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Title

"Probabilities and predictions – How heuristics and biases influence private investor behavior"

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Abstract

Classic economic theory supposes that its agents are rational in their decision making and action. Various empirical studies, however, indicate that individuals are by no means perfect rational utility maximizers. Evidence from cognitive psychology shows where humans abandon the rational path in decision making and utilize simple heuristics to draw conclusions quicker. These heuristics can potentially bias individual investor behavior and create situations in which investors are worse off because they do not follow the rational postulates of classic economic theory.

This thesis investigates the influence of heuristics and biases on individual investor behavior. Thereby, it examines various empirical studies concerned with investor behavior that contradicts the principles of classic economic theory. Explanations that stem from the area of cognitive psychology and the discipline of Behavioral Finance are utilized to explain this counterintuitive investor behavior. Indeed, empirical studies suggest that individuals are subject to heuristics and biases also when conducting investments. However, it remains difficult to determine the degree to which psychological factors influence investor decision making.

Keywords: Financial Markets, Investor Behavior, Behavioral Finance

JEL classification: G11, G12, G40, G41

I. Outline

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III. List of abbreviations

EMH	Efficient Markets Hypothesis
EPS	Earnings per share
EUT	Expected Utility Theory
SVI	Google search volume index

1 Introduction

1.1 Research problem

Classic economic theory grounds its models on the maxim of rational behavior of economic agents and predicts that individuals act to maximize their utility. It was mainly psychologists such as Nobel Prize laureate Daniel Kahneman or Amos Tversky that questioned the underlying conception of the human being based on their experimental evidence in cognitive psychology. The incorporation of psychological insights into economic theory ultimately led to the development of the discipline of Behavioral Finance that applies descriptive models of human behavior to investment theory, capital asset pricing and other domains of classic finance.

When examining the overwhelming empirical evidence of anomalies in real-world investor behavior, which contradicts with the models of classic economic theory, it becomes obvious that other aspects are needed when attempting to describe and explain investor and market behavior. This paper does not understand these aspects necessarily as a means to replace classic theory but rather to shed light on fields and phenomena that cannot be explained by it.

Therefore, the description and explanation of heuristics and biases, often referred to as “mental shortcuts”, utilized by individuals when assessing probabilities, making predictions, or deciding under uncertainty as basis for a better understanding of investor behavior is helpful. These heuristics and biases need to be examined within the framework of a behavioral approach to economic theory about market and investor behavior. Ultimately, the observed anomalies in investor behavior demand an explanation regarding the role that heuristics and biases play in the constitution of the observed behavior.

To serve this purpose, the aim of this thesis is to analyze how heuristics and biases influence private investor behavior by describing their impact on probability assessments, predictions, and decisions under uncertainty.

1.2 Research methodology

This thesis appraises the influence of heuristics and biases on private investor behavior by reviewing anomalies in markets that contradict the postulates of classic economic theory. Therefore, a qualitative descriptive approach to analyzing the respective heuristics and biases is demanded to ensure that their presence in real-world market behavior can be identified. In order to provide a sufficient overview of investor behavior anomalies in markets, a qualitative review of various empirical studies is needed. Lastly, based on the findings in psychological literature about heuristics and biases a deductive methodology is utilized to examine whether investor behavior anomalies can be ascribed to the existence of heuristics and biases.

To contextualize all relevant findings and contribute to a deeper understanding of heuristics and biases and their influence on private investor behavior, a literature-based theoretical approach is applied, which places a high importance on past empirical rather than normative research. Accordingly, findings of various researchers will be discussed. The research that is part of this thesis has been identified in online public access catalogues and selected based on the author’s understanding about the significance of the research for both the academic field and the purpose of this thesis paper.

1.3 Course of investigation

Following the research question of chapter 1.1, chapter two will provide a broad overview of the development from classic theory to Behavioral Finance. Thereby, it will briefly review the history of Behavioral Finance. Afterwards, important concepts of classic economic theory are introduced and explained. Consequently, findings from psychologic literature that challenge the validity of these concepts of classic theory are introduced as well.

Chapter three reviews a broad body of empirical research on anomalies in private investor behavior. Initially, findings on investor decision making and behavioral patterns are presented. Afterwards, an overview of how private investors are likely to process information is provided. The findings of chapter three are mainly based on the analysis of trading data that was provided to various researchers by private broker companies.

With respect to the research question, chapter four will again briefly review findings from the empirical studies and provide insights into a behavioral interpretation of the observed anomalies in private investor behavior. Thereby, various findings of chapter two are presented and supplemented by behavioral models of private investor behavior.

Chapter five concludes this thesis with a summary of the findings, which are critically reviewed afterwards. This is followed by an outlook into possible future research on the influence of heuristics and biases on private investor behavior.

2 Behavioral Finance theory

2.1 From classical theory to Behavioral Finance

2.1.1 Emergence of a new field of research

Financial economics might be the discipline of economics that incorporates the least amount of empirical insights about the behavior of its agents (De Bondt and Thaler, 1994, p. 1). However, when focusing on the historical developments and earlier works of economists such as Irving Fisher, John Maynard Keynes or Benjamin Graham, whose work was concerned with anomalies in human judgement, one can see that this has not always been the case (ibid.). In the late 1990s, theories of human behavior, often drawn from other social sciences such as psychology, sociology, and anthropology, have started to shape empirical research on financial markets again (Shiller, 1998, p. 1). Barberis and Thaler (2002, p. 2) argue that this development can be seen as an answer to the difficulties faced by traditional finance paradigms. The traditional finance paradigms are coined by the assumption of rational behavior of the economic agents and therefore will often, for the sake of simplicity, be referred to as "classic theory".

A major problem in classic theory which has been identified for instance by De Bondt and Thaler (1994, pp. 3-4) is the dual-purpose claim: according to the authors, classical theory often aims to provide models that are both normative and descriptive. The authors, thereby, do not question the validity of classical theory in normative regard but argue that the assumptions made about human behavior in these theories can hardly be proven empirically. Therefore, they question the descriptive character of rational theory and speak in favor of the development of descriptive models which are concerned with the behavior of agents in markets and organizations as a supplement to the normative models. They term this development of descriptive models as a supplement as their understanding of Behavioral Finance (ibid.).

Barberis and Thaler find many empirical studies in Behavioral Finance (some of which will be presented in the course of this thesis) that give reasons to doubt the validity of classic theory. Specifically, the authors see various instances of investors under- and overreacting to events such as earnings announcements, the extrapolation of past returns into future security prices, overconfidence in the ability to process information or excessive trading. These reactions cannot be explained by classical theory alone and are attributed by the authors to behavioral patterns (Barberis and Thaler, 2002, pp. 3-4).

A central element of classical theory, which is mainly violated by the various behavioral patterns mentioned above, is the Efficient Markets Hypothesis (EMH).[1] The basic model of EMH can be described as

$$P_t = E_t P'_t \tag{1}$$

where P_t is the security price today which is the expected price of a security in the future discounted to its present value (Shiller, 2003, p. 85). This shows the underlying notion of the EMH that any variations in stock prices must be based on some kind of new information about the fundamental (discounted) future value of a security. Therefore, efficient markets have asset prices that incorporate all relevant information (ibid.). According to Shiller (ibid., p. 83), EMH reached the height of its dominance in the 1970s. The assumption that stock prices only change when relevant information becomes public was prominent at that time and built the framework for many theories regarding capital asset pricing at that time. First systematic doubts to EMH emerged in the 1980s, when the phenomenon of excess volatility, i.e., stock price changes that are higher than EMH would predict, displayed a form of anomaly which could not be easily ignored by classic theory (ibid., p. 84). Specifically, Shiller (ibid., pp. 85-86) detected at that time that while the net present value of dividend payments developed quite stable over time, real stock prices fluctuated heavily around these values. Consequently, focus started shifting away from econometric models in the 1990s towards models that incorporated notions about human psychology and its relation to the financial market (ibid., p. 90). In this regard, Shiller relates mainly to the work of the psychologists Daniel Kahneman and Amos Tversky on human judgement under uncertainty, which will be presented in the following subchapters (ibid., p. 94).

[1] An extensive review of the Efficient Markets Hypothesis (EMH) will be provided in chapter 2.1.2.3

2.1.2 Perspectives of classic theory on judgements under risk or uncertainty

2.1.2.1 Expected utility and rational expectations

Perhaps, the best notion of utility and its difference to monetary units in economics is given by Markowitz (1959, pp. 207-208). Markowitz introduces an example where he proposes to measure the utilities of a 50/50 chance of winning or losing 10% in returns against the utilities for a safe return of 0%. Even though the expected value for both scenarios is 0%, the utility of the 50/50 chance can be negative for many individuals as losing something can have more weight than winning something in the equal amount. Still, he states that utility should not be mistaken for feelings or hedonistic interpretations of pain and pleasure. Rather, utility represents the degree to which an individual is willing to take risks to achieve certain outcomes (ibid., p. 208).

One central discussion around utilities, therefore, concerns the question of whether they can be expressed in numbers. The basic assumption to enable a numerical expression of utilities concerns a possibility to compare differences in utilities (von Neumann and Morgenstern, 1953, p. 17). Accordingly, people do not just need to have preferences but always need to be able to identify which alternative they prefer more when presented with two alternatives (ibid.). Von Neumann and Morgenstern (ibid., p. 18) illustrate the comparison of difference through an abstract example: When an individual is asked to choose between a sure prospect A and a 50/50 chance of B or C and it is known that he prefers A over B, but C over A, then his choice in this procedure allows inferences about the different utilities he assigns to each prospect. For instance, when he chooses the sure prospect, it can be assumed that his preference of A over B is greater than his preference of C over A (ibid.).

This is according with Briggs' (2019, n.p.) definition of utilities, who describes the utility of an act as a weighted outcome of all utilities of each possible outcome. The utility of a single outcome measures, thereby, the extent to which that outcome is preferable over its alternatives. Therefore, the weighing of each outcome displays the probability that it happens (ibid.). By that, Expected Utility Theory (EUT) is in most representations concerned with judgements under risk, meaning decision-making in situations where the probabilities of an event are commonly known.

There are several axioms that underly EUT. A simple representation of them is given by Markowitz (1959, p. 209) who defines the expected utility maxim following: "The expected utility maxim, stripped of any hedonistic interpretation, says that the individual should act as if 1) he attaches numbers, called their utility, to each possible outcome, and 2) when faced with chance alternatives he selects the one with the greatest expected value of utility." This definition my Markowitz finds representation in a similar way in the work of Friedman and Savage (1948, pp. 287-288) who argue that in choosing among alternatives a consumer behaves as if 1) he or she has a consistent set of preferences, 2) his or her preferences could be described by a function attaching certain numerical value (i.e., utility) to alternatives, and 3) his or her objective was to make the numerical value as large as possible. Several aspects of Friedman's and Savage's notion of the axioms find themselves in a more mathematical notation in the book of von Neumann and Morgenstern (1953, pp. 26-27). They argue that preferences can be either $A = B$, $A > B$ or $A < B$, but not several combinations of it. Furthermore, they assume transferable preferences, meaning if $A > B$ and $B > C$, it must be $A > C$, even when not explicitly stated. Lastly, they assume that if $A > B$, then even a chance of $(1 - p)A > B$, often labelled as the "substitution axiom" (ibid.).

Generally, Expected Utility Theory still has a prominent role even though it produces several anomalies (Shiller, 1998, p.3). These anomalies will be subject to discussion in the chapter 2.1.3 and 2.2.4.

2.1.2.2 Bayes Theorem

The Bayes Theorem is a probability calculation method meant to assess conditional probabilities, or, more simply speaking, the probability of an event θ2 under the condition that event θ1 is true (Gillenkirch, 2018, n.p.). The Bayes Theorem serves to transform a priori probabilities to a posteriori probabilities (ibid.).

For example, a savings and loan association assessing the probability of a customer defaulting on his loan payments may employ the Bayes Theorem. In this case, suppose, for simplicity, that a) 5% of all borrowers default and that b) the bank's internal credit analysis function correctly predicts a borrowers degree of creditworthiness in 80% of all cases. The Bayes Theorem can now be utilized to determine the probability that a customer defaults on his loan when the internal system already deemed him as unworthy of credit. The standard form of the Bayes Theorem is

$$w(\theta 2/\theta 1) = \frac{w(\theta 1/\theta 2) * w(\theta 2)}{w(\theta 1)} \qquad (2)$$

where $w(\theta 2/\theta 1)$ is the conditional probability of the event that the borrower defaults after the internal credit analysis predicted he would, $w(\theta 1/\theta 2)$ is the opposite conditional probability, $w(\theta 2)$ is the unconditional probability of default and $w(\theta 1)$ is the unconditional probability that the internal credit analysis predicts a default. $w(\theta 1)$ is calculated the following,

$$w(\theta 1) = 0.8 * 0.05 + 0.2 * 0.95 = 0.23 \tag{3}$$

and therefore,

$$w(\theta 2/\theta 1) = \frac{0.8*0.05}{0.23} = 0.174 \tag{4}$$

which means that the conditional or a posteriori probability that a customer, who was deemed as unworthy of credit, defaults on his loan is 17.4% (ibid.). The a priori default probability of 5% is increased by 12.4 percentage points when employing the Bayes Theorem.

Empirical research mainly by Kahneman and Tversky (cf. chapter 2.2.1 and chapter 2.2.2) has shown that the Bayes Theorem is counterintuitive for many individuals. When asked to estimate posterior probabilities it seems that many people place too much weight on $w(\theta 1/\theta 2)$ at the expense of the base rate $w(\theta 2)$.

2.1.2.3 Efficient Markets Hypothesis

The importance of the Efficient Markets Hypothesis (EMH) has already been indicated in chapter 2.1.1. The term itself was coined by Eugene Fama, but first evidence of the underlying concept can already be found in the 19th century (Shiller, 1998, pp. 1-2). Fama (1970, p. 383) is of the opinion that the capital market's primary role is to allocate ownership of an economy's capital stock. He deems a market efficient when prices of the securities in the market fully reflect all available information so that investors are aware of all necessary factors needed to accurately allocate their resources. To further define the term "fully reflect", Fama introduces three subsets of efficiency. In the weak form, information is just based on historical prices. In the semi-strong form, information in prices is not just reflected in their historical development but prices adjust to publicly available information such as earnings announcements. Lastly, the strong form of market efficiency reflects a status in which no investors or groups have monopolistic access to insider information relevant for price formations. The strong form would exclude the possibility of arbitrage trading (all ibid.).

In their critique of Fama's article, Grossman and Stiglitz (1980, p. 893) state that the assumption that all markets, including the market for information, are always in equilibrium and perfectly arbitraged is inconsistent whenever arbitrage is costly. When investors trade on private information, this reflects a costly process which would not occur if excess gains could not be earned in the market. Fama reflects on this and several other critiques in his second article about the EMH (1992, p. 1575) by rejecting the strong version of the EMH. The strong version would require all trading costs and costs of acquiring information to always be neutral. Fama speaks in favor of a less strict version, where prices reflect information to the degree that the marginal benefits of acting on information do not exceed the marginal costs. Still, he sees advantage in the strict version of the EMH when taken as a reference point as it allows to evaluate deviations in trading costs regarding their reasonability (ibid.).

To test whether information is fully reflected in prices, Fama brings up a model while acknowledging that measuring the appropriate reflection of information is hardly possible. To overcome this difficulty, he employs, based on the Sharpe-Lintner two-factor model of capital asset prices, a model in which conditions of market equilibrium are stated in terms of expected returns (Fama, 1970, p. 384). In this model, the expected value of an asset is stated as a function of its risk conditional on the available information about the underlying asset. This results in

$$E\left(\tilde{\rho}_{j,t+1}\middle|\Phi_t\right) = [1 + E\left(\tilde{r}_{j,t+1}\middle|\Phi_t\right)]p_{jt} \tag{5}$$

where E is the expected value operation, p_{jt} is the price of the security j at time t, $\tilde{\rho}_{j,t+1}$ is the price at $t+1$, $\tilde{r}_{j,t+1}$ is the percentage return of the security at $t+1$ and Φ is the general symbol for the set of information which is assumed to be fully reflected by the price at t (ibid). Hereby, the notion that the expected value at $t+1$ reflects all information available at point t bears an important implication as it rules out the possibility of any excess returns on expected profits in equilibrium, if equilibrium is accordingly defined as expected returns (ibid., p. 385).

Indeed, this would support the model which postulates that stock price changes follow a random walk, meaning that any stock price changes are independent and identically distributed (ibid., p. 386). The logical connection of the EMH and the random walk model, which is not discussed here in detail as this would go beyond the scope of the thesis, is an important factor for the following presentation and explanation of counterintuitive investor behavior in chapters three and four.

2.1.3 Prospect Theory

From all theories developed in other social sciences such as psychology or sociology, Prospect Theory might have the biggest influence on economic research (Shiller, 1998, p. 3). To all models, which aim at understanding asset prices or trading behaviors, an understanding about and assumption on how economic agents form preferences is important. In classic theory, the underlying concept for these models is often still presented by EUT, however, with Prospect Theory Daniel Kahneman and Amos Tversky developed an alternative that neglects the various assumptions of EUT brought up mainly by von Morgenstern and Neumann (Barberis and Thaler, 2002, p. 16).

Kahneman and Tversky argue that EUT does not display a valid description of how people form decisions under risk, which they state as their main motivation for developing a theory they labeled "Prospect Theory" (Kahneman and Tversky, 1979, p. 263). The basic assumption of EUT is that a prospect, an outcome with a respective probability, is accepted if the utility from receiving the prospect exceeds the utility of the assets already in possession. Therefore, EUT is concerned with final states rather than with gains or losses (ibid., p. 264). Besides the focus on final states, the authors furthermore criticize the underlying assumption that an individual's behavior is risk averse is any situation, making the expected utility function completely concave (ibid.).

Kahneman and Tversky present the "certainty effect" and the "reflection effect" (ibid., pp. 266-267) as two prominent examples where the underlying assumptions of EUT are violated. They construct the following two gambles:

Problem 1:

A: (4,000; 0.8) *or* *B: (3,000)*

Problem 2:

C: (4,000; 0.2) *or* *D: (3,000; 0.25)*

Most of the respondents in their experimental series preferred alternative B in problem 1 but alternative C in problem 2 (ibid.). It is critical to note that problem 2 is only a variation of problem 1 with changing probabilities. According to the substitution axiom of EUT (cf. chapter 2.1.2.1), if $B > A$ any $(1-p)B > A$ should be true. However, when probabilities are high, people tend to choose the safest outcome in the gamble. When probabilities are low or minimal, they prefer the higher outcome value, which constitutes the certainty effect. (Kahneman and Tversky, 1979, pp. 266-267). When presented with these positive prospects, the certainty effect seems solid, but the reflection effect comes up when the same gamble is presented in terms of losses rather than gains. There, most of the subjects choose alternative A in problem 1 and alternative D in problem 2 (ibid., p. 268). The two problems show that certainty increases the aversiveness of losses in the same way it increases the desirability of gains. Furthermore, in the domain of gains people are indeed risk averse but become risk seekers when presented with losses (ibid., pp. 268-269).

To propose an alternative for the second underlying assumption of EUT, the concern of final wealth states, the authors (ibid., p. 273) come up with following example:

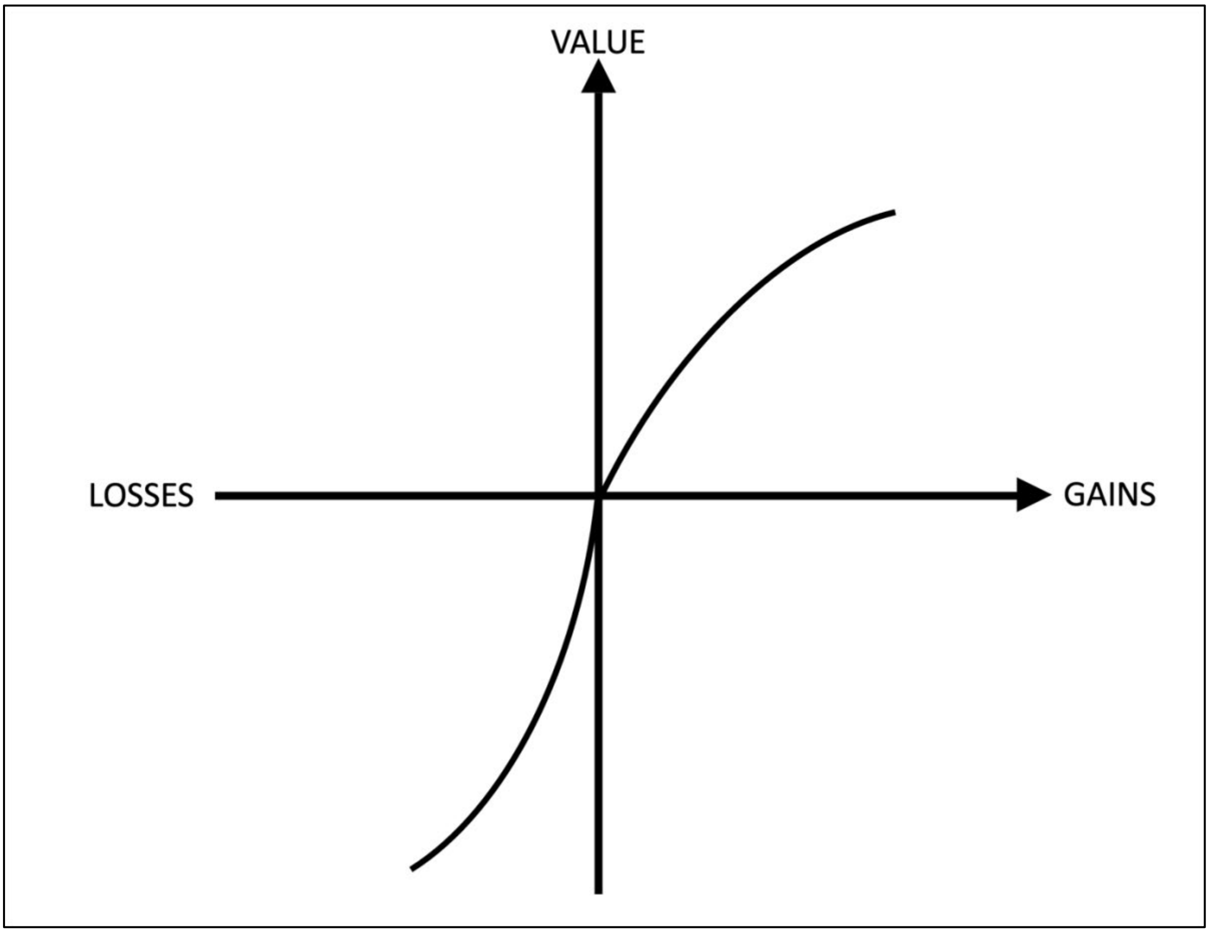
> *Problem 3: In addition to whatever you own, you have been given 1,000. You are now asked to choose between*
>
> *A: (1,000; 0.5) and B: (500)*
>
> *Problem 4: In addition to whatever you own, you have been given 2,000. You are now asked to choose between*
>
> *C: (-1000; 0.5) and D: (-500)*

Note that in terms of final wealth both gambles are the same. Still, a majority of respondents preferred B in problem 3 and C in problem 4 (ibid.). While first indicating the existence of the reflection effect again, the subjects should be indifferent about the choices if they were concerned about final wealth status. Hence, Kahneman and Tversky propose that people judge by the change of their wealth and not by the final status (ibid.).

The decision-making process is divided in two phases, editing and valuation (ibid., pp. 274-275). In the editing phase, a preliminary analysis of the offered prospects is conducted. Outcomes of gains and losses are perceived against a certain, neutral reference point. For instance, the current status of wealth. The authors attribute the various inconsistencies in preferences as a result from the editing of prospects (ibid., p. 274). In the valuation phase, prospects are evaluated and the highest value prospect is chosen. Thereby, an important operation takes place: individuals associate the probabilities of the prospects with a certain weight, which is not a probability measure but rather a measure of sentiment that assigns an overall value to the probability of an outcome and therefore displays a subjective measure (ibid., p. 275). The main difference in valuation phase is based on whether the gamble has strictly positive or negative outcomes or if outcomes can also be possibly zero. Whenever there are strictly positive/negative outcomes, the value of the prospects is mainly based on the subjective weight the subject assigns to the combination of the outcomes. If a possible outcome, instead, is zero and the probabilities of both events do not equal one in combination, the weight is assigned to both probabilities (ibid.).

The reported risk seeking behavior of individuals in the domain of losses leads Kahneman and Tversky to develop a value function that is, opposed to the function of expected utility, concave only for gains but convex for losses (ibid., p. 278). Furthermore, it is steeper for losses than it is for gains (ibid., p. 279).

Figure 1: Prospect Theory value function

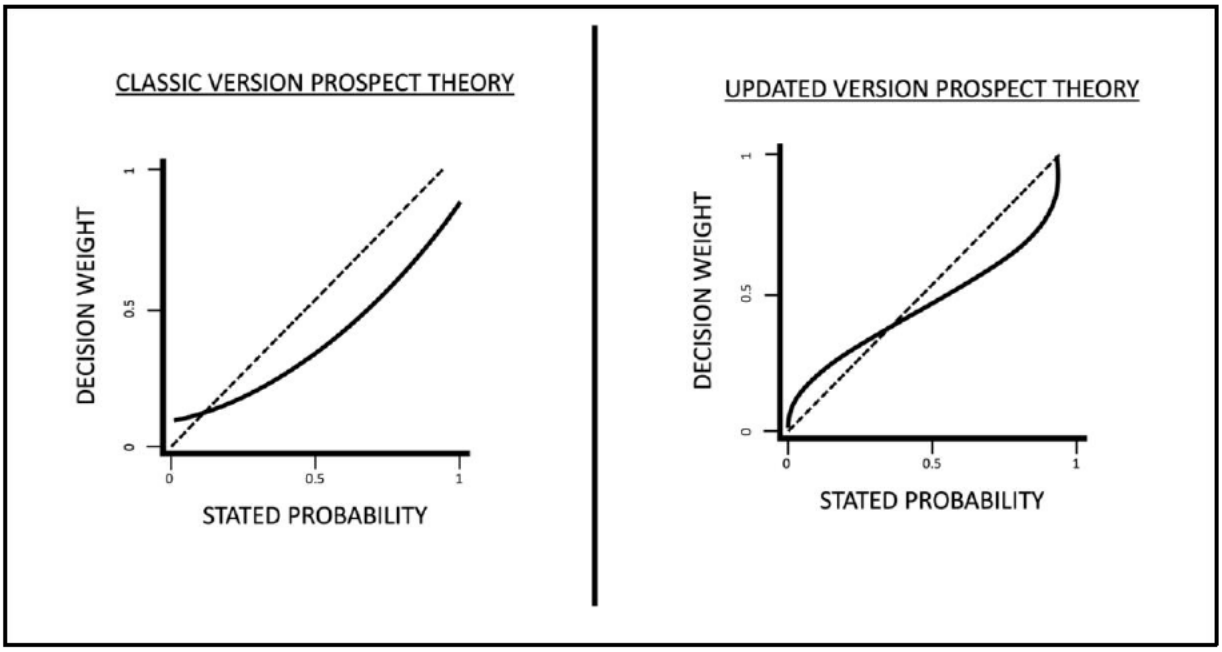


source: Author's own rendering based on Kahneman and Tversky, 1979, p. 279

As can be seen, the value function is an S-shaped curve, with the intersection of the concave and the convex curve being the subjective reference point, from which individuals evaluate gains and losses (ibid.).

The decision weights introduced earlier measure the impact certain events have on the desirability of prospects and do not represent perceived likelihoods (ibid., p. 280). In their updated version of Prospect Theory, the weighting function is changed as the initial version did not account for statistic dominance or the transferability axiom (cf. chapter 2.1.2.1) and as it furthermore could not easily be extended to prospects with various outcomes. Instead of transforming each probability separately, the updated weighting function transforms the entire cumulative distribution function of a prospect based on the weighting of involved probabilities and does so separately for gains and losses (Tversky and Kahneman, 1992, p. 299).

Figure 2: Prospect Theory weighting functions



source: Author's own rendering based on Kahneman and Tversky, 1979, p. 283 and Tversky and Kahneman, 1992, p. 313

All in all, past studies indicate that overweighting takes place especially for small probabilities while medium to large probabilities are underweighted (Kahneman and Tversky, 1979, p. 280). Where $\pi > p$ probabilities are overweighted and vice versa (note that in the later version of Prospect Theory, the authors note w instead of π for decision weights) (Tversky and Kahneman, 1992, pp. 312-313). Consequently, the authors observed people to be rather insensitive to differences in probabilities in the middle of weighting function range, while they react sensitively to changes in probabilities for very low or very high probabilities (ibid.).

2.2 Heuristics and biases

2.2.1 Representativeness

When asked to assess the likelihood of a certain event, people are often concerned with a question of how probable it is that one object originates from another or that one object belongs to another object's class. They perform their analysis by estimating the similarity between the objects rather than judging based on the likelihood (Tversky and Kahneman, 1974, p. 1124). Accordingly, people predict by employing a heuristic the authors call "representativeness", meaning they select or order outcomes by the degree to which the outcome represents the essential features of the presented evidence (Kahneman and Tversky, 1982a, pp. 48-49). The judgement by representativeness leads to a neglect of base rates and prior probabilities, sample sizes and information on predictive accuracy (Tversky and Kahneman, 1974, p. 1124).

In an experiment, Kahneman and Tversky (1982a, pp. 54-56) presented subjects with personality sketches of people belonging to a population where 130 people are engineers, and 70 people are lawyers. After reading the personality sketch, the authors asked the participants to state a respective probability that the person from the personality sketch is an engineer (lawyer). As the information in the personality sketch was basically meaningless, at least for inferring the profession of the described individual, the results of the probability measurements should represent the prior probabilities or base rates (ibid.). However, people only judged based on prior probabilities and base rates when they were presented with no information at all in the personality sketch (ibid., p. 53).

In another experiment, the authors asked participants to rank probabilities for the event that 40% [50%, 60%] of babies born per day were male in three different hospitals in a city that differed in the size of births recorded per day (Kahneman and Tversky, 1982b, pp. 38-41). The answers were transformed into probability distribution and showed equal results, no matter if the sample size was $N = 10\, births$ or $N = 1000\, births$ (ibid.). The results showed that when sample sizes are small people tend to underestimate variance while they overestimate it when sample sizes are large (ibid.). The expectation that small sample sizes possess the same characteristics as large sample sizes is denoted as the "belief in the law of small numbers" (Tversky and Kahneman, 1982a, p. 25).

When focusing on predictions based on representativeness, Kahneman and Tversky (1982a, p. 48) decide between categorical and numerical predictions. Categorical predictions are of a nominal form where for instance the winner of an election is predicted, while numerical predictions concern for instance the future value of a particular stock (ibid.). When predicting the future value of a stock, people will tend to assign to much weight to factors such as the company description and in how far this description is representative to the population of “good” companies. Therefore, when the company in question is highly representative, predictions of stock prices will be high and be insensitive to the reliability of the underlying evidence and the expected accuracy of the prediction (Tverksy and Kahneman, 1974, p. 1126). Normally, statistical prediction would require a) prior or background information (base rates), b) specific evidence of the event and c) expected accuracy of the prediction, i.e., an estimated probability of correct predictions (Kahneman and Tversky, 1982a, p. 51). The lower the expected accuracy, the closer the prediction should be to the prior probabilities as these are independent from the event information (ibid.).

Kahneman and Tversky (ibid., pp. 57-58; pp. 60-63) find that predictions are often indeed evaluations or translations. In several experimental settings, they presented two groups with the same information about, for instance, a student’s academic performance. They asked one group to evaluate the current performance and give the student a certain rank relative to how they suppose other students’ performances. The other group was then consequently asked to predict his academic success when graduating a few years later (ibid., pp. 57-58). Reliably, there were no significant differences between both groups’ assessments, demonstrating that individuals are likely to replace the prediction with an evaluation (ibid.).

Another characteristic of the representativeness heuristic is the belief in mean reversion, often also called the “gambler’s fallacy” (Tversky and Kahneman, 1982a, p. 24). It represents peoples’ strong expectation that laws of chance are also reflected in experiments with few repetitions. The most prominent example concerns the coin to be flipped five times that has already landed on heads four times. The expectation that the result of the next flip will be “tail” is strong and certainly stronger than the objective chances of 0.5 (ibid.). Accordingly, people also await to observe randomness in small samples and deem samples as more likely the more random they appear, which again refers to the law of small numbers (Kahneman and Tversky, 1982b, pp. 35-37).

Kahneman and Tversky (1982a, p. 24) conclude their remarks on the gambler's fallacy with the following statement: "Images such as 'errors cancel each other out' reflect the image of an active self-correcting process. Some familiar processes in in nature obey such laws: a deviation from a stable equilibrium produces a force that restores the equilibrium. The laws of chance, in contrast, do not work that way: deviations are not canceled as sampling proceeds, they are merely diluted".

The representativeness heuristic represents a major conflict between classic theory and Behavioral Finance which concerns several aspects in this chapter (cf. e.g., chapter 2.1.1): the conflict between normative and descriptive models. The representativeness heuristic is the counterpart of the Bayes Theorem and shows that individuals tend to disregard base rates and sample sizes when updating their posterior beliefs even though Bayes Theorem would predict otherwise (Kahneman and Tversky, 1982b, pp. 46-47). The authors argue that the insights of representativeness heuristic can also be transferred to unique and uncertain situations such as economic research (ibid.).

Grether (1980, pp. 547-548) aimed to create such situations in experiments which were more related to "real-world" applications and finds that Kahneman's and Tversky's findings are generally robust. His experiments were mainly decisive to rebut one prominent criticism of Kahneman's and Tversky's work, which supposed that subjects would act differently in the moment they deal with real-world situations in which financial rewards for acting according to classic theory are strong. Accordingly, Grether applied different and stronger financial rewards in his experiments and could not find any significant evidence of the reward system influencing the applied decision-making (ibid., pp. 553-555).

2.2.2 Availability

Another heuristic employed in the decision-making process is the availability heuristic. It mainly deals with two principles. First, the ease with which one retrieves information from memory, and the second being the ease with which one can construct processes in the mind (Kahneman and Tversky, 1982c, p. 201). Like the representativeness heuristic, the ease with which one retrieves information or constructs processes is used as a substitute for frequency and probability judgements (ibid.; Tversky and Kahneman, 1979, p. 1127). Life-long experience generally tells individuals that events of large classes are easier to recall than events of small classes and that associative connections between events are easier to make when two events frequently co-occur. Thus, judging the likelihood of an event by the ease with which one can mentally operate the retrieval or association of that event with other similar instances can be a suitable proxy for likelihood judgements. However, it can also have systematic biases (Tversky and Kahneman, 1982b, pp. 163-164).

When assessing the probability of an event under the availability heuristic by recalling similar instances, it may even be unnecessary to perform the process of retrieval. Rather, it may be sufficient to solely consider the ease with which one could do it (ibid., p. 164). To test for the recall or retrieval assumption the authors conducted an experiment. Subjects were read out four lists that contained the names of famous people. Each list contained 39 names, with two lists consisting of 19 males and 20 females and vice versa. The sex that made up for the smaller portion of the list contained what would be considered as the more famous names. After having heard the names, the subjects were asked to evaluate if the list contained more female or male names. Thereby, it turned out that subjects consequently judged the sex with the more famous names to be more numerous even though it had one person less in every instance (all ibid., p. 175).

Regarding co-occurrence, the authors (Tversky and Kahneman, 1979, p. 1128) find that people tend to overestimate the correlation between events when they happen at the same point in time as their judgement is based on how easy an event can be associated with another. The notion that co-occurrence is related to correlation can lead to flaws in probability judgements as it specifically disregards randomness, while on the other hand correlation between events that are temporally independent might be overlooked (ibid.).

As already introduced above, another important part of the availability heuristic is the process of simulation. When judging probabilities or frequencies based on the availability heuristic without having any information in memory to recall, one often judges by conceivability, meaning the likelihood of certain outcomes is judged based on how easy they are to imagine (ibid.). Individuals tend to produce outcomes based on the ease with which they can come up with these outcomes (Kahneman and Tversky, 1982c, pp. 201-202). One focus of the simulation process under the availability heuristics are the “studies of undoing” (ibid., pp. 202-203). They focus on the judgement of probabilities by individuals when input factors are changed, or certain pre-conditions are eliminated (ibid.). An example of the undoing studies concerns two travelers that live in the same hotel and need to catch two different flights at the same time at the same airport. Both leave the hotel at the same time, get stuck in a traffic jam, and miss their flight. However, traveler A's flight departed on time while traveler B's flight was delayed and left only five minutes before both finally reached the airport with 30 minutes delay (ibid., p. 203). The participants of the experiment judged that traveler B will feel more disappointed, as it is easier for him to imagine that he might have reached the airport just five minutes earlier while the same process is not likely to be imagined for traveler A (ibid.).

The undoing studies are mainly important for studying the role of emotions in judgement and decision-making as they show how people incorporate unrealized possibilities to compare their status quo with a situation that could have been (ibid., 206). Thereby, their perceived likelihood of an event is especially dependent on the consistency of the story, which is produced in their simulation process, favoring linear relationships of the kind $When\, A \rightarrow Then\, follows\, B$ (ibid., p. 207). In their search for consistency, individuals undervalue the importance of intermediate states which are produced by slow and incremental changes and therefore do not contribute to the causal character of the story (ibid.).

2.2.3 Overconfidence

Contrary to the availability heuristic and the representativeness heuristic, the overconfidence bias is less concerned with information gathering and processing but rather with how people arrive at decisions. Thereby, academic literature mainly divides between overconfidence as measured by miscalibration and overconfidence as measured by the notion of being better than average.

Calibration is defined as a category of prediction quality and is perceived to be good or sufficient if over a long run an assessor of probabilities exhibits a proportion of true probability judgements that equals the actual probability assigned (Lichtenstein et al., 1982, pp. 306-307). Generally, overconfidence, reflecting the belief to be more accurate in ones' assessments of probability than what is actually correct ($assigned\, probability\, for\, being\, correct - actually\, correct > 0$), seems to increase with the complexity of the task (ibid., pp. 315-316). Thereby, the occurrence of overconfidence seems to be irrespective of the area where probability assessments are conducted (ibid., pp. 322-323).

In an experiment by Alpert and Raiffa (1982, pp. 296), subjects had to fill out questionnaires where they stated their judgement quantiles [0.01; 0.25; 0.50; 0.75; 0.99] for several quantities with unknown values to them at the time of their assessment. For instance, they were asked about their respective quantile assessments of total egg production in the US in the year 1965 (ibid., p. 298). Before asked to state their quantiles, all fundamentals of decision-making theory were explained to them. (ibid., p. 296). Results show that only 33% of the true values were between the average lower and upper quartile assessments of the participants, while one would expect a well-calibrated assessment to reflect 50% of true values in this area (ibid., pp. 299-300). With a total of 1,000 answers from all subjects, one should expect a total of 20 surprises (i.e., values beyond the 0.01 to 0.99 quantile). In reality, there were 426 surprises (p. 301).

Another experiment concerned with calibration and miscalibration was developed by Oskamp (1982, p. 288) and focused on case-study judgements, meaning evaluations of how a patient in psychiatric treatment has reacted to several events that happened in his life by means of a multiple-choice questionnaire. It had underlying case material that was indeed real and Oskamp had trained psychologists, graduate psychology students and advanced undergraduate students with a course in personality assessment as participants (ibid., pp. 289-290). The experiment was divided into four stages. In each stage, the participants gained more information about the patient and at the end of each stage they were asked to revise their answers based on their new information. Lastly, they were asked to state their confidence that the judgements are correct in terms of percentage (ibid.). Results showed that no participant ever reached a 50% accuracy, with the average final accuracy being only 27.8% while the accompanying average level of confidence was 52.8% (ibid., p. 291). While the accuracy of judgements did not increase throughout the stages, the confidence in the judgements increased steadily after the participants were presented with new information (ibid., p. 291).

To test for the notion that people perceive themselves to be better than average, Svenson (1980, pp. 144-145) conducted an experiment with two groups of students in the US and Sweden which were asked to assess how safely and how skillful their driving abilities are in comparison to the other students in the room, with whom they were doing the experiment together. Answers were given on a 10-interval percentage scale. The results show that most of the participants perceive themselves to be safer or more skillful drivers than the rest of the participants in the groups (ibid., p. 145). Half of the students believed themselves to be among the most skillful 20% (30%) drivers and 88% (77%) viewed themselves to be safer than the median driver (ibid.).[2]

Svenson finds his results confirmed in other studies. For instance, he refers to the Brehmer's study from 1980 where a group of drivers, who were responsible for accidents and traffic violations before, perceived themselves to be equally as good drivers as another group which had never violated any traffic rules and had no history of accidents (ibid., 147).[3]

2.2.4 Regret aversion

In academic literature, the role of regret is defined in various ways. Representations of regret that resemble more of a heuristic in information processing and decision-making, and whole regret theories which constitute alternatives to Expected Utility Theory and Prospect Theory are presented in the following paragraphs.

The state in which regret will occur as a feeling is certainly when an individual finds out there was a better but forgone outcome compared to the actual choice he or she made (Tsiros and Mittal, 2000, p. 403). Still, regret can also be experienced when the decision-maker does not know for sure what could have happened when he or she had chosen differently, even though regret is felt stronger when information on an alternative outcome is present. Tsiros and Mittal (ibid.) attribute this process to the simulation process of the availability heuristic (cf. chapter 2.2.2). The status quo is probably the strongest predictor of experienced regret. When a decision outcome results in maintaining the status quo, regret is experienced when information on a better-forgone outcome is available. When a decision leads to changing the status quo, regret can be felt regardless of information on better-forgone outcomes (ibid., p. 404). Regret is especially strong when individuals find that they cannot undo a decision that leads to an outcome that is worse than what could have been, had they chosen differently (ibid.). The authors could confirm their assumptions in an experiment that

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[2] Parentheses indicate the results of the Swedish group.

[3] For a detailed review, please, refer to Brehmer, Berndt: In one word: not from experience, Acta Psychologica, Vol. 45 (1980), pp. 223-241

concerned the purchase decision of a laptop by choosing one of two brands (ibid., p. 406). When presented with information after the (hypothetical) purchase decision that the other brand did better in overall company or image development, subjects felt regret about their purchase decision even though they were clearly told the laptop they chose satisfied all demands they had. Information on brand development even significantly decreased the repurchase intentions of the participants (ibid.).

Regret is presented as an alternative to EUT by Bell (1982, p. 961). He hypothesizes that large parts of violations against the axioms underlying EUT can be explained by a factor that he labels "decision regret" (ibid.). Decision regret is defined as the feeling an individual experiences when comparing the results of his actual choice against the largest possible outcome of another possible decision (ibid., p. 963). In this sense, decision regret can be viewed as a more formal explanation of the better-forgone outcome that Tsiros and Mittal introduced. Bell does not necessarily view regret as a psychological bias or irrational motivator of decisions but rather as a natural consequence of realizing that someone had decided to his or her own detriment (ibid.). A critical question in EUT concerns the coexistence of peoples' preferences for gambling and insurances, i.e., paying a premium for preserving the very low chance of earning a high reward versus paying a premium for preventing the very low probability of a large loss. Bell argues that both are in accordance with regret theory, as taking on a bet or purchasing an insurance reduces the maximum possible regret between the decided outcome and what could have been (ibid., pp. 971-972). In this sense, he argues that downsides of doing nothing are high in terms of regret. Therefore, paying a small premium to not risk missing an opportunity is anticipated regret aversion (ibid.). While Bell believes that people are rather regret-averse than risk-averse, as assumed by EUT, he deems it necessary to evaluate how much of the potential asset position one is willing to give up for insuring himself or herself against anticipated regret for every individual (ibid., p. 979).

A similar idea of regret theory is modelled by Loomes and Sugden (1982, p. 808), who modified utility theory mainly by deciding between choiceless utility and utility after making a choice. Choiceless utility is described as a neutral and linear process as it is assumed that outcomes are perceived as not-influenceable because they are choiceless (ibid.). Contrary, when there are two actions to choose from and a state of the world occurs afterwards, the two different actions are compared regarding their consequences under the given state of the world. When an individual observes that choosing the other alternative would make him better off (worse off), regret (rejoicing) is experienced (ibid.).

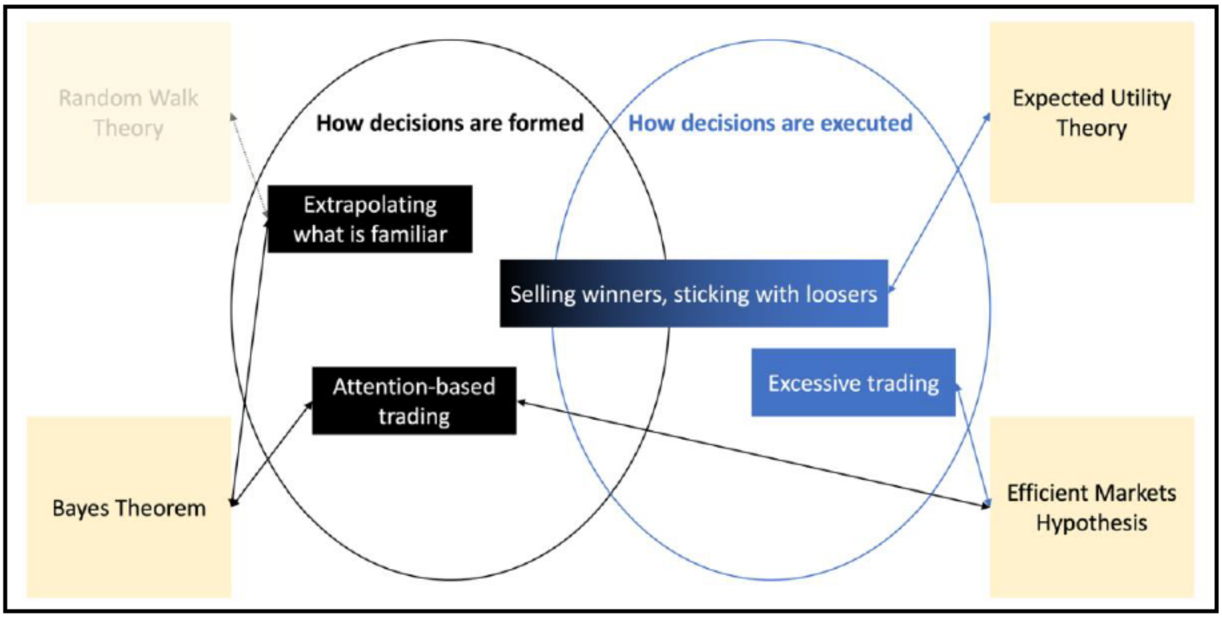
While the presented concepts of regret focus mainly on regret that is experienced by making choices and often states of not making choices are viewed as neutral reference points, Tykocinski and Pittman (1998, p. 607) introduce the concept of inaction inertia, which is defined as the stage in which one avoids deciding on a subsequent option of an action he or she once already did avoid deciding on. To give an example, imagine the decision to buy or not buy a stock. When one decides to not buy the stock but afterwards it increases heavily in value, one might feel reluctant to buy the stock at a later point in time, even if one believes in the further extrapolation of the current trend because of the feeling of a missed opportunity. The authors found that the most effective way to mitigate inaction inertia was to present individuals continuously with their missed choices (ibid., p. 609). The concept of inaction inertia shows that regret can also be felt when one decides to not act.

3 Empirical evidence on counterintuitive investor behavior

3.1 Excessive trading

The following sub-chapters review empirical studies concerned with counterintuitive investor behavior. Thereby, it should be made transparent that the author decided to deem anything as "counterintuitive" if it is at least partly in conflict with widely accepted, classic economic concepts such as the Expected Utility Theory, the Bayes Theorem, or the Efficient Markets Hypothesis. Whenever other concepts that can be attributed to classic theory are violated by empirical findings this will be made transparent. Having said this, to not go beyond the scope of the thesis, further explanations concerning other concepts of classic theory are comparably short, ensuring a basic understanding where needed. To enable a better understanding of the following empirical studies and where findings contradict classic theory, a first graphical overview is presented.

Figure 3: Overview empirical studies



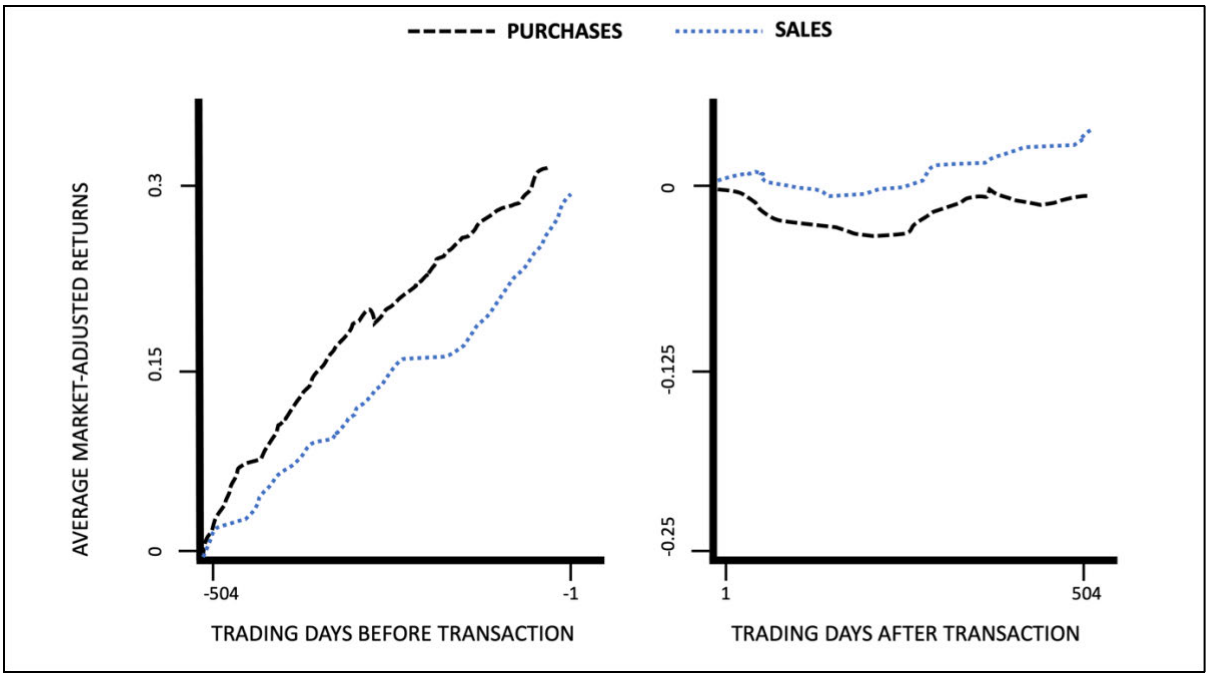
source: Author's own rendering based on the literature presented in chapter three

For judging the occurrence of excessive trading, let the reference point of classical theory be the Grossman and Stiglitz's model, which proposes that investors will trade when marginal benefit of doing so is equal or exceeds the marginal costs of the trade (cf. chapter 2.1.2.3). This reference point suffices for the purpose of the chapter and eventually presents a less strict judgmental basis for assessing the occurrence of excessive trading as the strong assumptions of EMHs as introduced by Fama (cf. ibid.). Barber and Odean disagree with Grossman's and Stiglitz' assumption and argue that overconfidence models predict that investors will trade to their detriment (2000, p. 774). Odean (1999, p. 1279) even argues that classic theory fails to explain the experienced high trading volumes before and during the time he published his article. In a dataset of a large retail brokerage, the authors find that gross returns earned by average households and individuals in aggregate are remarkably close to the return of an index fund over the same time period (Barber and Odean, 2000, p. 786). However, on average, the net returns underperform those of a value-weighted index funds by more than 100 basis points annually (ibid., p. 787). Concretely, the authors can prove that investors could have increased their annual result on average by 2% if they had kept their beginning-of-the-year portfolio rather than traded, showing that high turnover rates decrease net returns (ibid., pp. 788-789).

Odean argues that active or overconfident investors exhibit unrealistic beliefs about their expected trading profits which he provides as a reason for the engagement in costly trading behavior (1999, p. 1280). In an empirical study that incorporates a data set of 10,000 accounts from a nationwide discount brokerage between January 1987 to December 1993, the author determines whether securities purchased by the investors in the sample outperform those they sell by enough to cover the cost of trading. Furthermore, he determines whether the stocks the individual investors purchase underperform those they sell even when trading costs are ignored. Return horizons of four months, one year and two years following a transaction are controlled (ibid., pp. 1280-1282). The average costs of a round-trip trade are determined to be 5.9% based on bid-ask-spread and commissions. The results of Odean's analysis show that over the one-year period, for instance, the average return of securities purchased is 3.3% lower than the average returns on securities sold (ibid., p. 1284). The null hypothesis that the average returns for securities purchased are 5.9% or higher than those of securities sold can be rejected over all time horizons ($p < 0.001$) (ibid.). The null hypothesis that average returns on securities purchased are greater than or equal to average returns of securities sold ignoring transaction costs can be rejected over the four months and annual time horizon ($p < 0.002$) (ibid.). When excluding transactions that could be motivated by rational reasons such as tax-loss selling or portfolio rebalance the observed effect becomes even stronger: securities purchased underperform securities sold by an average of 5% (ibid., pp. 1284-1285).

The model of classic theory predicts risk-adjusted performance of high-turnover individuals or households to be higher than performance of low-turnover investors, with little difference in net returns (Barber and Odean, 2000, pp. 790-792). However, the expected utility for high turnover investors is lower than for low-turnover households as gross performance is about the same but net performance differs because of higher transaction costs for high-turnover households. In Barber's and Odean's study, high-turnover households tend to underperform low-turnover households by 5.5% to 9.6% annually based on net returns (ibid., pp. 792-793). On average, households in the top 20% in terms of turnover also underperform index funds by net of 5.5% annually (ibid.). Odean (1999, pp. 1288-1289) gives another interesting insight as he shows that both securities bought and sold by the investors have outperformed the market before. However, subsequent to their purchase decision, on average, the stocks they bought underperform not only the stocks they sell but also the market (ibid.).

Figure 4: Average market returns prior and following transactions



source: Author's own rendering based on Odean, 1998a, p. 1288

Another study of Weber and Glaser aims to correlate the trading behavior and especially the trading volume of individual investors with psychological insights that are drawn from a questionnaire of these investors (2007, pp. 7-8; pp. 9-11). Concretely, the authors employ a dataset from a German online discount brokerage that contains information on the transactional data of over 3,000 individual investors as well as information about their respective demographics (ibid., pp. 7-8). The corresponding online questionnaire was answered by 215 investors, who answered questions about calibration and the belief of being better than average. The calibration questions are similar to the ones presented in chapter 2.2.3 and regard financial knowledge (ibid., pp. 9-11). Regarding the better-than-average effect (BTA), the participants were asked to assess a) what percentage of investors at the discount brokerage has higher knowledge and b) what percentage of investors at the discount brokerage had higher returns from January 1997 to December 2000 (ibid., p. 15). A BTA score was calculated using the following formula

$$BTA_{score} = \frac{\alpha - 50}{50} \tag{6}$$

where α is the percentage assessment by the individuals. Thus, a BTA_{score} of 1 would imply that an investor considers himself better than anyone else while a score of -1 would represent the exact opposite (ibid.). To test the correlation between investment data and the questionnaire results, the authors run several regression models (ibid., pp. 19-22). They only find a significant positive influence of the BTA_{score} on the dependent variables like monthly turnover (ibid.). Possible interpretation of these findings will be provided in chapter 4.1.

In another study, Schlarbaum et al. analyze the trading abilities of 2,506 individual investors from a large retail brokerage between 1964 and December 1970, reviewing a total of 75,123 round-trip trades in terms of net realized returns (1978, pp. 303-304). When adjusting the returns for the risk factor (beta) according to a strict interpretation of the Capital Asset Pricing Model, the authors observe that individual investors engaging in round-trip trades on average choose stocks that are more volatile than the market ($\beta = 1.38$) (ibid., pp. 320-321). The net returns, adjusted for risk and volatility, show that even though investors seem to exhibit some degree of stock picking and trading skill, overall, it has to be doubted that this skill is sufficient to realize excess returns from active trading behavior (ibid.).

3.2 Selling winners, sticking with losers

The disposition effect, which describes the tendency to sell winning investments while holding on to investments that generate losses (Barberis and Xiong, 2009, p. 751), can be attributed to the field of counterintuitive investor behavior that is concerned with how investors execute decisions and how they trade. In this sense, the disposition effect is similar to the phenomenon of excessive trading. In the above-presented results of the Odean study from 1999 (cf. chapter 3.1), the existence of the disposition effect was also already indicated in the result that the average returns on securities purchased was below the return of securities sold. The following paragraphs focus on empirical studies that are specifically concerned with the existence of the disposition effect.

In their empirical study Shefrin and Statman (1985, p. 785) aim to assess whether buying and selling behavior can be attributed to classic theory trading motivations or to the disposition effect. Specifically, they regard the timing of loss and gain realization, as classic theory would motivate short-term loss realization and long-term gain realization to exploit tax benefits (ibid.).[4] The disposition effect would suggest the exact

[4] This is especially true for the US tax system. For a more detailed explanation of why this strategy would maximize tax efficiency, refer to the article at p. 785

opposite regarding the timing of return realization. The results show that tax-loss motivated selling is visible only in December, which is accordant with the results of Grinblatt and Keloharju regarding tax-loss motivated selling (2001, p. 603). When analyzing the trading behavior in the rest of the year, the disposition effect can be observed. Specifically, in round-trip trades losses account only for 40% of realized returns, irrespective of the underlying round-trip duration (Shefrin and Statman, 1985, pp. 785-786). Over the different round-trip durations, the ratio between realized gains and losses does not differ significantly, which at least allows the conclusion that disposition effect is likely to motivate a substantial part of trading behavior (ibid., pp. 786-787).

Grinblatt and Keloharju employed a data set that contained all records of Finnish stock market participants from December 1994 to January 1997. In their empirical study, they analyze possible trading motivations by comparing sell vs. hold decisions and sell vs. buy decisions (2001, pp. 591-594). In analyzing the sell versus hold decision, the authors control for the determinants of a binary dummy variable that takes the value of one when a sell decision is recorded (ibid., p. 597). For each day a sell is recorded, the authors examine all other stocks in the investor's portfolio and classify whether any of the holdings of the other stocks are sold. They find the data clearly shows a disposition effect which increases whenever gains or losses, respectively, increase as well (ibid., pp. 600-602). By comparing two density functions of realized and unrealized returns, the authors can show that far more gains are realized than losses, represented by the negative skewness of the density function for realized returns (ibid.).[5]

In another empirical study, Barber et al. aim to assess the influence of the disposition effect on repurchasing behavior (2010, p. 103). Therefore, they come up with two hypotheses.

> H1: Investors are less likely to repurchase stocks previously sold for a loss than stocks previously sold for a gain. Corresponding null hypothesis is that investors are neither more or less likely to repurchase stocks previously sold for a gain or a loss (ibid., p. 105).
>
> H2: Investors are less likely to repurchase stocks that have gone up in value since they sold it but are more likely to repurchase stocks that have gone down

[5] For a more detailed description about how the authors computed the probability density functions, please refer to pp. 591-596 as well as pp. 600-602 of their article.

in value since they sold them. Corresponding null hypothesis assumes equal likelihoods again (ibid.).

Data is obtained from the same data set employed in the Barber/Odean study from 2000 (cf. chapter 3.1). Generally, all repurchased stocks, be they previous gains or losses, are compared to all theoretical realized and unrealized opportunities of repurchasing (ibid., p. 107). Thereby, the authors develop the two ratios PWR (previous winners repurchased) and PLR (previous losers repurchased). This enables them to control for tax-motivated trading behavior, which would result in $PLR > PWR$ while results according to H1 would result in $PWR > PLR$. The null hypothesis reflects the status $PWR = PLR$ (ibid.). To test for H2, the authors employ an analogous method (ibid., pp. 107-108). Classic theory would predict that investors are indifferent between the choice of purchasing a stock that has been sold for a gain [increased in value since the sale] or for a loss [decreased in value since the sale] as past return patterns should not be predictive of cross-sectional differences in future returns (ibid.).

The results show, however, that investors repurchase stocks previously sold for a gain significantly more often than stocks previously sold for a loss (ibid., pp. 108-109). On average PWR is twice as high as PLR in one data set and almost 40% higher in the second data set. The differences are significant enough to reject the first null hypothesis. Consistent with H2, investors repurchase stocks that have increased in value since being sold only half the rate of stocks that have decreased value since being sold (ibid., p. 109). The difference is again significant, and the second null hypothesis can be rejected. Overall, the first effect seems to be more predictive of the investors' behavior than the second (ibid.).

Again, possible explanation for the observed inconsistencies with models of classic theory will be proposed in chapter 4.2.

3.3 Attention-based trading

While chapter 3.1 and 3.2 where mainly concerned with the active trading behavior and decision-making of investors, the following two sub-chapters will focus on the way investors process information and build grounds for their decision-making. There will be a special focus on how investors identify stocks to purchase as they face several thousands of opportunities for buying stocks. The following paragraphs examine how attention-grabbling events influence investor decision-making. This phenomenon is particularly interesting, as classic theory in form of the EMH would predict that fully rational investors should not be influenced by stocks catching their attention via news events or abnormal returns. Classic theory assumes that investors would believe information associated with these events is already priced in the stock and does not influence the future development of that stock (Barber and Odean, 2007, p. 790). Furthermore, the hypothesis of the random walk of stock prices (cf. chapter 2.1.2.3) would predict that future developments in returns are independent of past developments but resemble a random sequence. Following, the influence of past events in the form of past return patterns, abnormal trading volume and news events are reviewed in empirical studies. Note that the studies presented focus on several of these aspects, therefore, the results are mainly grouped by topic and not by the authors.

Grinblatt and Keloharju, whose study was already reviewed in chapter 3.2, further find that higher past returns are predictive of individual investor selling behavior (2001, pp. 611-612). When negative returns of large magnitude occur, especially over a short period of time, this predicts individual investor buying behavior (ibid.).

Barber and Odean (2007, p. 795) calculate buy-sell imbalances by order volume for days following an abnormal return and find slightly different results. When categorizing the abnormal returns in deciles, the curve of the following-day buy-sell imbalances is u-shaped, meaning the relative number of purchases is increasing for stocks that either performed very poorly the prior day or very well (ibid., pp. 799-801). While they cannot determine a direction of the past-return effect, they still find that abnormal returns in general cause increasing buying behavior.

Lee et al. (2008, p. 172) assess whether analysts' earnings per share (EPS) forecasts exhibit an upwards (downwards) bias in expansion (contraction) periods. They hypothesize that biases in growth forecasts are business cycle-related, resulting in forecasts being overly optimistic (pessimistic) when the economy is expanding (contracting) (ibid., p. 173). This would predict that current performance has a negative association with forecast errors, measured as $realized\ growth - forecasted\ growth$ (ibid.). Accordingly, they expect current performance to have a negative association with realized growth. The authors have a dataset at their disposal where forecasted EPS as well as realized EPS data is recorded (ibid.). A mean forecast error of -6.77 percentage points indicates that growth forecasts are reliably overly optimistic over time. Even though forecast errors are still negative in contraction periods, they are significantly less negative than in expansion periods (ibid., p. 176). By means of a simple regression model, the authors can prove a significant negative relationship between current performance and forecast errors (ibid., p. 177).[6] Concerning the relationship of current performance with realized growth, they do not just find it statistically significant but also find that realized growth is especially high after contraction periods which aggravates the negative relationship between both factors (ibid., p. 179).

To test the effect of abnormal trading volume, Barber and Odean (2007, pp. 793-794) compute abnormal trading volume as the trading volume of a particular day compared to the mean trading volume over the past 252 trading days, afterwards calculating buy-sell imbalances again for the day with the abnormal trading volumes. Thereby, they test whether the ratios between buys and sells change on days with abnormal trading volume. Results show that buy-sell imbalances increase nearly monotonically with trading volume, showing that with increasing trading volume especially the number of purchase decision compared to selling decision increases (ibid., p. 796-798).

The majority of literature on attention-based trading concentrates on the effect of news events. Barber and Odean (ibid., p. 785) hypothesize that people might at least in parts rely on news events to form investment decisions as attention is a limited resource and investors have limited time to conduct their investments. Consequently, they suppose that attention is especially relevant in buying decision where investors have to pick one out of thousands of stocks, while attention does not play a significant role in selling decisions where the parent population of stocks is only the own portfolio (ibid., p. 786). This is especially true as individual investors hardly sell short. The authors filter news from the Dow Jones News Service for the period from 1994 to 1999 and buy-sell imbalances are again calculated for days where companies appear in the news, noting that this measure can only be a proxy for attention as potentially many news such as press releases might be rather irrelevant (ibid., 795). Still, results show that buy-sell imbalances are higher for the days when a particular stock or company is featured in the news than for days when it is not. This supports their hypothesis that individual

[6] For reasons of clarity, the regression models are not explained here. Details on the formation of the models can be drawn from Barber and Odean, 2007, pp. 107 following.

investors are net-buyers of attention-grabbling stocks. Still, they note that the effect is not as strong as with trading volume or past return patterns (ibid., pp. 800-803).

A further study that incorporates a more concrete measure of investor attention is conducted by Da et al., who measure Google search volume index (SVI) values for stock ticker symbols from January 2004 to June 2008 (2011, pp. 1466-1467). They suppose that SVI values will be mainly influenced by individual investors as professional investors have other research tools such as Bloomberg terminals at their disposal (ibid., p. 1475). The authors find that an increase of 1% in SVI leads to a 0.0925% increase in individual orders for smaller order sizes (100 to 1,999 shares), significant at $p < 0.01$. Similar results can be obtained for turnover measures and for other order sizes (ibid., p. 1479). Interestingly, the authors find that the effect of SVI on order volume in their sample is strongest on the Madoff exchange marketplace (compared to NYSE and Archipelago), which is a market center paying for order flow and generally associated with less sophisticated investor clientele (ibid., pp. 1479-1480).

Barber and Loeffler (1993, p. 273) analyze the effects of monthly analyst recommendations of stocks in the “Dartboard column” in the Wall Street Journal on security prices, return and trading volumes in the days following the publication. Besides four picks by the analysts, the Dartboard column entails four stock picks that are randomly selected by the throw of four darts (ibid., p. 274). The stocks selected by the analysts experience on average a 4.06% abnormal return over the two-day period of publication date and the day afterwards. The dartboard picks in turn do not experience any significant abnormal returns (ibid., p. 276). Over a period of 25 days following the publication, the trend faces a partial reversal. Trading volume for the professional picks is twice as high as average trading volume in the security over the past periods would predict, with this pattern continuing to exist for at least six trading days following publication (ibid., p. 278).

Another study that focuses on analysts’ recommendations and their influence on individual investor behavior was conducted by Kliger and Kudryavtsev. Over a period from 2001 to 2006, the authors record analyst recommendation revisions as well as stock price and trading volume developments (ibid., pp. 53-54). The authors hypothesize that positive (negative) market index returns make individual investors more likely to react to recommendation upgrades (downgrades) (ibid., p. 55).

Furthermore, they suppose that this effect is decreased on days where risk availability is high, i.e., days with high volatility (ibid., p. 60). Results show that abnormal return reactions are significantly stronger when recommendation revisions are accompanied by related market returns. The effect is generally stronger for downgrade revisions (ibid., p. 56). A recommendation revision day is classified as risky when the market return of that day exceeds a half standard deviation of market returns over the sample period. The results of the analysis show that upgrade revisions on days with substantial market movements cause weaker price reactions (ibid., p. 60). The reaction to downgrades is still stronger than to upgrades, however, not as strong as on days with no substantial market movement.

Again, the results of the review of the empirical study will be interpreted and evaluated in chapter 4.3.

3.4 Extrapolating what is familiar

The following chapter focuses on empirical studies about investors who exhibit a behavior of extrapolating past trends into the future and showing particular preference for investment behavior with which they made good experience sometimes in the past. For the sake of transparency, it should be mentioned at this point that the dividing lines between extrapolation behavior and the reactions to attention-grabbling events are rather fluid. Therefore, certain similarities between the results of the studies from chapter 3.3 and 3.4 are observable.

Frieder (2004, p. 5) argues that investors are likely to exhibit an extrapolation bias, which she defines as generalizing from a little number of outcomes on larger future trends in development of stock performance. Thereby, she postulates that investors' belief updating is not Bayesian (ibid., p.6). A dataset with records of EPS forecasts, data on price, return, share volumes and number of trades, and actual EPS announcements is utilized to assess the influence of earnings surprises on investor trading behavior (ibid., pp. 7-8).[7]

Frieder hypothesizes that on average investors will be more likely to suppose that a string of consecutive positive earnings surprises will continue rather than reverse. To test this, the author compares order imbalances for stocks with a string of positive

[7] For a detailed description of how earnings surprises are calculated and how the author controls for other possible influences on investor behavior, please, refer to Frieder, 2004, p. 8; pp. 15-17.

(negative) earnings surprises with order imbalances of stocks with one isolated event of a positive (negative) earnings surprise (ibid., pp. 9-10). Results of the research show that the mean order imbalance change following a string of two positive earnings surprises is significantly higher than the average order imbalance (which is zero by definition). The effect increases with the string length (ibid., p. 18). The direction of the order imbalance shows that investors become net buyers of stocks with a series of positive earnings surprises (ibid.). To test for the effect of attention, Frieder finds that even though companies with only one positive earnings surprise also exhibit a changing order imbalance, effects are significantly stronger after a series of surprises (ibid.).

Furthermore, there are no significant differences in the returns in the following period for both the string and the no-string stocks, indicating that past performance is not necessarily predictive of future stock price developments. The returns in the second period after the earnings surprises are indeed even negatively correlated to the order balances, showing that investors are worse off by their extrapolation behavior (ibid., p. 19). The overall effects are stronger for companies that are smaller in terms of market capitalization and are followed by less analysts (ibid., pp. 31-32). Furthermore, the results show that investors mainly act on positive strings of events, which might very well be explained by the short sell constraint of individual investors (ibid., p. 35).

Huang finds in an empirical study about investor behavior that investors with a history of positive returns in a particular industry show a higher propensity to purchase new stocks in the same industry compared to investors who experienced losses in that industry (2017, p. 3). The author utilizes the same dataset that was employed in several studies of Barber and Odean and calculates returns for specific industries based on the stocks the individual investors own in that industry. When market-adjusted industry returns are positive, this is denoted as a positive experience (ibid., pp. 5-7). To test whether past positive experience increases the likelihood of an investor to buy another stock in the same industry, the author separates the returns experienced in an industry, ordered by market-adjusted returns, into five different groups. For each group, the probability of purchasing a stock in the same, the most similar and the most different industry is calculated, showing that the better the returns are, the higher is the probability of purchasing a new stock in the same or most similar industry (ibid., pp. 9-11). The influence of industry experience in general can be doubted as investors are equally likely to buy stocks in industries that did either particularly well or bad in the past, while they disregard industries with medium performance, which supports the hypothesis of attention-based investing presented earlier (ibid., p. 12). The effect of an increased likelihood to purchase stocks in the same industry disappears after approximately 17 months (ibid., p. 15).

Lastly, Huang computes several hypothetical portfolios for investors that based their purchasing decision on past good experience to control whether this behavior contributes to portfolio performance (ibid., p. 20). Therefore, he creates 1) a portfolio that consists of stocks of the industry the investor had good experience with but entails different stocks than those the investor bought, 2) a portfolio that consists of all industries an investor had good experience in and 3) a portfolio that just consists of stocks in the industry that had the highest return in the previous period regardless of whether the investor was invested here (ibid., p. 21). All three portfolios performed better on average than the actual stock picks of the individual investors. This is supportive of the claim that investors' industry picking ability is indeed good, while, on the other hand, their stock picking ability is poor (ibid., p. 22).

The presented results are interpreted in chapter 4.4.

4 Explanations of counterintuitive investor behavior applying Behavioral Finance theory

4.1 Overconfidence bias

The following sub-chapters aim at applying concepts of Behavioral Finance theory presented in chapters 2.1.3 and 2.2 in order to explain the results of the empirical studies in chapter three. Therefore, every sub-chapter will briefly recap the respective results and subsequently present possible explanations.

Chapter 3.1 established that investors with high turnover rates experience a decrease of net returns in comparison to investors with lower turnover rates. It was visible in several studies that active trading and high turnover is to the detriment of investors, mainly because of transaction costs but also partly because of poor stock picking skill. Therefore, it is of considerable importance to assess why investors trade comparably much, even though they would be better off when pursuing passive investment strategies.

Barber and Odean (2000, pp. 799-801) attribute the high levels of trading at least partly to the overconfidence bias and argue that overconfident traders overestimate the value of their private information which causes them to trade actively. Odean (1998, p. 1280) concludes that investors are not just overconfident about the precision of their information on which they trade but that their returns are so poor that he assumes that investors systematically misinterpret information available to them. Odean's notion is supported by Daniel et al. (1997, pp. 3-4) who argue that private signals are overinterpreted by investors, whereas when more public information becomes available over time, the initial market reactions caused by investors' overreaction are corrected. Still, the authors find overconfidence to be a persistent behavioral pattern of investors because of self-attribution. They argue that overconfidence increases whenever a private signal (e.g., buying a stock) is confirmed by public information (e.g., favorable news stories about the company). Vice versa, however, investors do not adjust their overconfidence when private signals are disconfirmed but are likely to attribute the divergence to external noise (ibid., p. 5). At that, the findings of Daniel et al. also give insights on why people tend to overreact on positive news announcements (cf. chapter 3.3) rather than on bad ones. It becomes visible that heuristics and biases are most probably active in combination rather than separately (ibid., pp. 21-22). This finding is confirmed by Griffin and Tversky (1992, p. 413) who suppose a simultaneous existence of the availability- and representativeness heuristic, and overconfidence. Specifically, people react more on recent information or extrapolate trends and do so more confidently the more information is available (ibid.).

Contrary to Daniel et al., Odean (1998, p. 1904; pp. 1910-1911) is of the opinion that for the increase of trading volume it does not matter whether investors receive private signals or public signals. The driver for increased trading, according to Odean, is either the overvaluing of information from private signals or the difference of opinion when interpreting information in public signals. This notion reflects the several forms of overconfidence presented in psychological studies (cf. chapter 2.2.3). At this point, it should be noted that there is not necessarily an accepted definition of how high "rational" trading volume would be. However, Odean is of the opinion that observed trading patterns, especially to the investors' own detriment, give reason to support the hypothesis that investors are motivated by their belief in the precision of private signals and by their overconfidence in interpreting public information (Odean, 1998, pp. 1910-1911). Harris and Raviv, accordingly, agree that excessive trading volume is mainly generated by differences of opinion regarding the value of the asset being traded and public information about the respective assets (1993, p. 490). De Bondt (1998, p. 834) argues that investors are too confident in assessing the future prospect of a particular stock, which he attributes to the anchoring effect that past prices and the most likely future predictions have. In that sense he agrees with the other researchers as he is of the opinion that investors' interpretations of public information are considering uncertainty about future developments too little, therefore coming to several differing results (ibid.).

Following the notions about the difference of opinion, it is worth considering the interpretation of the presented BTA-effect (cf. chapter 3.1). The better investors considered their abilities, the higher turnover rates they exhibited. The study of Glaser and Weber (2007, p. 31) gives an important insight into overconfidence bias as it indicates that it is the belief to be better than others that drives human behavior rather than the pure measurement of miscalibration often utilized in psychological studies (cf. chapter 3.1 and chapter 2.2.3). This would reflect the higher importance of opinion differences about public information (BTA) relative to the specific value attached to private information (miscalibration) as presented above.

4.2 Prospect Theory and regret aversion

Chapter 3.2 showed that investors are reluctant to realize losses while they are more likely to realize gains. Furthermore, the study of Barber et al. showed that stocks previously sold for a gain are more likely to be repurchased than stocks previously sold for a loss. Both observations are part of the disposition effect introduced earlier and are not predicted by classic economic theory.

Barber et al. (2010, p. 102) develop the hypothesis that a significant part of trading exists because investors want to realize returns emotionally rather than economically. They argue that even though investors are often unable to predict how alternative trades might affect their portfolio returns they are able to realize how a possible trade affects their emotions. The described repurchasing behavior (cf. chapter 3.2) is attributed to a naïve learning mechanism where individual investors aim at repeating actions that have caused emotional pleasure while they seek to avoid actions that have resulted in the opposite (ibid., p. 118). Without transaction costs, maximizing emotional utility could even be welfare increasing. In reality, however, where individual investors are likely to economically loose in trading against institutional investors, following a disposition effect or increasing emotional experience is relatively costly (ibid.). This notion reminds of the findings about regret aversion where researchers already supposed to view the relation between regret-avoiding behavior and utility as a trade-off situation (cf. chapter 2.2.4).

Shefrin and Statman are of the opinion that Kahneman's and Tversky's Prospect Theory already predicts a disposition effect (1985, p. 779). The notion of risk averse behavior in the domain of gains and risk-seeking behavior in the domain of losses is deemed sufficient to drive the disposition effect (ibid.). The authors furthermore refer to the concept of "mental accounting" introduced by Richard Thaler, which indicates that investors evaluate each investment as an individual account.[8] Shefrin and Statman argue that investors encounter severe problems when asked to close a mental account at a loss as they are likely to evaluate each investment separately rather than focusing on their whole portfolio, which could enable a disposition effect (ibid., p. 780). The authors are convinced that regret or regret aversion plays a major role in the reluctance to realize losses or close a mental account at a deficit (ibid., pp. 781-782).

Muermann and Volkman, however, detect a problem in the notion that regret and pride could drive the disposition effect. They raise the question if a regret-anticipating investor would not consider the opportunity that a stock continues rising after his or her selling decision and therefore experience regret also after realizing gains (Muermann and Volkman, 2007, p. 7). Therefore, they develop a model which assumes that investors only observe realized stock return if they hold a stock but not after they decide to sell it (ibid., p. 8). This assumption can be associated with the phenomenon of inaction inertia presented in chapter 2.2.4 where individuals dealt with uncomfortable situations by mainly avoiding them. Similar to Kahneman's and Tversky's assumption of a convex function for gains, Muermann and Volkman assume a convex function of pride which predicts that after an initial increase in value of a stock (and pride of the investor) any subsequent increases in pride will not add enough marginal units of pride to offset the risk which is associated with a value decrease of the investment (ibid., p. 11). This effect is not true for regret as the function is concave for regret, making it nearly choice-optimal to stick to a losing investment as the benefit associated with a

[8] For a more detailed explanation of the characteristics of mental accounting, please, refer to Thaler, Richard: Mental Accounting and Consumer Choice, Marketing Science, Vol. 4 (1985), Issue 3, pp. 199-214

subsequent increase of the investment is higher than the accompanying possibility of a further loss (ibid., p. 12).

Summers and Duxbury (2007, pp. 4-5) attribute the disposition effect also to regret aversion and provide the assumption that active choice is a necessary condition to produce a disposition effect. They support this assumption by means of an experiment in which participants both experience gains and losses of an investment, in one case chosen by them and in the other only inherited by the experimental design. They find that only under the condition of active choice of an investment a disposition effect is visible (ibid., pp. 27-29). The conclusion that active choice produces regret gives an incentive for investors to realize gains early and stick to losing investments longer (ibid., p. 30). Their conclusion goes hand in hand with the findings of Barber et al. indicating that investors realize emotional rather than economic returns.

A considerable difference between the observed disposition effect and classic economic theory is that investors seem to make a difference between paper gains (losses) and realized gains (losses). Barberis and Xiong (2009, pp. 773-774) develop two models of Prospect Theory that utilize different definitions of gains and losses. The complexity of the model reaches beyond the scope of this thesis, but, in short terms, their model predicts a disposition effect under the conditions of Prospect Theory only when gains and losses are defined as realized gains and losses (ibid., p. 777).

In their work on loss aversion, Kahneman and Tversky (1991, p. 1040) assume that the impact of a difference in value is perceived as greater when the difference is deemed a loss than when it is evaluated as a gain. Thereby, they shed light on the importance of reference points (cf. chapter 2.1.3), predicting that the same difference in value can be attributed as a gain or a loss dependent on the reference point (ibid., p. 1047). This assumption is possibly vital for explaining the disposition effect. Kahneman and Tversky focus more on the exchange of commercial or retail goods, still the discrepancy between the lowest price a seller is willing to obtain and the highest price a buyer is willing to pay observed by them in several experiments, might have implications for stock market transactions (cf. ibid., p. 1055). This discrepancy is called the “endowment effect” and concerns the reluctancy to sell things one already possesses (ibid.). Even though the authors rather tend to focus on trades, where the trading parties directly know each other, their finding that when a person is reluctant to sell something he or she already owns, he or she might be even more unlikely to do so when the price for this good is decreasing, could be applicable for the stock market as well (ibid., p. 1056). At least, it might have the potential to add some explanatory strength to the effects of regret aversion and Prospect Theory when aiming to explain the occurrence of the disposition effect.

4.3 Availability heuristic

Chapter 3.3 established that investors are most likely to be net buyers of attention-grabbling stocks, potentially even irrespective of the attention's underlying reasons. Furthermore, it became visible that high levels of attention create short-term buying pressures and price increases which are reversed after short time periods.

These findings contrast classic theory in which buying and selling are just opposite sides of the same coin and where investors should be equally likely to buy or sell securities with positive or negative external signals (Barber and Odean, 2007, p. 786). Therefore, it stands to reason that attention is a main indicator when many alternatives are present and preferences play a role only after a pre-choice was made because of attention (ibid., pp. 812-813).

When reviewing the study about Google search volume indices of stocks, the effects on prices show that recency of attention is a critical aspect for describing individual investor behavior (Da et al., 2011, 1497). The results of Da et al. confirm Barber's and Odean's hypothesis that investors are net buyers of attention-grabbling stocks and prove the existence of attention-induced price pressures (ibid.). The reversal of this attention-induced price pressure gives reason to believe that investors are often acting too late on information that draw their attention and that these information do not incorporate substantial value that would justify a long-term price change (Frieder, 2004, p. 35). Interestingly, Campbell et al. (2014, p. 39) find evidence that investors act on feedback of their trading activity, causing them to replicate trading behavior that has proven to be successful in the past. Earlier successful participation in buying pressure cascades might therefore cause investors to repeatedly participate in active buying of attention-grabbling stocks (ibid.).

It must be questioned whether the observed investor behavior can be attributed to the availability heuristic. Information that catch investors' attention are probably more available to them, however, whether they remind them of past (successful) scenarios or cause them to simulate a future successful investing scenario can only be speculated upon.

Chapter 3.3 furthermore found that analyst recommendations are tendentially more positive when the economy is expanding. It was also shown that analysts' recommendation reversals have stronger effects when the direction of the reversal Is accompanied by an according market movement. These effects on investor trading behavior were mitigated whenever risk in form of market volatility was comparably high. Barber and Loeffler (1993, p. 277), like Odean and Barber, attribute the observed reactions to analyst recommendations to price pressure. However, the interpretation of Lee et al. (2008, p. 183) draws attention on the availability heuristic. Their finding that recommendations are tendentially more optimistic when the economy is an expansion period indicates that analysts are subject to the availability heuristic (ibid.). In an expansion period, positive scenarios of stock price developments are just more available to them. Furthermore, the authors find a consistency in the relationship between analysts' forecasts or recommendations and actual investments, showing that also individual investors might project the overall economic development on their specific investments (ibid.).

Accordingly, Kliger and Kudryavtsev (2010, p. 60) find that their results support the availability heuristic because recommendation upgrades induce more investor reactions when they are accompanied by an upward market movement. The strength of the effect has a negative correlation with market capitalization of the underlying company, possibly because for smaller companies less information is available to investors, causing them to mainly rely on analysts' recommendations (ibid., pp. 55-56). Also, the finding that the reactions to recommendation reversals are weaker on days with substantial market movements support the availability hypothesis as it possibly causes investors to think about the riskiness of volatile markets (ibid., p. 63).

In various real-world economic interactions, the influence of the availability heuristic on human decision-making has already been observed. For instance, people exhibit a temporary reluctance to travel with airplanes after an event of a crash that was prominently featured in media (Chiodo et al., 2003, p. 12). These are cases, in which people's economic choices are influenced by the availability of accompanying information that have no or only little statistical influence on the choice outcome (ibid.). In that sense, an intraday upward market movement is not predictive of the possible prospects of a particular security, still, it seems to influence the investors' decision to buy that security.

4.4 Representativeness heuristic

Chapter 3.4 showed that investors are net buyers of stocks with a string of positive earnings surprises and that they believe in the extrapolation of past trends. This confirms results from cognitive psychology experiments, presented in chapter 2.2.1, which showed that one aspect of the representativeness heuristic is the people's belief that small sample sizes possess the same characteristics as the parent population they are drawn from.

Frieder (2004, p. 19) concludes that the increased buying of stocks with a string of positive earnings surprises cannot be deemed rational behavior as subsequent returns on these stocks are not different from stocks with isolated earnings surprises. Furthermore, the author notes that other informational aspects besides the earnings surprises, which might for instance be correlated with extensive news report due to the good performance, potentially motivate buying behavior (ibid., pp. 20-21).

The behavior observed by Frieder is often referred to as "overreaction" in other research. De Bondt and Thaler (1985, p. 795) suppose that overreaction is predictive of future stock price movements as substantial increases in prices after good news because of investors' overreaction will be reversed in following periods. The authors state that this occurs mainly because investors do not utilize the Bayes rule to adequately judge the importance of recent events for future results (ibid., p. 804).

Barberis et al. (1998, p. 313) define overreaction as the phenomenon characterized by average returns of stocks with a series of good news announcements being lower than average returns for stocks with a series of bad news announcements. The authors' findings go hand in hand with Frieder's observations. They find that investors can simultaneously under- and overreact (ibid., p. 308). When focusing on short time horizons such as one isolated earnings surprise, the belief in a reverse or relativization is higher and therefore buying pressure is comparably smaller, while when presented with subsequent earnings surprises, investors seem to believe in a pattern rather than in a reversal of the trend (ibid.). Barberis et al. are of the opinion that the observed investor behavior contradicts classic theory, as patterns in earnings growth are most likely to be nothing but a matter of randomness (ibid., p. 316). Concretely, the investors' behavior dissents with the random walk distribution of earnings or stock prices which is assumed by classic theory (ibid., pp. 318-319).

The simultaneous existence of under- and overreaction touches upon central aspects of representativeness heuristic: base rate underweighting and the gambler's fallacy (cf. chapter 2.2.1). Investors who underweight base rates conduct subsequent extrapolation of events, while investors who are subject to the gambler's fallacy believe in the mean reversion and expect fairness in random probability distributions (Shefrin and Statman, 1994, p. 332). Therefore, investors can become net buyers of stocks with a string of positive earnings surprises while they do not react to a single positive earnings surprise because they believe in the mean reversion.

Chapter 3.4 furthermore showed that investors are more likely to invest in new stocks in an industry they previously made good experience with rather than in industries where they owned stocks that decreased in value.

Huang (2017, p. 18) proposes that investors attribute higher importance to their experienced outcomes than to other available historical information about returns or companies' financial statements. Their posterior belief updating about a stock's chance of an increase in value is not Bayesian but mostly based on its representativeness to their latest own experience (ibid.). Huang, furthermore, finds that when measuring the similarity of the new stocks purchased to the old stocks and to the whole industry based on return distributions, investors are more likely to invest in the new stock, the more similar the return distribution is to their old investment (ibid., pp. 23-24). This could indicate that the industry is an important first filter based on representativeness but that the similarity between stocks is even more decisive. Concludingly, Huang's findings indicate that investors predict stocks' upward potential based on how representative it is to their last successful investments.

5 Conclusion

5.1 Summary

Individual investors seem to follow trading patterns that contradict the behavior predicted by the various postulates of what this thesis refers to as "classic theory". It should be mentioned that classic theory is also not a homogenous mass of models that all come to the same results about investor behavior. There are a lot of models that assume agents' behavior to be rational but exhibit various differences when predicting for instance asset prices or return patterns.

Therefore, it is more helpful to focus on the rationality assumption. There are behavioral patterns presented in this thesis that would need to be deemed "irrational" if EUT or the Bayes Theorem were taken for granted. However, as some of the Behavioral Finance researchers already indicated, with so many investors exhibiting these behavioral patterns it is questionable whether the category "irrational" is adequate.

A major aspect of concern presented in this thesis is information and how people process it. The studies presented give reason to believe that people are likely to overreact to rather meaningless information. Thereby, it can be divided between the heuristics or biases that influence the way people receive and process information and the ones that influence their decision making. It is important to notice that these processes of mental shortcuts most probably do not occur isolated. An information can be processed according to the availability heuristic and the following decision can be made based on the individual's overconfidence. Heuristics and biases influence individuals but also each other.

The understanding of heuristics and biases can potentially help to become a better investor. If an investor knows that he or she overreacts to news, trying to refrain from reports with catchy headlines might help him or her to decide more neutral and from a less emotional standpoint.

Overall, heuristics and biases seem to shape investor behavior in a way that contradicts with classic theory. Individuals are not perfectly rational economic agents; they try to make decisions that not necessarily earn the maximal economic return but give them the best feeling and minimize their regret afterwards. In that sense, EUT displays a good starting point to describe human behavior, however, it might be worth to consider revisiting the definition of utility to account for emotional aspects such as regret. Probabilities are assessed more subjectively than classic theory predicts. Therefore, predictions are based more on information that are statistically meaningless but catch the attention because they are "representative" of investors' beliefs about good investment opportunities or because they are just more noticeable than underlying prior information.

5.2 Critical acclaim

As already mentioned, heuristics and biases do not exist in an isolated form. They influence human decision making to different extents and it is often difficult to judge which of the various heuristics and biases drives a decision. Therefore, the thesis has some solid arguments to conclude that heuristics and biases influence private investor behavior. However, it cannot specify a degree of how strong the influence is in a particular instance or define exact situations in which heuristics and biases play a role. The experiments in cognitive psychology by Kahneman, Tversky and others have shown that heuristics and biases are principally systematic but that not every individual is influenced by them in the same way.

The investigation of the influence of heuristics and biases on private investor behavior is of a descriptive character. Therefore, the results of this thesis most likely would not seem sufficient for advocates of the normative nature of classical theory. Whether this is a detriment to the findings presented in this thesis shall remain subject to future scientific discussion. There are arguments for and against both descriptive and normative models of economic behavior. Certainly, the results of this thesis and its underlying research do not allow for valid predictions of market behavior or future returns.

Still, the author of this thesis is of the opinion that descriptive models of economic behavior are an important factor in economic theory. They are means to aid classic research wherever its normative models have shortcomings or contradict with empirical findings.

5.3 Outlook

Behavioral Finance brings economic sciences again more in a position of a social science discipline. Thereby, it contradicts the approach of classic theory and its models since the midst of the 20th century where researchers in economics aimed to discover regularities along the lines of the laws of physics. The author of this thesis believes in the strength of economics as a social science, which focuses on its acting agents and makes more realistic assumptions about their behavior. This is not only helpful to better understand the market behavior of investors but can furthermore find application in politics and other areas of economic life. Human decision making is subject to certain errors or biases. Understanding these is critical to be able to judge where they should perhaps be corrected and where it is better to not do that. This approach, often referred to as "nudging," is one of the younger disciplines in Behavioral Finance. It promises to be a fruitful field of research for the future, through various successful models of application, such as in tax collection in the UK or in reducing electricity consumption in the US.

There are also many research fields around financial markets theory, which have so far been played almost exclusively by classic theory. It should be a goal of future research in Behavioral Finance to test existing assumptions and to complement classic theory in places where its models are proven to have flaws by empirical studies. The role of Behavioral Finance in the future could thus amount to a kind of empirical control authority, which, however, can also repeatedly provide incentives through its observations of human behavior on markets to develop new models and critically question the current state of research.

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V. Declaration of originality

I hereby declare that this bachelor’s thesis and the work reported herein was composed by and originated entirely from me. Information derived from published and unpublished work of others has been acknowledged in the text and references are given in the list of references

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VI. Declaration of consent

I do hereby agree that my bachelor's thesis will be included in the department's library. Third party rights will not be violated.

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