly investment mistakes, such as re-investing in bad performing stocks.

Together, my findings contribute to a deeper understanding of how people attend to and learn from both available financial information as well as related past experiences. Further, the three studies provide experimental evidence for cognitive imprecisions driving investment behavior. I thereby address relevant, but so far open, issues within central strands of research. The core chapters enhance the empirical basis of cognitive imprecisions in individual investment decisions, explore sources of non-standard beliefs in an investment context, and shed light on resulting effects on individual investor wealth.

A main limitation of my findings relates to the "lack-of-realism critique" associated with lab experiments. It has been argued that some characteristics of the participants or experimental situations might interfere with the generalizability of laboratory results (Levitt and List, 2009). For example, lab experiments typically do not last more than a few hours. Psychology research, however, documents that decision-making can differ significantly between hot (short-run) and cold (long-run) states of the decision-maker (Loewenstein, 2005). In this case, when exploring behavioral phenomena, which are rather based on cold decision-making, inferences from short-run laboratory experiments might be misleading. Throughout the chapters, my work attempts to address this realism issue by carefully designing the experimental settings and procedures in order to capture the key features of real-world situations. For example, the experimental

design in Chapter 2 is based on a longer time horizon to capture long-term memory formation processes.

The findings of this dissertation open promising avenues for further research. First, this dissertation provides experimental evidence for how cognitive imprecisions can cause investment mistakes. Going forward, future work could explore how insights into cognitive foundations of investment behavior can be used to debias investors. Interventions that target common underlying cognitive processes have the potential to successfully generate a large behavioral response, improving investment decision-making. My chapters provide first insights into how debiasing interventions could look like (Chapter 1). Yet, further exploring interventions grounded in common cognitive factors might yield effective ways to help people make smarter investment decisions.

Second, two of my studies document that cognitive processes underlie subjects' belief formation. A promising area that requires further investigation within this topic is belief movement. Based on the intuition that belief changes should, on average, result in a reduction of uncertainty, Augenblick and Rabin (2018) provide a novel way to categorize central belief biases based on the excess or insufficient movement of beliefs relative to uncertainty reduction.[1] Augenblick and Lazarus (2018) use this approach to analyze changes in risk-neutral beliefs inferred from asset prices, applying this notion to beliefs in financial markets. Future work can explore cognitive sources of these excess or insufficient changes of beliefs in financial markets, applying an experimental approach. For example, the dynamics of biased memory over longer time horizons could be explored in relation to belief movements: forgetting own belief changes might hinder a reduction of subjective uncertainty.

Third, in my core chapters laboratory experiments are conducted to provide tight identification of cognitive factors and implement an objectively correct benchmark for people's beliefs and choices. In line with the possible limitation outlined above, a promising avenue for future research is complementing these findings with insights from the field. For example, one can combine findings from lab experiments with field data to better understand the interaction of cognitive mechanisms isolated in the lab, i.e., which factors dominate behavior in the field. Further, validating this dissertation's findings with field experiments might improve its relevance to policy (Levitt and List, 2009).

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[1]Four biases are embedded in their model, based on underweighting the prior (base-rate neglect), overweighting the prior (confirmation bias), underweighting the signal (underreaction), and overweighting the signal (overreaction).

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Appendix A

General Appendix

A.1 List, Short Summary, and Current Status of Papers (§6 (2, 5) PromO)

Investor Memory

Title in English: Investor Memory

Title in German: Das Gedächtnis von Investoren

Abstract in English: How does memory shape individuals' financial decisions? We find experimental evidence of a self-serving memory bias, which distorts beliefs and drives investment choices. Subjects who previously invested in a risky stock are more likely to remember positive investment outcomes and less likely to remember negative outcomes. In contrast, subjects who did not invest but merely observed the investment outcomes do not have this memory bias. Importantly, subjects do not adjust their behavior to account for the fallibility of their memory. After investing, they form overly optimistic beliefs and re-invest in the stock even when doing so reduces their expected return. The memory bias we document is relevant for understanding how people form expectations from experiences in financial markets and, more generally, for understanding household financial decision-making.

Abstract in German: Wie beeinflusst das Gedächtnis finanzielle Entscheidungen? In dieser Studie finden wir experimentelle Evidenz für einen selbstdienlichen Fehler in der Erinnerung von Investitionserträgen. Dieser Fehler verzerrt individuelle Erwartungen und beeinflusst darauffolgende Investitionsentscheidungen. Experimentteilnehmer, die zuvor in eine risikobehaftete Aktie investiert haben, erinnern sich eher an Anlageerfolge und weniger an Misserfolge. Im Gegensatz dazu haben Personen, die nicht investiert haben, sondern lediglich die Renditen aus der Investition beobachtet haben, unterliegen diesem Fehler in der Erinnerung nicht. Hervorzuheben ist, dass die Experimentteilnehmer ihr Verhalten nicht an diese Fehlbarkeit ihres Gedächtnisses anpassen. Nach einer Investition bilden sie zu optimistische Erwartungen bezüglich der zukünftigen Renditen der Aktie und investieren wieder in die Aktie, selbst wenn diese die erwartete Rendite der Teilnehmer verringert. Dieser von uns dokumentierte Fehler in der Erinnerung hilft zu erklären, wie Menschen Erwartungen auf der Basis von Erfahrungen in Finanzmärkten bilden, und generell, wie private Haushalte finanzielle Entscheidungen treffen.

Current status: Working Paper

Attention to Extreme Returns

Title in English: Attention to Extreme Returns

Title in German: Die Aufmerksamkeit für extreme Renditen

Abstract in English: It has been shown that individual investors are more likely to buy rather than sell stocks that catch their attention. This can lead to suboptimal choices when attention-attracting qualities of a stock may detract from its utility. This paper tests the causal effect of extreme returns on stock purchase behavior at the individual level by means of a controlled laboratory experiment. We find a strong asymmetry, as shares of stocks with recent extreme negative returns are more likely to be purchased than shares of stocks with recent less extreme negative returns. Yet, comparable patterns are not observed for stocks with positive returns. We further track subjects' eye movements and show that individual visual attention mediates our treatment effect. Interestingly, the results show that attention-driven purchase behavior occurs even in situations in which it reduces subjects' expected return.

Abstract in German: Bestehende Forschung zeigt, dass private Anleger eher Aktien kaufen als verkaufen, wenn diese ihre Aufmerksamkeit erregen. Das Verhalten kann zu suboptimalen Entscheidungen führen, wenn die aufmerksamkeitserregenden Eigenschaften einer Aktie von ihrem Nutzen ablenken. In einem Laborexperiment testen wir den kausalen Effekt extremer Aktienrenditen auf die individuelle Aufmerksamkeit sowie das Aktienkaufverhalten. Unsere Ergebnisse zeigen, dass extreme Renditen das Kaufvolumen von Aktien erhöhen. Interessanter Weise finden wir eine Asymmetrie. Aktien mit extrem negativen Renditen werden häufiger von Experimentteilnehmern gekauft, als Aktien mit weniger extremen negativen Renditen. Bei Aktien mit positiven Renditen können diese Kaufmuster jedoch nicht beobachtet werden. Zudem messen wir die Augenbewegungen der Teilnehmer während der Investitionsentscheidung. Die individuelle visuelle Aufmerksamkeit der Teilnehmer mediiert unseren Treatmenteffekt. Zudem zeigen die Ergebnisse, dass ein aufmerksamkeitsgeleitetes Kaufverhalten selbst in Situationen auftritt, in denen dies die erwartete Rendite der Teilnehmer verringert.

Current status: Working Paper

Categorization and Learning from Financial Information

Title in English: Categorization and Learning from Financial Information

Title in German: Kategorisierung und Wissensbildung auf Basis finanzieller Informationen

Abstract in English: This paper examines the role of coarse categories in individuals' learning from financial information. In particular, we (i) test theoretical predictions about categorical over- and underreaction to information by Mullainathan (2002) in an investment context, (ii) explore differences in category-based belief formation and (iii) link category-based beliefs to investment behavior. Our findings document that information aggregation along prominent categories in financial markets, such as industries, can affect people's beliefs and investment decision-making. Interestingly, we find differences across category types. Subjects form category-based beliefs when the observed stock belongs to "good" stock categories associated with gains. People then overreact to category changes, form overly optimistic beliefs, and invest significantly more in the stock. Yet, we find the opposite pattern if the stock belongs to "bad" stock categories associated with losses. People then seem to be generally sensitive to the stock's outcomes. Category changes do not distort their beliefs.

Abstract in German: In diesem Artikel wird die Rolle grober Kategorien in der Wissensbildung auf Basis finanzieller Informationen untersucht. Hierzu (i) überprüfen wir theoretische Modellvorhersagen zu Über- und Unterreaktionen auf Informationen von Mullainathan (2002) in einem Investitionskontext, (ii) untersuchen wir Unterschiede in der kategoriebasierten Erwartungsbildung und (iii) erforschen wir den Zusammenhang zwischen kategoriebasierten Erwartungen und darauffolgenden Investitionsentscheidungen. Unsere Ergebnisse dokumentieren, dass die Informationsaggregation anhand verbreiteter Kategorien in Finanzmärkten, wie z.B. anhand von Branchen, Erwartungen und Investitionsentscheidungen beeinflussen. Interessanterweise finden wir, dass Experimentteilnehmer unterschiedlich auf Informationen über- und unterreagieren. Sie bilden kategoriebasierte Erwartungen, wenn die beobachtete Aktie zu "guten" Aktienkategorien gehört, die mit Gewinnen verbunden sind. Die Teilnehmer reagieren dann zu stark auf Kategoriewechsel, bilden zu optimistische Erwartungen und investieren signifikant mehr in diese Aktie. Wir finden jedoch das umgekehrte Muster, wenn die Aktie zu "schlechten" Aktienkategorien gehört, die mit Verlusten verbunden sind. Experimentteilnehmer scheinen dann generell empfindlich auf die Erträge der Aktie zu reagieren. Änderungen in der Kategorie verzerren ihre Erwartungen nicht.

Current status: Working Paper

A.2 Statement of Personal Contribution (§6 (3) PromO)

This table displays my personal contribution to the articles contained in this dissertation. The categories used are based on PromO, the extent to which I contributed is outlined based on the following scale:

- My own contribution is 67-100%: A

- My own contribution is 34-66%: B

- My own contribution is 0-33%: C

Chapter	Co-Authors	Main Tasks		
		Theory and Design	**Emperical Execution**	**Preparation of Manuscript**
Investor Memory	Peiran Jiao, Paul Smeets	B	A	A
Attention to Extreme Returns	Moritz Lukas	B	B	B
Categorization and Learning from Financial Information	single-authored	A	A	A

A.3   Statutory Declaration (§6 (4) PromO)

Eidesstattliche Versicherung

Hiermit erkläre ich, Katrin Gödker, an Eides statt, dass ich die Dissertation mit dem Titel

Cognitive Foundations of Investor Behavior
The Role of Biased Memory, Imperfect Attention, and Categorical Thinking
in Individual Investment Decisions

selbständig und bei einer Zusammenarbeit mit anderen Wissenschaftlern gemäß den beige-fügten Darlegungen nach §6 (3) der Promotionsordnung der Fakultät für Wirtschafts- und Sozialwissenschaften vom 24. August 2010 verfasst habe. Andere als die von mir angegebenen Quellen und Hilfsmittel habe ich nicht benutzt.

Hamburg, 10. April 2019   Katrin Gödker

Verwaltung

Erklärung

Ich versichere, dass ich keine Promotionsberatung in Anspruch genommen habe und die Arbeit nicht schon einmal in einem früheren Promotionsverfahren angenommen oder als ungenügend beurteilt wurde.

Hamburg, 10. April 2019   Katrin Gödker