Opening the Black Box:

From an Individual Bias to Portfolio Performance

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Abstract

We suggest an experimental design that can help opening the black box of investor behavior by documenting a channel of how biases affect portfolio performance. We study two of the most important investor biases (overreaction and overconfidence), show how they are related, and analyze their consequences for portfolio choice and resulting portfolio performance in a controlled experimental setting with 104 participants. The main innovation of our study is that we go beyond just documenting a correlation between overconfidence on the one hand and investor behavior as well as resulting portfolio performance on the other hand. We empirically identify the precise channel (overreaction) which is proposed by some models. We find that subjects overreact on average, i.e. forecasts are too optimistic after positive signals and too pessimistic after negative signals. Furthermore, there is greater overreaction when subjects are more overconfident. Moreover, overreaction is related to risk taking in a portfolio choice task thereby adversely affecting portfolio efficiency.

Keywords: Overreaction, Underreaction, Overconfidence, Miscalibration, Portfolio Performance, Portfolio Risk, Risk Taking, Sharpe Ratio

JEL Classification Code: D1, G1

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1 Introduction

Behavioral research in investor behavior has made huge progress over the last years. This new evidence is summarized in several recent survey articles (see, e.g., Polkovnichenko (2010) or Zhu (2010)). Latest studies have, for example, shown that IQ (Grinblatt et al. (2011)), cognitive abilities (Christelis et al. (2010)), sensation seeking (Grinblatt and Keloharju (2009)), religion (Kumar et al. (2011)), genes (Barnea et al. (2010)), financial literacy (van Rooij et al. (2011)), political preferences (Kaustia and Torstila (2011)) and many other variables affect investor behavior.

While all these studies tremendously contribute to the progress which was made in understanding investor behavior, several important points remain open, however. Important questions arise which have to be addressed to further enhance our understanding of the behavior and performance of investors. How are all the above mentioned variables (or a subset of them) related? Note, that the above selection of variables is far from complete and that the above studies usually do not control for the long list of other variables shown to be correlated with investor behavior in the real world. And, even more crucial, what is the precise mechanism of how investor characteristics translate into investor behavior and resulting investor performance? The last question is especially important for theoretical finance. How should better descriptive theories look like? Which variables should be included in models? Answers to the above raised points are also important for banks that aim at improving financial products or investment advice offered to customers. Furthermore, regulators and politicians all around the world currently pursue activities which are designed to increase investor protection on the one hand or to enhance the level of financial literacy on the other hand without knowing which is the better way to help investors. Are attempts to increase financial literacy hopeless as genes are the main drivers of behavior?

In any case, the next steps of individual investor research should try to shed some light on how important variables are related precisely and, even more important, should more extensively analyze the mechanism or channel of *how* investor characteristics affect behavior and performance. Our paper is designed to tackle these points and thereby tries to push our knowledge of investor behavior one step further in this direction.

Our goal is to suggest one specific experimental design which is useful to address the above raised questions to "open the black box of investor behavior". The natural starting point of any analysis of investor behavior is to focus on portfolio choice. As our goal is to suggest a relevant and realistic but at the same time simple and parsimonious experimental design we focus on a simple allocation decision between two risky assets (i.e., two different stocks in our case) and a risk free asset. We do not claim that the precise situation analyzed which will be described in detail below is the most relevant decision situation investors have to deal with. Nor do we attempt and nor are we able to measure all variables on the long list of factors unearthed by researchers which are shown to be correlated with investor behavior. In order to circumvent the problem of potential omitted variables mainly associated with the usage of field data, we explicitly rely on an experimental set-up. The aim of our paper is to analyze one important and realistic aspect of investor behavior based on a "real problem" typically faced by investors which is also covered (at least in parts) in many empirical, experimental, and theoretical scientific articles. To sum up, our paper presents a way of how the above mentioned questions could be addressed in principal, thereby providing guidance for future research on how to design such a study.

More specifically, participants in our experiment observe charts of pairs of stocks which will be the basis for the above mentioned portfolio choice problem later on. 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 which is a helpful but imperfect signal. In other words: Subjects know what is going to happen in the future for sure. While this design might look quite unrealistic at first sight it is (designed to be) similar to what is happening when one firm in a specific industry announces earnings. This earnings announcement might also be relevant to judge the current state of other firms in the same industry which have not yet made an earnings announcement. Precisely this situation is studied by Thomas and Zhang (2008) using data from the field. They 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.

More generally, observing information or price developments for one financial time series while, at the same time, not knowing the development of other financial time series is precisely what happens to many (most?) investors every day. Investors usually observe daily market returns as they are, for example, extensively covered in the evening news. At the same time, they do not know the returns of individual stocks in their own portfolio, for example (Glaser and Weber (2007b)). One reason might be that investors simply do not track performance of their stock portfolio every day. In contrast, market returns are quite salient. Note, that this situation resembles our design but differs in the sense that actually realized charts of some times series are known to investors instead of "future realized charts". However, the underlying economic situation is similar and, at the same time, it is a real situation investors often face. Recent evidence underlines the relevance of this second interpretation of our design. Several studies document that market returns typically have stronger effects on market wide trading volume of individual stocks or trading volume of individual investors when compared to the respective more intuitive driver of volume: past returns of individual stocks in the case of individual stock trading volume (see Statman et al. (2006)) and past realized portfolio performance in the case of portfolio trading volume of individual investors (see Glaser and Weber (2009)). This more general example shows how relevant the situation analyzed in our paper actually is.

After making the above described predictions for stocks subjects were asked to form portfolios. The specific design of our study makes it possible to precisely measure important and often analyzed aspects of investor behavior such as overreaction, overconfidence, portfolio choice, and resulting portfolio performance within one setting, thereby making it possible to uncover some aspects of the black box of investor behavior and to document one channel of how biases translate into investor performance. Portfolio efficiency is thereby measured by the Sharpe ratio, a concept which is explained and extensively covered in almost every introductory finance textbook. Typically, studies present a correlation between, for example, overconfidence on the one hand and behavior or performance on the other hand. We identify the precise channel (overreaction) which is proposed by some models. We find that subjects overreact, i.e. forecasts are too optimistic after positive signals and too pessimistic after negative signals. Furthermore, there is greater overreaction when subjects are more overconfident. Moreover, overreaction is related to risk taking in a portfolio choice task thereby adversely affecting portfolio efficiency.

The rest of the paper is organized as follows. In the next section, we describe our experimental design in detail. Especially, we extensively present the relation of our design and the variables measured to existing research. Furthermore, we present a theoretical framework. In Section 3 the results are shown. Section 4 concludes.

2 Experimental Design: Overview, Relation to Literature, Theoretical Framework, and Details

2.1 Overview and Relation to Literature

When 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 (1998) analyzes a model where some investors think their signal is more accurate than it really is. Consequently, they overreact to their

[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).

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-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 on 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 paper 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 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

[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 provide 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 (1998), we find that overconfidence and overreaction are significantly positively correlated.

We also asked participants to form portfolios combining the stocks for which they were asked 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 performance of the portfolios, measured by their Sharpe ratio.

2.2 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:

$$F(\tilde{s}_j) - \tilde{v}_j = \alpha + \beta \tilde{s}_j + \tilde{z}_j, \tag{1}$$

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:

$$\frac{F - E(\tilde{v}|s)}{s - E(\tilde{s})} = \frac{\hat{E}(\tilde{v}|s) - E(\tilde{v}|s)}{s - E(\tilde{s})} = \hat{\delta} - \delta. \tag{2}$$

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 (1998) 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.

2.3 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. In addition, we explicitly used the words stocks and stock markets to make the task more realistic and understandable.[3]

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), $\eta^G_{i,j}$ (corresponding to the idiosyncratic shock of stock G) and $\eta^H_{i,j}$ (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.

[3] In pre-tests in which we used neutral framing subjects had problems with the task and advised us to use a stock related framing. In addition, using a stock related environment has been utilized in the literature frequently (see e.g. Glaser et al. (2007) and Biais and Weber (2009)).

2.4 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 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 excerpts of 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 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*.[4] Rational agents will have an *Overreaction-Beta* equal to 0. But agents who overreact will have positive betas.[5]

- We refer to the second measure as the *Median-Overreaction-Ratio*. Again consider a given participant. In line with Equation 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*.[6]

Participants were also asked to provide an upper bound and a lower bound such that there was only one chance out of ten that the final price would be outside the bounds.[7] 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) or Glaser and Weber (2010)). 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 (2007a) and Graham and Harvey (2005)). Finally, we take the average of this ratio across the 20 stocks

[4]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.

[5]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.

[6]We use median scores to control for outliers. However, our results remain fairly stable if we use the mean or the mode instead.

[7]Note that this is a standard way to measure overconfidence in the literature (see Graham and Harvey (2005), Glaser et al. (2010)), and Biais and Weber (2009) and directly connects to the psychological literature.

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

Glaser et al. (2010) and Moore and Healy (2008) have recently shown that different ways of assessing overconfidence that have implicitly been assumed to be equivalent, do not necessarily reflect the same unitary construct. Nosić and Weber (2009) go a step further and show that there is domain or context specificity of overconfidence. Thus, we measure miscalibration in a closely related context to overreaction to account for these findings. Note however that due to the use of the Keefer-Bodily approach there are no confounding effects and subjects with bad estimates do not necessarily need to be overconfident and vice versa.

After having provided their forecasts for two stocks (H_j and H_{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.

Finally, we also asked subjects questions about how they perceived themselves (see excerpts of the 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).

2.5 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.[8] 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 who 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.[9] 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 1.

Insert Figure 1 here

[8] We chose to recruit subjects majoring in finance or decision analysis as these subjects are better trained and educated and should be less prone to behavioral biases. Thus, any results should be harder to achieve in this population. Note however, that we ran the experiment in the second week of the term so that subjects did not have any specific knowledge about behavioral biases, yet. In addition, amongst others Glaser et al. (2010) show that a similar student population is not more prone to behavioral biases in a financial context than investment bankers and that it is worthwhile to analyze interesting research questions in experiments with students.

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

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 2 and discussed more thoroughly in the respective subsections.

Insert Figure 2 here

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 (1998) who argues that subjects tend to overweight attention-grabbing, anecdotal and graphical information, just the type of information we gave subjects.[10]

Both measures of overreaction are highly correlated with each other (*Spearman Rho* = 0.85). Figure 3 shows that, on average, subjects tend to overreact in our setting no matter

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

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.[11] 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.

Insert Figure 3 here

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 subject to obtain *Overconfidence-Person*.[12] We find substantial degrees of overconfidence in our setting with 76 subjects having an *Overconfidence-Person* score above -1 and a median *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. (2010) we also find substantial

[11] 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.

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

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.[13]

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 (1998) 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 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.

Insert Figure 4 here

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 (2009)

[13]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.

show that subjects who overreact fail to diversify properly and hold less efficient portfolios than subjects who do not overreact.

3.3.1 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.[14] 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).[15] These relations are illustrated in Figure 5 and Figure 6.

Insert Figure 5 here

Insert Figure 6 here

[14] 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.

[15] If we exclude subjects who 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.

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.[16] Furthermore, our data allows us to test an assumption common in various models on overconfidence (see e.g. Odean (1998) 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 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 to 4 analyze portfolios for which subjects receive a positive signal. For these portfolios we find that an 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

[16]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 also of high economic significance. Analyzing portfolios for which subjects receive a negative signal (see regressions 5 and 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 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 and 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.

Insert Table 1 here

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 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*.[17] To account for non-independent residuals within subjects we cluster our observations over subjects. A first look at the results in Table 2 reveals

[17]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.

that the results are mainly consistent with our previous findings in table 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 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.[18]

Insert Table 2 here

3.3.2 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 (2009) 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 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

[18]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.

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 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 who 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 who invest in portfolios that are less risky than the market portfolio and for subjects who 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 who underreact. Calculating Spearman rank correlation coefficients for the two parts separately we find a negative relation for subjects who 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 who underreact. This relation is illustrated by the dashed (dotted) lines in Figure 7 for subjects who overreact (underreact). The figure demonstrates that a higher level of over/underreaction gives rise to less efficient portfolios.

Insert Figure 7 here

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 3) and the disaggregated Sharpe ratio (see Table 4) as dependent variables. Table 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 our previous findings both overreaction measures have a significantly negative coefficient indicating that higher levels of overreaction lead to lower levels of portfolio efficiency.[19]

Insert Table 3 here

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. In Regressions 1 and 2 we only take observations for which *Overreaction-Ratio* is greater than zero indicating overreaction whereas in Regressions 3 and 4 we only take observations for which *Overreaction-Ratio* is below zero indicating underreaction.

The regressions in Table 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 and 4 indicate a highly negative effect of underreaction of approximately -0.3 on portfolio efficiency. Consistent with Daniel et al. (2001) and Biais and Weber (2009) 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

[19] 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.

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-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.[20]

Moreover, for Regressions 1 and 2 we find a significant effect for the course subjects are enrolled. subjects who 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 who are enrolled in the *Behavioral Finance* class which is part of the specialization in finance. A similar expertise effect is, for example, documented in Glaser et al. (2007). 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.

Insert Table 4 here

4 Conclusion

This paper 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

[20]As in section 3.3.2 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.

is consistent with findings in Thomas and Zhang (2008) who analyze a similar scenario empirically.

Examining the relationship between overreaction and psychological biases we focus on overconfidence and more exactly on miscalibration, on average. We document a substantial level of overconfidence with the majority of subjects being overconfident. 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. To sum up: Our experimental approach offers the advantage that we can explicitly measure the level of overreaction and relate it to psychological biases and financial consequences.

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Table 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 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

Table 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: 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

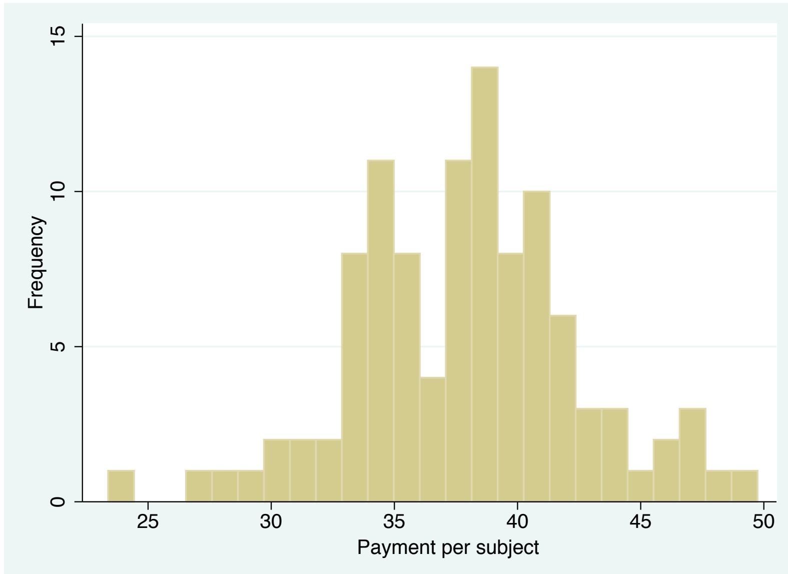


Figure 1: Payment per subject

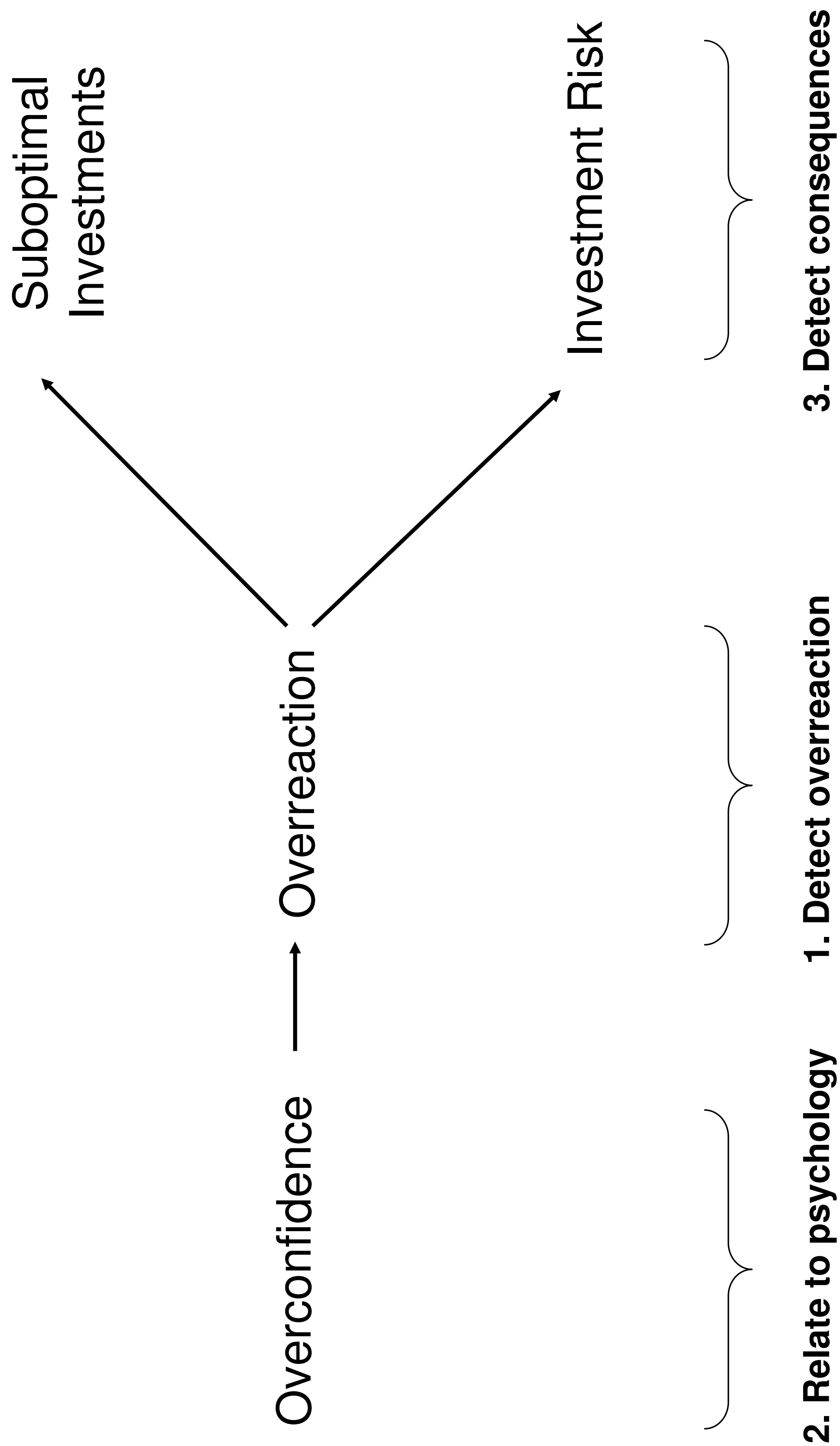


Figure 2: Overview of hypotheses

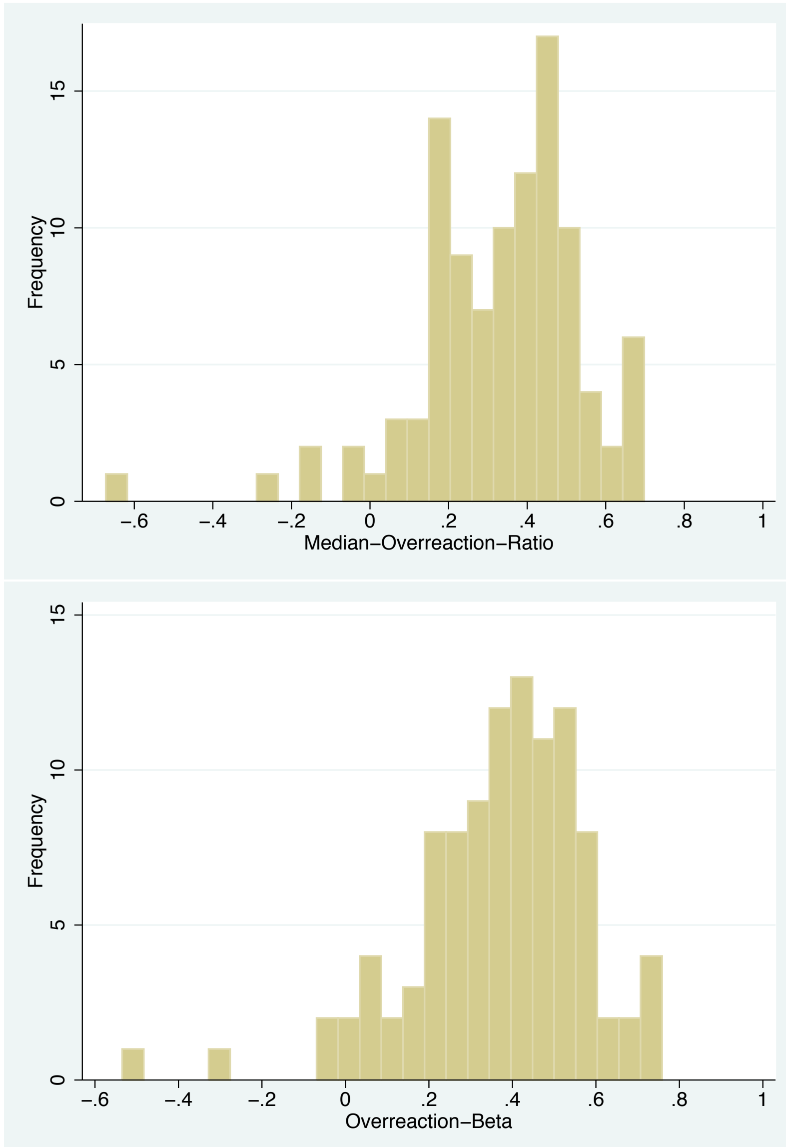


Figure 3: Histogram of *Median-Overreaction-Ratio* and *Overreaction-Beta*

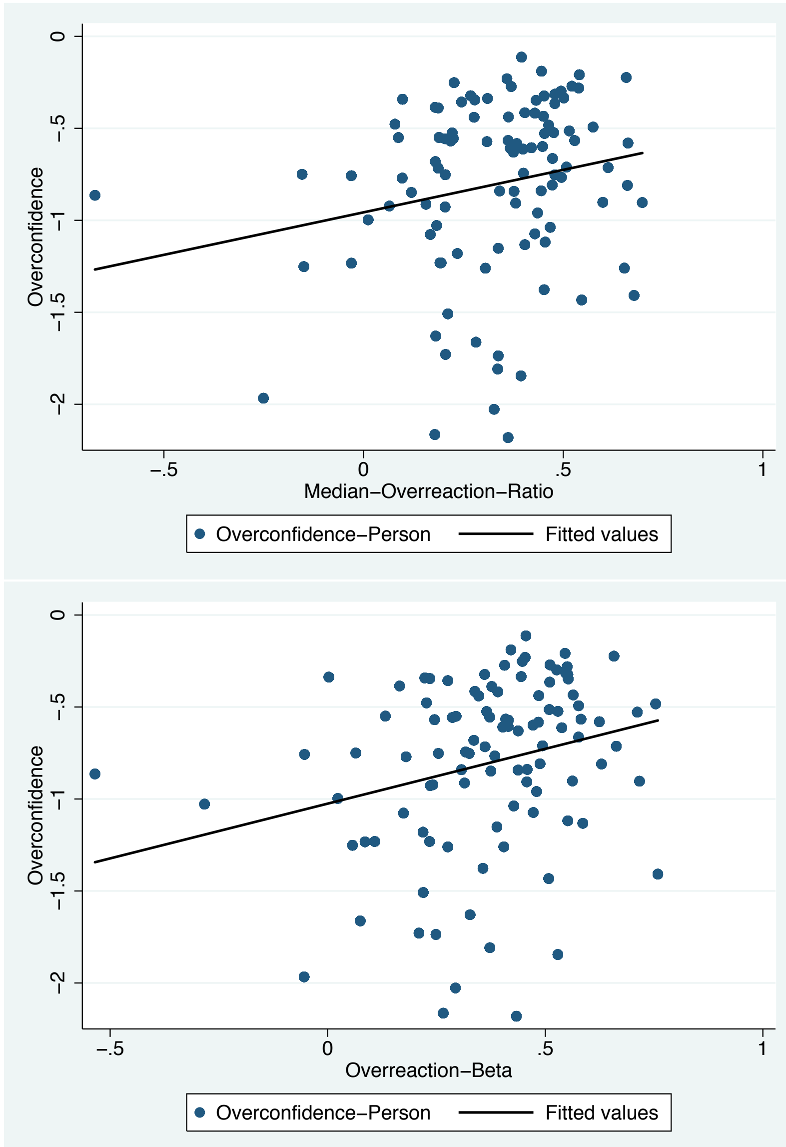


Figure 4: Relation overreaction and overconfidence

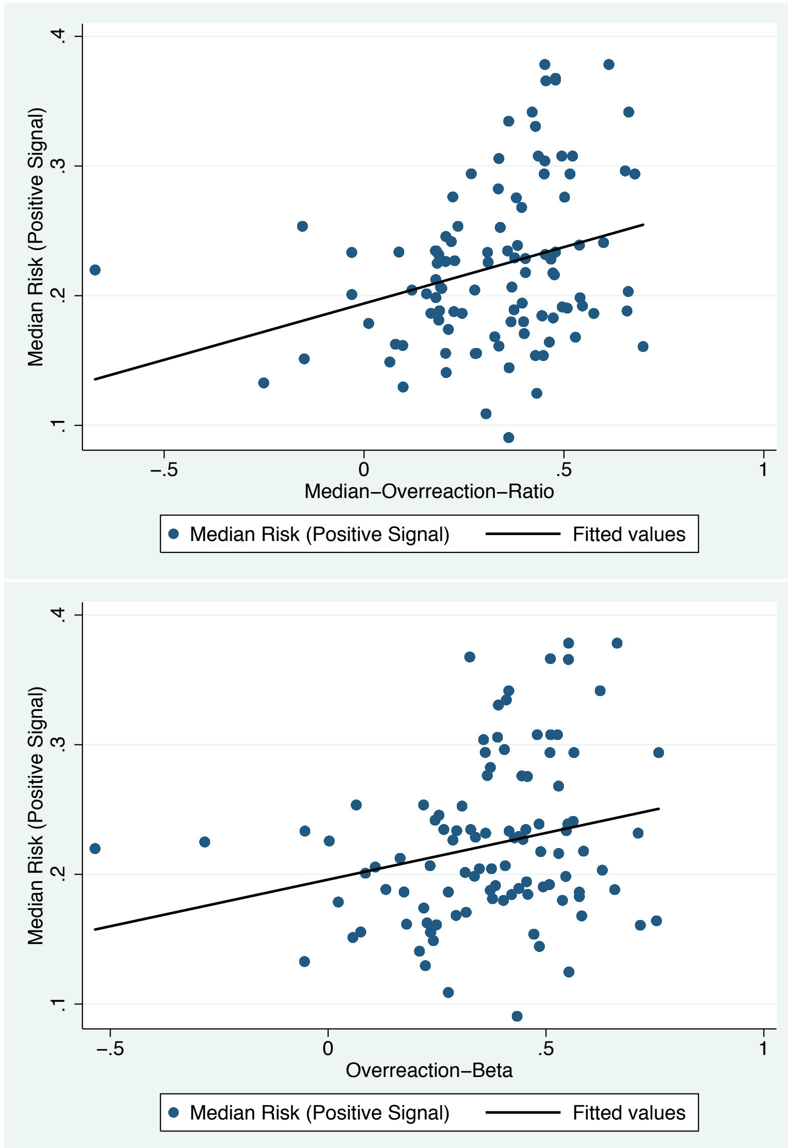


Figure 5: Relation overreaction and portfolio risk (questions with positive signal)

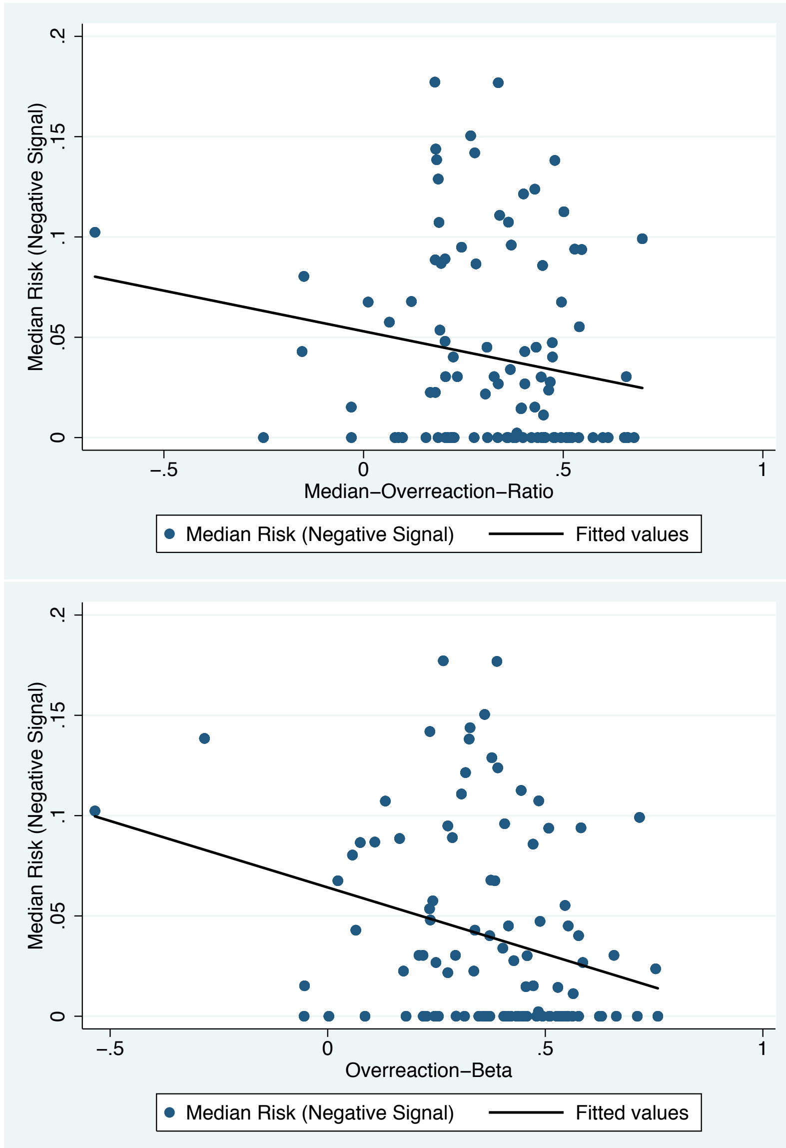


Figure 6: Relation overreaction and portfolio risk (questions with negative signal)

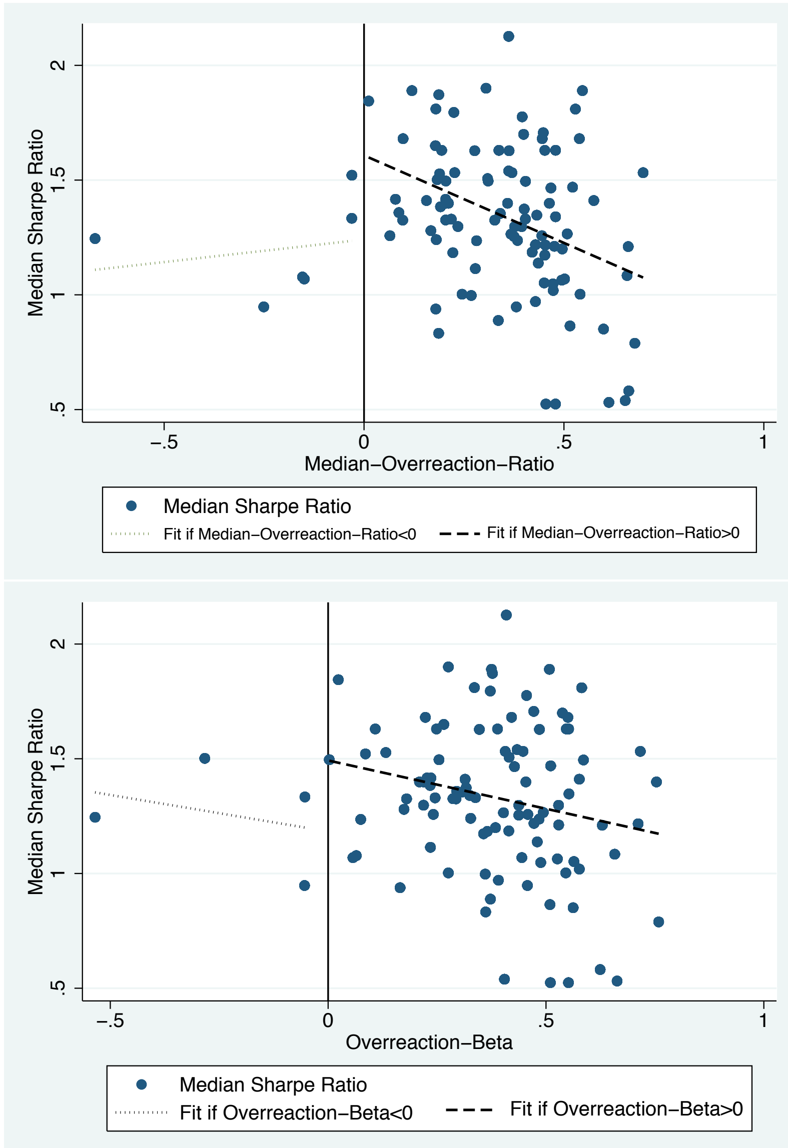


Figure 7: Relation overreaction and Sharpe ratio

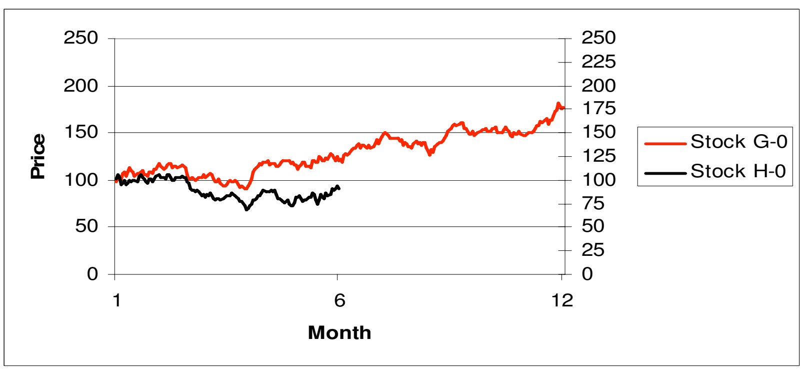
5 Appendix

Part A: Stock Price Forecasts - Instructions

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

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:

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

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

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

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

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

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.

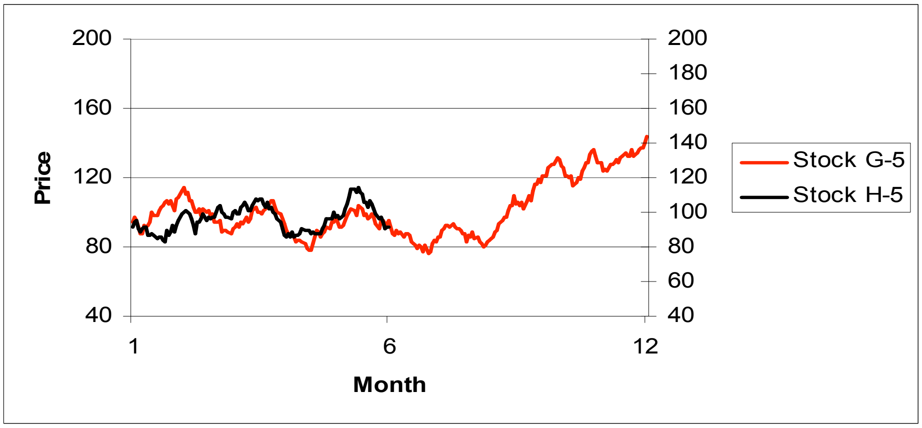
Part B: Portfolio Allocation - Payment Scheme

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.

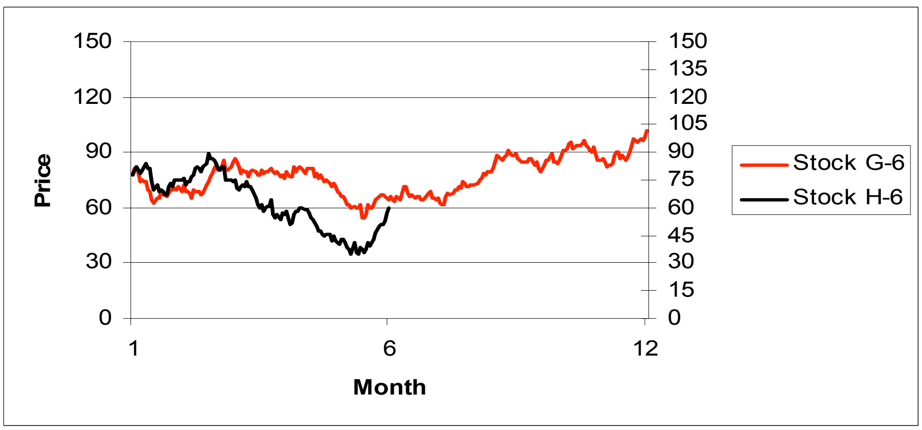
Your final payment for part B is equal to:

$$\text{Payment}^B = 15\,€ * (1 + \text{Realized Portfolio Return})$$

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 €

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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 willingness				Very high willingness

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