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The Influence of Expectations, Risk Attitudes, and Behavioral Biases on Investment Decisions

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Chapter 1

General Introduction

1.1 Motivation

Due to demographic changes social pension funds will be facing financing problems in the future and therefore, individuals are increasingly asked to take care of additional private retirement provisions by their own. In Germany, the legislator introduced various regulations and laws in the last few years in order to incentivize and increase amounts allocated to private retirement provisions with the help of governmentally subsidized pension plans such as *Riester Rente* or *Rürup-Rente*. Beyond the issue how much to save or invest for retirement the main issue investors have to deal with is asset allocation, i.e. how to divide savings or wealth in risky and risk free assets. The main focus of this thesis is to shed light on various important aspects of the asset allocation problem.

Economic research as well as evidence from the banking and finance industry indicates that individuals have problems dealing with these complex asset allocation tasks.

First, many subjects lack knowledge about financial markets in general and about the variety of financial products. This absence of sound financial literacy makes it hard for them to choose an ideal asset allocation. Second, many individuals suppress the retirement savings problem as they do not want to deal with these important decisions and postpone them again and again. Third, individuals err in their judgment of financial prod-

ucts and are prone to behavioral biases. For example, individuals are overconfident and overestimate their own abilities (for various facets of overconfidence see Langer (1975), Lichtenstein et al. (1982), Alpert and Raiffa (1982), and Russo and Schoemaker (1992)), they are prone to the hindsight bias and fail to remember how ignorant they were initially as "they knew it all along" (see Fischhoff (1975)) or they misinterpret the law of large numbers (Samuelson (1963)). As a result observed decision making in financial markets does not always appear to be consistent with rational behavior. Private investors tend to trade too much (see Odean (1999) and Barber and Odean (2000)), hold stocks of only a few companies in their portfolio (see Glaser (2003)), tend to prefer domestic stocks (see Lewis (1999) and Kilka and Weber (2000)) or apply naïve diversification strategies (Benartzi and Thaler (2001)). Oftentimes, these deviations from rational behavior are costly for private investors implying a reduction in net-wealth at the retirement age.

To know how to correct for behavioral biases that harm private investors' portfolio performance one needs to obtain a better understanding of the underlying mechanisms of these biases. How exactly and why do behavioral biases affect investors' decision making are two important questions which will be addressed in this thesis.

Governments and financial regulators have also recognized that these problems are highly relevant for individuals. Various regulations such as the Markets in Financial Instruments Directive (MiFID, 2004 and 2006) instruct financial institutions to assist customers as good as possible in these asset allocation tasks. More precisely, MiFID requires financial institutions to elicit information regarding the investment horizon, the holding period, and the client's risk profile.

In order to contribute to an enhanced understanding of how individuals reach asset allocation decisions, we us an inter-disciplinary approach to connect insights and knowledge from three fields of research: finance, economics, and psychology. Analyzing the asset allocation problem in more depth, this thesis provides new evidence on the influence of expectations, risk attitudes, and behavioral biases on investment decisions. Note that this thesis does not explicitly analyze the role of financial intermediaries in household finance (for an overview on this issue see Bluethgen et al. (2008)).

1.2 Normative Theory vs. Behavioral Finance

Risky decisions are ever present in finance. All financial investments be it the singular investment of 10,000 Euro or the decision for a pension plan involve decisions about risky prospects. Thus, risk plays a pervasive role when subjects need to evaluate financial investments or prospects. Until the 18th century the maximization of the expected value of a prospect or an investment was assumed to be the only rational decision rule. More formally, if p_i denotes the probability of an outcome x_i of a random variable X then according to the expected value maximization principle a subject should maximize the expected value of a prospect as follows:

$$EV(X) = \sum_{i=1}^{n} p_i \cdot x_i. \tag{1.1}$$

However, using the St. Petersburg paradox Bernoulli argues that most individuals are not willing to pay an infinite amount of money for prospects with infinite expected monetary value. He interprets this observation as evidence against the maximization of the expected value by subjects. Introducing the idea of subjects who maximize their expected utility and not the expected value, Bernoulli (1738 and 1954) solves the Paradox. The main feature of his expected utility framework is a diminishing marginal utility of wealth. Extending Bernoulli's work, von Neumann and Morgenstern (1947) provide an axiomatic foundation of normative decision behavior. The advantage of their approach is that they form a set of axioms how an expected utility maximizer should act instead of simply making loose assumptions. According to these axioms subjects maximize the expected utility $E[u(X)]$ of their individual utility u(X) as follows:

$$E[u(X)] = \sum_{i=1}^{n} p_i \cdot u(x_i). \tag{1.2}$$

In this setup a subject prefers lottery X to lottery Y $(X \succ Y)$ if and only if $E[u(X)] > E[u(Y)]$. Thus, differences in risky choice between two subjects need to arise because of differences in the specific shape of the utility function u(.) of each subject. Under expected utility theory risk aversion is equivalent to a concave utility function whereas

risk proneness corresponds to a convex utility function. Straightforward, a subject with a linear utility function is a risk neutral expected value maximizer.

Just a few years later Markowitz (1952) introduced a somewhat different approach of solving the St. Petersburg paradox in the context of financial economics. In Markowitz's framework a subject's preference or willingness to pay for a risky investment reflects a trade-off between the investment's expected return, which he calls a desirable thing, and its expected risk which he terms an undesirable thing. More formally a subject's preference for a risky prospect X is given by the following equation:

$$Preference\ (X) = Expected\ Return\ (X) - Risk\ Attitude \cdot Expected\ Variance\ (X).$$
$$(1.3)$$

Building on the premises of the risk-return trade-off and on the two-fund separation result (Tobin (1958), Treynor (1962), Sharpe (1964), Lintner (1965) and Mossin (1966) independently developed a single period financial market equilibrium model subsequently known as the Capital Asset Pricing Model (CAPM). This model argues that investors should invest into a mix of a risk free asset and the market portfolio and that the individual risk attitude determines the exact combination between these two investments. The CAPM is consistent with expected utility maximization for investors with quadratic utility functions or assets with normally distributed returns. Sarin and Weber (1993b), Albrecht et al. (1998), Jia et al. (1999) and Butler et al. (2005) show that it is possible to obtain consistency of risk-value models and expected utility preferences with a broader range of utility functions if the assumption that risk has to be equated by the variance of an asset is relaxed.

Both expected utility theory and traditional risk-return models have in common that differences in risky choices are based on differences in one single parameter, the individual risk attitude. In a normative framework risk attitude is simply a descriptive label for the shape of the utility function. If the utility function is twice differentiable, an investor's absolute level of risk aversion is traditionally measured by the absolute Arrow-Pratt coefficient: ARA(x) $= \frac{-u''(x)}{u'(x)}$ (see Pratt (1964) and Arrow (1965)). Another prominent measure

of risk aversion is the relative Arrow-Pratt coefficient of risk aversion RRA(x)= $\frac{-u''(x)}{u'(x)} \cdot x$.
Two examples for commonly used utility functions in financial economics are exponential
functions (e.g. $u(x) = \alpha + \beta \cdot e^{-cx}$) and power utility functions (e.g. $u(x) = \frac{x^{(1-\alpha)}}{1-\alpha}$). Ex-
ponential functions are characterized by constant absolute risk aversion (CARA) which
implies that the willingness to pay for a risky prospect or to insure against risks is not
affected by initial wealth. Moreover, power utility functions have the property of constant
relative risk aversion (CRRA). CRRA has the appealing intuition that investors always
distribute their wealth identically between a risky and a risk free asset, independently of
the amount to be invested.

Although risk attitudes are technically only parameters of a utility function in these con-
texts, they are often assumed to be stable personality traits (see Weber (1997)). However,
evidence in the literature suggests that this has not to be true. First, Slovic (1964 and
1972) shows that different assessment methods do not have to generate the same results.
Second, Weber et al. (2002), Johnson et al. (2004) and Hanoch et al. (2006) find evidence
for domain specific risk taking behavior as subjects do not take the same degree of risk in
different decision domains such as recreational, financial, or safety decisions. Third, based
on propositions in Kahneman and Tversky (1979) subjects seem to exhibit risk averse
behavior with respect to gains and risk seeking behavior with respect to losses. Fourth,
analyzing repeated decision making Samuelson (1963) finds that subjects' preference for
some lotteries depends on whether they are played repeatedly or not. These findings are a
first hint that risk attitudes are no stable personality trait and that there is no generally
accepted measure for a subject's attitude towards risks. This is because differences in risk
taking do not have to arise due to differences in risk attitudes but could arise due to
differences in other factors (for an overview on this issue see Weber and Johnson (2009)).

Behavioral extensions of risk-value models try to incorporate these findings by arguing
that two subjects interpret or perceive the risk of a prospect differently depending on both
personal and situational characteristics (see e.g. Sarin and Weber (1993b)). In these mod-
els risk taking behavior can be influenced by three different variables: subjective return
expectations, individual risk attitudes, and subjective risk perceptions. More formally, in

line with equation 1.3 the risk taking behavior or preference for an alternative can be decomposed as follows:

$$Preference\ (X) = Expected\ Return\ (X) - Risk\ Attitude \cdot Perceived\ Risk\ (X). \quad (1.4)$$

In contrast to traditional risk-return models in which expectations are homogenous and only risk attitudes differ between two subjects these more general models that have their roots in psychology are better able to explain seemingly puzzling findings on the non existent stability of risk taking behavior. The more general decomposition of risk taking behavior can explain differences in observed risk taking behavior between situations or over time as a consequence of different return expectations, different risk attitudes, and/or different risk perceptions. Experimental evidence in the behavioral literature suggests that there are significant differences in the level of risk perceptions and return expectations that might explain inconsistent risk taking behavior (see e.g. Weber and Bottom (1989), Weber and Milliman (1997), and Mellers et al. (1997)). Interestingly, a first glance at changes in risk attitudes across domains or over time in these studies seems to indicate that risk attitudes are not consistent. However, controlling for differences in risk perceptions across situations or over time all these studies show that the so called perceived risk attitude is a fairly stable construct.

Another behavioral approach addressing differences in risk taking behavior is Kahneman's and Tversky's prospect theory (see Kahneman and Tversky (1979) for the original idea of prospect theory and Tversky and Kahneman (1992) for an extension to cumulative prospect theory which solves the problem that stochastically dominated alternatives might be preferred). Prospect theory is a descriptive theory of choice that tries to explain how people make choices involving risk. The three main differences between prospect theory and expected utility theory are the following: first, within an editing phase subjects try to simplify their choice set. Second, instead of optimizing final overall wealth subjects maximize gains and losses relative to a reference point. Third, differences in the subjective evaluation of probabilities are captured by a probability weighting function which is typically said to overweight small probabilities and to underweight moderate and large

probabilities. Assuming risk averse behavior in the gain domain and risk seeking behavior in the loss domain Kahneman and Tversky adopt a value function that is concave in the gain domain and convex in the loss domain. Finally, assuming loss aversion, i.e. subjects value a loss of $100 more than a gain of $200, they propose a prospect value function with the following form:
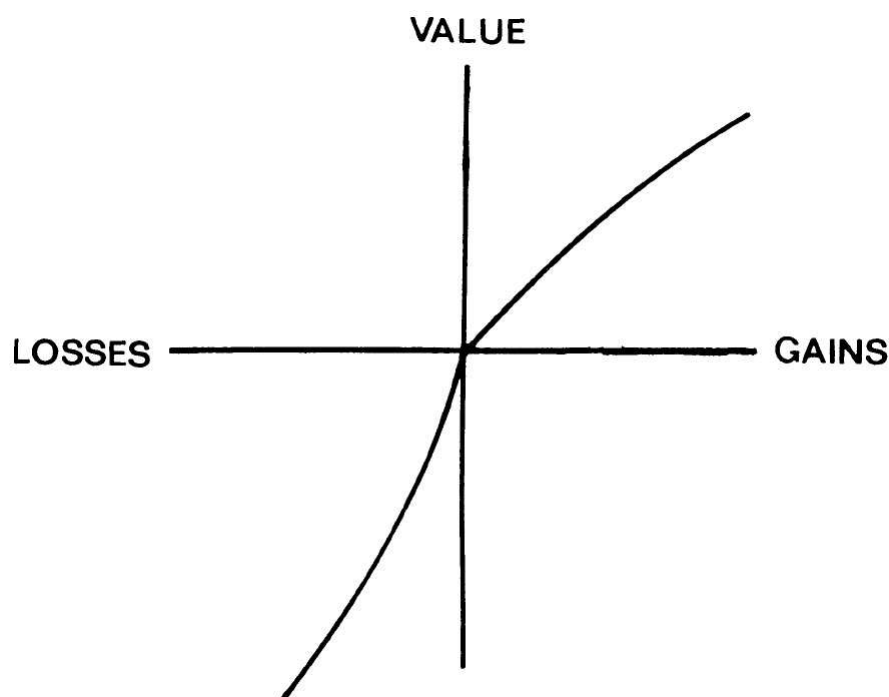
Figure 1.1: A hypothetical value function
(see Kahneman and Tversky, 1979)

In contrast to normative theories which prescribe how rational subjects should behave, descriptive theories simply try to explain how real subjects actually behave. Using insights from psychology and sociology, behavioral finance extends and modifies these normative approaches in a financial context.

1.3 Overview on Important Aspects of Risky Choice

1.3.1 Determinants of Risk Taking Behavior

As outlined in the previous section, various normative and descriptive theories of choice come to different conclusions which factors actually influence investors' risk taking behav-

ior. However, experimental and empirical evidence on determinants of risky choice is not abound. Whereas expected utility theory suggests that differences in risk taking behavior are only due to varying risk attitudes, more general risk-value models argue that the three factors subjective risk perceptions, risk attitude, and subjective return expectations can influence risky choices. Most evidence in the experimental psychological literature seems to provide evidence for the usefulness of these more general risk-value models such as the ones in Sarin and Weber (1993b), Bell (1995) and Butler et al. (2005).

Analyzing cross-cultural differences in choices for lotteries between subjects from the US, China, Germany, and Poland, Weber and Hsee (1998) detect substantial differences in risk taking behavior. However, they find remarkably high similarities in attitudes towards perceived risk indicating that differences in risky choices are mainly due to varying risk perceptions between respective countries and not due to differing risk attitudes. Moreover, Weber et al. (2005) show experimentally that the presentation format affects the risk taking behavior of subjects. Analyzing the effect of different presentation formats such as bar charts or density functions, they find that risk taking behavior can be biased in systematic ways depending on the way information about an asset is presented. More specifically, they illustrate that differences in subjective risk perceptions and subjective return expectations affect the risk taking behavior.

Similarly, Weber et al. (2002), Johnson et al. (2004), and Hanoch et al. (2006) show that subjects take different levels of risk depending on the domain they have to make the decision; i.e. subjects who engage in high recreational risk (sports & leisure domain) do not need to be derivatives traders (financial domain). The results of all studies suggest that risk taking is highly domain specific and that conventional risk attitudes that can be inferred from the shape of the utility function or from the actual behavior are no stable personality trait. Moreover, these studies suggest that risk taking within a broad domain tends to be fairly stable. However, it remains ambiguous how far-reaching these results are and what really constitutes a domain. Thus, it is still an open question whether risk attitudes that are inferred from lottery decisions should be used to predict investment behavior in a financial investment context.

Another interesting point concerning risk taking behavior of individual investors is that it seems to vary quite substantially over time. Staw (1976) finds evidence for greater risk taking after losses and less risk taking after gains and terms this finding "escalation of commitment". One of two major explanations for observing this effect is the shape of the value function in the gain and loss domain, respectively. The second explanation for an "escalation of commitment" effect in the loss domain is based on the self-justification hypothesis which argues that subjects stick to their actions as they do not want to admit that their past decisions were incorrect. Contrary to the findings on the "escalation of commitment" effect, Thaler and Johnson (1990) find that in some situations subjects take more risks following a gain and less risks after a loss and term this a "house money effect". Weber and Zuchel (2005) unify these apparently contradictory strands in the literature by providing evidence for the "house money effect" if decisions are framed as lotteries and evidence for "escalation of commitment" if decisions are framed as portfolio choices.

According to more general risk-value models changes in risk taking behavior over time could be triggered by changes in subjective risk perceptions, individual risk attitudes and/or subjective return expectations. The evidence in the literature indicates that risk attitudes seem to be fairly stable constructs if one accounts for changes in beliefs. Using large scale panel survey data Sahm (2007) (Michigan Health and Retirement Survey - HRS) and Klos (2008) (Socio-Economic-Panel - SOEP) provide first evidence for relatively high levels of stability over time. Moreover, studies analyzing the stability of risk attitudes in field experiments (see Andersen et al. (2008)) or in laboratory experiments (see Harrison et al. (2005) and Baucells and Villasis (2009)) tend to find the same result. All studies illustrate that the relation over time is not perfectly consistent. However, Sahm (2007) and Baucells and Villasis (2009) argue that observed deviations of risk attitudes from one period to the other can mostly be attributed to noise or errors and that risk attitudes tend to be perfectly stable if one accounts for these errors.

Thus, if risk attitudes tend to be fairly stable, then observable differences in risk taking are most probably due to changes in return expectations and/or changes in risk perceptions. Studies analyzing the dynamics of risk perceptions or return expectations find first

indications for these propositions. On the one hand, Weber and Milliman (1997) and Mellers et al. (1997) show that risk perceptions vary over time but that perceived risk attitudes remain highly stable. On the other hand, Shiller et al. (1996), Vissing-Jorgensen (2003) and Dominitz and Manski (2005) illustrate that return expectations also vary substantially over time. However, these studies do not analyze the economic consequences of changes in beliefs and do not relate changes in expectations to changes in risk taking behavior. Moreover, these studies cannot analyze whether changes in beliefs are due to past investment failure or success.

The presented evidence indicates that risk taking behavior is no stable trait but influenced by various factors such as the context of a decision or prior gains and losses. This implies that traditional risk attitudes as inferred from risky choices are no stable personality trait but influenced by various situational factors. However, perceived risk attitudes, i.e. risk attitudes that factor out situational differences seem to be more consistent across domains than conventional risk attitudes. Sarin and Weber (1993, p. 148) already argue in their overview of risk-value models that "except for some simple models, e.g. mean-variance, there is little empirical evidence on the predictive ability of risk-value models." Therefore, further research is needed to shed light on the determinants of risky choice in financial decisions in more detail.

1.3.2   The Effect of Behavioral Biases on the Processing of New Information and Risk Taking Behavior

Theoretical behavioral models show that various individual biases affect information processing and subsequently impact risk taking behavior as well. Some psychological biases that are often used in these models are overconfidence (see for various facets of overconfidence Langer (1975), Lichtenstein et al. (1982), Alpert and Raiffa (1982), and Russo and Schoemaker (1992)), hindsight bias (see Fischhoff (1975)), representativeness (see Kahneman and Tversky (1973)) or disposition effect (see Shefrin and Statman (1985)).

Many behavioral finance models motivate irrational investment behavior using overconfident investors. In these models all subjects receive private information and overconfident

investors are too sure that the received signal is correct and hence, put too much weight on it (see e.g. Kyle and Wang (1997), Benos (1998), Odean (1998b), Wang (1998), Daniel et al. (1998 and 2001), Fischer and Verrecchia (1999), Hirshleifer and Luo (2001), and Caballé and Sákovics (2003)). This results in a wrong assessment of means, i.e. individual misreaction to the signal and subsequently affects trading behavior as overconfident subjects trade more aggressively and diversify more poorly.

In addition to overconfidence, Biais and Weber (2007 and 2009) develop a theoretical model in which they study the consequences of the hindsight bias for investment and trading decisions. They show that hindsight biased agents are not able to remember their prior expectations correctly after observing a new signal and never seem to be surprised by new information, as "they knew it all along" (see e.g. Fischhoff (1975) and Camerer et al. (1989)). This results in hindsight biased agents underestimating the volatility of risky assets and overweighing the informational content of a signal and thus, overreacting to this signal. In addition, they illustrate that subjects who overreact more heavily due to the hindsight bias will invest in less efficient portfolios. Further behavioral biases that are modeled in theoretical studies are e.g. the disposition effect (see Grinblatt and Han (2005)) or the representativeness heuristic (see Barberis et al. (1998) and Sorescu and Subrahmanyam (2006)).

Regardless of the modeling approach all these studies show that behavioral biases result in enhanced trading volume, lower portfolio performance or more risky investment decisions. However, as we have seen in the previously presented models the link from a psychological bias to real economic consequences is a chain of various events. In most studies a bias leads subjects to misjudge the informational content of a signal. This results in a misreaction to the new signal which in turn can have various direct or indirect economic consequences. Figure 1.2 illustrates the chain of events in these models graphically.

However, empirical evidence on the relationship between psychological biases and economic variables is scarce as it is hard to relate underlying and unobservable personal attributes to economic decisions. Therefore, most empirical studies rely on crude prox-
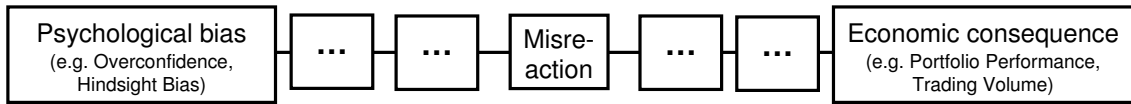
Figure 1.2: Relation of psychological biases and economic variables

ies for psychological biases such as gender, age or experience. Barber and Odean (2001) use the gender of subjects to proxy for overconfidence and show that more overconfident subjects, i.e. males, trade substantially more. In a similar vein, Barber and Odean (2002) analyze the trading behavior of subjects who switched from phone-based trading to online trading empirically. They argue that investors who had a good past performance attribute this good performance to their own abilities, grow more overconfident over time and switch to online trading. However, overconfidence leads subjects to trade more actively which in the end results in a subpar performance. Goetzmann and Kumar (2008) illustrate that under-diversification is correlated with investment decisions that are in line with overconfidence. They proxy for overconfidence using a subject's trading volume.

An obvious disadvantage of all purely empirical studies is their use of crude proxies for behavioral biases. Trying to improve this by combining survey responses with actual trading behavior of investors Dorn and Huberman (2005) show that those who think they know more about finance than the average investor churn their portfolios more often. Similarly Glaser and Weber (2007) find a relation between overconfidence and trading volume of real online broker customers. However, they show that only subjects who think they are better than the average trade more, whereas they cannot find a relationship between miscalibration and trading volume. Both studies elicit individual measures of overconfidence using responses to a questionnaire. Moreover, Fenton-O'Creevy et al. (2003) measure overconfidence of real traders in British investment banks or more precisely their illusion of control score within a laboratory experiment. Relating this illusion of control score to trading performance of traders the authors show that more illusion of control results in lower performance. Using a purely experimental approach, Biais et al. (2005) measure miscalibration of students in a questionnaire and subsequently let these students participate in an experimental trading market. Their results indicate a significantly negative relationship between miscalibration and trading performance.

However, previous empirical and experimental studies still treat the chain of events that is modeled in theoretical studies as some sort of black box. A noteable exception is the study by Biais and Weber (2009) who analyze the relationship between hindsight bias and risk perceptions as well as investment performance in a class experiment with students and in an experiment with investment bankers. First, they show that hindsight bias reduces volatility estimates. Second, they illustrate that more hindsight biased agents have lower performance. Extending their approach and shedding more light on the chain of events seems to be a promising road for future research. In particular, it seems interesting to analyze whether behavioral biases lead subjects to over- or underreact to new information and to relate this misreaction to an intuitive and direct economic measure of performance. As already pointed out by Biais et al. (2005, p. 308) "it could be interesting in future work to study when, why, and how particular forms of overconfidence (and other behavioral biases) will influence economic behavior".

Even though most researchers agree on the existence of psychological biases at an individual level and on their impact on individual risky decisions there is a fierce dispute if these behavioral biases affect outcomes in financial markets. Proponents of rationality often argue that in actual markets:

- agents have enough financial incentive and experience to avoid mistakes

- only a small number of rational agents are needed to make market outcomes rational

- agents who are less rational may learn implicitly from the actions of more rational agents

- agents who are less rational may be driven from the market by bankruptcy, either by natural forces or at the hands of more rational competitors

For an interesting discussion of these points, see Camerer (1987 and 1992).

Previous findings in the experimental literature show that individual biases do persist in market settings and do not vanish totally. Some studies find evidence for a lower bias in a market setting (see e.g. Camerer et al. (1989), Ganguly et al. (2000) or Sonnemann et al. (2008)), whereas other studies find evidence for even more pronounced degrees of bias in

market settings (see e.g. Gillette et al. (1999) or Seybert and Bloomfield (2009)). If a bias is lowered or even elevated in a market setting depends amongst others on the specific bias at hand and on the experimental approach of the study. Thus, if studies analyze the chain of events from a psychological bias to economic consequences in more depth using a novel experimental approach on an individual level, then it is not clear to what degree this bias will persist in a market setting. Hence, a further promising approach is to analyze these novel experimental approaches not only on an individual level but also in a real market environment.

1.4   Outline of the Thesis and Main Results

In order to contribute to a better understanding of individual and aggregate decision making under risk this thesis addresses the following research questions:

1. What are the main determinants of risky choice? Should financial institutions use lottery questions to elicit risk attitudes in a financial context? (Chapter 2)

2. Are risk attitudes and expectations stable over time? What drives changes in risk taking behavior? (Chapter 3)

3. Is overconfidence related to overreaction to new information? Do overreacting subjects invest in less efficient portfolios? (Chapter 4)

4. Is overreaction to new information present in a market setting where subjects receive feedback and can learn over time? (Chapter 5)

Thus, the main goal of this thesis is to analyze the influence of risk attitudes, expectations, and biases on decision making under risk. Figure 1.3 illustrates how the respective chapters of this thesis are related. The remainder of the general introduction will shortly summarize each chapter.

Chapter 2 of this thesis (joint work with Martin Weber) analyzes determinants of investors' risk taking behavior as well as the question how financial institutions should elicit their
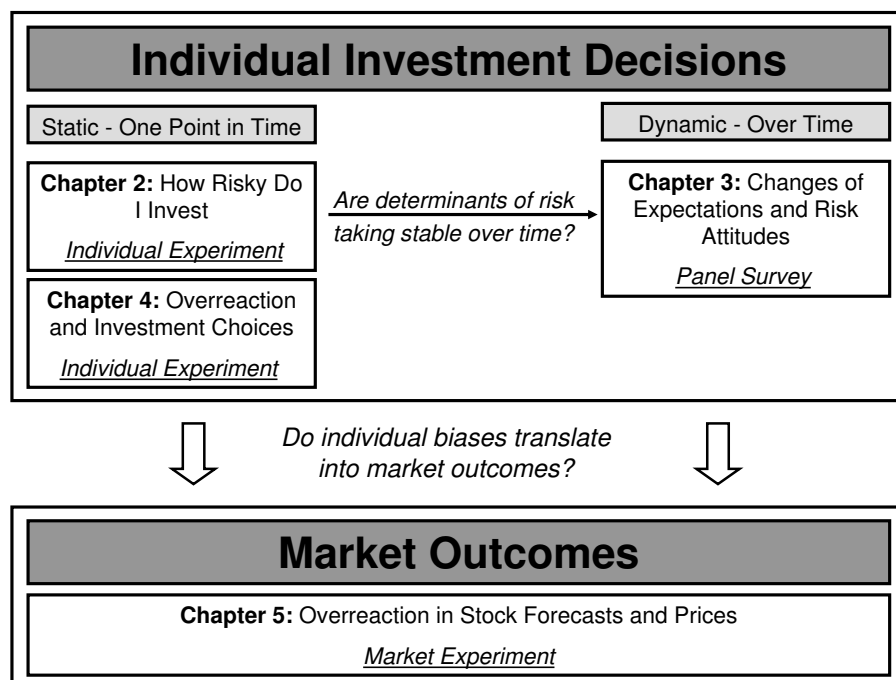
Figure 1.3: Outline of the thesis

customers' risk attitudes. Conducting a paper and pencil experiment at the University of Mannheim with 78 advanced students we show that investors' risk taking behavior in financial markets is highly affected by their subjective risk attitude and by the individuals' subjective risk and return expectations. However, the results indicate that statistical risk and return measures such as historical volatility or historical returns cannot predict risk taking behavior. In addition, we provide first evidence for extended domain specific risk taking behavior. We show that risk attitudes and risk perceptions that are inferred from lottery related investment tasks are not related to risk perceptions and risk taking behavior in a stock investment task. Hence, we conclude that financial institutions should not use lotteries to infer their customers' risk attitudes. In particular with regards to the MiFID which urges financial institutions to elicit their customers' risk preferences and risk profiles we believe this result to be also important for financial supervisors and practitioners.

In chapter 3 (joint work with Martin Weber) we analyze changes in expectations and risk attitudes and their impact on risk taking behavior. We use data from a repeated survey panel that was run with real online broker customers in September 2008, December 2008,

and March 2009. In all three surveys subjects' risk attitudes, risk expectations, return
expectations, and risk taking behavior, i.e. the proportion of wealth they are willing to
invest into the stock market compared to a risk free asset, were elicited. Using this unique
dataset we analyze whether risk taking, risk attitudes, and expectations change from one
quarter to the other and whether the latter two have an impact on risk taking behavior.
Our results indicate that risk taking behavior decreases substantially from September to
December and from December to March. Similarly, risk expectations and return expec-
tations also change substantially from one survey to the next one. In contrast, various
measures of risk attitudes are fairly stable over the time periods. Interestingly, observed
changes in risk taking behavior can primarily be attributed to changes in risk and re-
turn expectations but not to changes in past performance or changes in risk attitudes.
Moreover, our findings are valuable for practitioners - who are urged by MiFID (2006) to
elicit their customers' risk profiles and risk preferences - since we show that risk attitudes
remain fairly stable and that changes in investment behavior can mainly be attributed
to changes in expectations. Lastly, we illustrate that overconfidence seems to be a fairly
stable construct between September and December and tends to decrease slightly from
December to March.

Chapter 4 (joint work with Bruno Biais and Martin Weber) studies the degree of over-
reaction in a novel experimental setup. Replicating the design in the empirical study by
Thomas and Zhang (2008) we are able to analyze the chain of events in behavioral models
in a clean experimental environment. Our three main objectives are to find evidence for
overreaction to new information in a novel experimental design, to relate overreaction to
psychological biases, and to analyze whether overreaction has substantial financial con-
sequences. The experimental study was conducted with 104 students in September 2007
at the University of Mannheim. The majority of participants tend to overreact, however,
the degree of overreaction is very heterogeneous. A few subjects even underreact. Measur-
ing the degree of overconfidence (miscalibration) of each participant we find, consistent
with theoretical predictions, that more overconfident subjects overreact more heavily. In
a second step, we illustrate that overreaction has substantial economic consequences. Us-
ing two directly related economic consequences, portfolio risk and portfolio efficiency, we
find evidence for the following main findings: first, subjects who overreact more heavily

invest into riskier portfolios after good signals and less risky portfolios after bad signals. Second, we show that misreaction to new information, i.e. over- and underreaction harms portfolio efficiency, as measured by the Sharpe ratio. Providing experimental evidence for a relation of overreaction to overconfidence and to portfolio efficiency we shed first light on the chain of events in figure 1.2.

In chapter 5 (joint work with Martin Weber), we study the degree of individual and aggregate market overreaction in a dynamic experimental auction market in a similar design as in Thomas and Zhang (2008). In 13 sessions with overall 101 students we find overreaction to new information both in stock price forecasts and transaction prices. Interestingly, market forces seem not to help in lowering overreaction to new information in our novel experimental setting. Moreover, we uncover that subjects are not able to learn from their previous failures and thus do not correct their erroneous beliefs over the course of the experiment. That is to say, overreaction in our setting remains on a stable level although subjects can - at least in theory - learn from other market participants or from outcome feedback that has been provided to them. Finally, our experimental design allows us to test the relationship between heterogeneity of beliefs and trading volume. Previous theoretical studies on this issue show that the higher differences of opinion in a market are the higher the degree of trading volume (see e.g. Varian (1989) and Kandel and Pearson (1995)). The study in this chapter is the first that finds experimental evidence for a positive relation between differences of opinion and trading volume in a continuous auction market with several market participants.

Chapter 2

How Risky Do I Invest: The Role of Risk Attitudes, Risk Perceptions, and Overconfidence

2.1 Introduction

In the finance literature portfolio choices of investors are typically conceptualized in a risk-return framework. They are assumed to be a function of expected returns, expected risk and a subject's risk attitude. Most of these studies assume that investors employ the variance-covariance structure of an investment alternative to calculate its risk. Hence, individual risk attitude determines how much an investor allocates to risky and risk free assets, respectively. The line of reasoning is that all other things being equal more risk averse individuals should be inclined to hold less risky assets (see Samuelson (1969)).

Recently, studies have shown that intuitive risk measures such as subjective risk perception can better proxy for investors' intuition about financial risks than variance and standard deviation (see e.g. Weber et al. (2004) and Klos et al. (2005)). More general risk-return frameworks such as Sarin and Weber (1993b) and Jia et al. (1999) make it possible to incorporate these more appropriate measures of perceived risk so that the investment decision can be decomposed as follows:

$$Risk\ Taking \mathrel{\hat{=}} Perceived\ Return \ - \ Risk\ Attitude \cdot (Risk\ Perception). \qquad (2.1)$$

Hence, in this framework risk taking behavior is determined by three major components, perceived returns, subjects' risk attitudes, and perceived risks. Research in psychology and decision analysis has shown that risk perception does not need to be a stable construct and is influenced by various determinants (see Sitkin and Pablo (1992)). Weber and Milliman (1997) show that risk perception can vary over time and given previous investment success. Weber et al. (2005) and Diacon and Hasseldine (2007) document that the presentation format affects risk perception and consequently risk taking. Rettinger and Hastie (2001) and Weber et al. (2002) illustrate that differences in risk taking over various domains such as the financial domain (e.g. investment decision) and the health domain (e.g. seat-belt usage) can mainly be explained by differences in risk perceptions. More precisely, they show that risk perceptions vary substantially between different domains.

The present study offers a questionnaire analysis of portfolio choices, i.e. risk taking behavior of individual investors. We identify determinants actually driving the risk taking behavior of individuals, and analyze whether objective or subjective measures of risk and return are better able to explain subjects' risk taking behavior. In addition, we evaluate whether the domain in which perceived risk and return are elicited influence our findings and whether behavioral biases such as overconfidence and optimism can affect risk taking. To accomplish this we have to elicit risk attitudes, risk and return perceptions, and overconfidence in several domains, using various methods. This can be only done in an experimental or questionnaire setup. Therefore, we conducted a questionnaire study that allows us to assess the respective variables using a variety of approaches. In contrast to other studies, we analyze the effects of these variables elicited with various methods on risk taking behavior in two different domains in one single study.

We extend findings in the literature as follows: in line with more general risk-value models the risk taking behavior in the stock domain, i.e. portfolio choices, is determined by the riskiness and the return of an investment and also by the individual risk attitude. However, we show that not only subjective risk expectations but also subjective return expectations

are way better predictors of risk taking behavior in stocks than objective measures of risk and return such as historical volatilities and returns. Our results add to findings in Weber and Hsee (1998) who show that including subjective risk expectations instead of the variance of outcomes in lottery tasks improves the goodness of fit of regression analyses. We also show that these objective measures do not need to be related with the subjective ones as the within subject correlations between these variables are modestly positive at best and sometimes even negative. In addition, our results suggest that even two measures of subjective risk such as risk perception - measured on an 11-point Likert scale - and estimated volatility - as inferred from interval bounds - do not need to be highly correlated.

In line with many models on overconfidence and optimism (see e.g. Hirshleifer and Luo (2001)) we find that more overconfident and more optimistic subjects are going to invest into riskier portfolios. Previous experimental studies on the interaction between risk taking and overconfidence (Dorn and Huberman (2005) and Menkhoff et al. (2006)) were not able to detect a significant relationship between the two variables.

Furthermore, our results supplement findings in the literature on domain specificity (see e.g. Rettinger and Hastie (2001) and Weber et al. (2002)). First, we show that risk perception does not only vary between two distinct domains such as health and finance or between investment and gambling decisions but that risk perception can substantially vary even within a single domain between two very closely related investment opportunities. Second, our extended domain specificity result also applies to return expectations as only subjective return expectations are able to determine risk taking behavior in the stock domain. Third, only overconfidence in the stock domain is related to risk taking in stocks. Fourth, we find that subjective financial risk attitudes affect portfolio choices but that risk attitudes elicited in the lottery domain do not.

The problem to identify determinants of risk taking correctly is also highly relevant for practitioners in the financial sector. On the one hand, being able to assess behavior accurately is a competitive advantage for practitioners since it enables them to offer customized investment advice and bespoke products which are in line with the needs of their customers. On the other hand, in many countries financial advisors are legally obliged to evaluate the appropriateness of an investment for each customer. For example, in Europe

the Markets in Financial Instruments Directive (MiFID) by the European Parliament and the European Council (2004 and 2006) requires financial institutions to collect "information as is necessary for the firm to understand the essential facts about the customer (Article 35, 1)" and to elicit the customers' "preferences regarding risk taking, his risk profile, and the purpose of the investment (Article 35, 4)." With respect to the implementation of the MiFID, it is certainly interesting to notice that we cannot infer anything about subjects' risk taking decisions in stocks by asking them to judge artificial lotteries. In addition, our results show that investment advisors could also try to lower their customers' overconfidence level and explain them the consequences and risks of their decisions more thoroughly so that heavily overconfident subjects do not take risks that they do not want.

Our ultimate question in this chapter is centered around an investor who has to decide how much to invest into a risk free and a risky asset, respectively. Investors in financial markets are regularly exposed to these kinds of decisions and have to make a trade-off between risk and return. Typically, financial institutions ask their customers to make their investment decisions by showing them historical stock price charts of various investments. Hence, the main feature of our study is the following: participants were shown the stock price path of five different stocks over the last five years (see question 3.1.5 in the appendix of this chapter). For each stock they were asked to forecast the price in one year by submitting a best guess and an upper/lower bound. In addition, participants had to divide an amount of 10,000 Euro between a risk free asset and the respective stock. The main goal of our study is to offer direct evidence on how the determinants of risk taking, i.e. risk and return perceptions and risk attitudes, influence investment behavior in these kind of investment decisions. Before analyzing this question in more detail we want to illustrate the related literature more comprehensively.

Analyzing the link between risk attitude and risk taking Fellner and Maciejovsky (2007) report that the explanatory power of risk attitudes depends on the way these risk attitudes are elicited. To examine this more thoroughly we want to test which method of risk attitude elicitation allows us to make inferences about risk taking behavior of subjects in investments. Amongst others, Wärneryd (1996), Kapteyn and Teppa (2002), and Klos and

Weber (2003) provide evidence that intuitive subjective measures of risk seem to be better predictors of portfolio choice than more sophisticated methods such as lottery questions. Therefore, we use two risk attitude elicitation methods, based on certainty equivalents and on subjective self assessments, to analyze which of those two is a better predictor of risk taking. Thus, if risk attitudes are elicited in a lottery context, the typical line of reasoning that more risk averse individuals are going to invest into less risky portfolios should not be validated.

The riskiness and returns of an investment are unambiguously important determinants of risk taking behavior. However, analyzing individuals' decisions in lotteries Weber and Hsee (1998) find that objective risk, i.e. volatility, is not able to explain risk taking behavior as good as subjective risk. On the other hand, Klos et al. (2005) demonstrate that it is ambiguous how to measure subjective risk perception in repeated gambles and that it might be advisable to use various measures of subjective risk.

Moreover, Sitkin and Pablo (1992) and other models in the management literature posit that risk behavior is mainly determined by risk propensity and subjective risk perception and that this risk perception does not need to be stable but is influenced by domain specificity. Amongst others, Slovic (1972) and Rettinger and Hastie (2001) have shown that risk perceptions can vary over distinct domains such as financial and ethical and that this disparity can explain differences in observed risk behavior. Weber et al. (2002) even show that subjects might have differing risk perceptions in two closely related domains such as investment and gambling but that within a domain risk perceptions are pretty stable constructs.

In contrast, Dohmen et al. (2009) argue that eliciting individuals' global assessment of willingness to take risks is a useful predictor of their risk taking behavior in various domains. They show that a broadly formulated question such as "How willing are you to take risks, in general?" is the best all-around predictor of risk taking behavior in different domains. However, in contrast to our study which measures risk taking as the proportion a household invests in risky and risk free assets, respectively, they use binary variables that take the value 1 if a subject engages in the risky action at all and 0 otherwise. A possible explanation for the seemingly puzzling findings can be found in Brunnermeier

and Nagel (2008). They show that changes in wealth are related to the decision to invest in stocks, i.e. to a binary participation variable, but that changes in wealth essentially play no role in explaining changes in asset allocation, i.e. the decision how much to invest into a risk free and risky asset, respectively.

Since we elicit individuals' asset allocation decisions and not only their binary choice whether to engage in a risky action or not we hypothesize that the domain specificity result (see Weber et al. (2002)) should be prevalent in our study. More precisely, we think there should be an extended within domain specificity in the sense that risk perception and risk taking behavior in lottery investments does not need to be the same as in stock investments.

In addition, behavioral biases such as excessive optimism and overconfidence have been shown to have an influence on risk taking in various theoretical economic models (see e.g. Odean (1998b), Daniel et al. (2001) or Hirshleifer and Luo (2001)). These models argue that excessively optimistic subjects will have a higher expected value and hence a higher demand for a risky asset. In addition, they propose that overconfident investors have more extreme and in absolute values higher conditional expectation estimates and a lower conditional variance. Therefore, overconfident traders are going to take larger long or short positions in the risky asset.

However, theoretical predictions and empirical findings regarding the effect of overconfidence and risk taking do not coincide. For example, Dorn and Huberman (2005) and Menkhoff et al. (2006) show that risk taking behavior is not significantly related to overconfidence. Based on previous findings on domain specificity we think that this discrepancy exists because the empirical studies do not measure overconfidence and risk taking in the same closely related domain.

The remainder of this chapter is organized as follows. In section 2.2 we describe the design of the study and illustrate descriptive results. Section 2.3 contains the main results of the study, and section 2.4 provides a short summary and a conclusion.

2.2 Design and Descriptives

2.2.1 Questionnaire

In this section, we present a detailed overview of the variables and measures employed throughout our study. All variables were elicited in a questionnaire study. Overall, the questionnaire consisted of 11 pages, including a cover page and was divided into four main parts. A shortened version of the questionnaire can be found in the appendix. In part 1 we measured risk perception and risk taking with two different lottery approaches and subjective risk attitude in the financial domain. The second part of the questionnaire was used to elicit various overconfidence scores in a broader context. In part 3, the main part of the study, subjects were shown five stock price charts, displaying the stock price development over the last five years. This part was designed to measure subjective as well as objective risk and return measures and the resulting portfolio choice. Part 4 was used to measure familiarity with investments, knowledge and various personal variables. Table 2.1 summarizes and defines all variables used in the study and presents the method used to measure the respective variable.

Part 1

The first lottery task in part 1 asked subjects to divide an amount of 10,000 Euro between a risk free asset that pays a dividend of 3% and an infinitely divisible lottery that costs 10,000 Euro and pays out with a probability of 1/2, 12,000 Euro and 9,000 Euro, respectively. The score *Risk Taking (Lottery 1)* takes the value 0 if the subject invests the whole amount into the risk free asset and 100 if the subject invests only into the lottery. Moreover, *Risk Perception (Lottery 1)* reflects the perceived riskiness of a lottery and is measured on a Likert-scale from 0-10, where 0 indicates that subjects perceived no risk at all and 10 indicates that subjects perceived the risk to be very high. Using Likert-scales to elicit individual risk perception is a common procedure in the literature (see for example Weber and Hsee (1998) and Pennings and Wansink (2004)).

The second lottery in part 1 took a different approach of eliciting subjects' risk taking behavior by asking them to state their certainty equivalent for a lottery that pays 10,000

Table 2.1: Definition of variables

This table summarizes and defines variables used in the empirical analysis and illustrates the respective measurement method.

Variable	Measurement	Description
Part 1		
Risk Taking (Lottery 1)	Scale (0-100)	Measures the proportion of wealth an individual invests into lottery 1 ($p = \frac{1}{2}$, 12000 Euro and $q = \frac{1}{2}$, 9000 Euro).
Risk Perception (Lottery 1)	Scale (0-10)	Measures an individual's subjective risk perception for lottery 1 with endpoints "0 = no risk at all" and "10 = very high risk".
Risk Taking (Lottery 2)	Certainty Equivalent	Measures an individual's risk taking for lottery 2 ($p = \frac{1}{2}$, 10000 Euro; $q = \frac{1}{2}$, 0 Euro) based on the certainty-equivalent method. A higher certainty equivalent indicates a lower level of risk aversion.
Risk Attitude (Lottery 2)	Certainty Equivalent	Measures an individual's risk attitudes using the power utility function $u(x) = x^\alpha$.
Risk Perception (Lottery 2)	Scale (0-10)	Measures an individual's subjective risk perception for lottery 2 with endpoints "0 = no risk at all" and "10 = very high risk".
Subjective Risk Attitude	Scale (1-5)	Measures an individual's subjective risk attitude using the most common elicitation method in investment advice. A score of 1 indicates a high level of risk aversion and a score of 5 a low level.
Part 2		
Miscalibration (General Knowledge)	Confidence Intervals	Measures an individual's degree of miscalibration with respect to 10 questions concerning general knowledge.
Better Than Average (General Knowledge)	Self assessment vs. assessment of others	Measures overconfidence based on the comparison between the assessment of one's own performance and the assessment of the performance of the average subject in the general knowledge task.
Illusion of Control	Scale (0-1)	Based on answers to two statements, this variable measures the extent to which an individual thinks he / she can control random events. The endpoints indicate "0 = no control at all" and "1 = total control".
Part 3		
Risk Perception (Stocks)	Scale (0-10)	Measures an individual's subjective risk perception for a stock with endpoints "0 = no risk at all" and "10 = very high risk".
Risk Taking (Stocks)	Scale (0-100)	Measures, on a percentages basis, the amount of money an individual is willing to invest into each of the 5 stocks compared to a risk free asset and is used as a proxy for portfolio choice.
Expected Return (Stocks)	Point Estimate	Measures an individual's expected return for 5 different stocks.
Expected Volatility (Stocks)	Bounds	Measures an individual's expected volatility by transforming estimates of bounds into volatility estimates.
Optimism (Stocks)	Point Estimate	Measures the difference between subjective expected and historical return.
Miscalibration (Stocks)	Bounds	Measures an individual's miscalibration by standardizing expected volatility with historical volatility.
Better Than Average (Stocks)	Self assessment vs assessment of others	Measures overconfidence based on the comparison between the assessment of one's own performance and the assessment of the performance of the average subject in the stock price task.
Part 4		
Demographics		Various demographic variables such as age, gender, field of studies and the number of terms already studied.
Familiarity		Dummy variable that takes the value 1 if an individual has owned investment products within the last year and 0 otherwise.
Financial Knowledge	Scale (1-5)	Measures self assessed financial and statistical knowledge of subjects with endpoints "1 = very good" and "5 = bad".

Euro with probability 1/2 and 0 Euro otherwise. We elicited *Risk Taking (Lottery 2)* with the certainty equivalence method by repeatedly asking subjects whether they prefer a sure payment of x Euro or the lottery, with x ranging from 1,000 Euro to 9,000 Euro. This method also allows us to calculate risk attitudes in a lottery context utilizing a specific utility function. Inferring risk attitudes from certainty equivalents using a parametric approach is a common method in the literature (see e.g. Krahnen et al. (1997) and Dohmen et al. (2009)). To construct an explicit *Risk Attitude (Lottery 2)* score we follow the literature in decision analysis (see Tversky and Kahneman (1992)) and transform the stated certainty equivalents for lottery 2 into risk aversion parameters using the power utility function $u(x) = x^\alpha$.[1] In addition, *Risk Perception (Lottery 2)* was elicited in the same way as for lottery 1.

The last question in part 1 (*Subjective Risk Attitude*) asked participants to rate their willingness to take financial risks on a scale from 1 to 5 with the endpoints "1 = very low willingness" and "5 = very high willingness". This easy and quick classification method is the common method used in investment advice. In addition, subjective risk attitudes on Likert scales are also used in large scale survey such as the SOEP (see Dohmen et al. (2009)).

Part 2

In the second part of the questionnaire, participants first had to state 90% confidence intervals to 10 general knowledge questions, such as "How long is the Mississippi". More precisely, they had to submit upper (lower) bounds such that the true answer to each question should not exceed the upper bound (not fall short of the lower bound) with a probability of 95%. Confidence intervals are often used to detect miscalibration, i.e. overconfidence (Alpert and Raiffa (1982) and Russo and Schoemaker (1992)). A subject is classified as miscalibrated if he / she answers less than 9 questions correctly, i.e. the lower the *Miscalibration (General Knowledge)* score, the more overconfident the subject is.

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[1]Note that our results in section 2.3 remain stable if we simply use the certainty equivalents or CRRA transformations to derive a risk aversion parameter.

To measure whether an individual is prone to the better than average effect in the general knowledge context we asked subjects to assess how many intervals they and the average participant, respectively, answered correctly in the general knowledge task. The relating variable *Better Than Average (General Knowledge)* is calculated as the difference between these two answers and takes positive values for subjects that think they have answered more questions correctly than the average subject.

Moreover, within part 2 we also elicited *Illusion of Control* following the method in Dorn and Huberman (2005) and Glaser and Weber (2007). To estimate illusion of control, we consider the extent to which survey participants agree on a five-point scale from 1 (fully agree) to 5 (totally disagree) with the following statements: "I am able to identify stocks that will beat the market in the future" and "My stock forecasts are always correct". The Cronbach alpha for these two variables is 0.71 and is above the threshold which is normally assumed to indicate reliability (see Nunnally (1978)). Hence, we aggregate the answers to both questions, normalize them on a scale between 0 and 1 and calculate a joint illusion of control score. This illusion of control score takes a value of 1 if subjects are prone to the illusion of control bias and 0 if they are absolutely not prone to it.[2]

Part 3

In part 3, subjects were shown charts illustrating the stock price development of the following five DAX companies over the course of the last five years (see question 3.1.5 in the appendix): DaimlerChrysler, Infineon Technologies, Continental, Münchener Rück and Adidas. We used real stocks to make the task more realistic and controlled for individual experiences using subjective risk and return expectations. To construct the five stock charts we used daily closing prices for the time period November 2001 to November 2006 obtained from Thomson Financial Datastream. In line with, Glaser et al. (2007) we included firms with stable, upward and downward stock price trends. Furthermore, we standardized the area in which the stock graphs were displayed according to the method proposed by Lawrence and O'Connor (1993): the two bounds were chosen such that the

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[2]We also asked subjects whether they agree to the following statement "losses and gains in stock markets are just a matter of chance". Our results in the following sections do not change if we calculate illusion of control taking all three questions. However, the Cronbach alpha for all three questions decreases substantially to 0.5.

price at the end was approximately in the middle of the chart and the area in which the stock price chart was displayed fills about 40% of the total vertical dimension of the graph. This procedure was carried out to avoid that subjects would interpret the vertical endpoints of the graph as boundaries.

For all five stocks we elicited the following variables:

- *Risk Perception (Stocks)*

- *Risk Taking (Stocks)*

- *Expected Return (Stocks)*

- *Expected Volatility (Stocks)*

- *Better Than Average (Stocks)*

Risk Perception (Stocks) reflects the perceived riskiness of each stock and is measured on a Likert-scale from 0-10. Again, lower scores of risk perception indicate that subjects perceived the risk of the respective stock to be lower. To measure individuals' risk taking behavior or portfolio choice we asked them to allocate 10,000 Euro between the particular stock and a risk free asset that yields a yearly return of 3%, assuming an investment horizon of one year. The corresponding variable *Risk Taking (Stocks)* takes values from 0 to 100 with the endpoint 0 (100) indicating that the subject invests the whole amount into the risk free asset (risky stock).[3]

To measure the expected volatility and expected returns in the stock domain we asked individuals to state a median stock price forecast as well as upper and lower bounds for 90% confidence intervals for the stock price in one year. More precisely, we asked them to submit what they consider to be lower and upper bounds so that there is only a 5% chance that the price in one year will be below the lower bound and a 5% chance that it will be higher than the upper bound. We transformed all three stock price estimates for each subject and for all five stock charts into return estimates.[4]

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[3]Wärneryd (1996) illustrates that questions involving hypothetical risky choices seem to work quite well.

[4]The return estimates $r(s)$ for the three stock price estimates $p(s)$ for each stock i and each subject j are calculated as follows: $r(s)_i^j = \frac{p(s)_i^j - \overline{value_i}}{\overline{value_i}}$), with $\overline{value_i}$ indicating the price of stock i in November 2006.

Since we asked subjects to state median returns we first transform median estimates into mean estimates using the method proposed by Keefer and Bodily (1983) (*Expected Return (Stocks) = 0.63 · r(0.5) + 0.185 · (r(0.05) + r(0.95))*). Furthermore, we calculate a subject's optimism regarding the return of a stock as the difference between the expected and the historic return (*Optimism (Stocks) = Expected Return (Stocks) - Historical Return (Stocks)*). A higher score indicates a higher level of optimism.

Using the median forecast and both the upper and the lower bound allows us to get a measure for the expected volatility in the stock domain by using the methodology suggested in Keefer and Bodily (1983). This method transforms stated confidence intervals into volatility estimates[5] and has been widely used in the empirical literature (e.g. Graham and Harvey (2005), Ben-David et al. (2007), and Glaser et al. (2007)). The resulting variable *Expected Volatility (Stocks)* measures an individual's subjective volatility forecast for each stock. In addition to the expected volatility we can also compute an easily interpretable and standardized measure of miscalibration in the stock domain by dividing the estimated one year volatility by minus one times the historical volatility (*Miscalibration (Stocks)* $= -\frac{Expected\ Volatility\ (Stocks)}{Historical\ Volatility}$). This standardization yields a miscalibration measure which is close to 0 for excessively overconfident subjects and equal to -1 for perfectly calibrated subjects.[6]

Furthermore, we also asked individuals to assess for how many of the interval questions they and the average subject, respectively, indicated wide enough confidence intervals. Subjects prone to the better than average effect will assess their performance in the stock domain to be better than the average subject's performance. Hence, their *Better Than Average (Stocks)* score, representing the spread between these two answers, will be positive.

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[5]Keefer and Bodily (1983) propose that an extended Pearson-Turkey approximation is a widely applicable approximation for continuous probability distributions if one has information on the upper bound r(0.95), the lower bound r(0.05) and the median r(0.5). Since we collected exactly these three point estimates for every stock, we can use their proposed method to recover each respondents' probability distribution for each stock i by using the following formula: Volatility$_i$ = $\sqrt{[0.185 * r(0.05)_i^2 + 0.63 * r(0.5)_i^2 + 0.185 * r(0.95)_i^2] - [0.63 * r(0.5)_i + 0.185 * r(0.05)_i + 0.185 * r(0.95)_i]^2}$.

[6]We calculated one year volatilities for each stock by using daily returns for the last five years, exactly the same time period subjects were given in the questionnaire. To check for robustness, we computed historical one year volatility using non overlapping monthly and quarterly returns. The results are essentially the same and since the division is only a standardization we will in the following only report results with respect to one year volatilities on the basis of daily returns.

Part 4

Within part 4 we elicited demographic variables, knowledge, and familiarity with investments. Demographics include age, gender, field of study, and terms studied. We proxied for familiarity by asking the subjects to indicate the number of investment products they have owned within the last year. Subsequently, we generated a dummy variable *Familiarity* that takes the value 1 if a subject has invested in the last year and 0 otherwise. In the end, we measured both financial and statistical knowledge using simple self-assessment questions. Subjects had to indicate their knowledge in each field on a scale from 1 to 5, with 1 indicating very good knowledge and 5 indicating bad knowledge in the respective field.

2.2.2 Descriptive Statistics

The questionnaire was filled out by 78 students of a Behavioral Finance class and a Decision Analysis class at Mannheim University on November 15 and 16, 2006. It took the students on average 30 minutes to complete the questionnaire. All students who returned a completely filled out questionnaire automatically participated in a lottery which paid out in each case 30 Euro to overall 9 randomly selected participants. This amounts to an average payment of approximately 3.5 Euro per person. Since we asked students for their subjective perception of risky situations and for their subjective estimates of future stock prices we chose to pay out fixed amounts to avoid strategic behavior.[7]

The mean and median scores for all demographic and risk variables are presented in table 2.2. The average age of the participants is 24 years, with 32% of the respondents being female. Approximately 90% of the students in our sample study business administration or economics and are within their fourth year on average (6.8 semesters studied). About 57% of all respondents have held stocks or other assets within the last year. The self-reported

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[7]In addition, it is not common to pay participants with an incentive compatible payment scheme in surveys in which participants are asked to state confidence intervals or to submit their individual risk perception. A common example of such a large scale survey is the Duke/CFO Outlook Survey (see `http://www.cfosurvey.org`). Moreover, Cesarini et al. (2006) provide evidence that monetary incentives do not decrease miscalibration significantly. In a similar vein Camerer and Hogarth (1999) argue in their review of 74 experiments that rationality violations do not disappear purely by raising incentives.

Table 2.2: Descriptive statistics on demographics and risk

This table reports mean and median scores and standard deviations on demographic and risk variables. Numbers in parentheses indicate the possible range of answers for the respective variable.

	Mean Score	Median Score	Standard deviation
Female	0.316	0	
Age	24.027	23	5.288
Semester	6.808	7	1.751
Familiarity	0.566	1	
Statistical Knowledge (1-5)	2.776	3	0.838
Financial Knowledge (1-5)	3.342	3	1.009
Subjective Risk Attitude (1-5)	2.592	2.5	0.877
Risk Perception (Lottery 1) (1-10)	4.105	3	1.820
Risk Taking (Lottery 1) (1-100)	58.75	60	28.914
Risk Perception (Lottery 2) (1-10)	7.118	7	1.664
Risk Taking (Lottery 2) (1000-9000)	4144.737	4000	1201.406
Risk Perception (Stocks) (1-10)	5.426	6	1.914
Risk Taking (Stocks)	43.639	40	26.332

statistical knowledge score on a scale from 1 (very good) to five (bad) is approximately 2.8 and the one for financial knowledge is 3.3 indicating that students were slightly more confident in their statistical knowledge. For *Financial Knowledge* we find a significant difference for students in our Decision Analysis class (3.5) and our Behavioral Finance class (2.95). Table 2.2 further documents that participants stated an average subjective risk attitude of 2.6 on a scale from 1 to 5. The risk of participating in a two outcome lottery was perceived as higher (7.1) than the average risk for all five stocks (5.4). Moreover, the table shows that subjects invest on average 43.6% of their funds in part 3 of the questionnaire into the risky asset.

Analyzing the various overconfidence measures we have elicited, we find substantial degrees of overconfidence among subjects for most of our measures. However, the degree of overconfidence varies substantially, being relatively low for both better than average scores and being substantially high for both miscalibration scores. More precisely, for miscalibration in the general knowledge context we find that the average subject submits only six correct answers and for miscalibration in the stock context we find that the average subject states wide enough confidence intervals for less than two questions. Using Wilcoxon matched-pairs signed rank tests for both measures shows that there is substantial miscalibration in both domains (p-values < 0.0001). These findings are approximately in the same range as the results by Russo and Schoemaker (1992) who show that individuals submit on average answers that include the true answer in 40%-60%. Analyzing illusion of control, we find consistent with Dorn and Huberman (2005) that subjects are prone to the illusion of control bias. However, for better than average effects our results are not as clear-cut. On the one hand, we find slightly positive better than average scores in both domains. On the other hand, these effects are only weakly significant or not significant at all.

2.3   Results

In this section we analyze which factors actually govern risk taking behavior in a stock related context. As illustrated in section 2.1 individuals' risk taking behavior is argued to

be determined by three major components: risk attitude, perceived return and perceived risk (see equation 2.1). Recent work by Weber and Milliman (1997), Weber et al. (2002), and Klos et al. (2005) shows that subjectively perceived risks do not need to coincide with variance estimates and that perceived risks in one domain do not need to coincide with perceived risks in another one. To allow for these findings we elicited in our setup risk attitudes, risk perceptions, and return perceptions using various methods. In the following, we will first analyze determinants of risk taking behavior in the stock domain on an aggregate level before we turn to analyses on a disaggregate, single-stock level. In addition, we will also perform further robustness checks of our results.

2.3.1   Determinants of Risk Taking Behavior in Stocks on an Aggregate Level

Before analyzing factors that determine aggregate risk taking behavior, i.e. portfolio choices, in a multivariate setting we first carry out simple bivariate interactions between aggregated portfolio choice and variables argued to affect risk taking behavior of individuals. We use two major categories of determinants: first, variables that are not directly related to the stock domain such as *Subjective Risk Attitude* and lottery related variables (i.e. *Risk Perception (Lottery 1)*, *Risk Perception (Lottery 2)* and *Risk Attitude (Lottery 2)*). Second, risk and return perceptions in the stock domain such as *Risk Perception (Stocks)*, *Miscalibration (Stocks)*, and *Optimism (Stocks)*.[8]

To aggregate the variables in the stock domain we make use of three aggregation methods: first, we take the mean over all five stock questions. Second, we take the median over all five stock questions and third we use a dummy variables method for *Miscalibration (Stocks)* and *Optimism (Stocks)*. This dummy method assigns for each question a value of 1 to individuals who are excessively optimistic or overconfident and a value of 0 otherwise.

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[8]Using *Expected Volatility (Stocks)* and *Expected Return (Stocks)* instead of the standardized scores *Miscalibration (Stocks)* and *Optimism (Stocks)* yields robust results. However, as we use aggregated scores the interpretation of these scores that are not standardized by the respective historical variable is not as straightforward.

Since all three measures essentially yield the same results, subsequently we will only report the results for the aggregation rule using the mean score.[9]

However, before using these aggregated scores we have to assess the internal validity of each variables over the five questions. We have to check whether we find stable individual differences for the level of *Risk Taking (Stocks)*, *Risk Perception (Stocks)*, *Optimism (Stocks)* and *Miscalibration (Stocks)*, respectively. Hence, we calculate the Cronbach alphas for the four variables over all five questions. The Cronbach alphas vary between 0.59 (*Risk Perception (Stocks)*) and 0.88 (*Miscalibration (Stocks)* and *Risk Taking (Stocks)*). Since Nunnally (1978) argues that alphas above 0.7 are an indication for stable individual differences we will in the following aggregate analyses exclude *Risk Perception (Stocks)*.[10]

Having assessed the internal validity of our aggregated scores we study simple correlation coefficients between risk taking in the stock domain and determinants of risk taking. Panel A of table 2.3 illustrates Spearman correlation coefficients (1) and Pearson correlation coefficients (2) between *Risk Taking (Stocks)* and related variables. The results show that *Subjective Risk Attitude* is strongly positively related with *Mean Risk Taking (Stocks)*. Hence, subjects who have a higher *Subjective Risk Attitude* also invest on average into more risky portfolios. Panel A also shows that neither risk perceptions in both of our lotteries nor risk attitudes as inferred from certainty equivalents are able to determine individuals' average risk taking behavior. Moreover, we also find that *Mean Optimism (Stocks)* is not related to portfolio choices. However, *Miscalibration (Stocks)* is positively related to the average portfolio risk indicating that individuals who are more overconfident invest into substantially more risky portfolios.

To further strengthen our results on determinants of risk taking we analyze the relation between portfolio choice and its determinants in a multivariate setting controlling for various effects.[11] Panel A in table 2.4 presents results of ordinary least squares re-

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[9]Using the mean as an aggregation rule the stock related variables are calculated as follows: *Mean Risk Taking (Stocks)* = $[\sum_{i=1}^{5}$ Risk Taking$_i]/5$, *Mean Risk Perception (Stocks)* = $[\sum_{i=1}^{5}$ Risk Perception$_i]/5$, *Mean Miscalibration (Stocks)* = $[\sum_{i=1}^{5} -\frac{\text{Estimated volatility}_i}{\text{Historical volatility}_i}]/5$ and *Mean Optimism (Stocks)* = $[\sum_{i=1}^{5}$ Optimism$_i]/5$.

[10]Our results in the following analyses of aggregate risk taking are robust even if we include *Risk Perception (Stocks)*.

[11]Throughout the chapter we report results of simple ordinary least square regressions and fixed or random effects panel regressions although all of our dependent variables are theoretically bounded from both sides. However, in our dataset

Table 2.3: Correlation coefficients

Panel A of this table reports correlation coefficients between *Mean Risk Taking (Stocks)* and various aggregate determinants of risk taking behavior. Column (1) reports Spearman rank correlations whereas column (2) reports Pearson correlation coefficients. Panel B reports Spearman rank correlation coefficients between *Risk Taking (Lottery 1)* (column 3) or *Risk Taking (Lottery 2)* (column 4) and various aggregate determinants of risk taking behavior. p-values are reported in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

	Panel A		*Panel B*	
	(1)	*(2)*	*(3)*	*(4)*
Subjective Risk Attitude	0.350	0.415	0.427	0.445
	(0.002)***	(0.002)***	(0.000)***	(0.000)***
Risk Perception (Lottery 1)	-0.008	-0.053	-0.460	-0.313
	(0.949)	(0.648)	(0.000)***	(0.006)***
Risk Perception (Lottery 2)	-0.023	-0.083	-0.329	-0.504
	(0.847)	(0.474)	(0.004)***	(0.000)***
Risk Attitude (Lottery 2)	0.034	0.173	0.359	
	(0.770)	(0.136)	(0.002)***	
Mean Optimism (Stocks)	0.046	-0.013	0.001	0.130
	(0.692)	(0.915)	(0.990)	(0.263)
Mean Miscalibration (Stocks)	0.256	0.286	-0.083	-0.129
	(0.025)**	(0.012)**	(0.476)	(0.266)

Table 2.4: Determinants of risk taking behavior on an aggregate level

This table presents results of ordinary least squares regressions with heteroscedasticity consistent standard errors. Dependent variable in panel A (model 1 - 3) is *Mean Risk Taking (Stocks)*, dependent variable in panel B (model 4) is the level of risk taking in lottery 2 and in model (5) the level of risk taking in lottery 1. Independent variables are *Subjective Risk Attitude*, risk perceptions in lotteries, *Risk Attitude (Lottery 2)*, *Mean Optimism (Stocks)*, *Mean Miscalibration (Stocks)* and additional controls such as demographics, familiarity with stock investments, knowledge and various overconfidence measures. We report regression coefficients and p-values in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

	Panel A			*Panel B*	
	(1)	(2)	(3)	(4)	(5)
Subjective Risk Attitude	10.087	9.725	9.209	193.371	14.283
	(0.000)***	(0.000)***	(0.008)***	(0.218)	(0.001)***
Mean Optimism (Stocks)		17.369	27.099	-924.998	8.055
		(0.468)	(0.391)	(0.534)	(0.824)
Mean Miscalibration (Stocks)		13.594	17.157	-281.341	9.018
		(0.002)***	(0.013)**	(0.555)	(0.362)
Risk Perception (Lottery 1)			0.054	-147.161	-5.132
			(0.971)	(0.037)**	(0.003)***
Risk Perception (Lottery 2)			-0.651	-260.806	-1.546
			(0.672)	(0.006)***	(0.344)
Risk Attitude (Lottery 2)			-1.496		6.974
			(0.814)		(0.179)
Controls	No	No	Yes	Yes	Yes
Constant	17.493	31.192	0.238	3,524.679	2.659
	(0.015)**	(0.001)***	(0.995)	(0.082)*	(0.955)
Observations	76	76	71	71	71
Adjusted R-squared	0.161	0.221	0.083	0.308	0.322

gressions with *Mean Risk Taking (Stocks)* as dependent variable. Regression (1) shows that *Subjective Risk Attitude* can explain individuals' average risk taking in stocks significantly. Adding subjective risk and return perceptions in regression (2) in the form of *Miscalibration (Stocks)* and *Mean Optimism (Stocks)* improves the goodness of fit of our regression substantially. Including these subjective expectations yields the results that both *Subjective Risk Attitude* and *Miscalibration (Stocks)* are significant determinants of risk taking but not *Mean Optimism (Stocks)*. In regression (3) we add risk perceptions and risk attitude inferred from lotteries and further dependent variables such as demographics, familiarity with stock investments, knowledge and overconfidence measures in other domains. The results with regard to the significance of the two main dependent variables *Subjective Risk Attitude* and *Miscalibration (Stocks)* remain constant. However, none of our additional variables is significantly related to portfolio choices. In addition, adding all additional control variables decreases the goodness of fit of our regression indicated by the adjusted R-squared.

Overall, our analyses on the aggregate level suggest that risk taking of individuals is determined by their subjectively elicited risk attitude and by their level of overconfidence, i.e. miscalibration, and that other variables are not able to determine individuals' risk taking behavior. In the following subsection we will analyze whether our results also hold if we study the effects on a disaggregated single stock level.

2.3.2 Determinants of Risk Taking Behavior in Stocks on a Disaggregate Level

The analyses in the previous subsection have the disadvantage that we have to use aggregate scores and cannot control for question specific effects. To mitigate these problems we document in the following results of multivariate regressions of subjects' risk taking behavior performed on a single stock level. However, since it is possible that risk taking behavior between the five stocks may be correlated within individuals we cannot analyze the data by running simple ordinary least squares regressions. We account for the problem

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these theoretical bounds are almost never reached. In addition, we ran all our multivariate analyses using censored tobit regressions and obtained essentially the same results.

of possible non-independent residuals within individuals by using two approaches. First, we cluster our observations over subjects and analyze the relationship between risk and overconfidence on a single stock level using clustered ordinary least squares regressions. Clustering the data over subjects allows us to examine the individual effects on risk taking for each stock. Second, we use fixed effects and random effects panel regressions with the two dimensions subjects and stocks. Table 2.5 presents the results of these estimations.[12]

We have illustrated in previous sections that risk taking in a risk-return framework is assumed to be governed by a tradeoff between the return of an investment and its risk and also by an individual's risk attitude. In the finance literature it is common to equate expected returns by historical returns and expected risks by historical variance. Hence, the first regression in table 2.5 tries to explain subjects' risk taking in the stock domain using these variables. The regression results show that *Subjective Risk Attitude* and *Historical Volatility (Stocks)* determine the risk taking behavior. Subjects invest more into stocks if they are less risk averse and if the historical volatility of the stock is lower. Interestingly, historical stock returns are not able to determine the investment decision of subjects. However, this is not surprising as subjects in our study were mainly business students who learn in their studies that past performance is no perfect indication for future performance.

More general risk-value models argue that subjects might base their decisions more on subjective measures of risk and return instead of objective ones. Hence, it might be more appropriate to include subjective measures of risk and return such as *Expected Return (Stocks)* as well as *Risk Perception (Stocks)* and *Expected Volatility (Stocks)* into our regression as they could actually affect the level of risk taking more heavily. To accommodate for this proposition we include these variables instead of the historical ones in regression (2). Using both *Risk Perception (Stocks)* and *Expected Volatility (Stocks)* in a single regression might cause multicollinearity problems if the two variables were highly correlated with each other. However, we find that *Risk Perception (Stocks)* is hardly related with *Expected Volatility (Stocks)* as the within subject correlations are at best moderately positive with rank correlations of 0.12 (Kendall tau) and 0.16 (Spearman rho), respectively. This result suggests that the two subjective risk measures do not need to coincide and

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[12] Again, our results remain stable if we run the regressions using censored tobit instead of ordinary least squares.

Table 2.5: Determinants of risk taking behavior in stocks on a disaggregate level

This table presents clustered ordinary least squares as well as fixed effects and random effects panel regressions with the two dimensions subjects and stocks. Dependent variable in all regressions is *Risk Taking (Stocks)*. Regressions (1)-(4) present results of clustered ordinary least squares regressions where standard errors take clustering over subjects into account. Regression (5) presents results of a fixed effects model and column (6) documents results of a random effects model. Independent variables are *Subjective Risk Attitude*, *Risk Attitude (Lottery 2)*, *Optimism (Stocks)*, *Miscalibration (Stocks)*, historical return and volatility of each stock, subjective risk and return measures such as risk perception, expected volatility and expected return. Moreover, we include additional controls such as stock dummies, demographics, familiarity with stock investments, knowledge and various overconfidence measures. We report regression coefficients and p-values in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Subjective Risk Attitude	10.087	9.514	9.225	9.236		9.136
	(0.000)***	(0.001)***	(0.003)***	(0.003)***		(0.015)**
Risk Perception (Lottery 1)			0.297	0.226		0.350
			(0.826)	(0.866)		(0.822)
Risk Perception (Lottery 2)			-0.218	-0.231		-0.121
			(0.874)	(0.866)		(0.947)
Risk Attitude (Lottery 2)			-0.730	-0.291		-0.764
			(0.905)	(0.962)		(0.912)
Historical Return (Stocks)	2.569		4.339		4.290	4.310
	(0.654)		(0.387)		(0.436)	(0.431)
Historical Volatility (Stocks)	-50.558		-30.484		-39.377	-37.865
	(0.004)***		(0.119)		(0.013)**	(0.014)**
Expected Return (Stock)		24.622	30.851		30.034	30.349
		(0.018)**	(0.004)***		(0.000)***	(0.000)***
Optimism (Stocks)				33.690		
				(0.001)***		
Risk Perception (Stocks)		-3.723	-3.398	-3.280	-3.940	-3.873
		(0.000)***	(0.002)***	(0.003)***	(0.000)***	(0.000)***
Expected Volatility (Stock)		-26.530	-28.292		-18.331	-20.017
		(0.003)***	(0.007)***		(0.016)**	(0.005)***
Miscalibration (Stocks)				11.215		
				(0.003)***		
Controls	No	No	Yes	Yes		Yes
Stock Dummies	No	No	No	Yes		No
Constant	34.449	46.521	30.057	1.409	83.746	37.432
	(0.000)***	(0.000)***	(0.418)	(0.969)	(0.000)***	(0.408)
Observations	380	377	352	352	352	352
Adjusted R-squared	0.136	0.260	0.262	0.271		
Number of Groups					71	71
R-squared overall					0.166	0.301
R-squared within					0.308	0.308
R-squared between					0.093	0.296

is consistent with previous findings in the literature (see e.g. Klos et al. (2005) and We-
ber et al. (2005)). Furthermore, to control for possible multicollinearity problems in this
regression we carry out variance inflation factor tests.

The results of regression (2) document that indeed *Subjective Risk Attitude* and both
subjective risk and return measures in the stock domain significantly influence the risk
taking decision in the stock domain. We find on a single stock level that the higher a
subject perceives the expected return the more he / she invests into the stock. In a
similar vein the lower he /she perceives the risk of the investment subjectively and the
lower he / she expects the volatility to be the more risk he / she will take. Interestingly,
the adjusted R-squared in regression (2) is nearly twice as high as in the first regression.
Comparing these fits shows that regressions using objective risk measures do not predict
risk taking behavior nearly as well as regressions using subjective measures which provides
support for similar findings by Weber and Hsee (1998) in another context. Moreover, as
indicated by the results of the within subject correlations multicollinearity seems to be
no problem as all variance inflation factor scores are way below the critical threshold of
10, indicating a low degree of multicollinearity, if any.

In a next step we want to disentangle the role of objective and subjective risk and return
measures and analyze the interesting question on which measures subjects rather rely on
when making their decisions. To do this we run regression (3) and include both objective
and subjective measures at once. In addition, as various studies in the literature argue
that gender (see e.g. Eckel and Grossman (2008)), age, experience and knowledge (see e.g.
Barsky et al. (1997) and Donkers et al. (2001) who both use large scale survey studies
analyzing the whole population) might influence risk taking behavior we test this by
adding these variables in the same regression. We also include risk perceptions and risk
attitude in lotteries as additional control variables. As we might run into multicollinearity
problems in our analysis we first want to find if objective and subjective variables measure
distinct things before we carry out the regression.

Analyzing the within subject rank correlation coefficients (Kendall tau and Spearman)
between objective and subjective measures of risk and return we actually find support
for this proposition. Comparing historical returns with expected returns we even find a

slightly negative relation indicated by negative within subject rank correlations of -0.26 (Kendall tau) and -0.31 (Spearman rho). Taking a closer look at these within subject rank correlations we find that for less than 25% of all subjects the relationship between historical and expected returns is positive. These results suggest that subjects in our study exhibit slightly mean reverting beliefs. This mean reverting pattern can be explained by findings in Glaser et al. (2007) who show that studies asking subjects to submit price forecasts, such as ours, mostly document mean reverting beliefs whereas studies asking for returns document beliefs in trend continuation. Analyzing the relationship between historical and expected risk we find mixed evidence. Whereas expected and historical volatility are positively correlated (Kendall tau = 0.48; Spearman rho = 0.59) we do not find the same pattern for subjective risk perceptions and historical volatilities. The two variables have very low within subject correlations of 0.09 (Kendall tau) and 0.12 (Spearman rho) with only 52% of the subjects having positive correlation coefficients. These results suggest that objective and subjective risk and return variables do not need to measure the same thing and hence we include them in the same regression as independent variables.

The results in regression (3) confirm the proposition that individuals base their decisions more on subjective perceptions and expectations about risk and return than on historical measures of the same variables. Whereas historical risk and return measures do not affect risk taking significantly, all three of our subjective risk and return measures are highly significant. Interestingly, in line with previous findings in the literature (see e.g. Kapteyn and Teppa (2002) and Guiso and Paiella (2006)) and also in line with our findings on the aggregate level we find that risk perceptions and risk attitude elicited in a lottery context are not related to subjects' risk taking behavior.

Moreover, we cannot find a significant effect of demographics, familiarity with investments and knowledge on risk taking. We offer three explanations why this might be the case. First, our method of eliciting risk taking behavior is different from the self assessments and from lottery type questions typically used in the literature. Second, the variation with respect to age, experience and knowledge in our sample is much lower than in large surveys analyzing a representative sample of the total population. Third, in contrast to

other studies we are able to control for subjective risk and return estimates. Overall, taking a look at variance inflation factors reveals that multicollinearity should be no problem in our data as all scores are way below the critical threshold of 10.

In column (4) we re-run our regression from column (3) using the two standardized measures for risk and return expectations, *Optimism (Stocks)* and *Miscalibration (Stocks)* instead of *Expected Return (Stocks)* and *Expected Volatility (Stocks)*. Consistent with theoretical models on overconfidence and optimism (see e.g. Odean (1998b) and Coval and Thakor (2005)) and contrary to previous empirical studies (see e.g. Dorn and Huberman (2005) and Menkhoff et al. (2006)) we find that more overconfident and more optimistic subjects take more risks. Interestingly, this effect can only be found for miscalibration in the stock domain and not for any of our other overconfidence measures. This result is in line with theoretical studies that model overconfidence exclusively as miscalibration. The disadvantage of using *Optimism (Stocks)* and *Miscalibration (Stocks)* is that we use historical risk and return measures to standardize these variables. Hence, we have to drop *Historical Return (Stocks)* and *Historical Risk (Stocks)* as additional dependent variables in all regressions and cannot analyze whether objective or subjective measures are more appropriate determinants of risk taking. To control for stock specific characteristics we include stock dummies as additional control variables.

Instead of clustering over subjects and questions to control for non-independent residuals we also re-run the regressions using fixed and random effects models. Using a fixed effects model (see regression (5)) generates consistent estimates, however, its major disadvantage is that we cannot make a statement about the effect of risk attitude, demographics, knowledge and various overconfidence measures on risk taking since these variables do not vary over stocks for a subject. However, Hausman tests show that the null hypothesis that the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator cannot be rejected. Hence, we use random effects regressions to test the robustness of our results in the following. Regression (6) documents the results using random effects regressions. Overall, the results are pretty much in line with the findings of the clustered ordinary least squares regressions. Variables previously found to affect risk taking are again significant. In addition, *Historical Volatility*

(Stocks) has a significantly negative effect on risk taking. Other factors, in particular, risk attitude and risk perception in a lottery context and historical stock returns and a wide range of demographic variables are not able to determine subjects' risk taking behavior.

2.3.3   Further Results

In the previous sections we have shown that risk taking behavior is affected by an individual's risk attitude and by his / her subjective perceptions of risk and return. However, not all measures of risk perception, miscalibration, and risk attitude affect portfolio choices significantly. Risk perceptions and risk attitude inferred from lotteries or overconfidence measured in a more general domain are not able to determine risk taking behavior. We argue that this can be explained by an extended domain specificity or within domain specificity. This extended domain specificity goes beyond results on domain specificity by Rettinger and Hastie (2001) and Weber et al. (2002) who show that risk perceptions vary substantially over various distinct domains such as health and finance. More precisely, we argue that even within the domain of investment decisions risk perceptions differ if the decision is illustrated as a lottery or as a stock price chart and this has an impact on risk taking behavior. To test the robustness of extended domain specific behavior we analyze in the following determinants of risk taking in lotteries.

Analyzing the bivariate relation between *Risk Taking (Lottery 1)* or *Risk Taking (Lottery 2)* and various variables assumed to affect the risk taking behavior of individuals we find support for our extended domain specificity result. Panel B in table 2.3 illustrates that in contrast to risk taking behavior in the stock domain (panel A) both risk perceptions in the lottery domain (*Risk Perception (Lottery 1)* and *Risk Perception (Lottery 2)*) and *Risk Attitude (Lottery 2)* are related to risk taking in the lottery domain. Moreover, panel B also shows that previously highly significant determinants of risk taking behavior in the stock domain such as *Mean Miscalibration (Stocks)* are not related to risk taking behavior in lotteries. Controlling for additional effects in a multivariate analysis we find further support for the extended domain specificity in panel B of table 2.4. On the one hand, subjective risk and return perceptions in the stock domain affect portfolio choices

but do not affect risk taking behavior in the two different lottery tasks. On the other hand, risk perception in a lottery domain affects risk taking behavior in lotteries significantly.

Moreover, we also find evidence that this extended domain specificity result not only applies to risk perceptions but also to overconfidence. In the previous analyses we found that miscalibration in the stock domain significantly affects portfolio choices but that other measures of overconfidence do not. Analyzing the effect of overconfidence on risk taking in lotteries (Panel B of table 2.4) we find that no overconfidence measure can significantly determine risk taking behavior in both lotteries. We argue that this is due to the fact that risk taking and overconfidence are not elicited in the same domain. This extended domain specificity can also explain why previous empirical studies (see e.g. Dorn and Huberman (2005) and Menkhoff et al. (2006)) were not able find the theoretically proposed relationship between overconfidence and risk taking.

2.4 Conclusion

The main goal of this study was to analyze determinants of risk taking behavior. Consistent with risk-return models we present evidence that risk taking behavior is affected by subjective risk attitudes, risk perceptions, and return expectations. Analyzing determinants of risk taking behavior is also important for practitioners. This is in particular true because of the implementation of the MiFID which urges financial institutions to know their customers' risk preferences regarding risk taking and their risk profile.

One implication of our study is that objective measures of risk such as historical volatility and return are not able to determine risk taking behavior nearly as good as subjective measures, i.e. subjective risk and return perceptions. In particular historical returns seem to be a poor predictor of risk taking behavior. Moreover, we find substantial differences between subjective risk perceptions inferred from interval estimates and inferred from Likert scales. Our results also suggest that in line with theoretical models (e.g. Odean (1998b)) behavioral biases such as overconfidence and excessive optimism affect risk behavior significantly. Investment advisors could try to incorporate some of these findings in their advisory process by correcting for investors' erroneous beliefs. This correction could

be accomplished by enhancing the financial literacy of customers and by showing them that their desired investment is maybe more risky than initially thought.

We also find evidence for an extended domain specificity in our data. Determinants of risk taking behavior not only vary between two very distinct domains as was previously demonstrated by Weber et al. (2002) but even within the domain of investments. We show that determinants of risk behavior in the domain of lottery investments do not need to be able to predict risk taking in stock investments and vice versa. Hence, measuring risk attitudes using a lottery approach is useless if we want to predict risk taking behavior in the stock domain. Thus, eliciting customers' risk attitudes by asking them for their certainty equivalents, a method that has for example been used frequently in large scale panel surveys such as the Socio-Economic-Panel (SOEP) but also in the banking industry cannot predict risk taking behavior of individuals. The same extended domain specificity result also applies for the measures of overconfidence. Only miscalibration in the stock domain has an effect on portfolio choices but not overconfidence in a more general setup.

Future research needs to address whether our results for hypothetical and simplified port-folio decisions can be generalized to actual portfolio decisions. To accomplish this sort of study it could be insightful to cooperate with a bank and analyze bank customers' portfolio decisions in light of our findings. In addition, it is certainly of interest to analyze how these determinants of risk taking behavior change over time and how these changes influence risk taking behavior. More precisely, it could be interesting to find out whether previous investment success affects risk perception or overconfidence as has been argued in the literature. Moreover, since we have shown that overconfidence, i.e. miscalibration, has an impact on risk taking behavior it might be insightful to analyze possibilities to reduce the level of overconfidence. Studies in the psychological literature show that feedback can help in lowering the overconfidence bias (see for an extensive literature overview Balzer et al. (1989)), however, the sort of feedback that is given to subjects seems to be crucial. Hence, further research could also analyze effective ways of debiasing customers. Another promising line of research would be to analyze the question how to measure financial risk attitudes efficiently. Since we have shown that risk attitudes inferred from certainty equivalents are not an efficient way to measure risk preferences it might be interesting to

analyze in more depth the reliability and validity of graphical risk attitude measurement tools (see e.g. Goldstein et al. (2008)).

2.5   Appendix

1   Some Questions Concerning your Attitude towards Risk

In the first part of the questionnaire we would like to ask you to evaluate the riskiness of given situations. We are interested in finding out more about your personal preferences and attitudes with regard to the alternatives.

1.1   Consider the following situation:

You have an initial wealth of 10,000 Euro, which could be invested in a lottery (risky investment). Your wealth could increase to 12,000 Euro or decrease to 9,000 Euro, each with a probability of 50%.
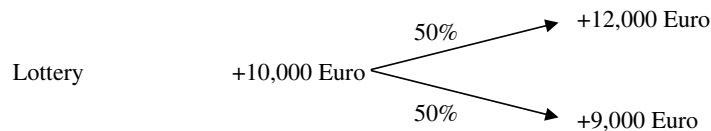
Lottery   +10,000 Euro
                                     50%   → +12,000 Euro

                                     50%   → +9,000 Euro

How do you assess the risk of the aforementioned lottery (risky investment) on a scale from 0 (no risk at all) to 10 (very high risk).

         0   1   2   3   4   5   6   7   8   9   10
         □—□—□—□—□—□—□—□—□—□—□

         No risk   Very high
         at all   risk
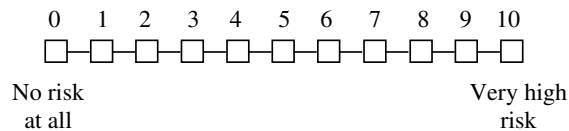
You could also invest the 10,000 Euro in a risk free alternative with a safe 3% interest rate.

Risk free
investment   +10,000 Euro ──────→ +10,300 Euro
                                        100%

Now consider the following scenario. You could invest your initial wealth of 10,000 Euro in either the lottery (risky investment) or in the risk free asset. How much would you invest in the lottery (risky investment) and in the risk free investment, respectively?

Please mark your answer on the following scale from 0 to 100, where 0 indicates that the full amount will be invested in the risk free alternative and 100 indicates that the full amount will be invested in the lottery (risky alternative).

         0   10   20   30   40   50   60   70   80   90   100
         |աԿ�|

         Total amount invested in   Total amount invested in the
           the risk free alternative   lottery (risky alternative)
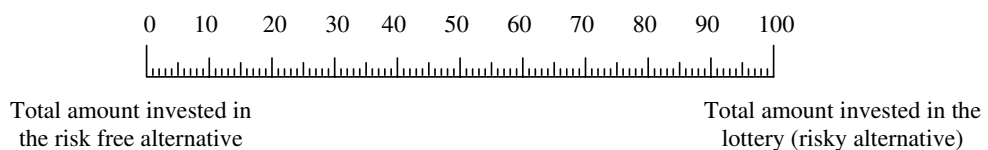
1.2 In the following situation you can again choose between a lottery (risky investment) and a risk free alternative.

The lottery either returns you an amount of 10,000 Euro or it returns nothing.
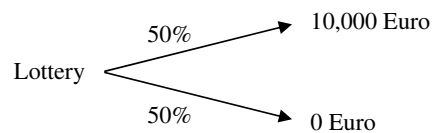
How do you assess the risk of the aforementioned lottery (risky investment) on a scale from 0 (no risk at all) to 10 (very high risk) if you can alternatively get 4,000 Euro.
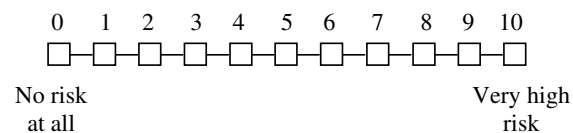
Now the amount you could alternatively get if you pick the risk free alternative will vary from 0 Euro to 10,000 Euro.

Please mark for each amount whether you prefer the participation in the lottery or the risk free amount.

Lottery		Risk – free amount	I prefer the lottery	I prefer the risk free amount
		9,000 Euro	O	O
		8,000 Euro	O	O
	10,000 Euro	7,000 Euro	O	O
50%		6,000 Euro	O	O
		5,000 Euro	O	O
		4,000 Euro	O	O
50%	0 Euro	3,000 Euro	O	O
		2,000 Euro	O	O
		1,000 Euro	O	O

1.3 How would you classify your willingness to take risks in financial decisions?

2

2   Estimation Questions

2.1   General Knowledge Task

We would like to know your estimates concerning the following 10 knowledge questions. Please state an upper and a lower bound to emphasize your estimates.

The correct answer should not:

… fall short of the **lower bound** with a high probability (95%). I.e. with 95% probability the correct answer should be above your lower bound.

… exceed the **upper bound** with a high probability (95%). I.e. with 95% probability the correct answer should be below your upper bound.

In other words we ask you to provide 10 intervals which contain the correct answer with a probability of **90%.**

	Lower bound (with 95% the value will be higher)	**Upper bound** (with 95% the value will be lower)
How long is the Mississippi in kilometers?		
In what year was Alfred Nobel born?		
How many countries are member of the NATO?		
How high is the Frankfurt „Messe Turm"?		
How many people are members of the 16th German "Bundestag" (= House of Parliament)?		
In which year did India gain its independence?		
How many country teams will participate in the qualifying for the UEFA European Football Championship 2008?		
How big is the equatorial diameter of the planet Mars in kilometers?		
What is the length of the Tower Bridge (London) in meters?		
How many people were employed at the Deutsche Bank in 2005?		

Please give us an estimate for the number of questions you answered correctly. How many times was the correct answer inside the range you gave?

_____ (Please give a number between 0 and 10)

Now we kindly ask you to give us an estimate for the number of questions the average participant in this study answered correctly. How many times was the correct answer inside the intervals the average participant gave?

_____ (Please give a number between 0 and 10)

2.2   Subjective self-estimation of your forecast ability

In the following, we kindly ask you to rate your forecasting ability. Therefore, you should tell us, to what extent you agree with each of the following statements:

I am able to identify stocks that will beat the market in the future.

| 1 | 2 | 3 | 4 | 5 |

Fully agree   Totally disagree

My stock forecasts are always correct.

| 1 | 2 | 3 | 4 | 5 |

Fully agree   Totally disagree

Losses and gains in stock markets are just a matter of chance.

| 1 | 2 | 3 | 4 | 5 |

Fully agree   Totally disagree

3   Stock Task

In the next question we are interested in getting to know your personal forecasts for real stock prices. For this purpose we show you the historical price charts of five stocks for five years. You should – given this information – make three statements concerning the future price of each stock. More precisely you should provide a best guess, a lower and an upper bound such that the correct answer to each question should:

… not fall short of the **lower bound** with a high probability (95%). I.e. with 95% probability the correct answer should be above your lower bound.

… equally likely be above respectively below the **Best Guess** (I.e. with a probability of 50% it should not be below your Best Guess and with a probability of 50% it should not be above your Best Guess)

… not exceed the **upper bound** with a high probability (95%). I.e. with 95% probability the correct answer should be below your upper bound.
…

In other words we kindly ask you to provide 5 ranges which contain the correct answer with a probability of 90%.

4

3.1.1 …

3.1.5) The chart below shows the historical stock price movements of Adidas for the last five years. What is your forecast for the price of the Adidas stock in one year? Please provide the following three estimates:
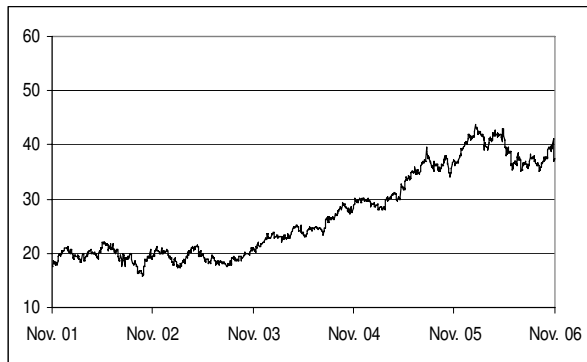
Lower bound (will be exceeded with a probability of 95%)

Estimate (median)

Upper bound (will fall short with a probability of 95%)

How do you assess the risk of the Adidas stock on a scale from 0 (no risk at all) to 10 (very high risk).

0   1   2   3   4   5   6   7   8   9   10

No risk
at all

Very high
risk
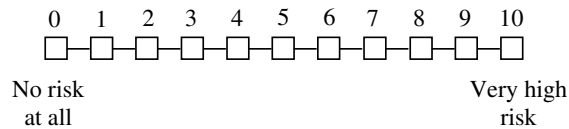
Now imagine you have an initial wealth of 10,000 Euro and you could invest this amount either in a risk free investment with a safe interest rate of 3% or in Adidas stocks. How much would you invest in the risk free alternative and in Adidas stocks, respectively?

Please mark your answer on the following scale from 0 to 100, where 0 indicates that the full amount will be invested in the risk free alternative and 100 indicates that the full amount will be invested in Adidas stocks.

0   10   20   30   40   50   60   70   80   90   100

Total amount invested in
the risk free alternative

Total amount invested
in Adidas stock
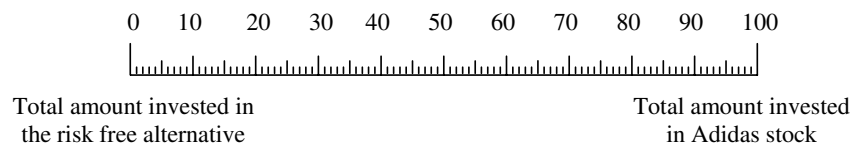
Please give us an estimate for the number of stock price intervals you answered correctly. I.e. how many times was the correct answer inside the range you gave?

_____ (Please give a number between 0 and 5)

Now we kindly ask you to give us an estimate for the number of stock price intervals the average participant in this study answered correctly. How many times was the correct answer inside the intervals the average participant gave?

_____ (Please give a number between 0 and 5)

4 Demographics

Age: _____

Sex: ○ female   ○ male

Line of studies: _____

Semester: _____

How many different investments products (e.g. shares, funds, bonds, certificates) did you hold within the last year?

○ 0   ○ 1-5   ○ 6-10   ○ more than 10

How do you rate your statistical knowledge?

1	2	3	4	5

very good   bad

How do you rate your knowledge about stock markets and financial markets?

1	2	3	4	5

very good   bad

Chapter 3

Changes of Expectations and Risk Attitudes and Their Impact on Risk Taking Behavior

3.1 Introduction

Both investment firms and researchers are eager to learn more about factors that influence subjects' risk taking behavior. In classic portfolio theory (see e.g. Markowitz (1952)) risk taking is argued to depend mainly on individuals' risk attitudes with the risk and return of an investment being equated by historical returns and historical volatilities. However, more general risk-value frameworks (see Sarin and Weber (1993b), Weber (1997), and Jia et al. (1999)) allow for heterogenous beliefs about the riskiness and the returns of an investment and model subjects' risk taking behavior as follows:

$$Risk\ Taking\ =\ f\ (Return\ Expectations,\ Risk\ Attitude,\ Risk\ Expectations) \quad (3.1)$$

Hence, changes in risk taking behavior should be caused by changes in one or more of these determinants of risk taking. Trying to incorporate this into the above equation we reformulate equation 3.1 as follows:

$$\Delta Risk\ Taking = f(\Delta_1\ Return\ Expectations, \Delta_2\ Risk\ Attitude, \Delta_3\ Risk\ Expectations)$$

$$(3.2)$$

Both researchers and practitioners argue that risk taking behavior varies substantially over time, i.e. from one point in time to the following. Commenting on the financial crisis in September 2008 the New York Times assessed: "investors around the world frantically moved their money into the safest investments, like Treasury bills". Researchers analyzing dynamics of risk taking behavior also argue that risk taking behavior can change substantially over time (see e.g. Staw (1976), Thaler and Johnson (1990), Weber and Zuchel (2005), and Malmendier and Nagel (2009)). However, it is still an unresolved question what actually drives changes in risk taking behavior. In more general risk-value frameworks, changes in risk taking can be due to changes in expectations or risk attitudes. Thus, the main goal of this study is to analyze whether *Return Expectations* (Δ_1), *Risk Attitudes* (Δ_2), or *Risk Expectations* (Δ_3) change over time and subsequently affect changes in *Risk Taking* (Δ).

Knowing more about changes in the determinants of risk taking behavior is in particular important because of the regulations of the Markets in Financial Instruments Directive (MiFID) by the European Parliament and the European Council (2004 and 2006). The MiFID requires investment firms to obtain "information as is necessary for the firm to understand the essential facts about the customer (Article 35, 1)" and to elicit the customers' "preferences regarding risk taking, his risk profile, and the purpose of the investment (Article 35, 4)." However, MiFID is not specific about how often investment advisors have to elicit risk preferences and risk profiles. To close this gap we analyze in the following whether risk attitudes or expectations of individuals change over time and whether these changes have an impact on risk taking behavior.

The main data were gathered via repeated internet surveys which were conducted in collaboration with the behavioral finance team at *Barclays Wealth* from September 2008 to March 2009. A big advantage of our study is that we use a unique dataset of real online

broker customers that includes information on the customers' expectations, risk attitudes, and risk taking behavior.[1]

Selected customers of *Barclays Wealth* were asked to participate repeatedly in a question- naire survey. The survey was run on a quarterly basis from September 2008 to March 2009. Overall 617 subjects participated at least once in the three surveys. Of these 617 subjects, 287 participated once, 181 twice, and 149 thrice. In all three surveys we elicited amongst others financial risk taking by asking subjects to divide an amount of £100,000 either into the stock market (FTSE-All-Share) or into a risk free asset with a safe interest rate of 4%. We also elicited subjective risk attitudes using three questions of *Barclays Wealth*'s psychometrically validated risk attitude scale. In addition, we elicited risk and return expectations of subjects for their own portfolio and for the market (FTSE-All-Share).

Using survey data has some pros and cons. On the one hand, it has the disadvantage that we do not observe actual behavior of people and that there might be potential selection and response biases. On the other hand, a big advantage is that relevant variables can be elicited in a clean environment and do not need to be indirectly inferred from actions and that in contrast to choice data one does not need to maintain the strong assumption that decision makers have objectively correct (i.e. rational) expectations (for an overview of some pros and cons of survey data see Manski (2005)). Surveys asking for individuals' expectations and beliefs are very common[2] and are highly influential both in academia and practice.

Our results indicate that - consistent with evidence in the financial media and with findings in the literature - risk taking behavior in the financial domain is indeed varying over time.

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[1] We would like to thank the behavioral finance team at *Barclays Wealth*, Pete Brooks, Greg Davies and Dan Egan for not only providing us with the data but also for very helpful comments, stimulating discussions, and help in designing the survey in collaboration with us. We are particularly grateful to Dan Egan for his invaluable help in collecting and collating the data and running the survey over multiple periods.

[2] A non exclusive list of such surveys in the U.S. are the University of Michigan Health and Retirement Study (HRS) survey `http://hrsonline.isr.umich.edu/index.php?p=qnaires`, the Survey of Economic Expectations `http://www.disc.wisc.edu/econexpect/Index.html`, the University of Michigan Survey of Consumers `http://www.sca.isr.umich.edu`, the UBS/Gallup survey `http://www.ropercenter.uconn.edu/data_access/data/datasets/ubs_investor.html`, and the Duke/CFO Business Outlook survey `http://www.cfosurvey.org/duke`. Two examples from Germany are the ZEW Bankprognosen survey `http://www.zew.de/de/publikationen/bankprognosen/index.php` and the Socio-Economic Panel `http://www.diw.de/deutsch/soep/29004.html`. Findings in some of these surveys are going to be discussed in section 3.2.

Risk taking is defined as the hypothetical amount subjects would invest into the stock market and a risk free asset, respectively. Subjects invest substantially less into risky assets in December than in September and also substantially less risky in March than in December. More specifically, the percentage invested into the risky asset drops from 56.02% in September to 52.77% in December and to 46.52% in March. Analyzing the main determinants of risk taking - risk attitudes as well as risk and return expectations - our findings are twofold. First, risk attitudes seem to remain fairly stable as the risk attitude score on a 7-point Likert scale changes from one survey to the other by more than 1 point only for approximately 20% of all subjects. Second Wilcoxon signed-rank tests show that risk and return expectations vary significantly from one survey to the other. Moreover, we show that changes in risk taking can mainly be attributed to changes in risk and return expectations and not to changes in risk attitudes. This result remains stable even if we control for individual past performance. Finally, we compare changes in risk expectations in relation to changes in actual risk, which is a measure of overconfidence. We show that this measure of overconfidence seems to be fairly stable initially and decreases in the long run.

These findings are important for practitioners in two ways: first, we show that risk attitudes are stable individual constructs that do not need to be elicited on a quarterly basis. Note that this line of argument cannot be generalized to all risk attitude measures currently used by practitioners. In particular inappropriate measures such as the ones that confound risk attitudes and expectations do not need to be stable over time. Second, we illustrate that subjective expectations are important determinants of risk taking behavior and that it might be worthwhile for practitioners to elicit their clients' expectations regularly.

Our study extends findings in the empirical and experimental literature. Up to now, there is no study documenting whether changes in expectations and/or changes in risk attitudes drive changes in risk taking behavior. However, there are several papers analyzing whether risk taking behavior actually changes over time. Malmendier and Nagel (2009) use real world data to show that individuals' personal experiences of macroeconomic shocks have long-lasting effects on their risk taking behavior. In the experimental literature Staw

(1976) and Thaler and Johnson (1990) show that risk taking behavior can depend on individual prior gains and losses. But both empirical and experimental studies are not able to disentangle the channel through which individual risk taking behavior changes over time; i.e. they are not able to analyze whether changes in risk taking behavior can be attributed to changes in risk attitudes or expectations or both. In contrast, our data basis allow us to explicitly analyze this issue for a sample of real bank customers.

Furthermore, most studies analyzing changes in expectations and risk attitudes investigate either changes in risk expectations (e.g. Weber and Milliman (1997)) or changes in return expectations (e.g. Shiller et al. (1996)) or changes in risk attitudes (e.g. Sahm (2007) and Klos (2008)) separately but not in one single study. Moreover, most of these studies are not able to relate changes in expectations and risk attitudes to changes in risk taking. Vissing-Jorgensen (2003) and Dominitz and Manski (2007) analyze the relation between the probability of holding stocks and expected equity returns. Using large scale survey data, they find that the probability of holding stocks is higher the higher expected returns are. We extend their findings in two ways: first, they do not analyze changes in expectations and consequently their influence on changes in risk taking behavior. Second, they proxy for risk taking by the probability of holding stocks whereas we analyze asset allocation decisions.

Another important advantage of our study is that the surveys we use were conducted in early September 2008 (6-20), December 2008 (6-20), and March 2009 (21-30). This unique dataset allows us to test if the turmoil on financial markets during this period such as the collapse of Lehman Brothers had substantial effects on risk attitudes, expectations, and risk taking behavior. In addition, using repeated survey data on real online broker customers to analyze changes in risk attitudes adds to the literature which often relies on student populations (see e.g. Baucells and Villasis (2009) or Harrison et al. (2005)) and offers substantial advantages. For example, we are able to control if differences in past portfolio performance or changes in market conditions drive changes in risk attitudes, expectations or risk taking behavior.

This chapter proceeds as follows: in section 3.2 we provide a literature review and formulate our hypotheses. Section 3.3 presents information on survey respondents and on the

survey design. The main results are reported in section 3.4 while the last section provides a discussion of our results and a short conclusion.

3.2   Related Literature and Hypotheses

Anecdotal evidence suggests that risk taking behavior of investors, i.e. their division of wealth between risky and risk free assets, can substantially vary over time and does not need to be perfectly stable. According to the Deutsche Aktieninstitut in the year 2000, at the height of the internet boom, 6.2 million people in Germany held part of their wealth in stocks. By 2008, in the course of the financial crisis, this number had dropped to only 3.5 million. In a similar vein, the Wall Street Journal (2008) reports in an article on December 5, 2008 that in response to the dramatic events on financial markets "investors pulled \$ 72 billion from stock funds in October alone" and moved their money into government bonds and cash holdings.

Thus, individuals risk taking behavior, i.e. their choice between risky and risk free assets, seems not to be perfectly stable over time. This temporal instability can be due to various factors: first, subjects do not need to exhibit the same level of risk aversion over time. Second, individual risk expectations and return expectations do not need to be stable and might be shaped by personal experiences. Third, important personal aspects such as income and wealth might change over time. All these factors can individually or jointly lead to changes in risk taking behavior over time. In the following we are going to illustrate general findings in the literature on the stability or non-stability of risk taking behavior. Subsequently, we are going to present more recent studies analyzing changes in risk attitudes and expectations over time, before we pick up the question why changes in risk taking over time occur.

Earlier studies in decision analysis on the stability of risk preferences or risky choices seem to confirm the anecdotal evidence. Camerer (1989) and Hey and Orme (1994) investigate the short term temporal reliability and stability of risky choices. Both studies confront subjects with the same set of choices at two points in time (less than 10 days apart). Their results indicate that individuals change their risk taking behavior in 25%-30% of

all cases. However, these studies do not explicitly analyze the role of prior gains or losses on subsequent risk taking behavior.

Staw (1976) analyzes exactly this and shows that risk taking behavior does not need to be stable and substantially depends on prior personal outcomes. He illustrates that subjects take significantly more risks following a loss than following a gain and terms this "escalation of commitment". The "escalation of commitment" hypothesis is also in line with findings in the literature on the disposition effect (see e.g. Odean (1998a) and Weber and Camerer (1998)). On the other hand, Thaler and Johnson (1990) argue that it is difficult to make generalizations about risk taking preferences. They show a reverse effect, i.e. enhanced risk taking in the gain domain, in two stage gambles which they term the "house money effect". Weber and Zuchel (2005) conduct an in-depth analysis of the two conflicting effects "escalation of commitment" and "house money effect" and show that the framing of the situation is important when analyzing changes in risk taking behavior. On the one hand, the "house money effect" is prevalent if a situation is framed as a lottery, on the other hand, the "escalation of commitment" effect is predominant if the situation resembles a portfolio investment.

These studies show that the personal experience of gains or losses in the past can influence subsequent risk taking behavior. In a slightly related context Malmendier and Nagel (2009) show that personal macroeconomic experiences seem to have a great impact on personal decisions and on the risk taking behavior of individuals. They illustrate that subjects who have experienced high inflation and bad market-returns throughout their lives invest substantially less risky than subjects who have experienced excellent market-returns in the course of their lives. However, they do explicitly state that their goal is not to analyze whether changes in beliefs or in risk aversion or a mix of both drive observed differences in risk taking behavior.

Overall, the presented evidence suggests that subjects need not take constant levels of risks in their investment decisions. Various factors such as changes in personal macroeconomic experiences or gains and losses in own investments might affect risk taking behavior in a dynamic setting. In a first step, we simply want to find evidence for the well-established claim that risk taking behavior does not need to be stable in our survey for the sample

period September 2008 to March 2009. Consistent with the aforementioned anecdotal evidence and findings in the literature we formulate hypothesis 1 as follows:

Hypothesis 1: Financial risk taking behavior varies over time

One important explanation for varying risk taking behavior over time often brought forward are changes in income or wealth. The fact that an increase in wealth should result in a higher level of risk taking or a decrease in relative risk aversion is a key implication of various difference habits models. Brunnermeier and Nagel (2008) use microdata to analyze this key implication of difference-habit models empirically. They show that wealth changes affect the decision to participate in stock markets but that they have hardly any effect on asset allocation decisions, i.e. on the proportion a household invests in risky and risk free assets, respectively. In a similar vein, Guiso et al. (2003) analyze stock ownership in major European countries and illustrate that the share of wealth invested in the stock market is independent of investors' wealth. Thus, both papers show that wealth effects cannot explain observed changes in risk taking behavior over time.

In more general risk-value frameworks variations in financial risk taking behavior over time can mainly be attributed to changes in risk and return expectations and/or changes in risk attitudes (see equation 3.1 and 3.2). In the following, we will review some more recent findings in the empirical and experimental literature on long run changes in risk attitudes and changes in expectations over time.

Changes in risk attitudes:

Studies analyzing long term changes in risk attitudes by confronting the same set of subjects with the same set of questions can be roughly classified into two groups. First, studies using data from large scale panel surveys such as the Socio-Economic Panel (SOEP) or the Michigan Health and Retirement Survey (HRS) which mostly use self-assessment tasks with answer possibilities on Likert-scales. Second, laboratory and field experiments using lottery related tasks to elicit risk attitudes and subsequently, changes in risk attitudes.

Using data from simple 11-point self-assessment tasks from the SOEP waves in 2004 and 2006, Klos (2008) analyzes the temporal stability of risk attitude measures. He shows that individual risk attitudes tend to be fairly stable over time and that the effect is in particular strong for those subjects that indicated the central category. Similarly, Sahm (2007) finds evidence for persistent differences between individuals but relatively high stability of risk attitudes within individuals over time using the HRS panel data set with more than 12,000 observations.

Andersen et al. (2008) use a field experiment with a representative sample of the Danish population and Harrison et al. (2005) a laboratory study with students to analyze the temporal stability of risk attitudes. Both studies obtain subjects' risk aversion measures using a multiple price list approach (see e.g. Holt and Laury (2002)). They find only slight variation of risk attitudes over time and conclude that risk attitudes seem to be a stable construct. In addition, Baucells and Villasis (2009) find similar results in a laboratory study in which they elicit risk attitudes using binary lottery choice tasks. They also find only small deviations in risk attitudes over time and argue that most of these changes disappear if one introduces noise.

Overall, evidence in research implies that risk attitudes seem not to change too much over the course of time and that observed changes can mainly be attributed to errors. Hence, our hypothesis is the following:

Hypothesis 2: Risk attitudes are fairly stable over time

Changes in risk and return expectations:

The original formulation of the capital asset pricing model (CAPM) is a static one-period model that assumes homogenous expectations (see e.g. Sharpe (1964) and Lintner (1965)). Subsequent studies extended these assumptions by considering heterogenous beliefs, time-varying expectations, and a dynamic investment problem of rational investors (see e.g. Merton (1973) and Miller (1977)). In contrast, behavioral approaches argue that some subjects misinterpret the informational content of a new signal and adjust their expecta-

tions inappropriately. Consequently, they over- or underreact to new information because of their biased expectations (see for an overview DeBondt (2000)). Both rational and behavioral studies agree that risk and return expectations can vary between subjects and also within subjects over time when new information comes into the market.

Changes in return expectations have been analyzed extensively in the empirical and experimental literature, mostly with repeatedly carried out large scale surveys. Dominitz and Manski (2005) analyze the dynamics of expectations in the Survey of Economic Expectations (1999-2001) and in the Michigan Survey of Consumers (2002-2004). They find that expectations are not perfectly stable over time but that differences between persons are larger than differences within persons over time.

Using a series of cross-section UBS/Gallup surveys, Fisher and Statman (2002) and Vissing-Jorgensen (2003) show that subjects' long and short term expectations change substantially over the course of time. Taking data from the 1998-2003 surveys, Vissing-Jorgensen (2003) illustrates that average 1-year expectations vary substantially from a high of 15.8% in January 2000 to a low of around 6% at the end of 2002. She argues that expectations and actual returns almost seem to move together. Analyzing the crash in the Japanese stock market Shiller et al. (1996) illustrate that a sharp drop in expectations for long run earnings growth could be observed for the period 1989-1994. They argue that changes in expectations probably have substantial economic effects but do not provide direct and unambiguous evidence on this issue.

Using a between-subjects design, Glaser and Weber (2005) demonstrate that return expectations after September 11 and the following market downturn are significantly higher than return expectations before the event indicating that subjects did believe in some sort of mean reversion. However, they note that there is no unambiguous ex ante prediction whether subjects will expect mean reversion or trend continuation in stock prices in response to such a dramatic event.

Risk perception or risk expectations are also often argued to be based on individuals' past experiences of a similar event or situation (see e.g. Ricciardi (2004)). In a similar vein, Loewenstein et al. (2001) hypothesize that decisions are evaluated at an emotional level

and that prior outcomes, good as well as bad ones, influence this emotional level and the way individuals perceive the risk of a situation.

Consistent with these hypotheses, Weber and Milliman (1997) and Mellers et al. (1997) experimentally show that risk perceptions change significantly over time after subjects have experienced either good or bad outcomes. More precisely, they show that risk attitudes are almost perfectly stable if one controls for changes in risk perceptions. Similarly, Glaser and Weber (2005) find that volatility estimates are significantly higher after the terror attacks of September 11 than before.

Overall, the evidence in the literature indicates that both risk and return expectations can vary substantially over time as they can e.g. be influenced by macroeconomic developments or individually experienced gains and losses. However, to come up with a general hypothesis whether risk and return expectations should rise or fall in response to the dramatic events in late 2008 is difficult. Hence, hypothesis 3 follows:

Hypothesis 3: Expectations vary over time

On the one hand, the presented evidence at the start of this section indicates that financial risk taking behavior does not need to be constant over the course of time and may vary given prior gains and losses or given macroeconomic changes. On the other hand, risk and return expectations - two major determinants of risk taking in risk-value models - have also been shown to vary over time, whereas risk attitudes seem to be fairly stable. Our data allow us to test explicitly what actually drives changes in risk taking. Consistent with the previously presented literature we assume that changes in risk taking over time are mainly driven by changes in risk and return expectations and not by changes in risk attitudes or past performance.[3]

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[3]Note that the goal of this study is not to test whether changes in risk and return expectations are based on rational motives or whether they are due to irrational motives such as misreaction to new information.

3.3   Data

3.3.1   Survey Respondents

Our analysis is based on a repeated questionnaire study that was run as part of a joint collaborative research project with the behavioral finance team at *Barclays Wealth* in September 2008, December 2008, and March 2009. About 90% of all subjects in the September sample completed the survey before September 12, i.e. before the bankruptcy of Lehman Brothers and the subsequent downturn on financial markets. Unfortunately, we do not have explicit information on the specific date each individual has completed the survey.

Before the September wave, a stratified sample of *Barclays Stockbrokers'* client base was drawn. To accomplish stratification, we grouped subjects according to their *Age, Number of deals per year, Number of holdings*, and *Portfolio value* into non-overlapping subgroups, so called strata. This procedure was used to improve the representativeness of the sample and in order to take care of our collaborating bank's desire to undersample subjects who trade very little (*Number of deals per year*≤1) or have a relatively low portfolio value (*Portfolio value*< £1,000). Thus, in all strata in which subjects were included that traded less than once a year or had a portfolio value of less than £1,000 a lower percentage of subjects were invited to participate in the survey than in the remaining strata. Note that although we did undersample, we did not exclude these subjects totally as still more than 16% of all approached individuals had a portfolio value below £1,000.

Overall, 19,251 clients were emailed and invited to participate in a repeated survey. This equals approximately 5% of all customers. Of the 19,251 individuals that were approached by email in late August/early September 2008 about 4,520 (23%) opened the email. Of those that opened the email, 849 (20%) went to the website and in the end, 479 out of these 849 subjects completed the survey in September. The response rate is slightly lower but still in the same ballpark as in similar studies by Dorn and Huberman (2005, 4%) and Glaser and Weber (2007, 7%). Both studies also sent an email to customers of an

online broker and asked them to participate in an online questionnaire. It took subjects on average 24 minutes to answer the survey.

The 479 subjects who participated in September were contacted again by email in late November/early December 2008 and invited to participate in a shorter version of the questionnaire.[4] Overall, 240 of the 479 subjects participated for a second time in December. In addition, *Barclays Wealth* sent out an email to further 700 customers that had not been contacted yet, in order to increase the number of subjects in future surveys.[5] This resulted in an additional 138 subjects joining the panel in December. These 138 subjects received the same questionnaire that was filled out by the 479 subjects in September and not the shorter December version. In March 2009, all 617 subjects that had previously participated in at least one round were contacted again and invited to participate in a further study. This time all subjects received the same, shorter version of the questionnaire. Overall, 287 subjects participated only once (214 in September and 73 in December) and 149 subjects participated in all three surveys. Of the remaining 181 subjects who participated twice, 91 participated in September and December, 65 in December and March, and 25 in September and March.

The main goal of the study is to analyze whether risk taking behavior, risk attitudes, and expectations change from September to December and from December to March and what might drive these changes. To analyze this we want to compare on an individual level subjects' responses to survey questions at the three points in time. In contrast to previous studies using one-time survey responses from online broker customers (see e.g. Dorn and Huberman (2005) and Glaser and Weber (2007)) our dataset consists of repeated observations and allows us to analyze changes in the main variables. However, an analysis of individual changes in the main variables is only possible for subjects that took part at least in two consecutive surveys, i.e. in September and in December or in December and March or in all three surveys. 240 subjects participated both in September and December

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[4]In contrast to the second version of the questionnaire we elicited in the first, longer version demographics, further individual characteristics and various behavioral client profiling questions. These questions are psychometrically validated and used by *Barclays Wealth* within the advisory process.

[5]These 700 had previously participated in another marketing related event of *Barclays Wealth* and had indicated their willingness to participate in surveys.

and 214 subjects participated both in December and March. In addition, 149 subjects participated in all three surveys.

To address a potential selection bias we compare the overall adult British population with survey participants and we also compare subjects who participated once with those that participated twice and thrice, respectively. Table 3.1 illustrates mean scores of demographics and further characteristics for various groups. The first two columns illustrate mean scores for all participants of our study (Group^{all}) and for the adult British population (GB^{all}), respectively. The next three columns illustrate the same scores separately for subjects that participated only once (Group^{once}, N=287), twice (Group^{twice}, N=181), and subjects that participated in all three surveys (Group^{thrice}, N=149).

The average age of all survey participants is 51.65 with two thirds of the subjects aged between 40 and 66; four years older than the average British adult. In addition, subjects in our sample are more likely to be married (0.65 vs. 0.52) or male (0.93 vs 0.49) compared to the British average. *Gross income* is highly skewed with an overall mean of £76,615.73 and an overall median of £55,000 and substantially larger than for the average Briton (£30,000). Clearly, our subjects are not likely to be representative of the typical British adult. However, we find a considerable variation in subject's answers which allows us to test our hypotheses. In addition, our finding that respondents to this kind of survey are predominately male and have a substantially larger gross income than the overall population is consistent with Dorn and Huberman (2005).

Comparing subjects that participated once (Group^{once}), twice (Group^{twice}), and thrice (Group^{thrice}), respectively, we find hardly any differences for the three subgroups. Only for the level of investable wealth that is measured in 9 categories from 1 (£0 - £10,000) to 9 (> £ 1 million) we find significant differences between the subgroups. Subjects that participated only once in the survey have a substantially lower investable wealth than subjects who participated thrice. Moreover subjects who participated thrice indicate higher wealth levels than those who participated twice. Since the main goal of our study is to analyze changes in various variables on an individual level over time, differences in wealth between the three subgroups should not be problematic.

Table 3.1: Demographic characteristics and descriptive statistics

The first two columns of this table report mean values of various demographics and descriptive statistics for participants of our study (Group^{all}) and for the adult British population (GB^{all}) (GB^{all} data are supplied through the Office for National Statistics). The next three columns report mean values of various demographics and descriptive statistics for a subset of participants that took part in all three surveys only once (Group^{once}), only twice (Group^{twice}) or in all three surveys (Group^{thrice}), separately. *Age, Number of dependants,* and *Gross income* are self-explanatory. *Gender* and *Marital status* are two dummy variables that take the value 1 if the subject is male and married, respectively. Investable wealth is measured in 9 categories from 1 (£0 - £10,000) to 9 (> £ 1 million). The last three columns report z-scores of Mann-Whitney rank-sum tests or binomial tests (for the two dummy variables) which test whether subjects that participated once, twice or thrice differ from the respective subgroup of subjects. * indicates significance at the 5% level and ** indicates significance at the 1% level.

	Group^{all}	GB^{all}	Group^{once}	Group^{twice}	Group^{thrice}	Diff.$^{twice-once}$	Diff.$^{thrice-once}$	Diff.$^{thrice-twice}$
Age	51.65	47.66	51.69	50.52	52.96	-0.667	1.082	1.595
Number of dependents	1.14	-	1.17	1.13	1.08	-0.328	-0.309	0.056
Gender	0.93	0.49	0.92	0.93	0.95	0.674	0.238	0.453
Gross income	76,615.73	30,000	71,446.59	85,718.92	76,631.4	1.157	0.902	-0.207
Marital status	0.65	0.52	0.67	0.65	0.62	0.647	0.314	0.601
Investable wealth	4.80	-	4.58	4.52	5.55	1.082	3.660**	3.488**

After having introduced the main variables in the following subsection, we are going to analyze whether the three groups of subjects (Group^{once}, Group^{twice}, and Group^{thrice}) differ in their response behavior in subsection 3.3.3.

3.3.2   Survey Design

This subsection presents the main variables that were elicited repeatedly within the surveys. All surveys were designed in close collaboration with the behavioral finance team at *Barclays Wealth* in order to get a better understanding of investors' behavior. Besides demographics and further individual characteristics that were described above and collected only in the first survey in which a subject participated we elicited the following variables repeatedly. The main variables are summarized in table 3.2.

(Financial) Risk taking: In the hypothetical risk taking task subjects were asked to invest an amount of £100,000 either into the stock market (FTSE-All-Share) or into a risk free asset with a safe interest rate of 4%. The higher the amount subjects allocate to the stock market the more risk are they willing to take in this hypothetical task. A big disadvantage of real transaction data is that it is hardly possible to obtain complete information on total asset holdings of individuals at all banks at which they have an account. Thus, although hypothetical risk taking is only an indirect proxy of risk taking behavior it is a measure for which we have all necessary information.

Risk attitudes: In the September and December surveys we use three questions from *Barclays Wealth*'s 8-question psychometric scale to assess subjects' risk attitudes. Brooks et al. (2008) show that this scale efficiently differentiates individuals from low risk tolerance to high risk tolerance and that the scale has high levels of reliability and validity. The three questions used in our study can be found in table 3.2. For all three questions we used a 7-point Likert scale with the endpoints "1 = Strongly Disagree" and "7 = Strongly Agree".[6] In the March survey only one of these three risk attitude measures was elicited

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[6]Amongst others Bollen and Barb (1981), Cicchetti et al. (1985), Preston and Colman (2000), Alwin and Krosnick (1991), and Weng (2004) show that reliability, validity, and discriminating power increases up to 7-point scales and that after this additional effects can hardly be observed. Moreover, Viswanathan et al. (2004) argue that the number of categories should be picked such that it is as close as possible to a natural number of categories for a specific question and that one shouldn't

Table 3.2: Definition of dynamic variables

This table summarizes and defines variables that were elicited repeatedly. Note that *Risk Attitude 6* and *Risk Attitude 7* were not elicited in the March survey.

Variable	Question / Description
Risk Taking	
Risk Taking	Measures, on a percentages basis, the (hypothetical) amount of money an individual is willing to invest into the FTSE-All-Share compared to a risk free asset with a 4% return. (0 = invest everything into the risk free asset ... 100 = invest everything into the risky stock market)
Risk Attitude	
Risk Attitude 2	"It is likely I would invest a significant sum in a high risk investment." (1 = Strongly disagree ... 7 = Strongly Agree)
Risk Attitude 6	"I am a financial risk taker." (1 = Strongly disagree ... 7 = Strongly Agree)
Risk Attitude 7	"Even if I experienced a significant loss on an investment, I would still consider making risky investments." (1 = Strongly disagree ... 7 = Strongly Agree)
Expectations	
Market-Return-Num.	Measures individuals' return expectations for the FTSE-All-Share in 3 months in percent
Market-Risk-Num.	Measures individuals' volatility expectations for the FTSE-All-Share in 3 months by transforming estimates of bounds into volatility estimates.
Market-Return-Subj.	"How would you rate the returns you expect from an investment in the UK stock market (FTSE-All- Share) over the next 3 months?" (1 = Extremely bad ... 7 = Extremely good)
Market-Risk-Subj.	"Over the next 3 months, how risky do you think the UK stock market (FTSE-All- Share) is?" (1 = Not risky at all ... 7 = Extremely risky)
Own-Return-Num.	Measures individuals' return expectations for the own portfolio at the bank in 3 months in percent
Own-Risk-Num.	Measures individuals' volatility expectations for the own portfolio at the bank in 3 months by transforming estimates of bounds into volatility estimates.
Own-Return-Subj.	"How would you rate the returns you expect from your own portfolio over the next 3 months?" (1 = Extremely bad ... 7 = Extremely good)
Own-Risk-Subj.	"Over the next 3 months, how risky do you think the investments in your own portfolio are?" (1 = Not risky at all ... 7 = Extremely risky)
Past Performance	
Perf.-External	What do you think the return of your investments held at other banks over the past 3 months was?
Perf.-Market-Num.	"What is your best estimate of the return of the UK stock market (FTSE-All-Share) over the past 3 months?"
Perf.-Market-Subj.	"How would you rate the returns of the UK stock markets (FTSE-All-Share) over the past 3 months?" (1 = Extremely bad ... 7 = Extremely good)
Perf.-Own-Num.	"What do you think the return of your own portfolio over the past 3 months was?"
Perf.-Own-Subj.	"How would you rate the returns of your own portfolio over the past 3 months?" (1 = Extremely bad ... 7 = Extremely good)

(*Risk Attitude 2*). We do not elicit risk attitudes from lotteries because of the extended domain specificity result in chapter 2 where we showed that risk attitudes inferred from lotteries are not related to investment behavior in stocks.

Expected return and expected risk: Since we have argued in sections 3.1 and 3.2 that subjective risk and return expectations are important determinants of risk taking behavior, we tried to elicit them extensively in the questionnaire. To do this we elicited subjects three months expectations for their own portfolio as well as for the overall stock market (FTSE-All-Share). We chose the three months forecasting period because the survey panel is also conducted on a quarterly basis. Since we have shown in chapter 2 that risk expectations elicited on a purely subjective scale need not to coincide with risk expectations elicited via confidence intervals, we utilize both qualitative and numeric approaches to measure subjects' expectations.

To measure risk and return expectations numerically we asked individuals to state a best guess (mean estimate) for the three month return as well as upper and lower bounds for 90% confidence intervals for the return in three months. More precisely, we asked them to submit what they consider to be lower and upper bounds so that there is only a 5% chance that the return in three months will be below the lower bound and a 5% chance that it will be higher than the upper bound. Numeric return expectations for the market (*Market-Return-Num.*) or for a subject's own portfolio (*Own-Return-Num.*) are simply equal to the best guess for the return of the market and for the own portfolio, respectively. However, to obtain a measure of numeric risk expectations is not as straightforward. We use the two point approximation suggested in Keefer and Bodily (1983) which transforms stated confidence intervals into volatility estimates and has been widely used in the empirical literature (e.g. chapter 2 of this thesis, Graham and Harvey (2005), Ben-David et al. (2007), and Glaser et al. (2005)). This transformation gives us the two risk expectation measures *Market-Risk-Num.* and *Own-Risk-Num.*

To get the two qualitative measures of return expectations (*Market-Return-Subj.* and *Own-Return-Subj.*) we ask subjects to classify both expected market and own portfolio

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use too many scales as this overburdens subjects and is too hard of a cognitive task for them. Hence, using 7-point Likert scales seems to be the best trade-off between understandability and reliability for our sample of *Barclays Wealth* customers.

returns on a 7-point Likert scale with the endpoints "1 = Extremely bad return" and "7 = Extremely good return". Similarly, the qualitative measures of risk expectations (*Market-Risk-Subj.* and *Own-Risk-Subj.*) are obtained by asking subjects to classify both expected market and own portfolio risk on a 7-point Likert scale with the endpoints "1 = Not risky at all" and "7 = Extremely risky".

Past performance: We use the following approach to control for the possibility that past investment returns affect changes in risk taking behavior. We elicit individuals' subjective estimates of past performance, both past stock markets performance (FTSE-All-Share) and past own portfolio performance within the last three months on a repeated basis. Similar to expectations we use two elicitation methods. First, we ask subjects to give us a numerical estimate of their own past returns or the stock markets past return in percent. Second, we ask subjects to judge past returns on 7-point Likert scales with the endpoints "1 = Extremely bad return" and "7 = Extremely good return". In addition, we also ask subjects to indicate their past performance at other online brokers, if applicable.

3.3.3 Differences in Groups

In the following, we analyze the selection bias problem and in this connection in particular the question if subjects that participated once, twice, and thrice, respectively, differ in their response style to the repeatedly elicited variables. Overall, we have 17 repeatedly elicited variables in September and December (and 15 in March): $1 \cdot$ risk taking, $3 \cdot$ risk attitude ($1 \cdot$ risk attitude in March), $8 \cdot$ expectations, and $5 \cdot$ past performance. The mean and median values for all variables in a given month are very similar between the three groups of subjects: Group^{once}, Group^{twice}, and Group^{thrice}.

We use a series of Mann-Whitney rank-sum tests to analyze whether the response behavior in the separate groups differs significantly. Comparing responses of Group^{once} subjects in September and December with those of subjects that participated repeatedly (Group^{twice} and Group^{thrice}) we find that only for 3 out of 34 variables there are statistically significant differences. Similarly, comparing subjects that participated twice with those that

participated thrice, we only find significant differences for 3 out of 49 variables.[7] In addition, the few significant differences are scattered over various variables with no clear-cut uniform effect. Hence, we argue that there is no indication that subjects who participated once differ substantially in their response behavior from those that participated twice or thrice. In addition, the same seems to be true if we compare subjects that participated twice and thrice directly.

3.4   Results

3.4.1   On the stability of risk taking, risk attitudes, and expectations

This subsection analyzes if risk taking, risk attitude, expectations, and past performance are stable individual traits or whether they change over our three observation periods. Thus, we compare the response behavior in September with the one in December and the one in December with the one in March. Table 3.3 reports mean scores of all repeatedly elicited variables in our sample, separately for the three months. We report mean values in each of the three months only for subjects that participated at least twice in the survey, however, our results are essentially the same if we compute the numbers for all 617 subjects or for the 149 subjects that participated thrice. The last two columns in table 3.3 report results of Wilcoxon signed-rank tests analyzing whether the difference between the two respective months is significant. To avoid the problem that differences in repeatedly elicited variables are driven by the fact that different subjects participated in separate months, we run these tests only for those subjects that participated in the two respective months.

For *Risk-Taking* we observe, consistent with hypothesis 1, that the share subjects are willing to invest into the market (FTSE-All-Share) varies substantially. It decreases from 56.02% in September to 52.77% in December to 46.52% in March. All differences are highly significant at the 1% level.

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[7]We compare response behavior of subjects that participated twice and thrice, respectively, for 17 variables in September, 17 variables in December, and 15 variables in March. This gives us a total of 49 comparisons.

Changes in risk attitudes are hardly observable for all three risk attitude measures. *Risk Attitude 2* and *Risk Attitude 7* are virtually the same in September and in December. *Risk Attitude 6* rises slightly from 4.43 to 4.61 from September to December. This difference is significant at the 5% level. However, this rise indicates that subjects seem to be less risk averse in December than in September which is seemingly at odds with our previous finding on lower levels of risk taking behavior in December. Since we only elicited *Risk Attitude 2* in March we can just analyze the change of this risk attitude measure from December to March. Table 3.3 shows that *Risk Attitude 2* decreased slightly from 3.63 to 3.55 in this time period with the decrease being not significant. In addition, analyzing the stability of risk attitudes on an individual level, we find that around 40% of all subjects do not change self-reported risk attitudes at all and that around 80% of all subjects do not change their self-reported risk attitude score by more than one point on the 7-point Likert scales. This stability of risk attitudes is consistent with findings in Sahm (2007) and Baucells and Villasis (2009) as well as with hypothesis 2.

Risk expectations or risk perceptions on the other hand, seem to change considerably over time. On the one hand, all four risk expectation measures *Market-Risk-Num.*, *Market-Risk-Subj.*, *Own-Risk-Num.*, and *Own-Risk-Subj.* are substantially higher in December than in September. On the other hand, *Own-Risk-Num.* is substantially lower in March than in December. All differences are highly significant on the 1% level. More precisely, both numerical risk measures or three month volatility estimates (*Market-Risk-Num.* and *Own-Risk-Num.*) rise from approximately 0.05 in September to 0.075 in December and drop slightly to around 0.07 in March.[8] The extreme rise of volatility estimates from September to December is consistent with Glaser and Weber (2005) who show in a between-subjects design that volatility estimates before 9/11 were substantially lower than after 9/11. In a similar vein, subjective risk expectations also rise substantially from September to December and remain almost stable from December to March. These findings indicate that subjects perceived both their own investments and investments into the market to be riskier in December than in September and that they perceived *Own-Risk-*

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[8]We will compare this change in volatility estimates with actual changes in market risk in subsection 3.4.3 in more detail.

Table 3.3: Differences in repeatedly elicited variables between rounds

This table reports mean values of all repeatedly elicited variables broken down by the month they were elicited for all subjects that took part in the survey at least twice. The last two columns indicate z-statistics of Wilcoxon signed-rank tests that test whether scores in December are significantly different from scores in September (Difference$^{Dec-Sept}$) or whether scores in March are significantly different from scores in December (Difference$^{March-Dec}$). Wilcoxon signed-rank tests are only carried out if a subjects has participated in the two respective months. * indicates significance at the 5% level and ** indicates significance at the 1% level.

	Sept. (N=265)	Dec. (N=305)	March (N=239)	Difference$^{Dec-Sept}$ z-score	Difference$^{March-Dec}$ z-score
Risk Taking					
Risk-Taking (Hypoth.)	56.02	52.77	46.52	-2.586**	-3.90**
Risk Attitude					
Risk Attitude 2	3.34	3.63	3.55	1.889	-0.731
Risk Attitude 6	4.43	4.61	-	2.511*	-
Risk Attitude 7	5.04	5.06	-	0.388	-
Expectations					
Market-Return-Num.	1.57	3.57	5.42	1.661	3.311**
Market-Risk-Num.	0.052	0.075	0.072	7.289**	-0.568
Market-Return-Subj.	3.5	3.67	3.84	1.089	-0.478
Market-Risk-Subj.	4.76	5.17	5.15	4.596**	1.533
Own-Return-Num.	4.38	6.23	8.18	2.941**	3.324**
Own-Risk-Num.	0.053	0.078	0.067	6.737**	-2.562**
Own-Return-Subj.	3.89	3.91	4.17	-1.092	2.599**
Own-Risk-Subj.	4.2	4.45	4.53	3.680**	1.287
Past Performance					
Perf-Ext.	-2.14	-12.57	-3.19	-7.406**	3.618**
Perf-Market-Num.	-8.2	-16.79	-6.96	-8.198**	7.782**
Perf-Market-Subj.	2.32	1.82	2.42	-7.426**	4.641**
Perf-Own-Num.	-7.7	-18.51	-8.48	-9.521**	7.03**
Perf-Own-Subj.	2.95	2.33	2.92	-7.256**	4.261**

Num. to be lower in March than in December. These changes in risk expectations are also in line with hypothesis 3.

For return expectations a similar picture emerges. For all return expectations measures (*Market-Return-Num.*, *Market-Return-Subj.*, *Own-Return-Num.*, and *Own-Return-Subj.*) subjects expect on average higher returns in December than in September. The same is true if we compare return expectations in March and in December, indicating that subjects became more and more optimistic over the three time periods. Wilcoxon signed-rank tests show that four of eight return expectations turn out to rise significantly ($p < 0.01$) from one quarter to the other. Overall, consistent with Vissing-Jorgensen (2003) and Shiller et al. (1996) as well as with hypothesis 3, we show that return expectations do vary substantially over time. More specifically, in our sample subjects get more and more optimistic over time.

Analyzing changes in past performance, we obtain a simple result. Most subjects judge past performance, be it their own or the markets' performance, from June to August and from December to March to be substantially higher than the performance in the time span September to December. This result is not surprising considering the fact that stock markets took a severe downturn in the last quarter of 2008. The performance of the FTSE-All-Share from September to December was approximately -20% and thus substantially worse than the performance in the time periods June to September (-10%) and December to March (-7%). Two interesting findings on subjects self-assessed past performance emerge: first, subjects numerical estimates of past market performance are not too far-off real market returns. Second, subjects judge their own past performance to be lower than the market performance, although they do not expect their own portfolio to be more risky than the market.

Our main findings are in line with previous findings in the literature and with our hypotheses 1 - 3. Risk taking behavior (see Malmendier and Nagel (2009)), risk expectations (see Glaser and Weber (2005)), and return expectations (see Vissing-Jorgensen (2003)) seem to vary over time whereas risk attitudes tend to be fairly stable (see Sahm (2007)). Moreover, our results remain stable if we analyze differences only for those subjects that participated thrice or if we include all observations at each point of time.

3.4.2   What Drives Changes in Risk Taking?

Having provided evidence for changes in risk taking behavior and expectations as well as evidence for relative high stability of risk attitudes we want to analyze what actually influences changes in risk taking behavior over time. As a first test of the functional relationship in equation 3.1 and 3.2 we analyze whether subjects' behavior is in accordance with the model propositions. Hence, we study whether subjects that take more risks in December (March) than in September (December) (Δ R.T.$^{+}$) become less risk averse, expect higher returns and/or perceive the risk of an investment in the market to be lower. And for subjects that take less risks in December (March) than in September (December) (Δ R.T.$^{-}$) we analyze whether they become more risk averse, expect lower returns and/or perceive the risk of an investment in the market to be higher.

A simple sign test indicates that 74 subjects in the period September to December and 99 subjects in the period December to March take less (more) risks over time although they become less (more) risk averse. We also find that 77 [64] subjects take more (less) risks although they expect numerical and subjective market returns to be lower (higher) in December than in September [in March than in December]. Finally, our results also indicate that 55 [67] subjects take more (less) risks although they perceive the riskiness of the market (numerical and subjective) to be higher (lower) in December than in September [in March than in December].

However, these numbers do not indicate that subjects behave not according to the model. It might well be that subjects who are less risk averse in December than in September [in March than in December] take a substantially lower level of risks because of lower return expectations and/or higher risk expectations. Hence, only those subjects that take more (less) risks although they are more (less) risk averse, expect lower (higher) returns and perceive the risk to be higher (lower) in December than in September [in March than in December] do not behave in accordance with the functional form.

Our results indicate that subjects do not behave in accordance with the functional form and thus violate some sort of dominance concept in less than 8.8% of all cases. If we assume that the probability to submit non intuitively correct risk attitude, risk expectations, and

return expectations to be $\frac{1}{2}$, respectively, then about 12.5% ($\frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2}$) of all subjects should not behave in accordance with the functional form. Since our results indicate this to be slightly lower, we interpret our findings as a first hint for the usefulness of more general risk-value frameworks (see Sarin and Weber (1993b) and Jia et al. (1999)).

Admittedly, the previous test is a weak test of model consistency and doesn't allow us to make inferences about what actually drives changes in risk taking behavior. To improve on this we analyze in table 3.4 the value of all risk attitude, expectation, and past performance measures separately for the two time periods September to December (left panel) and December to March (right panel). In each panel we report mean values of all variables for two distinct groups of subjects: first, subjects who take more risks from one survey to the next one (Δ R.T.$^+$) and second, subjects who take less risks from one survey to the next one (Δ R.T.$^-$). The last column in each panel reports results on Mann-Whitney rank-sum tests comparing the two groups Δ R.T.$^+$ and Δ R.T.$^-$.

Comparing changes in risk attitudes between the two groups shows hardly any differences for both panels.[9] Mann-Whitney rank-sum tests indicate that there is no significant relation between the way subjects adjust their risk attitude scores over time and changes in their risk taking behavior over time.

In addition, analyzing whether there are any differences in the way subjects update their own portfolio expectations between the two groups we mostly find no significant differences as changes in own portfolio expectations are fairly similar for both groups (Δ R.T.$^+$ and Δ R.T.$^-$). The only significant difference between the two groups of subjects can be observed for *Diff. Own-Risk-Num.* in the December to March panel. Subjects who take more risks in March than in December (Δ R.T.$^+$) expect their own portfolio returns to be higher in March than in December whereas subjects that take less risks in March than in December (Δ R.T.$^-$) expect their own portfolio returns to be lower in March than in December. This result is not highly significant and gets insignificant if we only analyze the subgroup of subjects that has participated in all three surveys.

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[9]Note that *Diff. Risk Attitude 6* and *Diff. Risk Attitude 7* were not elicited in March. Therefore, we cannot analyze changes in these variables from December to March.

Table 3.4: Changes in risk taking I

This table reports mean values of changes in risk attitudes, expectations and past performance separately for subjects who take more (less) risks in December compared to September in the left panel and for subjects who take more (less) risks in March compared to December in the right panel: Δ R.T.$^{+}$ (Δ R.T.$^{-}$). All change or differences variables are calculated for each subject separately simply as the value in December minus the value in September in the left panel and as the value in March minus the value in December in the right panel. The last column in each panel reports z-scores of a Mann-Whitney rank-sum test comparing the two groups of subjects. * indicates significance at the 5% level and ** indicates significance at the 1% level.

	September to December			December to March		
	Δ R.T.$^{+}$	Δ R.T.$^{-}$	Difference in differences	Δ R.T.$^{+}$	Δ R.T.$^{-}$	Difference in differences
Risk Attitude						
Diff. Risk Attitude 2	0.182	0.009	0.542	0.037	-0.093	1.192
Diff. Risk Attitude 6	-0.013	0.218	-1.232	-	-	-
Diff. Risk Attitude 7	0.026	-0.037	0.217	-	-	-
Expectations						
Diff. Market-Return-Num.	0.937	3.945	-0.072	3.129	0.523	1.395
Diff. Market-Risk-Num.	0.022	0.029	-0.621	0.004	-0.008	1.565
Diff. Market-Return-Subj.	0.395	-0.027	2.024*	0.509	0.052	2.468*
Diff. Market-Risk-Subj.	-0.052	0.555	-3.35**	-0.200	0.020	-1.21
Diff. Own-Return-Num.	2.980	3.252	0.245	3.148	3.414	0.556
Diff. Own-Risk-Num.	0.034	0.019	0.929	0.002	-0.015	2.092*
Diff. Own-Return-Subj.	-0.067	-0.018	0.041	0.296	0.021	1.332
Diff. Own-Risk-Subj.	0.240	0.321	-0.770	0.463	0.062	1.265
Past Performance						
Diff. Past Perf. External	-8.994	-14.830	0.556	5.571	4.467	0.152
Diff. Past Perf. Market Num.	-11.835	-5.880	-1.418	9.037	10.097	-0.702
Diff. Past Perf. Market Subj.	-0.697	-0.670	-0.174	0.352	0.680	-1.178
Diff. Past Perf. Self Num.	-13.000	-12.893	0.596	11.602	8.908	0.403
Diff. Past Perf. Self Subj.	-0.558	-0.873	1.482	0.741	0.144	2.375*

Interestingly, there are no significant differences between the two groups (Δ R.T.$^+$ and Δ R.T.$^-$) for *Diff. Market-Return-Num.* and *Diff. Market-Risk-Num.* in both panels. *Diff. Market-Return-Num.* is simply the numerical return estimate in December (March) minus the one in September (December) and positive in both groups and panels. Our results are the same if we calculate the numerical variables not as simple differences but as percentage changes. A similar picture emerges if we analyze *Diff. Market-Risk-Num.*

However, for subjective market risk and market return expectations we find substantial and stable differences between the two groups. Subjects who take more risks from one survey to the next one (Δ R.T.$^+$) expect subjective market returns (*Diff. Market-Return-Subj.*) to become substantially higher over time and grow by on average 0.395 and 0.509, respectively. Whereas subjects who take less risks in December than in September or less risks in March compared to December (Δ R.T.$^-$) expect subjective market returns to stay fairly stable over time. Differences in differences between the two groups are significant in both panels as indicated by z-scores of 2.024 and 2.468 and a first indication that changes in subjective market return expectations seem to be related to changes in investment behavior. This result remains stable even if re-run the analysis only for subjects that participated in all three surveys.

We find a reverse pattern for subjective market risk expectations: subjects in the group Δ R.T.$^-$ expect *Diff. Market-Risk-Subj.* to be positive on average (0.555 and 0.02) whereas subjects in the group Δ R.T.$^+$ expect it to be negative on average (-0.052 and -0.2). The difference in differences in the September to December panel is highly significant with a z-score of -3.35. In contrast, the difference in differences in the December to March panel is in the right direction but not significant. Moreover, table 3.4 also shows that changes in past performance estimates are hardly related to changes in risk taking behavior as only *Diff. Past Perf. Self Subj.* is significantly different for both groups.

These findings are first indications that changes in subjective market return and market risk expectations seem to be related to changes in investment behavior in markets. However, one problem of the previous analyses is that we can only apply it to subjects who take more or less risks from one period to the other. Thus, we omit all subjects that take

the same level of risk in two subsequent periods. The following analyses try to alleviate this problem.

In order to investigate the question what drives changes in risk taking behavior in more depth we use multivariate tobit regressions. We use tobit since our variables are censored from below (-100) and from above (+100). In table 3.5 we report results of clustered tobit regressions of changes in risk taking, from one point in time to the next one. Since we use both changes from September to December and changes from December to March in these analyses we need to drop *Diff. Risk Attitude 6* and *Diff. Risk Attitude 7* as they were not elicited in March. In addition, we also need to take into account that our observations do not need to be independent as 149 subjects participated in all three surveys and appear repeatedly in our sample of differences. We control for this by clustering our regressions over subjects.

The results in the first regression of table 3.5 indicate that *Diff. Risk Attitude 2* cannot explain changes in risk taking behavior. Interestingly, our results hold even if we re-run the regressions and exclude subjects that report the same risk attitude in September and in December or the same risk attitude in December and March.

Column 2 of table 3.5 illustrates that in contrast to changes in risk attitudes, changes in subjective expectations can explain changes in risk taking behavior. More precisely, the positive coefficient of 2.348 indicates a positive relation between *Diff. Market-Return-Subj.* and *Diff. Risk Taking.* The larger the market return expectations in December (March) are compared to September (December), the larger is the level of risk taking in December (March) compared to September (December). For changes in subjective market risk expectations (*Diff. Market-Risk-Subj.*) we find a reverse effect, indicated by the significantly negative coefficient of -2.208. Hence, the higher subjects' perceive the risk of the market in December (March) in comparison to September (December) the less risky they invest in December (March) compared to September (December). Our results remain essentially the same if we further require that *Diff. Risk Attitude 2* is not equal to zero.

Table 3.5: Changes in risk taking II

This table reports results of clustered tobit regressions where standard errors take clustering over subjects into account. Dependent variable in each model is changes in risk taking (*Diff. Risk Taking*). Independent variables are changes in: risk attitude, expectations, and past performance as well as demographic variables. All change or differences variables are calculated for each subject separately simply as the value in December (March) minus the value in September (December). p-values are reported in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)
Risk Attitude					
Diff. Risk Attitude 2	0.936		1.071	1.001	0.933
	(0.220)		(0.149)	(0.216)	(0.252)
Expectations					
Diff. Market-Return-Num.				0.151	0.038
				(0.256)	(0.714)
Diff. Market-Risk-Num.				4.451	5.349
				(0.870)	(0.846)
Diff. Market-Return-Subj.		2.348	2.327	1.934	2.013
		(0.017)**	(0.018)**	(0.049)**	(0.046)**
Diff. Market-Risk-Subj.		-2.208	-2.303	-2.529	-2.631
		(0.016)**	(0.015)**	(0.010)**	(0.009)***
Past Performance					
Diff. Past Perf. Market Num.				-0.164	
				(0.056)*	
Diff. Past Perf. Market Subj.					0.137
					(0.872)
Demographics	No	No	No	Yes	Yes
Dummy-Period	-2.124	-3.441	-2.978	-0.464	-3.489
	(0.470)	(0.242)	(0.312)	(0.886)	(0.283)
Constant	-4.366	-3.601	-3.803	4.694	5.478
	(0.021)**	(0.069)*	(0.054)*	(0.524)	(0.468)
Observations	434	435	431	396	396

In additional robustness tests we check whether our results also hold for the numerical risk and return expectations. Running the same regressions with numerical expectations instead of ordinal ones, we find that changes in numerical expectations cannot explain changes in risk taking behavior. This result remains stable even if we check for robustness by e.g. running the regressions separately for subjects that participated twice and thrice, respectively, or for those subjects that indicated certain levels of income or wealth, or for those that stated positive expected returns. This finding is consistent with first results in table 3.4 and in contrast to first findings in chapter 2 were we show with business and economics students that risk taking behavior can also be heavily influenced by subjective numerical risk and return expectations.

We can only hypothesize why we do not find a significant effect for the numerical variables in our dataset: first, in numerical values outliers such as an expected market return of 143% in three months which we actually observe in our dataset could affect our results.[10] Second, practitioners argue that ordinal ratings are more feasible and that most individuals with no specific background in economics seem to understand subjective ordinal ratings better than numerical ones. Thus, e.g. all rating agencies transform default probabilities or expected losses into ordinal scales. Since subjects in our study do not necessarily have a background in finance or economics this argument might be relevant for our dataset. Third, scanning the personal comments that subjects could submit after the March survey we find that many subjects regard the numerical questions to be too technical and confusing to answer. A further indication that subjects had problems stating numerical risk and return expectations is the fact that almost 23% (September), 24% (December), and 17% (March) of all subjects expect three month market (FTSE-All-Share) returns to be negative. Similarly, 9% (September), 13% (December), and 6% (March) of all subjects expect their own portfolio to generate negative returns. Although they expect negative market returns, most of these subjects allocate a positive amount of their money in the hypothetical risk taking task into the market.[11]

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[10]Note that this reasoning alone cannot explain the entire finding as it remains stable, even if we winsorize the data.

[11]An in depth analysis of why some subjects state negative expected returns and still invest into a portfolio is certainly interesting but not the scope of the present study.

The third regression tests whether our findings prevail if we analyze changes in subjective market expectations and *Diff. Risk Attitude 2* as independent variables jointly. Our main results remain stable. In the fourth and fifth column we include numerical expectations, past market performance, and various demographics as additional independent variables. Multicollinearity is no issue for the numerical expectations since the correlation between numerical and subjective risk and return expectations is relatively low, consistent with findings in chapter 2. However, multicollinearity becomes an issue if we try to include both past market performance measures at the same time. To avoid this problem we include *Diff. Past Perf. Market Num.* in regression four and *Diff. Past Perf. Market Subj.* in regression five, separately. Our main results with regard to expectations remain stable as both *Diff. Market-Risk-Subj.* and *Diff. Market-Return-Subj.* are still significant determinants of *Diff. Risk Taking.*

In addition, we find a slightly significant effect for *Diff. Past Perf. Market-Num.* in regression 4 if we run the regressions for all subjects. However, this result is not very stable as *Diff. Past Perf. Market-Num.* is not a significant determinant of *Diff. Risk Taking* if we re-run the regression only for those subjects that participated in all three surveys.

After having analyzed which factors drive changes in risk taking behavior from September to December and from December to March jointly, we turn to analyze this question separately for the two time periods. Table 3.6 reports results of simple tobit regression of changes in risk taking (*Diff. Risk Taking*) on various independent variables. All odd numbered models run the regressions for all difference variables in the time period September to December, whereas all even numbered models run the regressions for all difference variables in the time period December to March. We run the regressions only for those subjects that participated in all three surveys, i.e. for subjects for that we have an observation in both time periods.

Our finding that changes in *Diff. Risk Attitude 2* cannot explain changes in risk taking remains stable. In addition, for regressions which rely on data that were collected in September and December 2008 (1, 5, 7, and 9) we can also include *Diff. Risk Attitude 6* and *Diff. Risk Attitude 7* as additional independent variables. Both measures are also

Table 3.6: Changes in risk taking III

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Diff. Risk Attitude 2	0.760 (0.606)	-0.462 (0.728)			1.412 (0.387)	-0.321 (0.810)	1.586 (0.345)	-0.846 (0.520)	1.260 (0.483)	-0.921 (0.486)
Diff. Risk Attitude 6	0.469 (0.833)				1.900 (0.348)		2.011 (0.397)		2.043 (0.389)	
Diff. Risk Attitude 7	1.433 (0.332)				1.150 (0.471)		0.959 (0.575)		1.083 (0.525)	
Diff. Market-Return-Num.							-0.019 (0.913)	0.280 (0.253)	-0.075 (0.455)	0.165 (0.449)
Diff. Market-Risk-Num.							-48.940 (0.407)	41.831 (0.284)	-52.745 (0.377)	42.404 (0.276)
Diff. Market-Return-Subj.			2.832 (0.108)	3.794 (0.014)**	2.937 (0.054)*	3.725 (0.019)**	3.153 (0.094)*	2.716 (0.071)*	2.871 (0.135)	2.941 (0.048)**
Diff. Market-Risk-Subj.			-4.497 (0.005)***	-0.534 (0.716)	-4.883 (0.004)***	-0.537 (0.746)	-4.465 (0.007)***	-0.867 (0.617)	-4.503 (0.008)***	-1.019 (0.557)
Diff. Past Perf. Market Num.									-0.066 (0.643)	-0.156 (0.257)
Diff. Past Perf. Market Subj.									1.549 (0.344)	-0.308 (0.804)
Demographics	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Constant	-3.313 (0.163)	-5.966 (0.006)***	-1.423 (0.575)	-7.326 (0.000)***	-2.184 (0.366)	-7.062 (0.001)***	0.339 (0.983)	-3.516 (0.770)	2.377 (0.881)	-6.518 (0.592)
Observations	149	140	149	141	149	140	140	130	140	130

This table reports results of tobit regressions of changes in risk taking (*Diff. Risk Taking*) on changes in risk attitudes, expectations, and past performance as well as demographic variables, separately for the two time periods *September-December* and *December-March*. All change or differences variables in regressions 1, 3, 5, 7, and 9 are calculated for all subjects that participated in September and December simply as the value in December minus the value in September. All change or differences variables in regressions 2, 4, 6, 8, and 10 are calculated for all subjects that participated in December and March simply as the value in March minus the value in December. Subjects are only included in the analyses if they participated in all three surveys. p-values are reported in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

not able to explain changes in risk taking. These results remain stable even if we run the regressions for each risk attitude measure individually.

Interestingly, our result that changes in subjective market risk and return expectations can best explain *Diff. Risk Taking* remains fairly stable even if we run the analyses for the two subsample of observations separately. The coefficients for *Diff. Market-Return-Subj.* are almost stable and between 2.7 and 3.7 and mostly significant. Lower levels of significance can be driven by a lower number of observations. The results for *Diff. Market-Risk-Subj.* are not as clear-cut. *Diff. Market-Risk-Subj.* is always negative, however, only significant in odd-numbered regressions.

Why can changes in subjective risk expectations explain changes in risk taking only for the period September to December but not for the one from December to March? We can only speculate about this. A possible explanation could be that changes in risk expectations and subsequently changes in risk taking behavior are smaller and hardly existent in the second period from December to March, whereas they are existent in the period September to December, i.e. the period of large turmoils on financial markets.

Overall, all coefficients for *Diff. Market-Return-Subj.* and *Diff. Market-Risk-Subj.* point into the correct direction, however, the significance of our results is lower than in table 3.5. A possible explanation for the lower significance are a lower number of observations in the separated analyses.

3.4.3 Overconfidence over Time

Besides changes in risk and return expectations there is also a large strand of literature analyzing changes in the level of overconfidence over time. Gervais and Odean (2001) illustrate in a theoretical model that investors often attribute success to their own acumen while attributing failure to chance and term this "learning to be overconfident". This self-serving attribution bias results in subjects getting more overconfident after investment success and subsequently taking more risky actions but not more underconfident after investment failure. In the long run, however, frequent feedback lowers the self attribution bias and subjects get less overconfident. In line with the self attribution hypothesis, Barber

and Odean (2002) and Statman et al. (2006) show that overconfidence varies with prior past performance.

Experimental evidence on the evolution of overconfidence is equivocal. Deaves et al. (2005) find evidence for the "learning to be overconfident" hypothesis whereas Jonsson and Allwood (2003) find evidence for individual stability of overconfidence over time. To analyze the question whether overconfidence is stable or varies over time in more depth we compare the level of overconfidence (miscalibration) on an individual level in September, December, and March with each other using a confidence interval approach. Following the two-point approximation methodology suggested by Keefer and Bodily (1983) we transform estimates of confidence intervals, i.e. upper and lower bounds, into volatility estimates. To get a measure of overconfidence we simply compare the estimated volatility with a volatility benchmark: Overconfidence $= -\frac{Estimated\ volatility}{Volatility\ of\ the\ benchmark}$. This overconfidence measure enables us to analyze to what degree subjects adjusted their risk expectations in reaction to changes on financial markets and is thus related to our analyses in the previous subsections. Since we cannot calculate a volatility benchmark for each subject's portfolio we can only analyze individual overconfidence with regard to the market.

Our measure for estimated volatility is simply *Market-Risk-Num.* To obtain an adequate measure for the volatility of the benchmark, the FTSE-All-Share we can use two approaches. First, we can try to calculate historical volatilities for the FTSE-All-Share and relate these to the estimated volatilities (*Market-Risk-Num.*). However, one big disadvantage of historical volatilities is that the results heavily depend upon the time span that is used to calculate the historical volatility. This disadvantage is in particular severe due to the extreme turmoils that financial markets around the world have been experiencing between September and December. Second, we can use a measure of the implied volatility of the British stock market embedded in prices of out of the money index call and put options. However, there is no implied volatility index that is calculated for the FTSE-All-Share but only one for the FTSE-100 (VFTSE-100). Since the correlation between FTSE-All-Share and FTSE-100 is almost 1 ($\rho > 0.99$) we use the average VFTSE-100 levels for September 6-20 (0.15), December 6-20 (0.22), and March 21-30 (0.18) as our

volatility benchmarks. Thus, subjects who end up with an overconfidence score above -1 are overconfident whereas subjects with a score below -1 are underconfident.

As we have seen in table 3.3 our measure of estimated volatility (*Market-Risk-Num.*) in September is substantially smaller than in December and March implying that subjects adjusted their volatility estimates upwards. However, this adjustment of volatilities might be perfectly rational as subjects correctly incorporated that markets became substantially more risky over time. Our overconfidence measures which are simply the estimated volatilities inferred from the bounds divided by the average implied volatility in September, December, and March and normalized by minus one control for possible changes in the riskiness of the benchmark. We find mean overconfidence in September to be -0.36 (median=-0.31), mean overconfidence in December to be -0.34 (median=-0.28), and mean overconfidence in March to be -0.4 (median=-0.38). All scores are significantly larger than -1 indicating that subjects tend to set too tight bounds and thus underestimate volatilities.

Testing for differences in the degree of overconfidence between the September and the December wave we find no statistically significant difference using a Wilcoxon signed-rank test (p=0.28). Subjects correctly adjusted their volatility estimates upwards in reaction to the dramatic changes on financial markets. A similar result has been indirectly observed by Glaser and Weber (2005) in their analyses of DAX volatility forecasts before and after 9/11. However, analyzing the differences in the degree of overconfidence between March and December we find a significantly lower level of overconfidence in March than in December (p=0.002). Our results do not change if we control for subjects' past performance in the analyses.

Hence, the level of overconfidence remains fairly stable from September to December, i.e. in the phase of a huge downturn, and gets smaller from December to March. Why can we not find evidence for a self-serving attribution bias and thus initial increases in overconfidence after investment success and later on a reduction in overconfidence as subjects gain experience as proposed in the model of Gervais and Odean (2001)? The reason might simply be the fact that there is hardly any investment success in the first period from September to December. More than 87% of all investors state they did not have a positive portfolio return between September and December. Thus, overconfidence

remains fairly stable initially before a slight learning effect sets in. However, to analyze the dynamics of overconfidence in more depth we would need more observations over time.

3.5   Conclusion

Based on a repeated survey study that was run in collaboration with *Barclays Wealth* we document that real online broker customers' risk taking or investment behavior changes substantially from one quarter to the other. According to more general risk-value models these changes can be attributed to changes in expectations or changes in risk attitudes or both. We show that expectations vary substantially over time whereas risk attitudes seem to be fairly stable and do not vary too much over time. Furthermore, we show that changes in risk taking behavior seem to be mainly driven by changes in expectations and not changes in attitudes. This result is stable even if we control for past performance and demographics. Lastly, we provide evidence that overconfidence (miscalibration) of real investors seems to be relatively stable from September to December 2008 and tends to decrease slightly thereafter.

We extend previous findings in the literature on changes in risk taking, expectations, and risk attitudes as follows: first, our unique dataset allows us to analyze changes in risk taking, expectations, and risk attitudes of real online broker customers. Second, previous studies in the literature analyze only changes in risk taking (see e.g. Malmendier and Nagel (2009)) or only changes in expectations (see e.g. Vissing-Jorgensen (2003)) or only changes in risk attitudes (see e.g. Sahm (2007)) individually but not jointly. Thus, in contrast to our study they are not able to disentangle the channel through which risk taking behavior changes over time or they are not able to observe changes in risk taking behavior at all. Third, a major advantage of our survey is that the first round of surveys was conducted in the beginning of September 2008, i.e. just before the extreme turmoils recently experienced in financial markets. Hence, we are able to analyze the effect of substantial stock price drops on risk attitudes and expectations by comparing the expectations and attitudes shortly before the crisis and during the crisis using the same panel of investors. Fourth, our dataset is the first one that allows us to test predictions in the study by Gervais and

Odean (2001) on the stability of overconfidence with real investors where one is able to control for previous investment success.

Our findings should be valuable for practitioners in banking. We show that risk attitudes - if measured correctly and without confounding effects - seem to be fairly stable and that changes in risk taking behavior seem to be caused by changes in expectations and not by changes in risk attitudes or changes in past performance. Thus, practitioners who are urged by MiFID (2006) to elicit their customers' risk profiles and risk preferences can argue that elicitation of risk attitudes needs not to be carried out on a quarterly basis. Moreover, our results indicate that it might be worthwhile for practitioners to elicit their clients' expectations as they seem to underestimate the volatility of the market substantially and as this underestimation seems to persist over time.

Future research could combine repeatedly elicited survey data with data on portfolio holdings and trading activity and thus extend findings in previous studies who analyze the relationship between trading data and a one-time survey (see Dorn and Huberman (2005) and Glaser and Weber (2007)). Moreover, it seems interesting to analyze whether the extreme events in financial markets in recent months have long-lasting effects on risk attitudes and expectations as well as on the actual asset allocations of economic agents.

Chapter 4

Overreaction and Investment Choices: An Experimental Analysis

4.1 Introduction

On observing new information, agents should update their beliefs. Rational agents will do so using Bayes rule. But irrational agents may overreact to the signals they observe. Such agents, after observing positive news would become exaggeratedly optimistic, and after bad news exaggeratedly pessimistic. Kahneman and Tversky (1973) offer one of the first experimental studies of this phenomenon.[1]

Overreaction can have significant economic effects, especially in financial markets where information and signal processing are crucial. In this context, it can generate mispricing and reduce investment performance. Odean (1998b) analyzes a model where some investors think their signal is more accurate than it is really. Consequently, they overreact to their signals, and market prices also overreact. Daniel et al. (2001) extend the CAPM to the case of overconfident investors. Such investors form what they perceive to be mean-

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[1] Subjects were given information and asked to predict the future grades of students. The information they were given could be of one of three possible types: i) the previous grades of the students, ii) a measure of their mental concentration, iii) a measure of their sense of humor. While i) was a useful signal, participants should have realized that ii) was less relevant, and iii) practically irrelevant. And yet, participants reacted almost as strongly to ii) and iii) as to i).

variance efficient portfolios. But, to the extent that they overreact to signals, they fail to diversify properly, and stocks are mispriced.

Several empirical studies based on stock market data are consistent with these views. If prices initially overreact to information and then drift back towards rational pricing, there will be mean reversion. This is what DeBondt and Thaler (1985, 1987) found. In their sample, past winners end up earning negative returns, while past losers earn positive returns. While these early studies were based on stock prices only, more recent studies endeavored to take into account information and forecasts. DeBondt and Thaler (1990) study analysts' forecasts. Regressing actual earnings changes onto forecasted earning per shares they rejected the hypothesis that forecasts were unbiased expectations. Their results suggest that forecasts are too extreme and then tend to be corrected. This is consistent with overreaction.

Thomas and Zhang (2008) study market reactions to earnings announcements. They consider pairs of stocks in the same industry for which earnings announcements occur sequentially. Suppose earnings are announced first for stock G, and then, some time later, for H. Since G and H are in the same industry, the first announcement is relevant for the second stock. Consistently with this view, Thomas and Zhang (2008) find that the price of stock H reacts to the announcement for stock G. But, if investors were rational this reaction should be on average correct. In contradiction with this hypothesis, Thomas and Zhang (2008) find that positive stock H reactions are followed by price declines when earnings are announced for H. And negative reactions tend to be followed by price increases. This, again, is consistent with overreaction.

The goal of the present chapter is to complement these studies by offering direct evidence on information signals, beliefs and financial decisions. We take advantage of a controlled experimental setting to directly test if agents' beliefs overreact to signals and whether this affects performance. To achieve this, we designed a new financial decision making experiment in which we gave signals to participants, and then elicited their forecasts and observed their investment decisions. The experiment was run at Mannheim University in September 2007. 104 students participated and the experiment lasted around one hour. To strengthen the incentives of the students, we paid them according to the accuracy of

their forecasts and the performance of their financial decisions. Payment per participant ranged between 23.38 Euro and 49.74 Euro, with an average of 37.87 Euro.

The main features of the experimental design were the following. For 20 pairs of stocks, participants were shown price paths. For each pair of stocks, participants were told that the two stocks were in the same industry and that the return on each stock reflected common market shocks and common industry shocks, as well as idiosyncratic shocks. For each pair of stocks (G and H), participants were shown the price path of stock G for the whole year. For stock H, participants were shown the price path for the first half of the year only. Participants were asked to forecast the price of H at the end of the year. To do so they could use the path of G during the entire year as a signal.[2]

A strong positive return on G during the second half of the year is a positive signal for H, signalling a positive return for that stock. Rational participants should take this into account, while bearing in mind that this signal is imperfect, since each stock also has an idiosyncratic component. But if agents are prone to overreaction, they will react too optimistically after positive signals, and too pessimistically after negative signals. To test if participants overreact we study whether their forecast error is correlated with the signals they receive. The forecast error is defined as the difference between the forecast of the agent and the conditional expected value of the stock at the end of the year. For each participant, we regressed across stocks this error onto the signal. While under rational expectations the regression coefficient which we will later on refer to as *Overreaction-Beta* should be 0, for the majority of participants we obtained positive estimates.

As an alternative measure of overreaction, we took the ratio of forecasting error to the innovation in the signal. If they overreact, agents will overestimate the final price of H after seeing good signals, and they will underestimate it after negative signals. Hence the ratio will tend to be positive. In contrast, if agents are rational, the ratio will on average

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[2]This task is thus similar to that analyzed by Thomas and Zhang (2008): both their paper and ours consider pairs of stocks; and in both studies information on G is obtained before information on H, and can thus serve as a signal to forecast the evolution of H. The difference is that Thomas and Zhang (2008) run a field experiment while we conduct a lab experiment. The advantage of the former approach is that observed outcomes are unquestionably economically meaningful while the advantage of the latter is that beliefs and information can be observed more directly. It is interesting that, in the present case, the results of both approaches are consistent with one another.

be zero. Thus, to measure the overreaction bias of the agent, we took the median of this ratio (*Median-Overreaction-Ratio*), across the 20 stocks the agents had to forecast. We find that, on average, participants tend to overreact. We also found this second measure of overreaction to be highly correlated with the first one.

In addition to their forecast of the price at the end of the year, participants are asked to give an upper bound and a lower bound, such that there is only one chance out of ten that the final price is outside these bounds. Thus, we can estimate the degree of overconfidence, or miscalibration, of the participants. Basically, miscalibrated agents estimate confidence intervals which are too narrow. In line with the theoretical model of Odean (1998b), we find that overconfidence and overreaction are significantly positively correlated.

We also asked the participants to form portfolios combining the stocks for which they had to form predictions. Correlating these portfolio choices to overreaction, we can test if this bias affects financial decisions and performance. We find that, when they overreact more, agents allocate a greater (resp. lower) fraction of their wealth to stocks with positive (resp. negative) signals. We also find that such over– and under–weighting reduces the performance of the portfolios, measured by their Sharpe ratio.

In the next section we describe our experimental design. In section 4.3 the results are presented. Section 4.4 concludes.

4.2   Experimental Design

4.2.1   Theoretical Framework

In our experiment, participants observe the realization of the price of a stock. They must use it as a signal about the price of another stock in the same industry. Denote by $\tilde{s}$ the signal and by $\tilde{v}$ the price to be forecasted. They are such that:

$$\tilde{s} = \tilde{v} + \tilde{e},$$

where $\tilde{v}$ and $\tilde{e}$ are independent. A rational forecast $F(s) = E(\tilde{v}|s)$ must be such that the prediction error $F - \tilde{v}$ is independent from the signal. Hence, for a cross section of independent stocks $j = 1, ..., N$, we must have that, in the regression:

$$F(\tilde{s}_j) - \tilde{v}_j = \alpha + \beta \tilde{s}_j + \tilde{z}_j, \tag{4.1}$$

the two coefficients are not significantly different from 0. In contrast, if the agent overreacts, he / she will put too much weight on the signals. As a result β will not be equal to 0.

To gain more insights on this point in a tractable framework, assume the random variables are jointly normal. Thus,

$$E(\tilde{v}|s) = E(\tilde{v}) + \delta(s - E(\tilde{s})),$$

where:

$$\delta = \frac{cov(\tilde{v}, \tilde{s})}{var(\tilde{s})} = \frac{cov(\tilde{v}, \tilde{v} + \tilde{e})}{var(\tilde{v} + \tilde{e})} = \frac{Var(\tilde{v})}{Var(\tilde{v}) + Var(\tilde{e})}.$$

δ measures the reaction of the agent to the innovation in the signal. An agent who overreacts will overestimate δ. His biased forecast will be:

$$\hat{E}(\tilde{v}|s) = E(\tilde{v}) + \hat{\delta}(s - E(\tilde{s})),$$

with $\hat{\delta} > \delta$.

In this context, when observing the forecast F of an agent, we can infer if this agent is biased, and how much. In the experiment, as explained below, we know the data generating process and can thus compute the rational forecast: $\hat{E}(\tilde{v}|s)$. We can then infer the magnitude bias by subtracting the rational forecast from the observed one, and normalizing this difference by the innovation in the signal. Indeed:

$$\frac{F - E(\tilde{v}|s)}{s - E(\tilde{s})} = \frac{\hat{E}(\tilde{v}|s) - E(\tilde{v}|s)}{s - E(\tilde{s})} = \hat{\delta} - \delta. \tag{4.2}$$

If the agent is rational, this ratio is equal to 0, while if the agent is prone to the overreaction bias, the ratio will be positive.

Odean (1998b) and Daniel et al. (2001) model investment decisions when investors are overconfident in the sense that they are miscalibrated, i.e., they overestimate the precision of their information. In our simple specification, this can be modeled as underestimating the variance of the noise term $\tilde{e}$ in the signal $\tilde{s}$. Thus, while a rational agent correctly estimates the variance $Var(\tilde{e})$, a miscalibrated agent underestimates it and perceives the variance to be $\kappa Var(\tilde{e})$, where $\kappa < 1$. Hence, the miscalibrated agent will form conditional expectations using a biased coefficient to react to the signal:

$$\hat{\delta} = \frac{Var(\tilde{v})}{Var(\tilde{v}) + \kappa Var(\tilde{e})} > \delta.$$

Thus, miscalibration generates overreaction to signals.

4.2.2   Simulated Price Paths

As explained below, we asked participants to process information inferred from stock price paths. We had the choice between showing participants real stock price paths from field data and simulated price paths. We chose the latter for two reasons. First, this enabled us to control the data generating process, make sure that the 20 tasks are indeed independently and identically distributed, and compute rational expectations forecasts, reactions to signals and confidence intervals. Second, this made the task anonymous and minimized the risk that participants would project into the task views from their personal experience.

To generate twenty pairs of price paths over one year, we drew for each trading day $i = 1, ..., 252$ and each pair $j = 1, ..., 20$ three shocks: $\epsilon_{i,j}$ (corresponding to the common industry shock), $\eta_{i,j}^{G}$ (corresponding to the idiosyncratic shock of stock G) and $\eta_{i,j}^{H}$ (corresponding to the idiosyncratic shock of stock H). All these daily shocks are i.i.d, normally distributed with mean 0.025 and standard deviation 2.0. We then calculated the stock price for trading day i by adding the industry and firm specific shocks onto the stock price of the previous day.

4.2.3 Questionnaires and Measurement

The questionnaire was filled out by 104 students, from two classes at the University of Mannheim, in September 2007 (see an extract of the questionnaire in the appendix). Participants were shown 20 pairs of stock price paths, generated as explained above. In each pair, for one stock (G) they saw the path of daily stock prices for the whole year, while for the other stock (H) they only saw the first six months. Two examples of such graphs are depicted in the questionnaire in the appendix. For each pair of stocks, participants were told that the two stocks were in the same industry and that the return on each stock reflected common market shocks and common industry shocks, as well as idiosyncratic shocks specific to that stock. For each pair of stocks the subjects were asked to forecast the final price of stock H at the end of the year. In the notations we introduced above, the final price of stock H at the end of the year corresponds to $\tilde{v}$, while the signal $\tilde{s}$ corresponds to the return on stock G over the second half of the year.

To incentivize the participants we rewarded them as a function of the accuracy of their forecast, as explained in the questionnaire in the appendix. We were also concerned that the participants would find the task too repetitive. To avoid this we scaled up each pair of stocks, by multiplying the initial value and all shocks for each pair by a random number between 0 and 2. We also constructed each graph with great care in order to avoid distorting effects. All graphs had the same size and look and varied only in the scaling on the vertical axes. Since the scaling can influence the risk perception of subjects we standardized the scaling procedure using insights from Lawrence and O'Connor (1992 and 1993) and Glaser et al. (2007). The scaling on the vertical axes was chosen such that the differences between the highest and lowest stock price over the course of twelve months fill approximately 40% of the vertical dimension of the graph. In addition, the number of horizontal lines is standardized to be either three or four. Also, to control for order effects we randomized the 10 questions and distributed six different versions of the questionnaire.

We used the forecasts of the participants to measure their overreaction bias. We thus constructed two measures of the bias for each participant.

- We refer to the first measure as the *Overreaction-Beta*. Consider a given participant: in line with equation 4.1 we regressed, across the 20 stocks, the forecast error of the participant onto the signal he / she observed. The regression coefficient obtained for this participant is referred to hereafter as his / her *Overreaction-Beta*.[3] Rational agents will have an *Overreaction-Beta* equal to 0. But agents who overreact will have positive betas.[4]

- We refer to the second measure as the *Median-Overreaction-Ratio*. Again consider a given participant. In line with equation 4.2 we computed for this participant, for each of the 20 stocks, the ratio of forecast error to the innovation in his / her signal (*Overreaction-Ratio*). We then took the median across the 20 stocks and refer to the aggregate score hereafter as the *Median-Overreaction-Ratio* of this agent. For rational agents *Median-Overreaction-Ratio* should be 0. Agents who overreact to signals will have a positive *Median-Overreaction-Ratio*.

The participants were also asked to give an upper bound and a lower bound such that there was one only one chance out of ten that the final price would be outside the bounds. One way to measure the miscalibration of the agent is to count the number of cases for which the final price was outside the confidence interval given by the agent (see Biais et al. (2005)). The measure we use is slightly different. It relies on the notion, well fitted for investment contexts, that miscalibrated agents tend to underestimate risk. For each stock, we infer from the confidence interval given by the agent the standard deviation it implies for returns. To do this, we use the two point approximation method proposed by Keefer and Bodily (1983). And then we divide this implied standard deviation by the conditional standard deviation of the returns and standardize everything by multiplying it with -1 (see e.g. Glaser and Weber (2007), Graham and Harvey (2005), and chapter 2 of this thesis). Finally, we take the average of this ratio across the 20 stocks to generate

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[3]As we multiplied each stock price with a random number between 0 and 2 to make the task less repetitive we divide both forecast error and signal with this random number to run the regressions with i.i.d. variables. However, our results are robust if we simply run the regressions using forecast error and signal without adjusting for the standardization parameter.

[4]Our results in the following sections are essentially the same if we use the true drawn realizations instead of relying on the parametric assumptions. Using realizations we calculate the forecasting error simply as the difference between forecast and realization.

our *Overconfidence-Person* score. The larger this score, the more overconfident the agent with extremely overconfident subjects having a score close to zero.

After having provided their forecasts for two stocks (G_j and G_{j+1}) subjects were asked to allocate an amount of 10,000 Euro between these two stocks and a risk free asset generating a return of 0%. These kinds of portfolio allocation tasks are pretty common in the literature (see e.g. Kroll et al. (1988) and Weber and Milliman (1997)). Subjects were explicitly told that the two risky assets were from different industries and hence not correlated with each other. This portfolio allocation task was carried out for ten pairs of stocks. Short sales and borrowing were not allowed. In this portfolio allocation task, subjects were paid according to the returns of their constructed portfolios. More precisely, we told them that we would randomly pick one of the portfolios and calculate the return of this portfolio. The payment for this task being then equal to 15 Euro times one plus the return on the portfolio. The exact payment mechanism is illustrated in the appendix in section 4.5.

Finally, we also asked subjects questions about how they perceived themselves (see questionnaire in the appendix.) For example we asked how much they were averse to risk, how competent they felt about statistics and how competent they felt in finance. We asked them to answer on a scale ranging from 1 (very good / very risk averse) to 5 (bad / less risk averse).

4.2.4 Participants

The data was collected on September 19, 2007. One week before the data collection we announced within the lectures Decision Analysis and Behavioral Finance that we would perform an interesting experiment for which students could register. This registration process was carried out to ensure that only participants with a minimum level of knowledge of financial markets would participate. The study was carried through in one large auditorium and subjects were randomly assigned a seat when entering the auditorium. In order to avoid cheating we distributed six versions of the questionnaire that differed

in the order of the questions and instructed subjects that they would not be paid if they would try to collude with others.

By and large, 104 students participated in the paper and pencil experiment. 56 students were enrolled in the Behavioral Finance class, 31 in the Decision Analysis class, and 15 students attended both classes while two students did not indicate the class they were attending. It took subjects approximately 55 minutes to finish the questionnaire.[5] The average subject was 24 years old with 83% of the subjects aged between 21 and 26. We find an almost equal split between males and females for our Decision Analysis class and a strong majority (76%) of males for the Behavioral Finance class. Overall, subjects in our experiment were predominantly male 70%.

To obtain the *Risk Aversion* score we multiply subjects' willingness to take risks with -1. The average subjective *Risk Aversion* score was -2.9 and subjects indicated a slightly better knowledge in statistics (2.9) than in finance (3.1). Subjects attending both classes indicated a slightly better self-assessed knowledge in statistics (2.5) and in finance (2.7). The overall payment for all subjects was on average 37.87 Euro with payments ranging from 23.38 Euro to 49.74 Euro. The heterogeneity of the overall payment structure can be seen in figure 4.1.
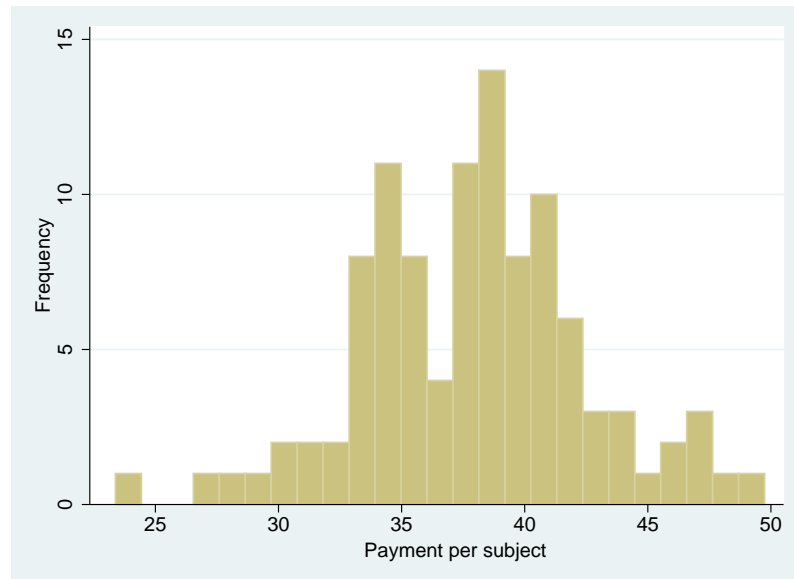

Figure 4.1: Payment per subject

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[5]Interestingly, subjects in a pre-test without payments needed only approximately 35 minutes to finish the questionnaire.

4.3 Empirical Analysis

Overall, we have three main hypotheses that we want to test with our experimental setup. First, we argue that overreaction to new signals should be prevalent in our setting. Second, overreaction should be related to psychological biases such as miscalibration. And third, overreaction should have some real financial consequences, i.e. we should find a relation between overreaction and portfolio risk as well as portfolio efficiency. Our three main blocks of hypotheses are illustrated in figure 4.2 and discussed more thoroughly in the respective subsections.
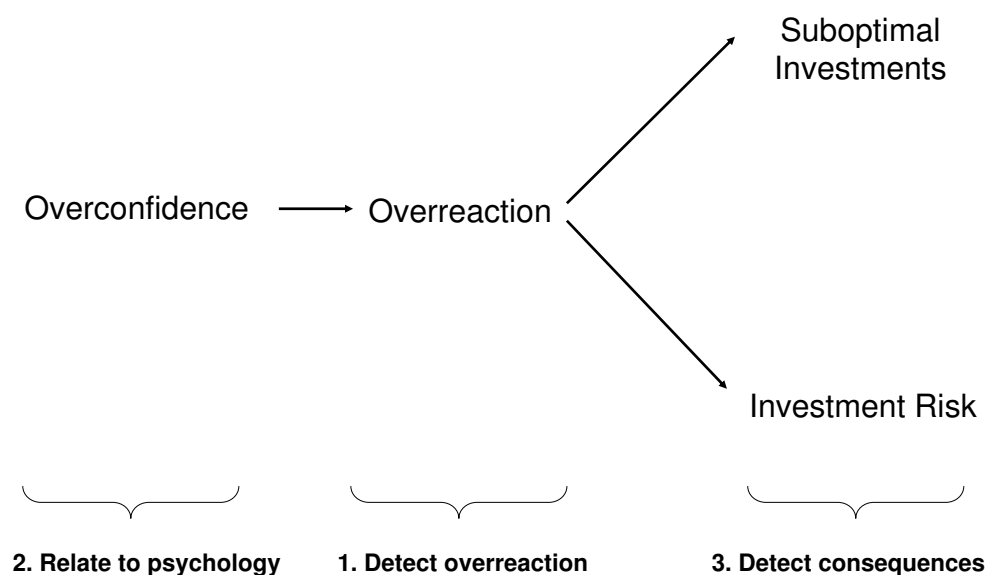
Figure 4.2: Overview of hypotheses

4.3.1 The Level of Overreaction

The first goal of this study is to detect the degree of misreaction for each subject in our setting. Some studies analyzing the level of misreaction find evidence for overreaction whereas other studies find that subjects exhibit the tendency to underreact to signals (for an overview of the diverging results in the literature see Barberis et al. (1998) and

DeBondt (2000)). Both Griffin and Tversky (1992) and Bloomfield et al. (2000) argue that the weight of a signal, i.e. its statistical reliability, and the strength of a signal, i.e. its magnitude, determine if subjects overreact or underreact. They reason that overreaction should be prevalent if the signal is of high strength and low weight. In line with the findings by Thomas and Zhang (2008) who analyze a similar setting as ours empirically we hypothesize that subjects tend on average to overreact to information about a related stock as the signal in our setting is of relatively high strength and low weight. Observing overreaction in our experimental setting is also consistent with Odean (1998b) who argues that subjects tend to overweight attention-grabbing, anecdotal and graphical information, just the type of information we gave subjects.[6]

Both measures of overreaction are highly correlated with each other ($Spearman\ Rho =$ 0.85). Figure 4.3 shows that subjects tend on average to overreact in our setting no matter if we measure overreaction as *Median-Overreaction-Ratio* or *Overreaction-Beta*. For both measures, a large majority of subjects have a positive overreaction score and exhibit the tendency to overreact to the signal, whereas only a few subjects underreact to the signal.[7] The average *Median-Overreaction-Ratio* is 0.33. To assess the internal psychometric consistency of this overreaction measure we compute its Cronbach alpha. The Cronbach alpha is 0.8 and thus above the threshold of 0.7 that is often assumed to indicate acceptable psychometric reliability (see Nunnally (1978)). The beta coefficients in our regression of forecast error onto signal are also mostly positive with an average *Overreaction-Beta* of 0.37. Taking a closer look at the coefficients we find 91 (2) significantly positive (negative) coefficients and only 11 insignificant coefficients. However, there seems to be substantial variation in the degree of both *Median-Overreaction-Ratio* and *Overreaction-Ratio* with the scores ranging from -0.67 to 0.76. In the following subsections, we want to analyze whether these individual differences in overreaction are systematically related with other traits like overconfidence and performance.

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[6]Overreaction to the graphical signal might also be interpreted as underreaction to the verbal information that was provided to subjects.

[7]We obtain very similar results if we aggregate *Median-Overreaction-Ratio* using the mean instead of the median. Moreover, there are no substantial differences if we run our analyses for questions with a positive and negative signal separately.
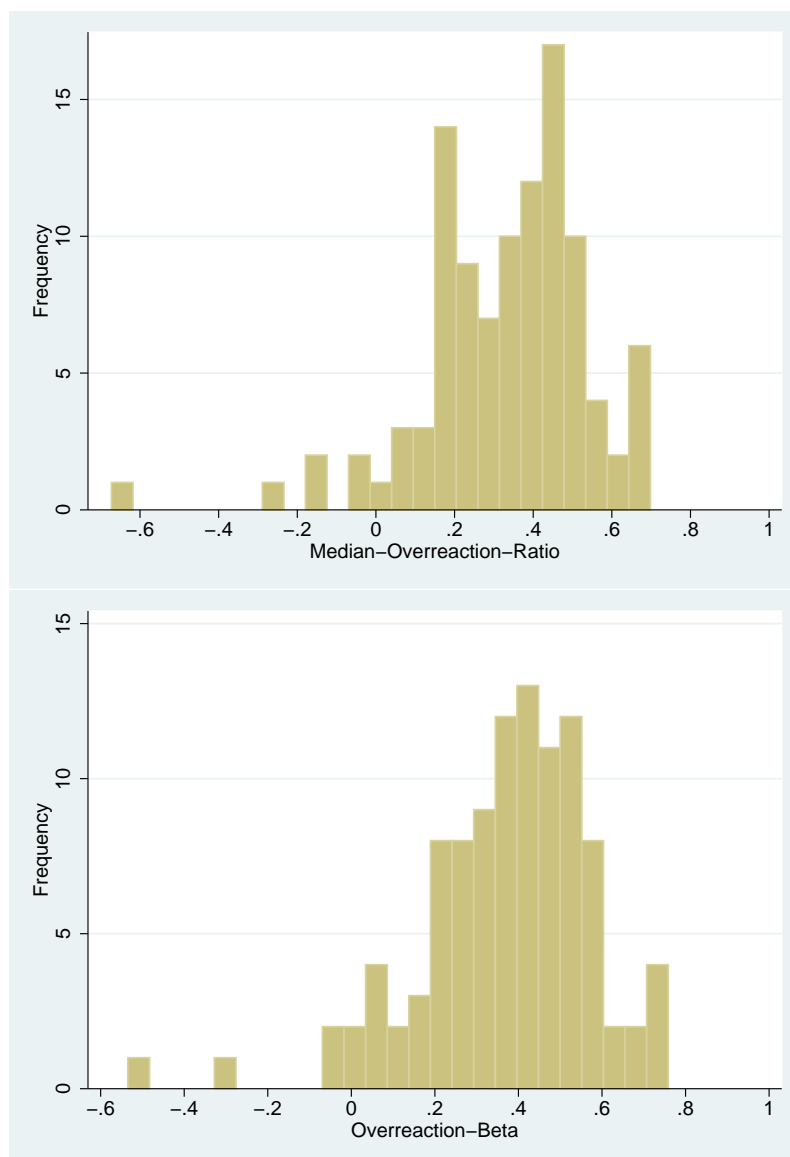
Figure 4.3: Histogram of *Median-Overreaction-Ratio* and *Overreaction-Beta*

4.3.2   Miscalibration Determining the Level of Overreaction

Before we can test whether more miscalibrated subjects overreact more strongly we have
to show that we have a substantial degree of overconfidence in our experimental setting.
Hence, we calculate *Overconfidence* for each stock using the two point approximation
method proposed by Keefer and Bodily (1983) and aggregate these scores for each sub-
ject to obtain *Overconfidence-Person*.[8] We find substantial degrees of overconfidence in
our setting with 76 subjects having an *Overconfidence-Person* score above -1 and a me-

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[8]Testing the internal reliability of our overconfidence score we find a Cronbach alpha above 0.9.

dian *Overconfidence-Person* score of -0.71 roughly the same size DeBondt (1998) finds on average in his analysis of Fox Valley investors. A Wilcoxon signed rank test indicates that *Overconfidence-Person* is significantly larger than -1 suggesting a prevalence of overconfidence in our sample. Moreover, in line with Glaser et al. (2005) we also find substantial heterogeneity in the degree of overconfidence in our sample as the *Overconfidence-Person* scores range from -2.2 for the most underconfident subjects to -0.11 for the most overconfident ones.[9]

If the hypothesis that more overconfident subjects tend to overreact more strongly, since they overweight the informativeness of the signal, holds (see e.g. Odean (1998b) and Hirshleifer and Luo (2001)) we should find a significantly positive relation between *Overconfidence-Person* and both of our overreaction measures. The relation should be positive since a higher *Overconfidence-Person* score indicates higher levels of overconfidence. Figure 4.4 illustrates the relation between both overreaction measures and *Overconfidence-Person*. The Spearman rank correlation coefficient between *Overconfidence-Person* and both overreaction measures is significantly positive (Rho = 0.24 at a significance level of 0.02 for *Median-Overreaction-Ratio* and Rho = 0.31 at a significance level of less than 0.01 for *Overreaction-Beta*). Moreover, our results for this relationship are stable if we control for demographic aspects and self-assessed knowledge or risk aversion. Thus, we can confirm our hypothesis that more overconfident subjects overreact more strongly.

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[9]We also calculated for each person the number of questions for which the conditional expected value or the realized value were between the stated upper and lower bounds. The correlation between these two new overconfidence measures and our measure calculated from implied standard deviations was above 0.9. In addition, results in the following sections were essentially the same if we use these two other measures in the further calculations.
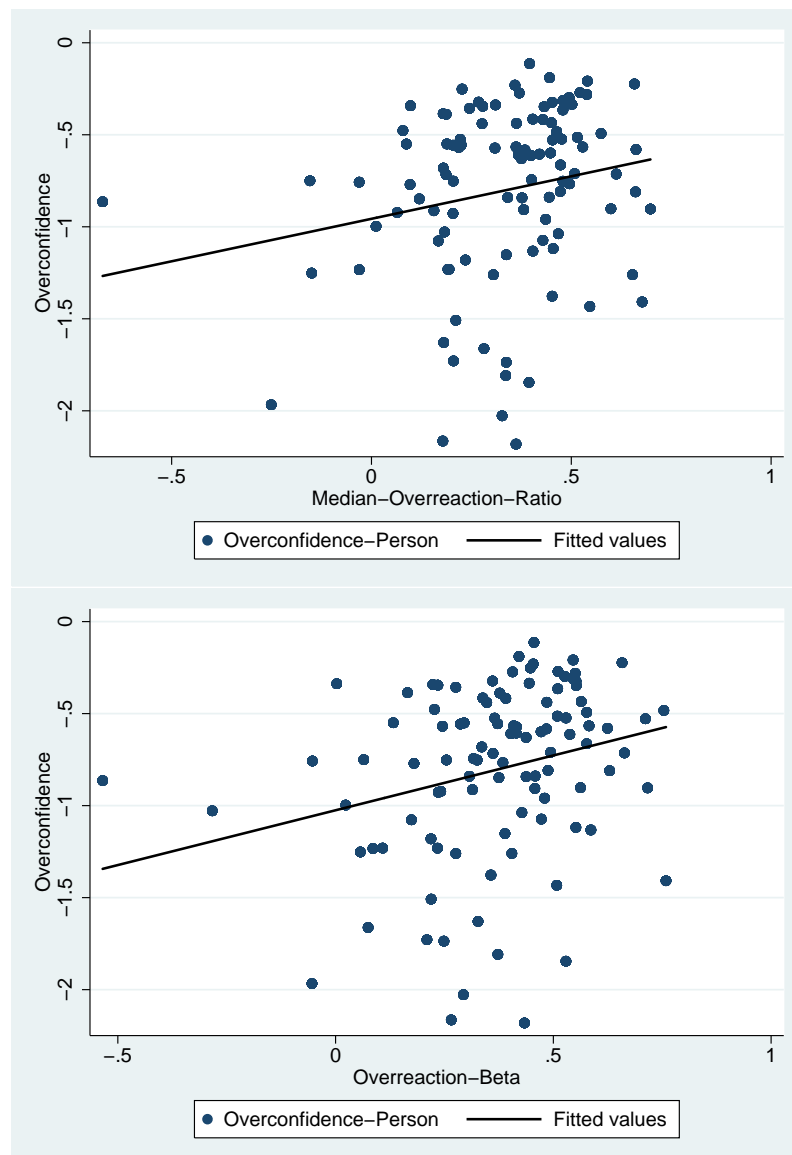
Figure 4.4: Relation overreaction and overconfidence

4.3.3 Economic Significance of Overreaction

Our findings imply that subjects in our experiment overreact on average to signals and that there is substantial heterogeneity in the degree of overreaction. We also show a positive relation between overconfidence scores and overreaction indicating that more overconfident subjects tend to overreact more strongly. Besides analyzing the degree of overreaction and its relation to psychological biases we want to analyze the financial consequences of overreaction. Financial consequences of overreaction are in the literature argued to be twofold. Fischer and Verrecchia (1999) and Hirshleifer and Luo (2001) argue

that subjects who overreact are - owing to overconfidence - willing to take more risks in their investments to exploit mispricings. Daniel et al. (2001) and Biais and Weber (2007) show that subjects who overreact fail to diversify properly and hold less efficient portfolios than subjects who do not overreact.

The Effect of Overreaction on Risk Taking

The main goal of this section is to analyze whether overreaction has an influence on the riskiness of portfolio decisions. As we did not allow subjects to take short positions in any asset we should observe a twofold effect of overreaction on risk taking. After a good signal overreacting subjects overweight the positive effects of the signal and invest more heavily in the risky asset whereas after a bad signal they overweight the negative effects of the signal and invest less heavily into the risky asset.[10] Before we test this relationship on a disaggregate level, we want to test if it also holds on an aggregate level. Therefore, we correlate each subject's median portfolio risk which equals his / her median portfolio volatility with both overreaction measures. However, since our hypothesis depends on the sign of the signal we do this analysis separately for questions for which subjects received positive (*Median Risk*$^+$) and negative (*Median Risk*$^-$) signals. Our hypothesis is that we should find a significantly positive correlation between both constructs for good signals and a significantly negative correlation for bad signals.

Indeed, for portfolios with a positive signal the Spearman rank correlation of *Median Risk*$^+$ with *Median-Overreaction-Ratio* is 0.28 (p-value < 0.01) and the correlation with *Overreaction-Beta* is 0.24 (p-value $= 0.01$). For portfolios with a negative signal the Spearman rank correlation of *Median Risk*$^-$ with *Median-Overreaction-Ratio* is -0.21 (p-value $= 0.03$) and the correlation with *Overreaction-Beta* is -0.28 (p-value < 0.01).[11] These relations are illustrated in figure 4.5 and figure 4.6.

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[10]If we would have allowed short sales more overreacting subjects should have taken larger short positions in stocks with a negative signal than rational subjects.

[11]If we exclude subjects that decide not to invest into any of the risky assets, i.e. subjects whose portfolio risk is zero, our results weaken as we lose a substantial number of observations. The correlation coefficients are still negative, however, not statistically significant.
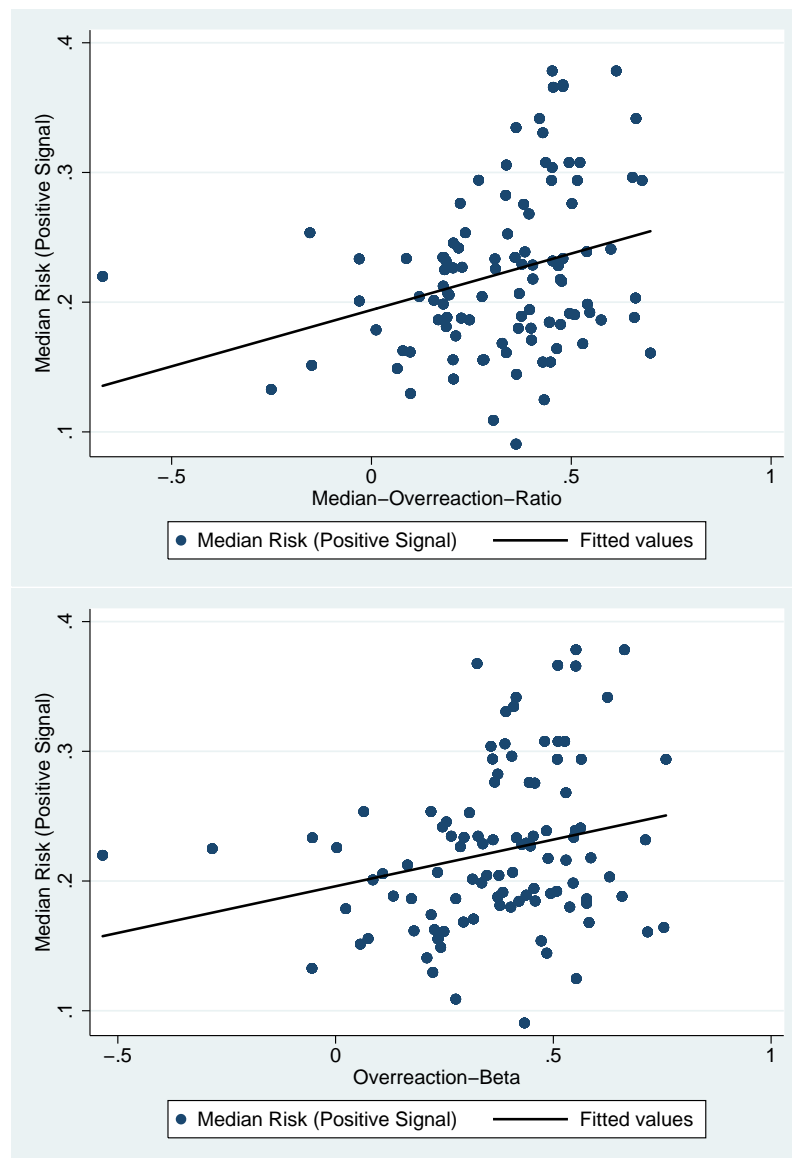
Figure 4.5: Relation overreaction and portfolio risk (questions with positive signal)
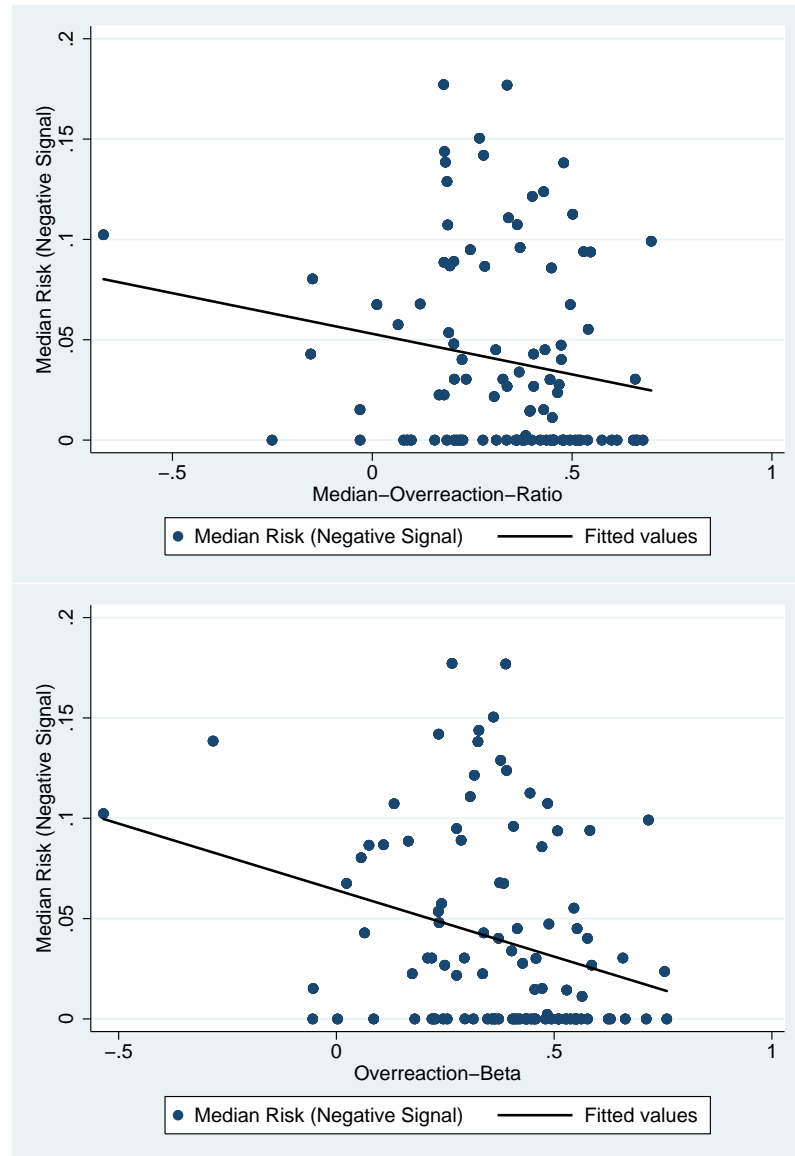
Figure 4.6: Relation overreaction and portfolio risk (questions with negative signal)

An important issue in this context is if our results that a higher level of overreaction leads subjects to take more risks after good signals and less risks after bad signals are driven by other factors such as risk attitudes, gender, cultural background or overconfidence. Risk attitudes are the most prominent factor for which we want to control for in the following. In risk-return frameworks commonly used in the finance literature (see e.g. Markowitz (1952)) risk taking is governed by the risk and the return of an investment and by a subject's risk attitude. Hence, the more risk averse a subject is the less risk he / she will take. Various studies also argue that there is a gender effect in risk taking and that

females take substantially less risks than men in investment decisions (for an overview of the literature see Eckel and Grossman (2008)).

Moreover, we want to analyze whether the cultural background of subjects could influence the risk taking behavior. In line with Weber and Hsee (1998) we argue that German subjects who are from a more individualistic society should invest into less risky portfolios than subjects from more collectivist societies.[12] Furthermore, our data allows us to test an assumption common in various models on overconfidence (see e.g. Odean (1998b) and Daniel et al. (2001)) that more overconfident subjects are going to take more risks. In addition to these factors, we will also control for the age of the subjects, the course they are enrolled, their semester, and their self assessed knowledge in finance and in statistics.

Table 4.1 documents that both *Median-Overreaction-Ratio* and *Overreaction-Beta* are significantly related to *Median Risk*$^+$ and *Median Risk*$^-$ even if we control for additional factors. Regressions in columns 1 - 4 analyze portfolios for which subjects receive a positive signal. For these portfolios we find that an in increase in the overreaction score by one results in a 5.4 to 7.0 percentage points increase of *Median Risk*$^+$ no matter if we control for overconfidence in the regression (columns 2 and 4) or not. Since *Median Risk*$^+$ is on average 0.22 this implies that the effect of both overreaction scores on portfolio risk is also of high economic significance. Analyzing portfolios for which subjects receive a negative signal (see regressions 5 & 6) we find, consistent with the bivariate analyses, a negative effect indicating that more overreacting subjects take substantially less risks in these scenarios.

Moreover, for those questions for which subjects received a positive signal our control variables indicate additional statistically significant effects. First, *Median Risk*$^+$ of males

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[12]Hsee and Weber (1999) and Weber and Hsee (1998) find significant cross-cultural differences in risk taking. More specifically, they argue that subjects who live in a more collectivist society like China take substantially more risks than subjects who live in a more individualistic society such as the USA. They term this the "cushion-hypothesis". The line of reasoning is that subjects from less individualistic societies can rely on their family, i.e. have a cushion, to help them in case of need. Since we collected data on the native-language of the subjects we are able to test this cultural hypothesis. As only 29 out of 104 subjects are not Germans we generate a dummy variable that takes the value of 1 if the subject is a native speaker in German and 0 otherwise. The average individualism score according to Hofstede (1980) in the Non-German group which consists of Russian, Chinese, Bulgarian, and French subjects is 36.7 and thus lower than the one for Germans which is 67. Hence, Germans who are part of a more individualistic society should invest into less risky portfolios.

is approximately 4 percentage points higher than the one of females. This result is in line with findings in Donkers et al. (2001) and Dohmen et al. (2005) who show that males take substantially more risks in their financial decisions. As hypothesized we also find a significant negative effect of *Risk Aversion* on *Median Risk$^+$*. Thus, less risk averse subjects are investing into riskier portfolios. In addition, we also find weak support for cultural differences (see Bontempo et al. (1997) and Weber and Hsee (1998)) as German subjects hold less risky portfolios than Non-Germans. However, this effect is only weakly significant and vanishes if we control for overconfidence. However, we cannot observe these effects for *Median Risk$^-$* in columns 5 & 6. This difference between questions for which subjects received a positive or a negative signal could be analyzed more thoroughly in future research. Furthermore, in line with Dorn and Huberman (2005) and Menkhoff et al. (2006) we do not find a direct effect of overconfidence on portfolio risk but only an indirect effect of overconfidence on risk taking mediated by overreaction.

Now that we have found evidence for the hypothesized relationship between overreaction and portfolio risk on the aggregate level, we turn to analyze the relationship on a disaggregate level. Hence, we re-run the regressions from table 4.1, but instead of using aggregate scores for each subject we run our regressions for each question individually controlling for question fixed effects using dummies. As *Overreaction-Beta* is an aggregate measure that is constant for each person over all questions we use in the following disaggregated analyses only *Overreaction-Ratio*.[13] To account for non-independent residuals within subjects we cluster our observations over subjects.

A first look at the results in table 4.2 reveals that the results are mainly consistent with our previous findings in table 4.1. Higher levels of overreaction result in riskier portfolio investments after positive signals and less risky portfolio investments after negative signals. The effect of *Overreaction-Ratio* on *Risk$^+$* and *Risk$^-$* is highly significant regardless whether we control for overconfidence or not. In addition, we find that after having observed a positive signal men hold substantially more risky portfolios than women, and more risk averse subjects invest into less risky positions. We also find support for the

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[13]To get a single score for the two variables *Overreaction-Ratio* and *Overconfidence* that are calculated for each stock, i.e. twice for every portfolio allocation question, we simply take the mean of the variables for each portfolio allocation task.

Table 4.1: Median risk regressions

This table presents results on the relation between a subject's median portfolio risk (the median portfolio risk for portfolios for which subjects received a positive signal is indicated by $^+$ and the median portfolio risk for portfolios for which subjects received a negative signal is indicated by $^-$) and *Age*, *Gender* (the dummy variable takes the value 1 if the subject is male), *Decision Analysis*, *Behavioral Finance*, and *Both* (the dummy variables take the value 1 if the subject attends the respective class), *Semesters*, *German* (the dummy variable takes the value 1 if a subject's mother language is German), *Risk Aversion* (the variable is defined on a scale from -1 = highly risk averse to -5 = not risk averse at all), *Statistical Knowledge* and *Financial Knowledge* (both variables are defined on a scale from 1 = very high knowledge to 5 = very low knowledge), *Median-Overreaction-Ratio*, *Overreaction-Beta*, and *Overconfidence-Person* using ordinary least squares regressions with heteroscedasticity consistent standard errors. We report regression coefficients and p-values in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Med. Risk$^+$	Med. Risk$^+$	Med. Risk$^+$	Med. Risk$^+$	Med. Risk$^-$	Med. Risk$^-$
Age	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.830)	(0.820)	(0.568)	(0.580)	(0.791)	(0.640)
Gender	0.040	0.040	0.042	0.042	-0.012	-0.013
	(0.023)**	(0.021)**	(0.019)**	(0.018)**	(0.352)	(0.308)
Behavioral Finance	-0.015	-0.013	-0.012	-0.009	0.023	0.022
	(0.234)	(0.339)	(0.373)	(0.490)	(0.042)**	(0.058)*
Both	-0.009	-0.004	-0.007	-0.002	0.017	0.019
	(0.643)	(0.854)	(0.722)	(0.933)	(0.235)	(0.199)
Semesters	0.001	0.001	0.002	0.002	0.001	0.000
	(0.696)	(0.603)	(0.516)	(0.453)	(0.821)	(0.954)
German	-0.026	-0.024	-0.027	-0.025	0.001	0.002
	(0.086)*	(0.116)	(0.075)*	(0.104)	(0.924)	(0.860)
Risk Aversion	-0.017	-0.017	-0.017	-0.017	-0.010	-0.010
	(0.005)***	(0.006)***	(0.006)***	(0.007)***	(0.120)	(0.126)
Statistical Knowledge	-0.009	-0.008	-0.010	-0.008	0.008	0.006
	(0.242)	(0.329)	(0.229)	(0.311)	(0.306)	(0.363)
Financial Knowledge	0.007	0.007	0.006	0.006	0.003	0.004
	(0.404)	(0.460)	(0.477)	(0.528)	(0.687)	(0.583)
Median-Overreaction-Ratio	0.070	0.064			-0.037	
	(0.010)***	(0.020)**			(0.089)*	
Overreaction-Beta			0.061	0.054		-0.067
			(0.030)**	(0.059)*		(0.002)***
Overconfidence-Person		0.012		0.013	0.006	0.010
		(0.433)		(0.407)	(0.659)	(0.459)
Constant	0.152	0.157	0.155	0.161	-0.021	-0.004
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.669)	(0.937)
Observations	101	101	101	101	101	101
R-squared	0.257	0.263	0.243	0.250	0.129	0.175

Table 4.2: Risk regressions

This table presents results on the relation between the risk of a portfolio (the risk for portfolios for which subjects received a positive signal is indicated by $^+$ and the risk for portfolios for which subjects received a negative signal is indicated by $^-$) and *Age*, *Gender* (the dummy variable takes the value 1 if the subject is male), *Decision Analysis*, *Behavioral Finance*, and *Both* (the dummy variables take the value 1 if the subject attends the respective class), *Semesters*, *German* (the dummy variable takes the value 1 if a subject's mother language is German), *Risk Aversion* (the variable is defined on a scale from -1 = highly risk averse to -5 = not risk averse at all), *Statistical Knowledge* and *Financial Knowledge* (both variables are defined on a scale from 1 = very high knowledge to 5 = very low knowledge), *Overreaction-Ratio*, *Overreaction-Beta*, and *Overconfidence* using clustered least squares regressions (number of clusters is equal to 101). We report regression coefficients and p-values in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	$Risk^+$	$Risk^+$	$Risk^-$	$Risk^-$
Age	-0.001	-0.001	0.000	0.000
	(0.563)	(0.551)	(0.605)	(0.619)
Gender	0.049	0.048	-0.007	-0.008
	(0.002)***	(0.002)***	(0.473)	(0.423)
Behavioral Finance	-0.013	-0.010	0.015	0.016
	(0.334)	(0.452)	(0.088)*	(0.060)*
Both	-0.002	0.003	0.015	0.018
	(0.918)	(0.877)	(0.244)	(0.160)
Semesters	0.001	0.002	-0.001	-0.001
	(0.631)	(0.524)	(0.625)	(0.757)
German	-0.029	-0.027	-0.001	0.001
	(0.040)**	(0.054)*	(0.919)	(0.903)
Risk Aversion	-0.021	-0.021	-0.008	-0.008
	(0.001)***	(0.001)***	(0.080)*	(0.082)*
Statistical Knowledge	-0.008	-0.007	0.006	0.007
	(0.287)	(0.416)	(0.332)	(0.248)
Financial Knowledge	0.003	0.003	0.006	0.005
	(0.703)	(0.781)	(0.275)	(0.334)
Overreaction-Ratio	0.035	0.033	-0.052	-0.054
	(0.008)***	(0.010)**	(0.000)***	(0.000)***
Overconfidence		0.015		0.009
		(0.278)		(0.206)
Constant	0.139	0.143	0.005	0.009
	(0.003)***	(0.002)***	(0.893)	(0.819)
Observations	705	705	303	303
R-squared	0.472	0.474	0.214	0.220

cultural hypothesis as the dummy variable *German* is significantly negative. Once again, the additional effects of *Gender* and *German* cannot be observed for portfolios for which subjects received a negative signal.[14]

The Effect of Overreaction on Portfolio Efficiency

A further consequence of overreaction that we want to test in the following is the relationship between overreaction and portfolio performance. Biais and Weber (2007) show in their theoretical model that subjects who overreact, i.e. put too much weight on private signals, will have a lower investment performance. Hence, in our experimental setting we expect to observe that subjects will hold less efficient portfolios the more they overreact. However, we found a substantial degree of heterogeneity in the level of overreaction with some subjects even underreacting and thus putting not enough weight on the signal (see subsection 4.3.1). We argue that these underreacting subjects should also invest into less efficient portfolios than rational subjects. This should result in a hump-shaped relation between overreaction and portfolio efficiency with rational subjects having the highest efficiency and efficiency decreasing with higher levels of misreaction.

To analyze this relationship in more detail we first have to define the term efficiency of a portfolio. Our measure of portfolio efficiency is the ex-ante *Sharpe-Ratio* for each subject and each portfolio. To calculate the *Sharpe-Ratio* for a subject's portfolio we use conditional expected returns and conditional expected standard deviation. Calculating the *Sharpe-Ratio* makes only sense for stocks with a positive conditional expected return, and thus we exclude in the following analyses all stocks with a negative conditional expected return.

In addition, as we imposed short selling constraints on our subjects, i.e. we did not allow them to short sell assets in order to invest more into the other assets, the capital market

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[14]Instead of clustering over subjects to control for non-independent residuals we also re-run the regressions using fixed and random effects models. We obtain essentially the same results using these models. However, both models have their disadvantages. A Hausman test shows that the random effects model needs not to generate consistent estimates. Although, the fixed effects model generates consistent estimates its major disadvantage is that we cannot make a statement about the effect of demographics, risk attitude, and knowledge on risk taking. Hence, we only make use of clustered ordinary least squares regressions where we control for question specific effects.

line is no straight-line. Thus, we cannot make the general statement that a higher *Sharpe-Ratio* implies a more efficient portfolio as it is possible that subjects that want to take more risks can only do so by investing a relatively large amount into the riskier stock. Due to the short selling constraint portfolios of these subjects have a lower Sharpe ratio than portfolios of subjects that invest into the market portfolio. But we cannot infer that they are less efficient as they offer the only possibility to take on more risk. However, for subjects that invest in portfolios that are less risky than the market portfolio and for subjects that invest into the risk free asset the risk constraint is not binding. Hence, in our further analyses we omit 152 out of 728 portfolios that are to the right of the market portfolio, i.e. that are riskier than the market portfolio, and for which subjects did not invest into the risk free asset. Therefore, in the following analyses we only take portfolios for which the short selling constraint is not binding.

To document the link between overreaction and portfolio efficiency we calculate Spearman rank correlation coefficients between portfolio efficiency and *Median-Overreaction-Ratio* and *Overreaction-Beta*, respectively. However, as our hypothesis implies that stronger misreaction (overreaction or underreaction) leads to less efficient portfolios we divide our sample into two unbalanced parts. One part is composed of subjects that overreact and the other, substantially smaller one of subjects that underreact. Calculating Spearman rank correlation coefficients for the two parts separately we find a negative relation for subjects that overreact with coefficients of -0.33 for *Median-Overreaction-Ratio* ($p-value < 0.01$) and -0.18 for *Overreaction-Beta* ($p-value = 0.07$) and a tentatively positive effect for the six subjects that underreact. This relation is illustrated by the dashed (dotted) lines in figure 4.7 for subjects that overreact (underreact). The figure demonstrates that a higher level of over/underreaction gives rise to less efficient portfolios.

While the above evidence indicates an effect of overreaction on portfolio efficiency we want to analyze whether this effect is stable if we control for additional variables. To analyze this in more detail we run regressions with the median Sharpe ratio (see table 4.3) and the disaggregated Sharpe ratio (see table 4.4) as dependent variables. Table 4.3 documents the relation between portfolio efficiency and both overreaction measures on an aggregate level using additional controls for all observations for which subjects overreact. Consistent with
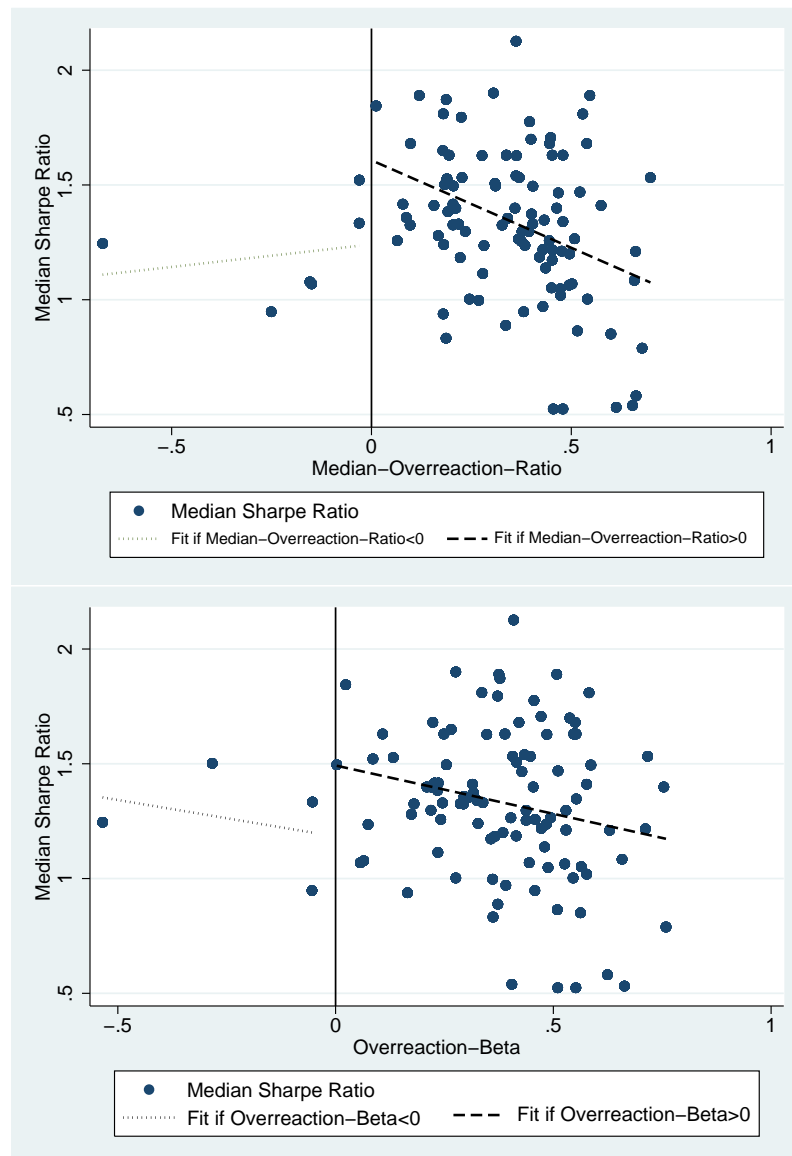
Figure 4.7: Relation overreaction and Sharpe ratio

our previous findings both overreaction measures have a significantly negative coefficient indicating that higher levels of overreaction lead to lower levels of portfolio efficiency.[15]

In addition, we re-run our regressions on a single question level instead of an aggregate level and account for non-independent residuals within subjects by clustering over subjects. Again, we only make use of *Overreaction-Ratio* as *Overreaction-Beta* is constant for all subjects. Additionally, we control for question effects using dummy variables. The results of these regressions are illustrated in table 4.4. In regressions 1 & 2 we only take observations for which *Overreaction-Ratio* is greater than zero indicating overreaction whereas in regressions 3 & 4 we only take observations for which *Overreaction-Ratio* is below zero indicating underreaction.

The regressions in table 4.4 show the twofold effect of overreaction on portfolio efficiency on a single stock level. The more subjects misreact the lower is their portfolio efficiency. On the one hand, we find highly significantly negative overreaction coefficients of approximately -0.145 in the first two regressions no matter if we control for overconfidence or not. On the other hand, our results in regressions 3 & 4 indicate a highly negative effect of underreaction of approximately -0.3 on portfolio efficiency. Thus, the higher the overreaction score, i.e. the less subjects underreact, the more efficient is their portfolio.

Consistent with Daniel et al. (2001) and Biais and Weber (2007) we show that misreaction to signals, i.e. overreaction or underreaction, is costly for investors and harms their performance. Minimizing the level of misreaction can have a substantial effect on a subjects portfolio efficiency as measured with the *Sharpe-Ratio*. Interestingly, the coefficient of *Overreaction-Ratio* on portfolio efficiency is in absolute terms much larger if we analyze underreaction than if we analyze overreaction. Future research might want to analyze this difference in more depth. Overall, our findings are in line with the hypothesis of a hump-

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[15]Regressing the median Sharpe ratio of subjects' portfolios on various control variables for underreacting subjects only is not reasonable as the number of underreacting subjects is six and four, respectively, and thus too low to make any inferences about the relationship between overreaction and portfolio efficiency while controlling for additional variables.

Table 4.3: Median Sharpe ratio regressions

This table presents results on the relation between a subject's median portfolio efficiency measured with the Sharpe ratio and *Age*, *Gender* (the dummy variable takes the value 1 if the subject is male), *Decision Analysis*, *Behavioral Finance*, and *Both* (the dummy variables take the value 1 if the subject attends the respective class), *Semesters*, *German* (the dummy variable takes the value 1 if a subject's mother language is German), *Risk Aversion* (the variable is defined on a scale from -1 = highly risk averse to -5 = not risk averse at all), *Statistical Knowledge* and *Financial Knowledge* (both variables are defined on a scale from 1 = very high knowledge to 5 = very low knowledge), *Median-Overreaction-Ratio*, *Overreaction-Beta*, and *Overconfidence-Person* using ordinary least squares regressions with heteroscedasticity consistent standard errors. Both regressions are only run for subjects for which the respective overreaction score was greater than zero indicating overreaction. We report regression coefficients and p-values in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Median-Sharpe$^{OR>0}$	Median-Sharpe$^{OR>0}$
Age	0.007	-0.006
	(0.729)	(0.397)
Gender	-0.049	-0.082
	(0.555)	(0.345)
Behavioral Finance	0.049	0.001
	(0.540)	(0.991)
Both	0.081	0.019
	(0.441)	(0.862)
Semesters	0.011	0.016
	(0.559)	(0.325)
German	-0.052	-0.044
	(0.578)	(0.658)
Risk Aversion	0.060	0.059
	(0.137)	(0.170)
Statistical Knowledge	-0.040	-0.027
	(0.373)	(0.566)
Financial Knowledge	-0.007	-0.006
	(0.877)	(0.904)
Median-Overreaction-Ratio	-0.772	
	(0.001)***	
Overreaction-Beta		-0.450
		(0.034)**
Overconfidence-Person	0.024	0.016
	(0.743)	(0.821)
Constant	1.717	1.885
	(0.000)***	(0.000)***
Observations	95	97
R-squared	0.189	0.118

Table 4.4: Sharpe ratio regressions

This table presents results on the relation between the efficiency of a portfolio measured as the *Sharpe-Ratio* and *Age*, *Gender* (the dummy variable takes the value 1 if the subject is male), *Decision Analysis*, *Behavioral Finance*, and *Both* (the dummy variables take the value 1 if the subject attends the respective class), *Semesters*, *German* (the dummy variable takes the value 1 if a subject's mother language is German), *Risk Aversion* (the variable is defined on a scale from -1 = highly risk averse to -5 = not risk averse at all), *Statistical Knowledge* and *Financial Knowledge* (both variables are defined on a scale from 1 = very high knowledge to 5 = very low knowledge), *Overreaction-Ratio*, *Overreaction-Beta*, and *Overconfidence* using clustered least squares regressions (number of clusters is equal to 101). Regression 1 & 2 are run using only observations for which the respective overreaction score indicates overreaction: we indicate this by Sharpe$^{OR>0}$. For regression 3 & 4 we use only observations for which we find negative overreaction, i.e. underreaction and indicate this with Sharpe$^{OR<0}$. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Sharpe$^{OR>0}$	Sharpe$^{OR>0}$	Sharpe$^{OR<0}$	Sharpe$^{OR<0}$
Age	0.004	0.005	-0.002	-0.003
	(0.435)	(0.343)	(0.506)	(0.448)
Gender	-0.067	-0.067	0.129	0.136
	(0.055)*	(0.057)*	(0.122)	(0.094)*
Behavioral Finance	0.090	0.082	0.015	0.005
	(0.025)**	(0.038)**	(0.793)	(0.922)
Both	0.113	0.093	0.023	0.008
	(0.018)**	(0.045)**	(0.800)	(0.939)
Semesters	-0.009	-0.010	-0.012	-0.014
	(0.247)	(0.174)	(0.334)	(0.275)
German	0.037	0.028	-0.109	-0.115
	(0.358)	(0.501)	(0.165)	(0.131)
Risk Aversion	0.032	0.030	-0.024	-0.023
	(0.104)	(0.112)	(0.416)	(0.442)
Statistical Knowledge	-0.025	-0.031	0.053	0.048
	(0.212)	(0.114)	(0.105)	(0.151)
Financial Knowledge	-0.021	-0.018	-0.048	-0.047
	(0.248)	(0.329)	(0.095)*	(0.102)
Overreaction-Ratio	-0.145	-0.142	0.297	0.308
	(0.000)***	(0.000)***	(0.007)***	(0.005)***
Overconfidence		-0.052		-0.041
		(0.059)*		(0.409)
Constant	1.994	1.963	1.982	1.980
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	421	421	137	137
R-squared	0.811	0.812	0.654	0.655

shaped relation between portfolio efficiency and overreaction. Hence, the closer subjects are to the rational benchmark the more efficient the portfolios are they are investing.[16]

Moreover, for regressions 1 & 2 we find a significant effect for the course subjects are enrolled. Subjects that are enrolled in the *Decision Analysis* class which is a more general topic course not only for students specializing in finance tend to invest into worse performing portfolios than subjects that are enrolled in the *Behavioral Finance* class which is part of the specialization in finance. This is indicated by the positive coefficients of *Behavioral Finance* and *Both.* Mahani and Poteshman (2008) provide similar evidence by showing that unsophisticated option market investors overreact to news on underlying stock and consequently have a lower performance. Further control variables are not strongly significant, just as in the regressions on the aggregate level.

4.4 Conclusion

This study experimentally analyzes the existence of overreaction, its relation to psychological biases, and its financial consequences. We introduce a new experimental design that asks subjects to estimate the future price of an asset given the information on another, related asset. This design allows us to measure the level of overreaction explicitly. We measure overreaction using two highly correlated measures: our first measure of overreaction is simply the ratio of forecasting error to innovation in the signal (*Overreaction-Ratio*) and our second measure of overreaction is the slope of a regression of error onto signal (*Overreaction-Beta*). Overall, we find evidence for strong overreaction in our data which is consistent with findings in Thomas and Zhang (2008) who analyze a similar scenario empirically. However, there seems to be large heterogeneity in the level of overreaction as few subjects are even prone to underreaction.

Examining the relationship between overreaction and psychological biases we focus on overconfidence and more exactly on miscalibration. We document a substantial level of

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[16]As in section 4.3.3 we re-run the regressions using fixed and random effects models. We obtain essentially the same results using these models. However, a Hausman test shows that the random effects model needs not to generate consistent estimates and thus we abstain from using it.

overconfidence with the majority of subjects being overconfident but also a few subjects being underconfident. Relating overconfidence to overreaction we find, as hypothesized, that more overconfident subjects tend to overreact more heavily.

Moreover, we analyze the effect of overreaction on subjects' portfolio risk and on their portfolio efficiency. We show that after having received a positive signal overreacting subjects take substantially more risks than rational subjects. In addition, our results support findings in the literature that show an effect of gender (see Eckel and Grossman (2008)), risk aversion (see Barsky et al. (1997)), and culture (see Weber and Hsee (1998)) on risk taking. Also in line with our hypothesis we show that after receiving a negative signal overreacting subjects invest into substantially less risky portfolios. This effect can be attributed to the short selling constraint which was imposed by us to make the task more realistic and less complex.

Relating portfolio efficiency to overreaction we find no linear relation but more of a hump-shaped relation. This hump-shape implies that portfolio efficiency is lower the more a subject overreacts or underreacts. Analyzing the effect of overreaction and underreaction separately we find exactly this effect. Moreover, our results rely on decisions that have substantial monetary effects. We pay subjects an hourly compensation that is on average five times as high as the hourly wage of undergraduate research assistants.

Our experimental approach offers the advantage that we can explicitly measure the level of overreaction and relate it to psychological biases and financial consequences. In a similar experiment that was run with professional bond traders we used price paths from real assets instead of artificial ones. The results are robust and show that even professional bond traders tend to overreact to these kind of signals.

Future research could utilize our experimental approach and analyze whether other psychological traits such as the use of the representativeness heuristic (see Barberis et al. (1998)) or the hindsight bias (see Biais and Weber (2007)) influence subjects' information processing, i.e. their level of overreaction, and subsequently their investment behavior. It could also be of interest to analyze whether other forms of overconfidence like the better than average effect or illusion of control are related to overreaction and correspondingly

to investment behavior in this context. Moreover, future research could study in an experimental market setting whether markets populated with agents who overreact more strongly will yield different price patterns or even less efficient prices. Another promising direction, in the spirit of Griffin and Tversky (1992) and Bloomfield et al. (2000), would be to study whether the level of overreaction varies depending on the weight of the signal subjects receive. Higher weight levels and subsequently lower levels of overreaction should be observed if the industry specific shock is of higher weight than the firm specific shock, i.e. if the two stocks in one graph are more highly correlated. In a similar vein, it would also be interesting to analyze how the level of overreaction changes if the time periods for which subjects receive graphical information are varied. Finally, it would be interesting to analyze whether subjects that overreact in our experimental setting and consequently have less efficient portfolios will also tend to invest into less efficient portfolios in reality.

4.5   Appendix

Questionnaire

Dear participants,

we would like to welcome you to this questionnaire study which is a joint research project of the University of Mannheim and Toulouse University. The study is sponsored by the European Union within the „European Network for the Advancement of Behavioural Economics" (ENABLE). The main part of the study consists of 10 questions that should be answered sequentially. Each of the 10 questions is made up of two parts, part A and part B. Within part A we kindly ask you to submit your stock price forecasts for two stocks by stating a lower bound, a best estimate, and an upper bound. Part B asks you to construct your preferred portfolio, choosing between two stocks and a risk free asset. In addition to these ten questions we are going to ask you several shorter questions where you have to indicate how you see yourself and your colleagues, respectively.

As a thank you for taking part in our survey, we are paying you a performance-related participation compensation. This compensation depends only upon your performance in the two parts A and B of the questionnaire. How your compensation is determined exactly is going to be explained in the instructions to this study, following on the next pages.

As researchers we heavily rely on the quality of our collected data. Thus, we would kindly ask you to take your time filling out this questionnaire and not to communicate with other participants of the study.

Thank you very much for your assistance and enjoy the questionnaire.

<table>
<tr><td>Part A: Stock Price Forecasts - Instructions</td></tr>
</table>

We are interested in the question how financial markets really work. Therefore, we need to understand how you form expectations about future stock prices. In part A you will see stock price charts, each with two stocks.

The two stocks shown in each graph are from the **same industry** and hence **positively correlated**. More precisely, future stock price changes are random and depend upon a common **industry-specific** shock and a **stock-specific** shock. The magnitude of the two shocks is **on average equal** and the shocks have the **same statistical distribution**. In addition, we know that these distributions in the first 6 months are identical to the distributions in the following 6 months, i.e. the distributions remain constant.

For one stock (*Stock G-0*) we are going to show you the stock price chart for all 12 months whereas for the other stock (*Stock H-0*) we are going to show you the stock price chart only for the first 6 months.
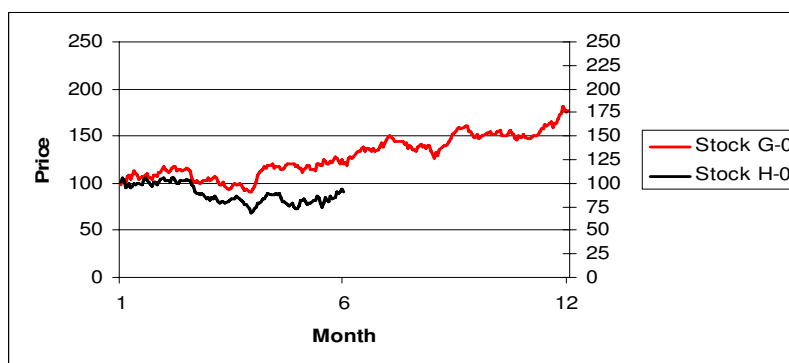
We kindly ask you to forecast the stock price of *Stock H-0* in 6 months, i.e. at t = 12. The only information given to you is the stock price performance of *Stock H-0* for the first 6 months and the stock price performance of *Stock G-0* for the whole observation period. In part A you are asked to make three statements concerning the future stock price: a **lower bound**, a **best guess,** and an **upper bound**.

- The best guess should be equal to the value where you expect the price of *Stock H-0* to be in 6 months (i.e. at time t = 12)
- You should set the bounds such that only in 1 out of 10 questions the actually realized stock price is outside your provided bounds. Hence, you should provide an upper and a lower bound such that you are 90% sure that the realized value of *Stock H-0* at time t = 12 falls between the two

2

Part A: Stock Price Forecasts – Payment Scheme

Your payment in part A depends only on the quality of your best guesses. I.e. the smaller the difference between your best guess and the actually realized stock price is, the higher is your payment going to be.

To determine your payment exactly we calculate for each of the 20 exercises (10 questions each with 2 exercises) in part A your so called error. This error is the absolute margin between your best guess and the actually realized stock price:

$$\text{Error}_i = |\text{ Best Guess}_i - \text{Actually Realied Price}_i| \qquad\qquad i = 1, 2, …, 20$$

Then we calculate your average error over all 20 exercises in part A as:

$$\text{Average Error} = \frac{\sum_{i=1}^{20} \text{Error}_i}{20}$$

Your final payment for part A is the maximum of 0 € and 50 € minus your average error and is calculated using the following formula:

$$\text{Payment}^A = \text{Max}\left\{0\,€\,;\,50\,€\,-\,Average\ Error\right\}$$

Thus, in a best case scenario your payment in part A can be up to 50 € and in the worst case your payment is going to be 0 €.

Part B: Portfolio Allocation - Instructions

In every of the 10 portfolio allocation questions in part B we kindly ask you to invest at **time t = 6** a given amount of **10,000 €**. Your investment opportunities in every question include a risk free asset that generates a return of 0% and two risky stocks. The two stocks in part B are the same stocks for which you provided stock price estimates in part A of the respective question.

You are asked to allocate the amount of 10,000 € – from your point of view – optimally between the risk free asset and the two stocks. However, you can only invest **amounts greater or equal to zero** into each of the three assets. I.e. you **cannot sell one asset short** and invest a higher amount of money into the remaining two assets. Moreover, you are only offered these three investment opportunities and hence you must divide the whole amount of 10,000 € between them.

Part B: Portfolio Allocation - Payment Scheme

At the end of the study we are going to calculate realized returns for each stock for the time period t = 6 to t = 12. Then we are going to pick **1 of the 10 questions** randomly and are going to calculate the realized return of your stated portfolio.

Your final payment for part B is equal to:

$$\text{Payment}^B = 15\,€ * (1 + \text{Realized Portfolio Return})$$
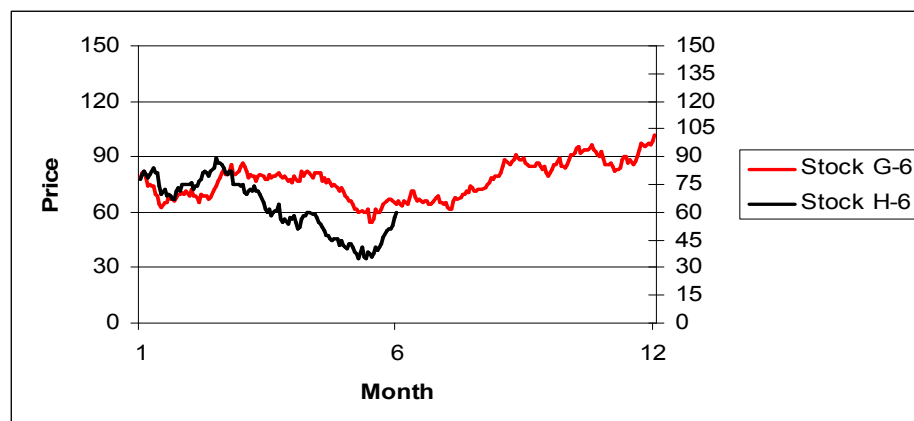
Question 3.A: Stock Price Forecasts
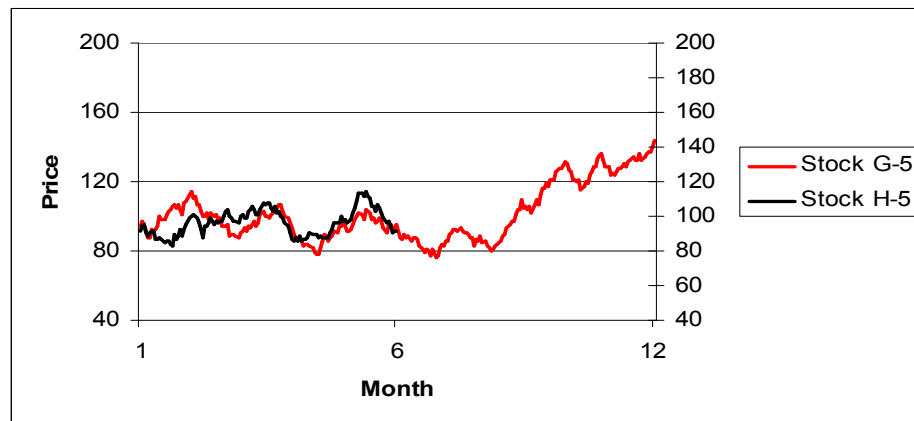
Lower bound for stock H-5	Best guess for stock H-5	Upper bound for stock H-5
€	€	€

Lower bound for stock H-6	Best guess for stock H-6	Upper bound for stock H-6
€	€	€

Question 3.B: Portfolio Allocation

In the following situation we kindly ask you to divide 10,000 € at time t = 6 between the following three investment opportunities: Stock H-5, Stock H-6 and a risk free asset, that generates a return of 0 %. The two stocks are from different industries and hence they are not subject to the same industry-specific shock.

Amount invested in risk free asset	Amount invested in Stock H-5	Amount invested in Stock H-6
€	€	€

The three amounts should add up to 10,000 €

4

Some questions about how you see yourself:

How do you rate your statistical knowledge?

1	2	3	4	5

very good   bad

How do you rate your knowledge about stock markets and financial markets?

1	2	3	4	5

very good   bad

In this questionnaire, we asked you to provide upper and lower bounds for 20 exercises related to stock price expectations (part A). For how many of these exercises do you think the final value is outside the range you gave?

_____ (Please give a number between 0 and 20)

In this questionnaire, we asked all subjects to provide upper and lower bounds for 20 exercises related to stock price expectations (part A). For how many of these exercises do you think the final value is outside the range provided by the average participant?

_____ (Please give a number between 0 and 20)

Some final questions about you:

Age: _____

Gender: ○ female   ○ male

Line of studies: _____

Semester: _____

How would you classify your willingness to take risks in financial decisions?

1	2	3	4	5

Very low   Very high
willingness   willingness

5

Chapter 5

Overreaction in Stock Forecasts and Prices

5.1 Introduction

Behavioral finance shows that individual biases such as the disposition effect (Odean (1998a) and Weber and Camerer (1998)), hindsight bias (Biais and Weber (2009)) or overconfidence (Camerer and Lovallo (1999) and Biais et al. (2005)) can affect individual decision making. In addition, both theoretical and experimental behavioral studies argue that markets are not always fully efficient and that market forces are not fully able to correct for individual biases (see e.g. Camerer (1987), Jegadeesh and Titman (1995), or Scheinkman and Xiong (2003)). However, it is still ambiguous whether and why individual biases prevail in market outcomes and if rational explanations are more capable to explain some market anomalies. Some studies for example show that individual biases vanish totally or are significantly reduced by market forces whereas other studies illustrate that individual biases remain fairly stable or even get more pronounced on an aggregate level.

On the one hand, analyzing abstract Bayesian updating tasks Camerer (1987) and Ganguly et al. (1994 and 2000) show that probability judgment errors or biases can indeed persist in market settings. However, they show that the bias on an aggregate level is reduced. In a similar vein, Camerer et al. (1989) analyzing the hindsight bias, Kluger

and Wyatt (2000) studying judgment errors in the Monty Hall problem, and Sonnemann et al. (2008) analyzing partition-dependence, show that market experience mitigates the respective bias but is not able to eliminate it completely. On the other hand, Gillette et al. (1999), Bloomfield et al. (2000), and Nelson et al. (2001) find that underreaction to signals in a coin-spin scenario shows the same extent in markets and on an individual level. Similarly, Seybert and Bloomfield (2009) find hardly any evidence for a wishful thinking bias on an individual level but strong evidence for wishful betting on an aggregate market level.

In addition, van Boven et al. (2003) and Weber and Welfens (2007) show that a bias gets smaller over repeated interactions of the same commodity or in the course of a trading round but that this learning does not generalize to interactions with a new asset or commodity. Budescu and Maciejovsky (2005) conclude that "expecting biases to disappear completely or, alternatively, to always persist are overly simplistic positions". Overall, findings in the literature indicate that the question whether markets can correct for individual biases depends on the structure of the market, the task on hand, the sort of feedback that subjects receive or the individual bias that is analyzed.

The main goal of this chapter is to analyze whether individual over- or underreaction to changes in the fundamental value of a stock, i.e. to new information, affects market outcomes in a setting similar to the one empirically analyzed by Thomas and Zhang (2008). Thomas and Zhang (2008) study market reactions to earnings announcements by considering pairs of stocks from the same industry which announce earnings sequentially. More precisely, they show that the market price of a firm that has not yet announced earnings moves too far upward (downward) in reaction to good (bad) earnings reports of an early-announcing peer and is corrected when the late-announcing firm's earnings are subsequently revealed. Thus, their findings suggest that stock prices for the late announcers overreact to the information transfer from the early-announcing peer. Overreaction (underreaction) in this context means that subjects put too much (little) weight on new information. However, using empirical data it is not possible to rule out other explanations for misreaction or to analyze in more detail, how individuals react to new information about the fundamental value of a stock and whether this individual misreaction affects

market variables. Misreaction in this context is simply defined as the absolute level of over- or underreaction.

Since the empirical and experimental evidence on how individual misreaction affects market outcomes is scarce, we apply the individual level approach of chapter 4 to an experimental trading market. The main features of our design are as follows: first, we give subjects the stock price charts of two related stocks (G and H) for the last six months and ask them to estimate the price of one of the two stocks (H) in six months. After having provided a best estimate for stock H subjects are able to trade this stock for two minutes in a single-unit open-book double auction market. After two minutes of trading the subjects receive additional information about the other stock (G) and are asked to update their estimates regarding the price of stock H in six months. Subsequently, subjects get the possibility to trade stock H in a single-unit open-book double auction market again for two minutes. Overall, each subject trades in 8 of these experimental rounds, consisting of two trading periods of 120 seconds and two estimation tasks.

This experimental design allows us to relate individual level overreaction to market level overreaction in an almost realistic setting, similar to the one in Thomas and Zhang (2008). However, in contrast to their empirical approach we are able to explicitly calculate the rational benchmark, and thus can rule out that risk or market microstructure effects drive results on overreaction in markets. Moreover, using this clean design we are able to quantify the exact degree of overreaction both on an individual and market level, and thus can compare findings in the individual-level-study of chapter 4 with the aggregate level study by Thomas and Zhang (2008).

Previous empirical and experimental evidence on the relation between individual level misreaction and its effect on market parameters is scarce. On the one hand, most experimental studies investigate the level of overreaction or underreaction on an individual level (see e.g. Kahneman and Tversky (1973), Griffin and Tversky (1992), Bloomfield and Hales (2002), Offerman and Sonnemans (2004), and chapter 4 of this thesis). On the other hand, empirical studies are mostly providing evidence for aggregate market overreaction (see e.g. DeBondt and Thaler (1985, 1987, and 1990)), Sorescu and Subrahmanyam (2006), and Thomas and Zhang (2008)). Evidence on the question how individual misreaction to new

information translates into market outcomes is scarce (see for notable exceptions Gillette et al. (1999), Bloomfield et al. (2000), and Nelson et al. (2001)) and relies almost exclusively on the classical Griffin and Tversky (1992) coin-spin scenario where subjects need to indicate if a coin is heads- or tail-biased.

Our main findings can be summarized as follows: we observe strong and persistent overreaction for individual estimates as well as for market prices following both - good and bad news. The level of overreaction in estimates is in the same range as in the individual-level experiment in chapter 4 of this thesis. Interestingly, aggregate overreaction in transaction prices is not substantially lower. Thus, market forces are not able to correct for individual biases which is in line with experimental findings in Gillette et al. (1999) who show that underreaction in their experiment is even slightly higher in markets than on an individual level. Moreover, our finding that overreaction does prevail in markets is also consistent with behavioral models arguing that individual biases affect market outcomes (Odean (1998b), Sorescu and Subrahmanyam (2006), and Biais et al. (2005)). In addition, we provide evidence that learning effects within a 120-second trading period and learning effects over the course of the experiment are hardly observable. Lastly, up to our knowledge our study is the first to find experimental evidence for the theoretically proposed positive relation between differences of opinion and trading volume (Varian (1989), Harris and Raviv (1993), and Kandel and Pearson (1995)) in experimental markets with more than two traders.

In the next section we review the related literature on misreaction and their impact on market factors and form our hypotheses. Section 5.3 presents our experimental design and procedure as well as some descriptive statistics. The main results of our study are reported in section 5.4. Section 5.5 concludes with a short discussion of our findings and an outlook for future research.

5.2 Related Literature and Hypotheses

5.2.1 Related Literature

The study in chapter 4 of this thesis offers direct experimental evidence on the relationship between information signals, beliefs, and financial decisions. Using a novel experimental design in which subjects are asked to estimate the future price of an asset, incorporating the stock price development of a related asset as information signal, the study in chapter 4 has three main findings: first, in this experimental environment a substantial level of overreaction seems to exist which is in line with findings in Griffin and Tversky (1992) on an individual level and Thomas and Zhang (2008) on an aggregate level. Second, analyzing the relation between individual overreaction and psychological biases it is evident that more overconfident subjects tend to overreact more heavily. Third, the results of the study in chapter 4 show that individual overreaction has an impact on financial variables such as portfolio risk and portfolio efficiency.

However, it is not clear whether overreaction on an individual level translates to overreaction in a market setting. Proponents of rational approaches often argue that just a few rational subjects are sufficient to make market outcomes rational, that random mistakes cancel out or that in the long run less rational subjects learn from more rational subjects in the market (for further comments on this debate see Camerer (1987)). In the following, we will first review the theoretical literature on individual and market overreaction and then illustrate existing empirical and experimental evidence on this issue.[1]

Theoretical models

Using various behavioral biases such as overconfidence or hindsight many behavioral models argue that individual overreaction has a substantial impact on market variables.[2] Amongst others, Daniel et al. (1998 and 2001), Odean (1998b), and Fischer and Verrec-

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[1]We have argued in section 5.1 that the question whether individual biases can be corrected by market forces seems to depend amongst others on the bias that is analyzed. Since we analyze over- or underreaction to new information we will only illustrate studies analyzing this sort of bias.

[2]In addition, Grinblatt and Han (2005) show that individual underreaction caused by behaviorally affected traders has also an influence on market prices in the equilibrium

chia (1999) model financial markets with overconfident individuals. These overconfident individuals overweight the precision and overestimate the quality of a private signal that they receive. This directly results in an individual overreaction to the signal. Consequences of this individual overreaction are the wrong assessment of means, a more aggressive trading behavior, and a poor portfolio diversification. How exactly this individual overreaction affects market variables depends on the information structure of the market and on the proportion of overconfident investors in the market. However, almost all studies show that individual overreaction of some investors results in aggregate, market overreaction and has substantial effects on market demand and market prices.

In a similar vein, Biais and Weber (2007) theoretically show that hindsight biased agents overreact to new information and put too much weight on a private signal. The intuition behind is that hindsight biased agents incorrectly remember their prior expectations, and thus overweight the informational content of new information. In their CAPM-like framework individual overreaction of hindsight biased agents affects equilibrium prices and holdings.

A third strand of literature tries to reconcile two patterns that seem contradictory: the representativeness heuristic (Kahneman and Tversky, 1973) and the conservatism bias (Edwards, 1968). Griffin and Tversky (1992) argue that subjects focus too much on the strength of a new information, i.e. the degree to which it is favorable, and not enough on its weight, i.e. its statistical reliability. They use the evaluation of recommendation letters as an example. Here the strength refers to how positive or warm the letter's content is and the weight refers to the credibility and knowledge of the writer. They argue that the representativeness heuristic and hence overreaction to new information prevails in situations in which subjects receive new information which is characterized by high strength and low weight. In the recommendation letter example this corresponds to a very nice recommendation letter from a person with low credibility. Barberis et al. (1998) and Sorescu and Subrahmanyam (2006) develop theoretical models that extend these findings and implications to financial markets. In line with the proposition in Griffin and Tversky (1992) both studies propose that individual overreaction is present in situations that are characterized by high strength and low weight and affects aggregate market prices and overall demand.

Empirical and experimental evidence

Although most behavioral models argue that individual overreaction automatically impacts market variables and does not cancel out in the aggregate, the experimental and empirical evidence on this issue is not unequivocal. Most empirical and experimental studies analyze either the level of overreaction on an individual level or on an aggregate level but not simultaneously. In the following we will first review selected studies analyzing individual overreaction before we document findings in the literature on aggregate market overreaction. In the end we will present some of the very few studies analyzing both individual and aggregate market overreaction.[3]

In one of the first experimental studies on overreaction Kahneman and Tversky (1973) show that subjects tend to put too much weight on meaningless and practically irrelevant information. Another strand of the literature uses the so called coin-spin design to detect over- or underreaction on an individual level (see Griffin and Tversky (1992)). In this design subjects know that the coin that is going to be spun is either heads- or tails-biased with a prior probability of 0.5. After having observed a specific number of spins subjects are asked to report an updated probability conditional on the observed signal which is simply the number of heads and tails in the conducted spins. Findings in Griffin and Tversky (1992), Offerman and Sonnemans (2004), and Massey and Wu (2005) confirm that individual overreaction is present if subjects receive information with relatively high strength and low weight. A different kind of test of individual overreaction to new information has been carried out by Bloomfield and Hales (2002). They test the predictions in the theoretical model of Barberis et al. (1998) in a simple experimental environment in which subjects have to predict the next step of a random walk. They find substantial levels of individual overreaction in this setting.

The overreaction phenomenon on the aggregate market level has also been amply documented in the empirical literature. DeBondt and Thaler (1985 and 1987) find that past

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[3]Since the study in chapter 4 has shown that overreaction should be prevalent in our experimental setting as the signal seems to be of relatively low weight and high strength we will only list a few exemplary studies finding empirical or experimental evidence for underreaction: Abarbanell and Bernard (1992), Hong et al. (2000), and Weber and Welfens (2007).

winners tend to be future losers and vice versa which they interpret as evidence for over-reaction. Analyzing the price reaction to analysts' forecast revisions Sorescu and Sub-rahmanyam (2006) find evidence for the strength and weight hypothesis by Griffin and Tversky (1992). Using an analyst's ability and experience as a proxy for the weight of a signal and the dramatic nature of an event, i.e. the level of a down- or upgrade, as a proxy for the strength of a signal they test the hypotheses in Griffin and Tversky (1992). Consistent with their hypothesis, they show that for signals with relatively high strength and low weight market prices tend to overreact. Their results imply aggregate overreaction for large down- or upgrades (high strength) by inexperienced analysts from investment banks with a relatively bad reputation (low weight). The study by Thomas and Zhang (2008) which resembles our experimental design the best also finds evidence for overreaction on a market level. Analyzing subsequent earnings announcements by different firms from the same industry they document that both the price of an announcing firm and the price of a non-announcing firm from the same industry move in the same direction. However, this price response of the non-announcing firm is negatively related to its price response when it subsequently announces earnings. This result indicates that prices for subsequent announcers overreact to an early announcer's earnings and are corrected later on.

As mentioned above the empirical and experimental findings on overreaction on both - individual and aggregate level - are scarce. Using a security markets task that is closely related to the previously described coin-spin scenarios Bloomfield et al. (2000) and Nelson et al. (2001) document that individual misreaction, i.e. misreaction in stock forecasts, also translates into aggregate misreaction, i.e. misreaction in prices. However, their analyses show that underreaction in prices and forecasts is approximately the same whereas overreaction is significantly larger in stock forecasts than in prices. Both studies use a clearinghouse market where all three individuals' in a market have to choose a linear demand schedule by setting a reservation price and a slope. Market clearing prices are determined by a computer and set such that demand equals supply in the three person economy.

Moreover, Hommes et al. (2005) find evidence for individual and aggregate overreaction in an experimental prediction market. In their setting market prices are generated by an

asset pricing model with heterogenous beliefs. More specifically, in this design a computer determines market prices by taking the average beliefs of all market participants and adding some extra noise term. The authors find that in 8 out of 10 markets individual overreaction results in aggregate overreaction.

In another experimental asset market, Gillette et al. (1999) give participants public information about the liquidating dividend of an asset in every third trading period. They use both double-continuous auction markets and call markets with trading periods of 120 seconds. The trading structure of their market closely resembles ours. Their main results show that underreaction in forecasts is even larger than underreaction in market prices indicating that the standard argument that individual mistakes will cancel out and individual misreaction will be corrected by market forces does not need to apply to these kind of asset markets.

5.2.2 Hypotheses

We analyze a similar setting in a static environment with no trading market and no feedback in chapter 4. Consistent with these findings, we expect that after observing a good signal subjects state expectations that are higher than the fundamental value and after observing a bad signal expectations that are lower than the fundamental value. As they put too much weight on these signals subjects are expected to overreact in their stock forecasts.

Moreover, we hypothesize that the results with regard to market prices should resemble empirical findings in Thomas and Zhang (2008). They analyze aggregate overreaction in prices in a dynamic empirical setting that is very similar to ours. Their main finding is that stock prices for a late announcing firm overreact to the information signal inherent in the early announcer's earnings and that this overreaction is not corrected till the late announcing firm reveals its earnings. Thus, in our design we should observe that prices for a firm should overreact to information or signals about a related firm in the same industry.

Furthermore, in agreement with Gillette et al. (1999) and Nelson et al. (2001) we assume that misreaction (i.e. the absolute value of over- or underreaction) in market prices is not substantially smaller than misreaction in individual forecasts as individual biases are not corrected by market forces. Hypotheses 1a, 1b and 1c capture these intuitions.

Hypothesis 1a: Subjects tend to overreact to new information about related stocks when submitting stock forecasts.

Hypothesis 1b: Market prices tend to overreact to new information about related stocks.

Hypothesis 1c: Misreaction in market prices is not lower than misreaction in stock forecasts.

Besides analyzing how individuals process new information and how market prices react to new information we want to analyze the effects of overreaction in the long run. If overreaction in our experimental setting is a systematic bias then it should not diminish, even though subjects have the possibility to learn from the past and to acquire experience. Stable levels of overreaction over the course of the 120 seconds of a trading round imply that less rational subjects are not able to learn from the actions of more rational subjects. Moreover, we argue that there is no learning effect over various rounds. The level of overreaction in the first few rounds is not significantly larger than the level of overreaction in the later rounds.

The view that overreaction does not vanish with the course of the experiment is consistent with findings in Offerman and Sonnemans (2004) who show that overreaction in the coin-spin scenario does not disappear even if subjects are trained and have more experience with the task at hand.

Furthermore, psychological evidence indicates that outcome feedback is not as efficient at lowering biases as other forms of feedback such as cognitive or task information feedback (see e.g. Benson and Önkal (1992) or Goodwin et al. (2004)). Since outcome feedback is the major feedback subjects receive in financial markets and in order to keep our design as realistic as possible we restrict our feedback to simple outcome feedback. Moreover, most

other studies analyzing whether individual biases are corrected by market forces also only give subjects outcome feedback.

Consistent with findings in Offerman and Sonnemans (2004) who also analyze the role of overreaction in a dynamic setting we propose the following three learning hypotheses:

Hypothesis 2a: Learning within a round: Overreaction in stock prices remains stable in the course of a round.

Hypothesis 2b: Learning over rounds: Overreaction in stock forecasts does not diminish over the course of the experiment.

Hypothesis 2c: Learning over rounds: Overreaction in stock prices does not diminish over the course of the experiment.

In addition to analyzing the level of individual and market overreaction in an experimental asset market our design allows us to test further insights from theoretical models. According to Milgrom and Stokey (1982) even in the wake of new private information no trade should occur if agents have rational expectations. However, Varian (1989) argues that trade can be triggered by heterogenous beliefs of market participants. These heterogenous beliefs or differences in opinion appear if subjects have differing prior beliefs and/or if subjects interpret new public information differently. Related to this Harris and Raviv (1993) and Kandel and Pearson (1995) show that in speculative markets differences of opinion can explain observed high levels of trading volume. In a similar vein, Cao and Ou-Yang (2009) show that differences of opinion or disagreement about the mean of new information has an impact on trading volume in stocks but does not affect trading volume in options. All models on differences of opinion have one thing in common: the straightforward implication that trading volume is higher the more heterogenous the traders' beliefs are.

Empirical and experimental evidence on the relation between differences of opinion and trading volume is scarce but seems to confirm the theoretical models. Antweiler and Frank (2004) analyze the effect of Internet stock message boards on trading volume in stock markets. Comparing the level of disagreement in these messages with trading volume they

find evidence for the theoretical propositions. Other studies in the accounting literature (see e.g. Bamber et al. (1997)) support this view and show that trading volume around earnings announcements is related to different aspects of disagreement among agents. Furthermore, Hales (2009) shows experimentally that subjects in a 2-person economy trade more aggressively if they receive more diverging signals. He argues that this aggressive trading volume can be reduced if subjects are not asked to forecast the value of a stock but the level of disagreement between agents in an economy. Hypothesis 3 captures the main intuition of the differences of opinion literature.

Hypothesis 3: Trading volume is higher if subjects in a market have more differences of opinion, i.e. more diverging expectations.

5.3 Experimental Design and Procedure

5.3.1 Theoretical Framework

Similar to the framework in chapter 4 subjects in our study observe a signal ($\tilde{s}$) about the price of a stock ($\tilde{v}$). Since the signal is noisy it can be decomposed as follows:

$$\tilde{s} = \tilde{v} + \tilde{e}.$$

In our experimental setup subjects know that all random variables are identically, jointly normal, and independently distributed. Thus, using the projection theorem we can calculate the rational Bayesian benchmark:

$$E(\tilde{v}|s) = E(\tilde{v}) + \frac{cov(\tilde{v}, \tilde{s})}{var(\tilde{s})}(s - E(\tilde{s})) = E(\tilde{v}) + \delta(s - E(\tilde{s})). \tag{5.1}$$

δ which is equal to $\frac{cov(\tilde{v},\tilde{s})}{var(\tilde{s})}$ corresponds to the level of overreaction in this design. Thus, subjects who overweight the informational content of a signal will overestimate δ and submit a biased forecast:

$$F = \hat{E}(\tilde{v}|s) = E(\tilde{v}) + \hat{\delta}(s - E(\tilde{s})), \tag{5.2}$$

Comparing equations 5.1 and 5.2 we can derive a simple measure of overreaction:

$$\frac{F - E(\tilde{v}|s)}{s - E(\tilde{s})} = \frac{\hat{E}(\tilde{v}|s) - E(\tilde{v}|s)}{s - E(\tilde{s})} = \hat{\delta} - \delta. \tag{5.3}$$

If $\hat{\delta} > \delta$ we observe overreaction as a subject's forecast to a surprisingly good signal is larger than the conditional expectation ($F > E(\tilde{v}|s)$) and smaller than the conditional expectation ($F < E(\tilde{v}|s)$) in case of a surprisingly bad signal. If on the other hand our overreaction measure is smaller than 0 we observe underreaction. If misreaction in our experiment is not systematic we should find that it should cancel out on average.[4] We are going to describe the data generating process, the experimental procedure and the calculation of the rational benchmark in more detail in the following subsections.

5.3.2 Basic Design

The experiment consists of three main parts: an instruction phase, a trading phase, and a questionnaire. The instruction phase allows subjects to get familiar with the trading environment and to gain experience with the trading mechanism. It also gives subjects information about the payoff structure.

The trading phase consists of a sequence of 8 consecutive rounds. At the beginning of each round subjects were shown a graph illustrating the stock price movement of two related stocks G and H for the last 6 months. Subjects were told that stock price changes of both stocks at a given day i in trading round j depend upon a firm specific shock $\eta_{i,j}^{H}$ (for stock H) and $\eta_{i,j}^{G}$ (for stock G) and upon an industry shock $\epsilon_{i,j}$ which is common to both stocks. Moreover, subjects knew that these daily shocks are i.i.d., normally distributed,

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[4]In contrast to the analyses in chapter 4 we do not use *Overreaction-Beta* as additional measure of overreaction in this study. Since *Overreaction-Beta* is simply defined as the coefficient of a simple ordinary least squares regression of forecasting error onto signal for each person it is not really applicable to use it in our market design as subjects have traded only with 8 different stocks and we would need to base our analyses on regression coefficients that are based on 8 observations.

and stationary over time.[5] Then subjects were asked to provide three estimates for the price of stock H at time t = 12: a best guess as well as a lower and an upper bound. They were told to set the lower (upper) bound so that the price of stock H at time t = 12 would fall below (be above) the bound with a very low probability of 5%. Figure 5.1 illustrates the computer screen in the estimation task.
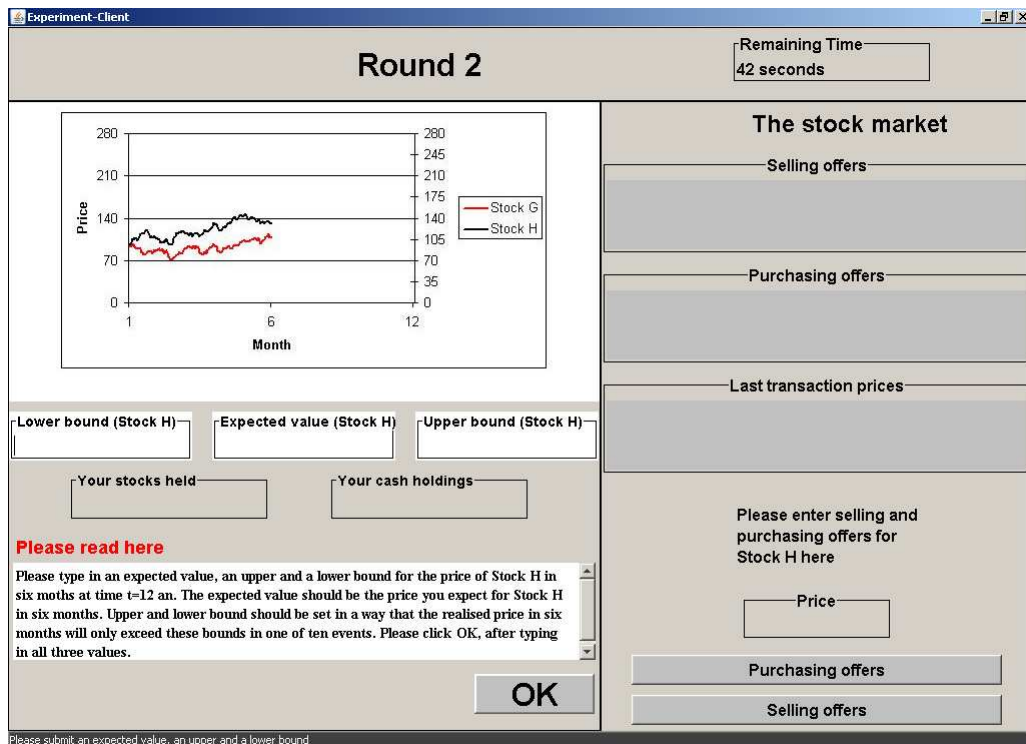

Figure 5.1: Estimation screen

The figure illustrates the screen of the estimation task in the first period of round 2. In the upper left-hand part the price development for the two stocks G and H in the first 6 months is displayed. In the three white boxes below the graph subjects can submit their three estimates (lower bound, best guess, and upper bound) for the price of stock H at t = 12. The remaining time for this task is shown in the upper right-hand part. The trading boxes on the right-hand side of the graph are in the estimation task inactive and are going to be explained in the following.

After having provided these three values subjects received an initial endowment of 1,500 monetary units and 5 shares of stock H and were allowed to start trading the stock with all other market participants for 120 seconds. Trading took place in a single-unit open-book

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[5]The simulation of the price paths was similar to the one in chapter 4. The only difference was that instead of using daily shocks with a mean of 0.025 we use daily shocks with no trend, i.e. a mean of 0.

double auction market similar to the market experiments of Plott and Sunder (1982 and 1988) and Weber and Welfens (2007). After 120 seconds trading was stopped and subjects received the stock price development of the related stock G for the second 6 months as an additional information. Incorporating this new information or signal, they were asked again to provide a best guess as well as a lower and upper bound for the price of stock H at time t = 12. Having provided these estimates the trading floor opened again and subjects could trade with each other for further 120 seconds. Figure 5.2 illustrates the computer screen of the trading market for the second period of a round.
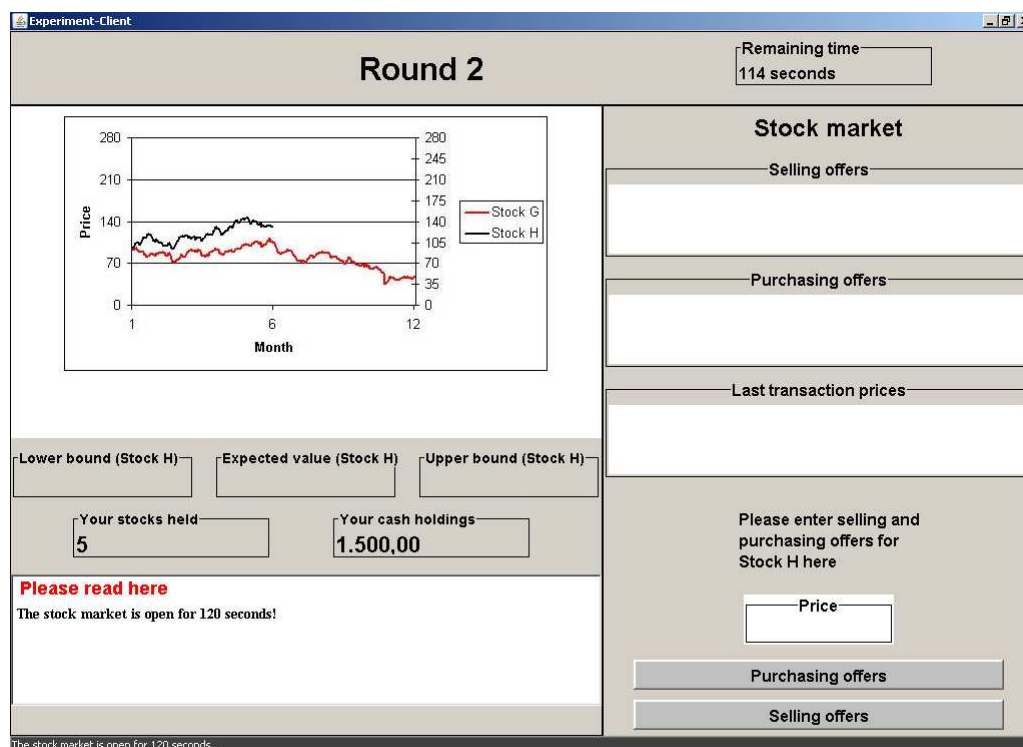

Figure 5.2: Trading screen

The figure illustrates the screen of the trading task in the second period of round 2. In the upper left-hand part the price development for stock H in the first 6 months and the price development of stock G over all 12 months is displayed. The three estimation boxes are inactive and the values subjects had previously submitted are not shown anymore. The trading boxes on the right-hand side are activated and show all selling offers, purchasing offers, and the last transaction prices. Purchasing offers are sorted highest to lowest, selling offers lowest to highest, and transaction prices are sorted by time. A subject's own selling or purchasing orders are illustrated in red whereas all remaining orders are displayed in black. To submit an order subject's simply had to type in a price and click on the button "Submit a selling order" and "Submit a purchasing order", respectively.

After further 120 seconds the trading floor closed for a second time and subjects were informed about the realized price of stock H at time t = 12, the round ended and the next round started. Thus, in each trading round the trading floor is open for overall four minutes, two minutes before signal revelation and two minutes after signal revelation. Note that the 2·2 minute trading periods are exactly the same as the ones in Weber and Welfens (2007). Moreover, other studies that analyze the existence of individual biases in market settings also use two minute (Gillette et al. (1999)), three minute (Camerer (1987)), and four minute (Camerer (1987), Camerer et al. (1989), and Lei et al. (2001)) trading periods. Since some of these studies show that individual biases are reduced substantially by market forces the length of our periods should be sufficient to offer the possibility of learning in our experimental design as well. Figure 5.3 summarizes the course of an experimental round.
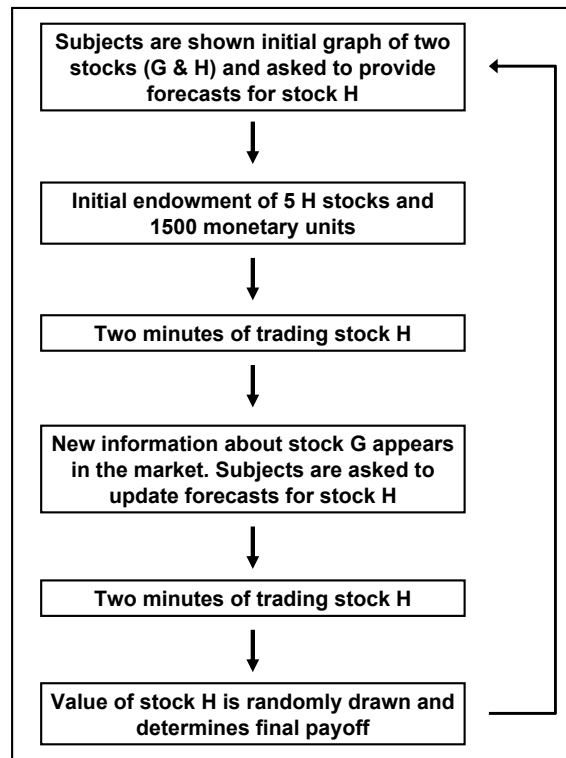

Figure 5.3: Course of the experiment
The figure shows the course of each round in the market experiment.

Subjects know that the true price of stock H at the end of each round is determined by the sum of all daily firm H specific shocks and all industry shocks that are common to

both firms in each graph. Using Bayesian updating subjects have all necessary information to calculate the conditional expected value of stock H at time t = 12 (trading day 252) in round j as well as the variance given a particular signal s explicitly. The signal in this case is simply the stock price development of the related stock (G) in the second 6 months which is given to subjects before the second turn of trading. Hence, the conditional expectation follows:

$$E(\tilde{v}_{i,j}^H \mid s_j) = v_{i,j}^H + E\sum \cdot[(\tilde{\eta}_{i,j}^H)] + \frac{1}{2} \cdot s_j. \tag{5.4}$$

Using the conditional expectation in equation 5.4 we can calculate the level of overreaction for each stock price forecast and each transaction price by plugging it into equation 5.3.

Subjects in our market are informed about the exact underlying process that generates stock prices and they see the entire order book with all purchase and sell orders as well as past transaction prices. Own orders are illustrated in red whereas orders from all other subjects are illustrated in black. Purchase orders in the experimental markets require that a subject has enough monetary units to pay the specified price as we did not allow for any short sales. Selling orders only enter the order book if a subject holds a positive number of shares. In addition, subjects can not submit a selling order which is below their own already existing purchasing order or set a purchasing order which is above their own already existing selling order.

Since our experimental market is a single-unit open-book double auction market subjects can only place one selling order and one purchasing order at a time. If subjects already have a purchasing (selling) order in the books, they can replace it by entering a new purchasing (selling) order. Market clearing happens automatically and in continuous time and transaction prices are always equal to the price of the more senior order. To control for order effects the order in which various stocks appear is varied over different markets. After having finished all 8 rounds of trading with two trading periods each, a questionnaire starts automatically. In the questionnaire we elicit demographics such as age, gender, and line of studies.

5.3.3   Procedure and Descriptive Statistics

The experiment was programmed in Java and run at the University of Mannheim in November 2008. In 11 of overall 13 sessions we had 8 students who made up one market whereas in the other two sessions we had 6 and 7 students, respectively. Since Lei et al. (2001) and Noussair et al. (2008) also have markets with varying numbers of participants (6-8) we carry out the analyses for all 13 sessions. However, our results remain stable if we exclude the two sessions with less than 8 subjects.

Thus, we had a total of 101 students, 51 male and 50 female, who participated in our experiments. In every session we had 8 rounds of trading, each with two 120-second trading periods which gives us a total of 208 trading periods or 416 minutes of trading.[6] The average age of all subjects was 24.7 and approximately one half of the participants studied economics or business administration. The average processing time for the whole experiment including the instruction phase, the trading phase, and the questionnaire was 80 minutes.

Subjects' payment was determined as follows: subjects received a flat payment of 4 Euro for filling out the questionnaire and a variable, performance based payment for their participation in the 8 rounds of the experimental market. More specifically, the performance based payment was equal to 0.06% of the overall final wealth for all 8 rounds. The final wealth at the end of a single round was simply the amount of monetary units at the end of the round plus the number of stocks held multiplied with the realized value of the stock. Earnings averaged 13.35 Euro per subject.

Overall, we observe 4,157 buy orders and 4,282 sell orders with a total of 2,063 transactions. Interestingly, the number of trades in the first trading period of a round, i.e. before subjects received a signal, is substantially higher than the number of trades in the second trading period of a round, i.e. after subjects received the signal. In the first part of a round 1,194 transactions were conducted whereas in the second part of a round only 869 trans-

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[6]In pre-tests with more than 8 rounds of two 120-second trading periods subjects indicated to us that the task was to strenuous and advised us to reduce the number of rounds. Moreover, the number of rounds is close to the one in various other studies such as Sarin and Weber (1993, 2 and 8 rounds) or Weber and Welfens (2007, 10 rounds).

actions were completed. These findings are in line with Weber and Welfens (2007) who also find substantially lower levels of trading after a fundamental shock. These numbers point out to a high trading volume of 11.5 transactions in the first 120-second trading period of a round, i.e. before a signal, and 8.4 transactions in the latter 120 seconds, i.e. after the signal was received.

Moreover, we find that the number of shares held by subjects at the end of a period varies substantially from a low of 0 to a high of 23. Hence, similar to other experimental asset markets (such as Plott and Sunder (1982 and 1988) and Weber and Welfens (2007)), these findings are a first indication for relatively high levels of trading volume.

5.4 Results

5.4.1 Existence of Overreaction

The first goal of the market experiment was to detect the level of overreaction in individual stock forecasts and aggregate market prices with a design similar to Thomas and Zhang (2008). Since we want to analyze the level of overreaction to a given signal we can only use observations from the second trading period of a round, i.e. from the period where subjects know the stock price of the related stock G for the entire time period. In order to analyze overreaction in stock forecasts of all traders we compute their overreaction score using equation 5.3 and plug in their best guess as forecasts F. Similar to the results in chapter 4 we find overreaction to the signal about a related stock on an individual level in our experimental markets.

The upper graph in figure 5.4 illustrates the distribution of overreaction scores in stock forecasts for each stock and subject separately. Both the median (0.35) and the mean (0.41) score are significantly larger than zero, indicating substantial levels of overreaction. However, there is substantial variation in the level of overreaction in our sample with the

scores ranging from -1.5 to 3.2. In other words, for a majority of 599 observations we find forecasts indicating overreaction, but for 195 forecasts we also observe underreaction.[7]

The middle graph in figure 5.4 shows the average overreaction score in forecasts for each person. Interestingly, mean (0.41) and median (0.41) overreaction are in the same range as for each stock separately. However, almost all subjects tend to overreact on average with only 6 out of 101 subjects having a mean overreaction score of less than 0. This finding is a first hint that the level of overreaction varies heavily over different rounds but that there is a general and highly significant ($p < 0.01$) tendency for overreaction (more details on this issue will follow later in this subsection).

Analyzing the level of overreaction in market prices, a similar picture arises with a mean overreaction score in prices of 0.42 and a median score of 0.32. The lower graph in figure 5.4 illustrates the level of overreaction in market prices. We find that a large majority of 637 transactions are conducted at overreacting prices whereas only 232 transactions are conducted at underreacting prices. Using a Wilcoxon signed-rank test and a t-test we find that overreaction in prices is significantly larger than 0 ($p < 0.01$). However, both tests implicitly assume that transaction prices are independent. This is not the case as our experimental market is a single-unit open-book double auction market where subjects can repeatedly buy and sell the asset. To control for this we analyze the level of overreaction only for the first transaction in each trading period after subjects received a signal which gives us a total of 104 observations (13 sessions · 8 rounds). The mean (median) level of overreaction for the first transaction in each trading period is 0.43 (0.30) which is significantly larger than 0. In addition, a Mann-Whitney rank-sum test shows that the level of overreaction for the first transactions is not substantially different from the level of all other transactions ($p = 0.85$).

Another problem for the interpretation of overreaction in transaction prices might be the existence of short selling constraints. For example, after a good signal subjects who overreact are willing to buy the stock at prices which are too high whereas subjects who react rationally are not able to drive the market prices down to the rational level by

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[7]Keep in mind that both overreaction in forecasts and overreaction in prices can only be calculated for the second two minute trading period in each round, i.e. after the signal was revealed.
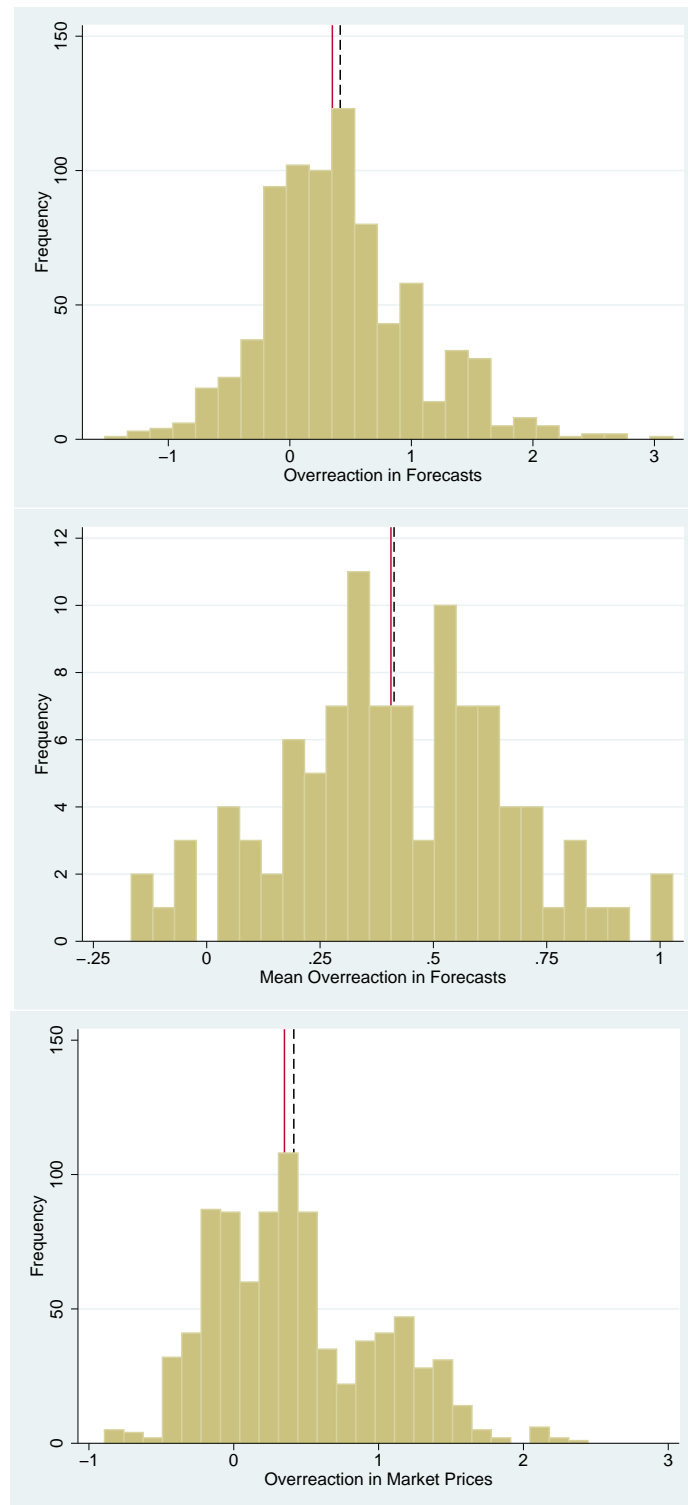
Figure 5.4: Overreaction histograms

The figure shows the level of overall overreaction in stock forecasts (upper graph), the level of average overreaction for each person in stock forecasts (middle graph), and the level of overreaction in market prices (lower graph). Mean values are indicated by the dotted black line and median values by the continuous red line.

selling more than their five inventory stocks at seemingly inflated prices. We control for the short selling problem using two approaches: first, similar to the non-independency problem above, we show that overreaction for the first transaction in each trading period is not smaller than for all observations ($p = 0.85$). The fact that the short selling constraint is not binding in the first transaction after a signal revelation and that overreaction is still present is a first indication that without short selling constraints overreaction would not abate. Second, we exclude all markets in which at least one subject hits the boundary and ends up with 0 assets in his / her portfolio. Analyzing the level of overreaction for markets where the short selling constraint is not binding we find a significantly positive mean overreaction score in prices of 0.5 and a median score of 0.41. A Mann-Whitney rank-sum test shows that the level of overreaction in prices is even larger than the level of overreaction in markets where the short selling constraint is binding ($p < 0.01$). Thus, we believe that short selling constraints cannot explain the substantial levels of overreaction in our markets.

Overall, both overreaction in forecasts and in prices are in the same ballpark as the level of overreaction in chapter 4 where we find average median overreaction scores of 0.33 and 0.37. Similar to these results, we also observe large heterogeneity of overreaction, with some subjects providing almost rational estimates and trading at rational prices but with a majority of subjects overreacting to the new information. Moreover, our results support empirical findings on overreaction in Thomas and Zhang (2008) in a clean experimental design, where we can control for other possible explanations. Thus, both hypothesis 1a and hypothesis 1b are supported by our results.

Next, we turn to hypothesis 1c and analyze whether market forces help reducing the level of misreaction, i.e. over- or underreaction. Figure 5.5 illustrates the median level of misreaction in forecasts and market prices for each stock separately. Comparing the level of misreaction in forecasts and prices for each stock separately we find that self-regulating forces of the market do not seem to help in lowering misreaction of subjects. For 7 out of 8 stocks median misreaction in prices is even larger than the median misreaction in stock forecasts. Thus, the standard argument that self-regulating forces of markets will correct for erroneous individual beliefs and hence result in less overreaction does not apply in our

experimental market. We have illustrated previously, that there is a large heterogeneity of overreaction with some subjects having almost perfectly rational expectations. Thus, we can rule out the argument that market forces do not help in lowering the individual bias due to the fact that there are no traders in the market with rational expectations. This finding is in line with Gillette et al. (1999) who show for a different kind of task that individual misreaction in a continuous double auction market is slightly smaller than aggregate market misreaction which supports hypothesis 1c.
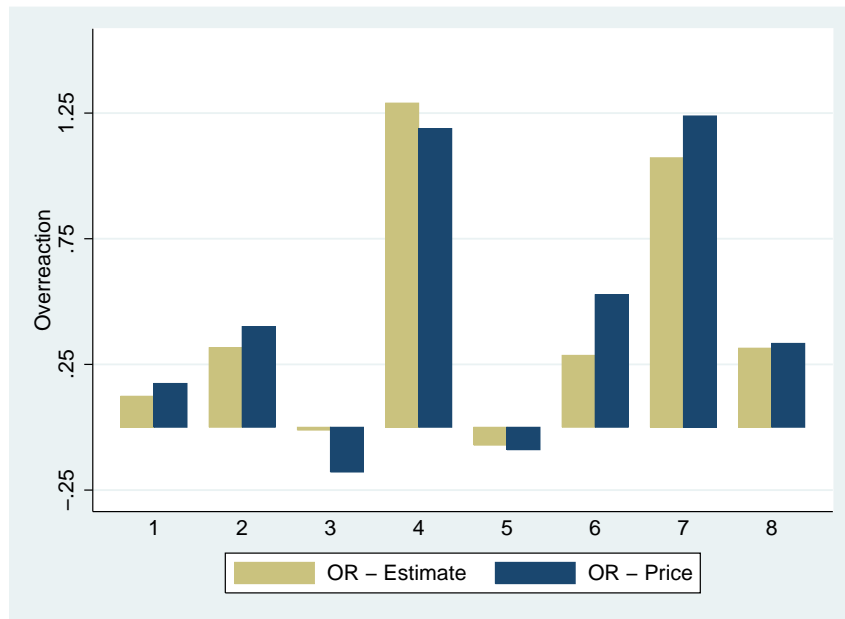

Figure 5.5: Overreaction prices vs. overreaction forecasts

The figure illustrates the level of overreaction in transaction prices (OR - Price) and in estimates (OR - Estimate) for all 8 stocks separately. A positive value on the y-axis indicates overreaction whereas a negative value indicates underreaction.

In the following we want to analyze in more detail why market forces or more specifically traders with rational estimates fail to lower misreaction. The first 3 columns of table 5.1 show the median overreaction score in stock forecasts of subjects who bought stocks ($Median - OR^{Buyer}$), subjects who sold stocks ($Median - OR^{Seller}$), and all subjects, regardless whether they traded the stock or not ($Median - OR^{All}$), for each stock separately. Column 4 shows the median overreaction score derived from prices ($Median - OR^{Prices}$) broken down by stocks. The results confirm our previous assumption that the level of

Table 5.1: Misreaction in prices vs. misreaction in forecasts

Column (1) to (3) of this table report the median overreaction scores in the forecasting task for buyers ($Median-OR^{Buyer}$), sellers ($Median-OR^{Seller}$), and all subjects in the market ($Median-OR^{All}$) separately for each stock. Column (4) reports the median overreaction score in transaction prices ($Median-OR^{Price}$) separately for each stock. $^+$ ($^-$) signs in the first column indicate that subjects received a good (bad) signal.

Stock	(1) $Median-OR^{Buyer}$	(2) $Median-OR^{All}$	(3) $Median-OR^{Seller}$	(4) $Median-OR^{Price}$
1^+	0.377	0.123	0.123	0.174
2^-	0.317	0.317	0.485	0.400
3^-	-0.206	-0.011	0.072	-0.178
4^+	1.290	1.290	1.290	1.189
5^+	0.110	-0.070	-0.162	-0.089
6^-	0.165	0.286	0.527	0.527
7^+	1.072	1.072	1.072	1.239
8^+	0.315	0.315	0.315	0.334

overreaction varies heavily with the stock analyzed. For most stocks subjects tend to overreact to the signal, however, for two stocks (stock 3 and 5) most subjects show the tendency to underreact.[8]

The results in table 5.1 also suggest that some sort of "winner's curse" might explain the finding that misreaction in market prices is not smaller than misreaction in forecasts. For stocks with a good signal which are marked by a $^+$ sign in table 5.1, buyers are excessively optimistic and keep prices too high whereas for stocks with a bad signal which are marked by a $^-$ sign in table 5.1, sellers are excessively pessimistic and keep prices too low. In other words, after good signals buyers heavily overreact and are willing to pay a price which is way above the rational benchmark and even above the average forecast whereas after a

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[8]We try to analyze why overreaction is present for some stocks and why underreaction is present for some other stocks. As we varied the order in which stocks were presented, ordering effects cannot explain our finding. According to Griffin and Tversky (1992) subjects should overreact for signals with high strength and low weight and underreact to signals with low strength and high weight. In our experimental setup the weight of a signal is fixed due to the fact that the stock prices depend upon a common industry shock and the correlation between the two prices should be 0.5 on average. The strength of a signal is equal to the percentage change in the stock price of stock G. Hence, overreaction should be higher the more extreme and lower the less extreme the signal is. However, our results show that for the two stocks with the lowest (stock 1) and the highest (stock 8) signal the level of overreaction is somewhere in the middle. Furthermore, even if we assume that the weight is not fixed but is inferred from the correlation between the two stocks in the graph the pattern of overreaction and underreaction cannot be explained by differences in signal strength and weight. Thus, further research is required to analyze what factors influence the level of overreaction and underreaction exactly.

bad signal sellers heavily overreact and are willing to sell at a price which is way below the rational benchmark and even below the average forecast. Thus, buyers - after a good signal - and sellers - after a bad signal - suffer from what we call a "winner's curse" and cause transactions to be executed at overreacting prices.

5.4.2 Learning to Overreact Less

In addition to finding evidence for the existence of individual and market overreaction we are interested in analyzing the effects of overreaction in the long-run. More precisely, we would like to know if subjects are able to learn to overreact less with more trading experience. Subjects gain trading experience in two ways: first, within the course of a round as they are able to learn from the bids and asks of other subjects and second, over rounds as they receive outcome feedback at the end of each round. In the following, we will first analyze learning within a round and then learning over rounds.

Figure 5.6 shows the average (upper graph) and the median (lower graph) overreaction scores for each trading second in the second trading period of a round. To measure whether there is a learning effect within a round we estimate a simple partial adjustment model similar to the one in Camerer (1987), Camerer et al. (1989), and Weber and Welfens (2007):

$$OR_t = \alpha + \beta \cdot OR_{t-1}. \tag{5.5}$$

Hence, we calculate the level of average overreaction in second t as a function of average overreaction in the previous second. As also can be seen in the graphs there are hardly any learning effects and the level of overreaction remains fairly stable over time. Moreover, in line with Camerer (1987) we estimate the degree of equilibrium bias $OR^{Equilibrium}$ consistently by the estimator $\hat{OR} = \frac{\hat{\alpha}}{(1-\hat{\beta})}$, where $\hat{\alpha}$ and $\hat{\beta}$ denote ordinary least squares estimators of α and β from equation 5.5. Fitting with an ordinary least squares regression results in $\hat{\alpha} = 0.456$ and $\hat{\beta} = -0.112$ with $\hat{\beta}$ not being significantly different from 0.
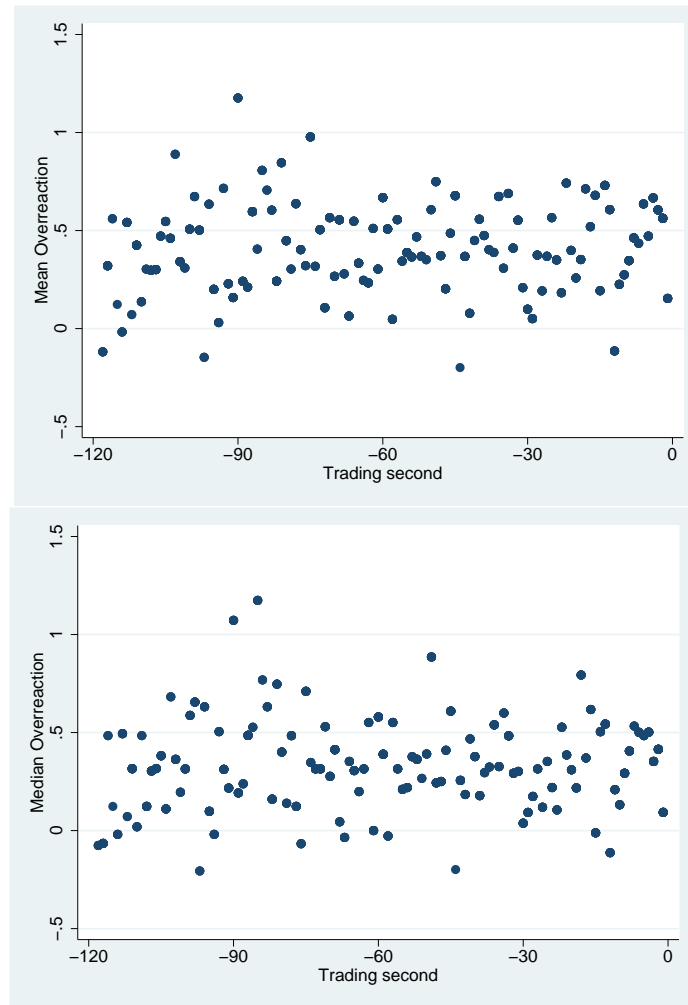
Figure 5.6: Learning within a round

The upper graph shows average overreaction scores in transaction prices over all rounds and the lower graph shows median overreaction scores in transaction prices over all rounds, for each trading second separately.

Table 5.2: Learning within a round

This table reports mean ($Overreaction^{Mean}$) and median ($Overreaction^{Median}$) overreaction scores in trans-
action prices as well as the proportion of transactions at overreacting prices for six time intervals of twenty
seconds. Overreaction is calculated for every transaction separately and afterwards aggregated for each twenty
seconds trading period.

Seconds	$Overreaction^{Mean}$	$Overreaction^{Median}$	$Overreaction^{Proportion}$
-120 to -101	0.354	0.296	68.14
-100 to -81	0.451	0.315	71.85
-80 to -61	0.411	0.322	69.33
-60 to -41	0.429	0.325	77.27
-40 to -21	0.403	0.315	75.17
-20 to -0	0.454	0.372	76.16

Furthermore, the equilibrium bias $\hat{OR} = \frac{\hat{\alpha}}{(1-\hat{\beta})} = 0.41$ and thus substantially larger than 0.

To analyze findings on learning within a round in more depth we split the 120-second trading period into six 20 seconds intervals and calculate three overreaction scores for each interval separately. Table 5.2 reports $Overreaction^{Mean}$ and $Overreaction^{Median}$ which are simply the mean and median overreaction in each time span and $Overreaction^{Proportion}$ which is the proportion of transactions that were carried out at overreacting prices in a given time span. A series of binomial tests which analyzes whether most transactions were carried out at overreacting prices indicates that overreaction is prevalent in each time interval. The same results emerge if we use Wilcoxon signed-rank tests.

Moreover, the numbers in the respective time intervals seem to be very similar and closely related. Using a series of Mann-Whitney rank-sum test we find that no single difference between two time spans is significant indicating that learning effects are hardly existent within a round and that the level of overreaction is stable over time. Hence, we do not observe any learning effects within a round, consistent with hypothesis 2a.[9]

Besides learning within a round subjects could also gain experience over the course of the experiment and learn from the outcome feedback that is provided to them. For a more

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[9]Our results remain stable if we split the 120-second trading period in 3, 4, or 10 time spans of equal length.

Table 5.3: Learning over rounds

This table reports mean and median overreaction scores in forecasts ($OR^{Estimates}$) and transaction prices (OR^{Prices}) as well as the proportion of overreacting forecasts and prices for each trading round separately.

	$OR^{Estimates}$			OR^{Prices}		
	Mean	Median	Prop.	Mean	Median	Prop.
Round 1	0.256	0.315	78	0.088	0.296	70.71
Round 2	0.567	0.485	79	0.702	0.485	91.76
Round 3	0.076	0.072	59	0.134	0.045	54.62
Round 4	0.673	0.712	76	0.724	0.547	83.05
Round 5	0.503	0.292	67	0.270	-0.071	40.35
Round 6	0.145	0.165	73	0.116	0.021	56.47
Round 7	0.757	0.678	89	0.937	0.906	99.07
Round 8	0.353	0.377	79	0.384	0.377	88.73

detailed test, we report means and medians of overreaction as well as the proportion of overreacting forecasts or transactions for each trading round in table 5.3. Looking at the results we find very large differences between single rounds[10], however, we are not able to detect a significant trend. Our results that overreaction does not disappear with learning effects are stable even if we control for financial expertise which is proxied by the number of finance courses a subject attended or other demographic variables.

Overall, the findings in this subsection confirm our hypotheses 2a, 2b, and 2c. Overreaction remains stable even though subjects acquire more experience and have the possibility to learn both from the actions of other subjects and from outcome feedback. This is in line with results in Offerman and Sonnemans (2004) who show that overreaction in the coin-spin scenario is present even if subjects receive extensive training. It is also in line with findings in Bloomfield et al. (2000) and Kraemer and Weber (2004) who show that expertise is of no help in lowering overreaction. Similarly, Benson and Önkal (1992) and Goodwin et al. (2004) point out that outcome feedback is hardly effective at reducing biases. Moreover, the results in Thomas and Zhang (2008) who analyze a similar setting to ours empirically also suggest that this kind of overreaction to earnings announcements of related firms is a stable construct in real-world markets.

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[10]Note, that we control for order effects by varying the sequence in which graphs were presented.

5.4.3 Differences of Opinion and Trading Volume

As reported in subsection 5.3.3 subjects seem to be engaged in relatively high levels of trading volume with on average 9.9 transaction in each 120-second trading period. In this experimental setup two testable explanations for the observed high trading volume can be brought forward: first, differences in risk attitudes between traders and second, heterogenous beliefs about the value of a stock, i.e. differences of opinion.

To show whether trading volume can be explained by risk sharing motives we compare the trading volume, i.e. the number of shares traded, in each trading period with the level of differences in risk attitudes between buyer and seller ($Differences\ Risk\ Aversion^{MaxMin}$). Risk Aversion was simply measured for each person on a five point Likert scale with the endpoints "1 = high risk aversion" and "5 = very low risk aversion". $Differ$-$ences\ Risk\ Aversion^{MaxMin}$ is simply defined as the difference between the most risk averse and the least risk averse subject in each session.[11] Running a clustered least square regression of the level of trading volume on the differences in risk attitudes between the two traders we are not able to find a significant effect. Differences in risk attitudes cannot explain the observed high levels of trading volume (see model 1 in table 5.4).

The second argument that is often brought forward to explain high levels of trading are differences of opinion. Amongst others, Varian (1989), Harris and Raviv (1993) or Kandel and Pearson (1995) propose that excessive trading volume can be explained by heterogenous beliefs among market participants. Since we elicited beliefs of all market participants in each period in the estimation phases we are able to analyze this theoretical proposition in our experimental setup.

Using forecasts (best guesses) that were submitted by all subjects in the estimation part of the experiment before each 120-second trading period we construct three distinct differences of opinion measures. Our first measure ($Differences\ of\ Opinion^{MaxMin}$) is simply the difference between the most optimistic, i.e. highest best guess, and the most pes-

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[11]Alternatively, we also compute $Differences\ Risk\ Aversion^{Std.}$ which is the standard deviation of all subjects' risk attitude measures in each session and relate it to the varying measures of differences of opinion. The results of the following analyses are essentially the same.

Table 5.4: Trading volume and differences of opinion vs. differences in risk attitudes

This table presents results on the relation between trading volume and differences of opinion as well as differences in risk attitudes using clustered least squares regressions (number of clusters is equal to 13). Trading volume in regressions (1) to (3) is simply the number of shares traded and in regression (4) the relation of shares traded in the second 120 trading seconds of a round divided by the number of shares traded in the first 120 trading seconds of a round. Our first measure of differences of opinion is $Differences\ of\ Opinion^{MaxMin}$ which is simply the difference between the most optimistic and the most pessimistic forecast in each 120-second trading period. $Differences\ of\ Opinion^{Std}$ is simply the standard deviation of all forecasts in each 120-second trading period. $Change\ in\ Dispersion$ is defined as the difference in the variation of expectations between the second and the first 120-second trading period in each round. Changes in the level of risk aversion $Differences\ Risk\ Aversion^{MaxMin}$ are simply the difference between the most risk averse and least risk averse subject in each trading market. We report regression coefficients and p-values in parentheses.* indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) Shares traded	(2) Shares traded	(3) Shares traded	(4) Change in shares traded
$Differences\ of\ Opinion^{MaxMin}$		0.049		
		(0.002)***		
$Differences\ of\ Opinion^{Std}$			0.128	
			(0.003)***	
$Change\ in\ Dispersion$				0.017
				(0.003)***
$Differences\ Risk\ Aversion^{MaxMin}$	1.541	1.494	1.496	0.101
	(0.157)	(0.163)	(0.173)	(0.145)
Constant	6.600	4.566	4.768	0.602
	(0.011)**	(0.058)*	(0.056)*	(0.002)***
Observations	208	208	208	104
Adjusted R-squared	0.058	0.093	0.082	0.083

simistic, i.e. lowest best guess, in each 120-second trading period. The second measure is the standard deviation of all subjects' best guesses (*Differences of Opinion*^{Std}) before each 120-second trading period (see Morse et al. (1991) and Bamber et al. (1997)). Our last measure of differences of opinion, *Change in Dispersion*, is also adopted from Bamber et al. (1997). It measures the change in the standard deviation of forecasts in each trading round before and after signal revelation. More specifically, it is defined as the standard deviation of beliefs in the second trading period of a round minus the standard deviation of beliefs in the previous 120-second trading period of a round. For the first two measures we have 208 different observations (13 *sessions* · 8 *rounds* · 2 *trading periods per round*) and for the third measure we have 104 observations (13 *sessions* · 8 *rounds*).

The upper graph in figure 5.7 illustrates the relation between *Differences of Opinion*^{MaxMin} and the number of shares traded in each of the 208 periods. The fitted line of a clustered least square regression and the positive Spearman correlation of 0.23 (Wilcoxon signed-rank test: $p < 0.01$) are a first indication that trading volume is positively related to differences of opinion. A similar picture emerges if we take a look at the middle graph in figure 5.7. *Differences of Opinion*^{Std} is positively related to trading volume (Spearman's rho = 0.21 and $p < 0.01$). The lower graph in figure 5.7 illustrates the relation between *Change in Dispersion* and *Change in shares traded*. The variable *Change in shares traded* is defined as the relation between the number of shares traded in the second period of a round (i.e. after signal revelation), divided by the number of shares traded in the first period of a round. Similar to the results in the two upper graphs we observe a positive relation (Spearman's rho = 0.20 and $p = 0.04$).

However, one problem of correlation analysis is that we cannot account for non-independent residuals over sessions. Hence, we additionally run ordinary least squares regressions in which we cluster our observations over sessions for each difference of opinion measure separately and additionally control for differences in risk attitudes. The result in the second column of table 5.4 supports our graphical findings as the coefficient of *Differences of Opinion*^{MaxMin} is significantly positive. If the difference between the most optimistic and the most pessimistic forecast is 50, then the number of shares traded in a market rises by 2.45 compared to a market with perfectly homogenous beliefs. Interest-
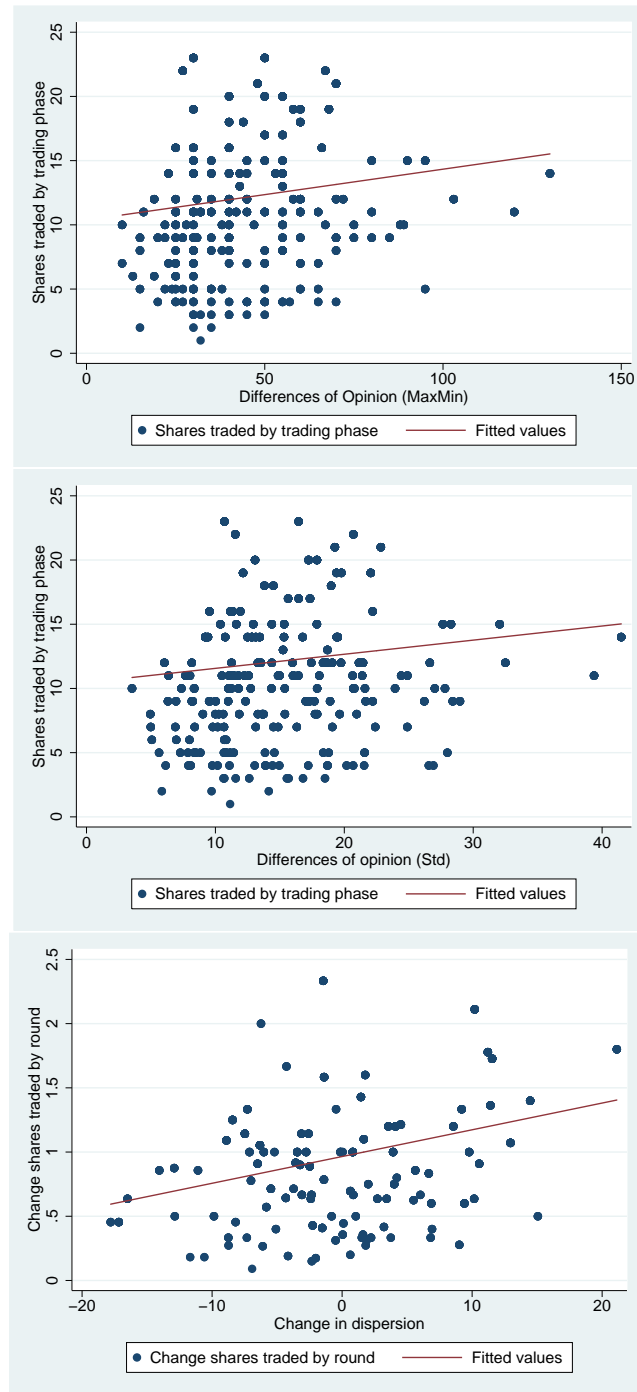
Figure 5.7: Differences of opinion and trading volume

The two upper graphs illustrate the relation between number of shares that were traded in each 120-second trading period and two distinct measures for differences of opinion. The differences of opinion measure in the upper graph is simply the absolute difference between the most optimistic forecast and the most pessimistic forecast of subjects (*Differences of Opinion (MaxMin)*) in each 120-second trading period. Similarly, the differences of opinion measure in the middle graph is the standard deviation of all forecasts (*Differences of Opinion (Std.)*) in each 120-second trading period. The lower graph illustrates for each session and stock separately, how a change in the variation of expectations (*Change in Dispersion*) is related to a change in trading volume.

ingly, *Differences Risk Aversion*^{MaxMin} cannot explain trading volume. Similar results emerge if we analyze the relation between *Differences of Opinion*^{Std} and trading volume in regression 3. Our second measure of difference of opinion is also positively related to the number of shares traded in each period.

Regression 4 analyzes the relation between *Change in Dispersion* and the change in the number of shares traded in the second period of a round compared to the first period of a round. Since we only have one observation for each round the number of observations drops to 104 (13 *sessions* · 8 *rounds*). The positive coefficient of *Change in Dispersion* indicates that the larger the standard deviation in forecasts in the second period of a round, compared to the first one, the larger the fraction of shares traded in the second period of a round compared to the first one. Again, *Differences Risk Aversion*^{MaxMin} are not able to explain trading volume.

Overall, the findings on the positive relation between differences of opinion and trading volume are consistent with first experimental evidence in simple 2-subject call markets (see Hales (2009)) and support our hypothesis 3. Interestingly, not the differences in risk attitudes but solely the differences of opinions are significantly related to trading volume. In addition, one could argue that finding evidence on the theoretically proposed relationship between differences of opinion and trading volume is a further indication that our data seems to be quite reasonable.

5.5   Conclusion

This chapter extends the individual-level-study of the previous chapter to a simple experimental trading market. We analyze if subjects are able to update their beliefs according to Bayes rule or if they misreact when they receive new information about a stock and consequently if market prices overreact. Consistent with findings in chapter 4, subjects in our setting overreact to new information on an individual level. Additionally, we find evidence for aggregate overreaction in market prices, consistent with Thomas and Zhang (2008). Interestingly, consistent with propositions in theoretical models (e.g. Odean (1998b) and Biais and Weber (2007)) and findings in the experimental literature (Gillette

et al. (1999)) individual misreaction translates into market outcomes as misreaction in transaction prices is not lower than in individual estimates.

Furthermore, we analyze if overreaction both on an individual and market level diminishes over time, i.e. if subjects are able to learn from the actions of other subjects or from the outcomes in previous rounds. Our results indicate that learning effects can neither be observed within a two minute trading period nor over various rounds. Hence, overreaction in this setting seems to be a stable construct. This finding is consistent with Offerman and Sonnemans (2004) who illustrate individual overreaction to be persistent in their coin-spin design even though subjects receive extensive training. In addition, evidence in psychology indicates that outcome feedback, exactly the sort of feedback subjects receive in our experiment, is not very effective at reducing biases (Benson and Önkal (1992) and Goodwin et al. (2004)).

Lastly, we are able to provide experimental evidence for a positive relation between differences of opinion and trading volume. Although theoretical evidence on this relation is prevalent (Varian (1989), Harris and Raviv (1993), and Kandel and Pearson (1995)) empirical and experimental studies have mainly ignored this relation. A notable exception is the study by Hales (2009) who shows that trading volume is larger if two traders receive more differing signals in a simple two-trader call market. We extend his findings to a more realistic environment by showing that trading volume is also larger if the disagreement about future stock price among all market participants is larger in a continuous auction market.

Further research should analyze if different sorts of feedback, such as cognitive or task information feedback, could help in lowering both individual and market biases. Previous findings on the role of different sorts of feedback on the level of overconfidence has shown that in particular outcome feedback is not helpful in lowering biases. In addition, it could be fruitful to study the high differences in the level of overreaction between stocks in more detail. Varying the degree of signal strength and weight or the length of the forecasting period might help in determining reasons for the large heterogeneity of over- and underreaction.

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