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

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Abstract

Our study analyzes the determinants of investors' risk taking behavior. We find that investors' risk taking behavior is affected by their subjective risk attitude in the financial domain and by the risk and return of an investment alternative. Our results also suggest that, consistent with previous findings in the literature, objective or historical return and volatility of a stock are not as good predictors of risk taking behavior as are subjective risk and return measures. Moreover, we illustrate that overconfidence, or more precisely miscalibration, has an impact on risk behavior as predicted by theoretical models. However, our results regarding the effect of various determinants on risk taking behavior heavily depend on the content domain in which the respective determinant is elicited. We interpret this as an indication for an extended content domain specificity. In particular with regard to the Markets of Financial Instruments Directive (MiFID), we believe practitioners could improve on their investment advising process by incorporating some of the determinants that, by our argument, influence investment behavior.

Keywords: Overconfidence, Risk Attitude, Risk Perception, Return Perception, Risk Taking, Extended Content Domain Specificity

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 base their decision on the variance-covariance structure of an investment alternative to calculate the investment alternative's risk. Hence, individual risk attitude determines how much an investor allocates to risky and risk free assets. The line of reasoning is that, all other things being equal, individuals with a higher risk aversion should be inclined to hold less risky assets (see Samuelson (1969)).

Recent studies have shown that intuitive risk measures such as subjective risk perception can better proxy for investors' intuition about financial risks than can 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 (1993) and Jia et al. (1999) allow for the incorporation of these more appropriate measures of perceived risk so that the investment decision may be decomposed as follows:

$$Risk\ Taking = f(Perceived\ Return,\ Risk\ Attitude,\ Risk\ Perception) \qquad (1)$$

Hence, in this framework risk taking behavior is determined by three major components, namely perceived returns, subjects' risk attitudes and perceived risks. Research in psychology and decision analysis has provided extensive evidence for procedure (in)variance (for an overview on this topic see Lichtenstein and Slovic (2006)). Procedure variance implies that different methods of measuring a given construct (such as preferences or perceptions) may not result in a unitary construct. Weber et al. (2005), Diacon and Hasseldine (2007), and Vrecko et al. (2009) document that the presentation format affects risk perception and, consequently, also impacts risk taking. Rettinger and Hastie (2001), Weber et al. (2002), and Baucells and Rata (2006) illustrate that differences in risk taking over various content 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, these studies show that risk perceptions vary substantially between different content domains.[1]

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 content domains 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 need to elicit risk attitudes, risk and return perceptions as well as overconfidence in several content domains, using various methods. This can be only done in an experimental or questionnaire setup. We have therefore 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 content domains in one single study.

Our ultimate question in this paper is centered around an investor who has to decide how

[1]Note that the term domain is often used to refer to gains and losses as well as to different problem, content or assessment classes. Consistent with Rettinger and Hastie (2001) and Weber et al. (2002) we use the term domain or content domain to refer to distinct content domains and not to gains or losses.

to split a given amount between risky and risk-free assets. 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). 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 allocate an amount of 10,000 Euro to a combination of a risk free asset and the respective stock. The main goal of our paper 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.

We extend findings in the literature as follows: in line with more general risk-value models, the risk taking behavior in the stock domain, as evidenced for instance by portfolio choices, is determined by the riskiness and the return of an investment and also by the individual risk attitude. However, we show that subjective risk expectations and subjective return expectations are significantly better predictors of risk taking behavior in stocks than are 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. Moreover, our results are also consistent with Johnson et al. (2004) and Hanoch et al. (2006) who show that subjective return expectations can help predict risk taking behavior. We also show that these objective measures may not be related to 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) may not be highly correlated.

In line with many models on overconfidence and optimism (see e.g. Hirshleifer and Luo (2001)) we find that subjects exhibiting a higher degree of overconfidence and being more optimistic are likely 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 content domain specificity (see e.g. Rettinger and Hastie (2001), Weber et al. (2002), and Baucells and Rata (2006)). First, we show that risk perception does not only vary between two distinct content domains (such as health and finance) or between investment and gambling decisions, but that risk perception can substantially vary even within a single content domain between two very closely related investment opportunities. Second, our extended content 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, we extend findings in Moore and Healy (2008), who show that different ways of assessing overconfidence do not need to reflect the same unitary construct, as follows: we find both an assessment-procedure-specific component of overconfidence as well as a content domain specific effect of overconfidence on risk taking as 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.

Correctly identifying determinants of risk taking 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 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 (§ 35, 1)") and to elicit the customers' "preferences regarding risk taking, his risk profile, and the purpose of the investment (§ 35, 4)." With respect to the implementation of the MiFID, it is certainly interesting to note that we cannot infer anything about subjects' risk taking decisions in stock market settings by asking them to judge artificial lotteries. In addition, our results show that investment advisors could also try to lower their customers' overconfidence levels and explain the consequences and risks of their decisions more thoroughly so that heavily overconfident subjects do not take risks they do not want.

The remainder of the paper is organized as follows. In section 2 we describe the design of the study and illustrate descriptive results. Section 3 contains the main results of the study, and section 4 provides a short summary and conclusion.

2 Design and Descriptive Statistics

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 1 summarizes and defines all variables used in the study and presents the methods used to measure the respective variables.

Insert Table 1 here

Part 1 The first lottery task in part 1 asked subjects to split 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 12,000 Euro or 9,000 Euro, each with probability 1/2. 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 to elicit subjects' risk taking behavior by asking them to state their certainty equivalent for a lottery that pays 10,000 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 would 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 $u(x) = x^{\alpha}$.[2] In addition, *Risk Perception (Lottery 2)* was elicited in the same way as for lottery 1.

The last question in part 1 (*Subjective Financial 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 surveys such as the Socio-Economic-

[2]Note that our results in section 3 remain stable if we simply use the certainty equivalents or CRRA transformations to derive a risk aversion parameter.

Panel (SOEP) (see Dohmen et al. (2009)).

Part 2 In the second part of the questionnaire, participants first had to state 90% confidence intervals for 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.

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 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 correctly more questions 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 hence 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.[3]

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 from November 2001 to November 2006 obtained from Thomson Financial Datastream. In line with Glaser et al. (2007), we included firms with stable, upward as well as 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 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 the problem that subjects might interpret the vertical endpoints of the graph as boundaries.

For all five stocks we elicited the following variables:

- *Risk Perception (Stocks)*
- *Risk Taking (Stocks)*
- *Subjective Expected Return (Stocks)*

[3]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.

- *Subjective 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).[4]

To measure the subjective expected volatility and subjective 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[5] 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.[6]

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) (*Subjective*

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

[5]Note that the term confidence interval should not be confounded with confidence intervals in statistical hypothesis testing.

[6]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.

Expected Return (Stocks) $= 0.63 \cdot r(0.5) + 0.185 \cdot (r(0.05) + r(0.95))$. 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)* = *Subjective Expected Return (Stocks)* - *Historical Return (Stocks)*); a higher score indicates a higher level of optimism.

Using the median forecast as well as both the upper and the lower bound allows us to obtain a measure for the subjective 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[7] 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 *Subjective Expected Volatility (Stocks)* measures an individual's subjective volatility forecast for each stock. In addition to the subjective 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 ($Miscalibration\ (Stocks) = -\frac{SubjectiveExpected\ Volatility\ (Stocks)}{Historical\ Volatility}$). This standardization yields a miscalibration measure, which is close to 0 for excessively overconfident subjects and equal to -1 for perfectly calibrated subjects.[8]

[7] 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 have 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: $\text{Volatility}_i = \sqrt{[0.185 * \text{r}(0.05)_i^2 + 0.63 * \text{r}(0.5)_i^2 + 0.185 * \text{r}(0.95)_i^2] - [0.63 * \text{r}(0.5)_i + 0.185 * \text{r}(0.05)_i + 0.185 * \text{r}(0.95)_i]^2}$.

[8] 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 as 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.

Furthermore, we also asked individuals to predict the number of interval questions for which 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.

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 hardly any knowledge in the respective field.

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. On average, it took the students 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 an overall number of 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.[9]

The mean and median scores for all demographic and risk variables are presented in Table 2. The average age of the participants is 24 years, with 31.6% 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 56.6% of all respondents have held stocks or other stock market related assets within the last year. The self-reported statistical knowledge score on a scale from 1 (very good) to five (bad) is approximately 2.8 and the score 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 further documents that participants stated an average subjective financial 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 in part 3 of the questionnaire, subjects invest an average of 43.6% of their funds 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

[9]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.

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 and that the median overconfidence score is 0.782. Using Wilcoxon matched-pairs signed rank tests for both measures, we show that there is substantial miscalibration in both content 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% of cases. Analyzing illusion of control, we find - consistent with Dorn and Huberman (2005) - that subjects are prone to the illusion of control bias, with a score of 0.279 which is significantly larger than 0. 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 content domains; on the other hand, these effects are only weakly significant or not significant at all.[10] In addition, note that our measures of overconfidence are not highly correlated. This finding is in line with Glaser et al. (2005) and Moore and Healy (2008) who show that different ways of assessing overconfidence need not reflect the same construct.

Insert Table 2 here

[10]We use better than average in calibration questions since almost all theoretical models show a relation between risk taking and overconfidence using miscalibration as a proxy for overconfidence. Nonetheless, future research could certainly analyze whether a general better than average effect in investments is related to risk taking behavior.

3 Results

In this section we analyze which factors actually govern risk taking behavior in a stock related context. As illustrated in section 1, individuals' risk taking behavior is argued to be determined by three major components: risk attitude, perceived return and perceived risk (see equation 1). Recent work by Weber and Milliman (1997), Weber et al. (2002) and Klos et al. (2005) shows that subjectively perceived risks need not coincide with variance estimates and that perceived risks in one content domain need not coincide with perceived risks in another. To allow for these findings we elicited 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.

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

Before we analyze factors that determine aggregate risk taking behavior, i.e. portfolio choices, in a multivariate setting, we first perform simple bivariate interactions between aggregate portfolio choices 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 Financial 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)*.[11]

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. Since all three measures essentially yield the same results, we will subsequently only report the results for the aggregation rule using the mean score.[12]

However, before using these aggregated scores, we need to assess the internal validity of each variable over the five questions. We need to ascertain 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)*.[13]

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

[11] Using *Subjective Expected Volatility (Stocks)* and *Subjective 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 not standardized by the respective historical variable is not as straightforward.

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

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

A of Table 3 illustrates Spearman correlation coefficients (1) and Pearson correlation coefficients (2) between *Risk Taking (Stocks)* and related variables. The results show that *Subjective Financial Risk Attitude* is strongly positively related with *Mean Risk Taking (Stocks)*. Hence, subjects who have a higher *Subjective Financial Risk Attitude* also (on average) invest into more risky portfolios.

This finding is in line with Dohmen et al. (2009) who argue that eliciting individuals' willingness to take risks in the financial domain is a useful predictor of their risk taking behavior in the financial domain. Moreover, the results in Dohmen et al. (2009) indicate 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 content domains. However, the question whether subjects really have an underlying stable preference that is valid in all content domains is highly controversial. Amongst others, MacCrimmon and Wehrung (1986) were not able to find that global self assessments of risk attitudes are good predictors of risky choice in all content domains. Note, however, that our study only intends to show that *Subjective Financial Risk Attitude* is related to risk taking behavior in the financial domain (both in a lottery and a stock context) and not to risk taking behavior in any content domain.

Panel A also shows that neither risk perceptions in both of our lotteries nor risk attitudes as inferred from certainty equivalents are sufficient to determine individuals' average risk taking behavior. The first point is an extension of the findings in Weber et al. (2002) and Blais and Weber (2006) on content domain specificity and will be discussed more thoroughly in section 3.3. The second point is in line with findings in Wärneryd (1996), Kapteyn and Teppa (2002), and Klos and Weber (2003) who provide evidence that intuitive subjective measures of risk seem to be better predictors of portfolio choice than more sophisticated methods such as certainty equivalents. 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. The positive relation between overconfidence and risk taking is consistent with theoretical predictions in the models of Odean (1998), Daniel et al. (2001), and Hirshleifer and Luo (2001).

Insert Table 3 here

To further strengthen our results on determinants of risk taking, we analyze the relationship between portfolio choice and its determinants in a multivariate setting, controlling for various effects.[14] Panel A in Table 4 presents results of ordinary least squares regressions with *Mean Risk Taking (Stocks)* as the dependent variable. Regression (1) shows that *Subjective Financial Risk Attitude* can significantly explain individuals' average risk taking in stocks. 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 Financial Risk Attitude* and *Miscalibration (Stocks)* are significant determinants of risk taking but *Mean Optimism (Stocks)* is not a significant determinant. 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 content domains. The results with re-

[14]Throughout the paper 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, these theoretical bounds are almost never reached in our dataset. In addition, we ran all our multivariate analyses using censored tobit regressions and obtained essentially the same results.

gard to the significance of the two main dependent variables *Subjective Financial Risk Attitude* and *Miscalibration (Stocks)* remain constant. However, none of our additional variables is significantly related to portfolio choices. Furthermore, adding all additional control variables does not increase the goodness of fit of our regression dramatically as indicated by the adjusted R-squared.

Insert Table 4 here

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 explain 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.

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 next document 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 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, and thus controlling for within-person correlations, 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.[15] Table 5 presents the results of these estimations.[16]

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 as well as by an individual's risk attitude. In the finance literature, it is common to equate expected returns with historical returns and expected risks with historical variance. Hence, the first regression in Table 5 tries to explain subjects' risk taking in the stock domain using these variables. The regression results show that *Subjective Financial 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 explain 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 not a perfect indication of future performance.

Insert Table 5 here

More general risk-value models argue that subjects might base their decisions more on subjective measures of risk and return than on objective ones. It hence might be more appropriate to include subjective measures of risk and return (such as *Subjective Expected Return (Stocks)* as well as *Risk Perception (Stocks)* and *Subjective Expected Volatility*

[15]For a more in-depth textbook analysis of clustered analyses and/or fixed effects and random effects panel regressions see Wooldridge (2003). Moreover, Petersen (2009) compares various approaches to get around the problem of correlated observations and provides a good intuition for these methods.

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

(Stocks)) into our regression as they could affect the actual level of risk taking more heavily. To accommodate for this proposition, we include these variables, replacing their historical counterparts in regression (2). Using both *Risk Perception (Stocks)* and *Subjective 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 correlated with *Subjective 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). This result suggests that the two subjective risk measures need not coincide and is consistent with previous findings in the literature (see e.g. Klos et al. (2005) and Weber 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 Financial Risk Attitude* and both subjective risk and return measures in the stock domain significantly influence the risk taking decision in the stock domain. On a single stock level, we find 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 subjectively perceives the risk of the investment 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 do 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 of which measures subjects rather rely on when making their decisions. To do this, we run regression (3) and include both objective and subjective measures simultaneously. 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 ascertain whether objective and subjective variables measure distinct concepts before carrying out the regression.

Analyzing the within-subject rank correlation coefficients (Kendall tau and Spearman) between objective and subjective measures of risk and return, we find support for this proposition. Comparing historical returns with subjective 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 subjective expected returns is positive. These results suggest that the 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 subjective 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 may not measure the same concept and we may hence 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; while historical risk and return measures do not significantly affect risk taking, 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 either demographics, familiarity with investments and knowledge on risk taking. We offer three explanations for 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 well 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 *Subjective Expected Return (Stocks)* and *Subjective Expected Volatility (Stocks)*. Consistent with theoretical models on overconfidence and optimism (see e.g. Odean (1998) 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)* lies in the fact that we use historical risk and return measures to standardize these variables; we hence 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; its major disadvantage, however, is that we cannot make a statement about the effect of risk attitude, demographics, knowledge and various overconfidence measures on risk taking as 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. We hence 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 mostly in line with the findings of the clustered ordinary least squares regressions, with variables previously found to affect risk taking again being 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 as well as historical stock returns and a wide range of demographic variables - are not able to determine subjects' risk taking behavior.

In the following, we want to address the concern that the sequence in which the questions were asked might drive some of our results. One possible line of reasoning would be that subjects might recall their answers and try to be consistent in related questions. Note, however, that consistency arguments cannot explain all our findings as the average risk taking behavior on a single stock level varies substantially from 33.9% (in stock 2) to 48.4% (in stock 3).

In addition, although we observe variations in subjects' risk taking behavior, their *Subjective Financial Risk Attitude* is a stable predictor of risk taking behavior even if we analyze this relationship on a single-stock level, i.e. for each stock separately. Interestingly, we cannot find evidence that the relationship between *Subjective Financial Risk Attitude* and *Risk Taking (Stocks)* is stronger for the stock that was shown first and for which subjects should have the best recall compared to the stock that was shown last and for which recall should be less strong. The Spearman correlation coefficient for the relationship between *Subjective Financial Risk Attitude* and *Risk Taking (Stock 1)* is 0.349, and correspondingly equal to 0.354 for the relationship between *Subjective Financial Risk Attitude* and *Risk Taking (Stock 5)*. These findings indicate that recall and consistency seem not to be the main driving force behind our results.

Furthermore, the act of eliciting risk attitudes as well as risk and return expectations before the risk taking behavior was chosen on purpose as it best reflects the advisory process. In practice, investors should think about their expectations, i.e. “what return do I expect” and “how risky is the investment going to be” as well as about their subjective risk attitude before making an investment decision. This line of reasoning is also expressed in the MiFID, which requires financial institutions to elicit their customers’ risk attitudes and risk profiles before giving them advice on their investment behavior. In addition, measuring risk taking behavior and risk perceptions in a predetermined order which is the same for various decisions is common in the literature (see e.g. Weber and Hsee (1998)).

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 significantly affect portfolio choices. Risk perceptions and risk attitude inferred from lotteries or overconfidence measured in a more general content domain are not capable of determining risk taking behavior, whereas risk attitudes in a broader, not overly specific finance context are. We argue that this can be explained by an extended content domain specificity, or within-content-domain specificity. This extended content domain specificity goes beyond results on content domain specificity by Rettinger and Hastie (2001) and Weber et al. (2002) who show that risk perceptions vary substantially over various distinct content domains (such as health and finance). More precisely, we argue that differences in risk taking in apparently different decision contexts (lotteries vs. stocks) can be associated with differences in the perception of the riskiness of these decisions.[17] To test the robustness of extended content domain specific behavior, we next analyze determinants of risk taking in lotteries.

Analyzing the bivariate relationship 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 content domain specificity result. Panel B in Table 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 content domain specificity in panel B of Table 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 significantly affects risk taking behavior in lotteries. Further research could analyze whether this extended content domain specificity result can also be observed for subjective risk attitudes. To accomplish this, one would simply need to elicit subjective risk attitudes both in a lottery context and in a stock context and relate it to risk taking behavior in both content domains.

Moreover, we also find evidence that this extended content domain specificity result not

[17] Note, we don't argue that lottery and stock decisions are formally equivalent. We rather argue that subjects who perceive the riskiness of a lottery investment to be high might perceive the riskiness of a stock investment as low and vice versa and that variations in risk perception can explain variations in risk taking between the two context domains.

only applies to risk perceptions, but to overconfidence as well. In the previous analyses we found that miscalibration in the stock domain significantly affects portfolio choices, whereas other measures of overconfidence do not. Analyzing the effect of overconfidence on risk taking in lotteries (Panel B of Table 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 content domain. This result extends findings in Moore and Healy (2008) by showing that there is not only an assessment procedure specific component of overconfidence but also a content domain specific component. In addition, our extended content domain specificity result 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.

4 Conclusions

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 in an investment context is affected by subjective risk attitudes, risk perceptions and return expectations. Analyzing determinants of financial risk taking behavior is also important for practitioners. This is particularly true because of the implementation of the Markets of Financial Instruments Directive (MiFID), which urges financial institutions to be aware of 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 well as subjective measures, i.e. subjective risk and return perceptions; especially 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 those inferred from Likert scales. Our results also suggest that, in line with theoretical models (e.g. Odean (1998)), behavioral biases such as overconfidence and excessive optimism significantly affect risk behavior. 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 as well as by showing them that their desired investment is maybe more risky than initially perceived by them.

We also find evidence for an extended content domain specificity in our data. Determinants of risk taking behavior not only vary between two very distinct content 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 need not be able to predict risk taking in stock investments, and vice versa. Measuring risk attitudes using a lottery approach is hence useless if we want to predict risk taking behavior in the stock domain. It thus seems that 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) as well as in the banking industry) cannot predict risk taking behavior of individuals. The same extended content domain specificity result also applies to 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 portfolio decisions can be generalized to actual portfolio decisions. To accomplish this sort of study, it might prove insightful to cooperate with a bank and analyze bank customers' portfolio decisions in light of our findings. In addition, it would certainly be of interest to analyze how these determinants of risk taking behavior change over time and how these changes influence risk taking behavior; to be more precise, it could be interesting to determine 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 possible ways of reducing 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 type of feedback 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 of efficient measurement of financial risk attitudes. 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)).

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Table 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 Financial Risk Attitude	Scale (1-5)	Measures an individual's subjective risk attitude in the financial domain 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.
Subjective Expected Return (Stocks)	Point Estimate	Measures an individual's expected return for 5 different stocks.
Subjective 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 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".

Table 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 Financial 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
Miscalibration (General Knowledge) (0-10)	5.87	6	2.076
Miscalibration (Stocks) (≤ 0)	-0.945	-0.782	0.394
Illusion of Control (0-1)	0.28	0.25	0.201
Better Than Average (General Knowledge)	0.075	0	0.195
Better Than Average (Stocks)	0.046	0	0.212

Table 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 Financial 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 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 Financial 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 Financial 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

Table 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 Financial 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, subjective expected volatility and subjective 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 Financial 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)**
Subjective Expected Return (Stocks)		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)***
Subjective Expected Volatility (Stocks)		-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

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 $\xrightarrow{50\%}$ +12,000 Euro

Lottery +10,000 Euro $\xrightarrow{50\%}$ +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 at all — Very high 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 $\xrightarrow[100\%]{}$ +10,300 Euro

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?

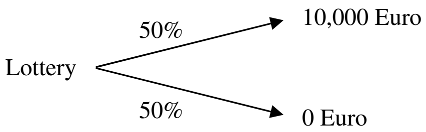
Please mark your answer on the following scale from 0 to 100, where 0 indicates that the full amount will be invested in the risk free alternative and 100 indicates that the full amount will be invested in the lottery (risky alternative).

0 10 20 30 40 50 60 70 80 90 100

Total amount invested in the risk free alternative — Total amount invested in the 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.

0	1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
No risk at all										Very high risk

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
50% → 10,000 Euro; 50% → 0 Euro	9,000 Euro	O	O
	8,000 Euro	O	O
	7,000 Euro	O	O
	6,000 Euro	O	O
	5,000 Euro	O	O
	4,000 Euro	O	O
	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?

1	2	3	4	5
☐	☐	☐	☐	☐
Very low willingness				Very high willingness

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%.

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

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