Determinants of Risk Taking Behavior: The role of Risk Attitudes, Risk Perceptions and Beliefs

Alen Nosić and Martin Weber*

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Abstract

Our study analyzes the determinants of investors' risk taking behavior. We find that investors' risk taking behavior such as portfolio choices can be predicted using risk attitudes, risk perceptions and belief measures such as optimism and overconfidence. However, the predictive power of these determinants heavily depends on the domain in which they were elicited. More specifically, risk attitudes, risk perceptions and beliefs only allow us to predict investors' risk taking behavior if they are elicited in an investment related context. We believe our results could benefit practitioners who could incorporate some of the determinants we have used in their investment advisory process.

Keywords: Overconfidence, Optimism, Risk Attitude, Risk Perception, Risk Taking, Domain Specificity

JEL Classification Code: G1

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*Alen Nosić is from the Lehrstuhl für Bankbetriebslehre, Universität Mannheim, L 5, 2, 68131 Mannheim. E-Mail: nosic@bank.BWL.uni-mannheim.de. Martin Weber is from the Lehrstuhl für Bankbetriebslehre, Universität Mannheim, L 5, 2, 68131 Mannheim and CEPR, London. E-Mail: weber@bank.BWL.uni-mannheim.de. We would like to thank seminar participants at the University of Mannheim and the GfeW 2007 conference for valuable comments and insights. Financial support from the Deutsche Forschungsgemeinschaft, SFB 504, at the University of Mannheim, is gratefully acknowledged.

1 Introduction

Analyzing portfolio choices of investors and predicting their risk taking behavior is an integral part of both decision research and investment advice. The main incentive for researchers to study risk taking behavior of individuals is to better understand how these individuals make their decisions and to identify which factors influence these decisions. The main incentive for investment advisors to predict risk taking behavior of their (potential) customers consists of two parts. On the one hand, being able to predict behavior correctly is a competitive advantage since it enables investment advisors to offer customized investment advice and bespoken products which are in line with the needs of their customers. On the other hand, in many countries financial advisors are legally obliged to evaluate the appropriateness of an investment for each customer. For example, in Europe the Markets in Financial Instruments Directive (MiFID) by the European Parliament and the European Council (2004 and 2006) requires financial institutions to collect "information as is necessary for the firm to understand the essential facts about the customer (§ 19, 1)" and to elicit "the customers' preferences regarding risk taking, his risk profile and the purpose of the investment (§ 19, 4)."

From a normative point of view the risk taking behavior of an investor can be seen as "a mixture between risk aversion of the Arrow-Pratt type and beliefs about future payoffs on risky investments, especially stocks" (Malmendier and Nagel (2007)).

The fact that preferences, i.e. risk attitudes play a major role in determining risk taking behavior of investors can be traced back to work by Markowitz (1952). In a CAPM like environment (see for example Lintner (1965)) in which the two-fund separation theorem holds (see Tobin (1958)) individual risk attitudes determine how much an investor allocates to risky and risk-free assets. The line of reasoning is that all other things being equal more risk averse individuals should be inclined to hold less risky assets (see Samuelson (1969) and for a textbook overview Brealey et al. (2006)). Most of these studies assume that beliefs do not vary with investors and that individual risk preferences are the sole determinant of risk taking behavior. However, more recent studies also explicitly analyze the link between beliefs about future payoffs of risky investments and risk taking. Beliefs can be split into two parts; beliefs about returns of the risky investment (Optimism) and secondly beliefs about the volatility of returns (Confidence). With regards to optimism, Coval and Thakor (2005) amongst others argue that investors who are more optimistic about future returns should allocate more money into an investment, thereby taking more risks. In addition, numerous finance models analyzing the role of investors confidence about future stock returns show that overconfident investors do take more risks than rational traders (for an extensive overview, see Glaser et al. (2004)).

Recently, researchers have also tried to analyze the link between preferences or beliefs and risk taking behavior from a descriptive point of view. Various empirical studies, both in the field and in an experimental environment (see e.g. Kapteyn and Teppa (2002) and Fellner and Maciejovsky (2007)) document mixed results with respect to the relationship between preferences and risk taking. Whereas some studies find a weak link between elicited risk attitudes and risk taking behavior others cannot find any significant relationship between these two constructs. In a similar manner empirical studies explicitly analyzing the link between overconfidence and risk taking cannot find clear-cut evidence that overconfident investors actually do take more risks (see e.g. Dorn and Huberman (2005) and Menkhoff et al. (2006)). These studies seem to indicate that there is some sort of domain specificity, i.e. the strength of the relationship depends at least partly on the domain in which risk attitudes and beliefs are measured. Another interesting finding regarding beliefs in the experimental literature is that individuals seem to be both overly optimistic about future outcomes and prone to the overconfidence bias (see e.g. Lichtenstein et al. (1982)) and that these biases can lead to distortions in risk taking behavior. In addition, researchers in psychology and finance argue that perceptions of risks are a third important determinant of choice behavior (see Weber and Milliman (1997) and Pennings and Wansink (2004)). Hence, the way investors subjectively perceive the risk of an investment seems to be able to predict their actions. The determinants of risk taking behavior from a descriptive point of view are illustrated in figure 1. Dotted lines in this figure indicate that the findings on the relationship between risk taking and the corresponding determinant are ambiguous and depend to some extent on the measurement method used.

Insert figure 1 here

Our study offers an experimental analysis of portfolio choices, i.e. risk taking behavior of individual investors. We try to identify determinants actually driving the risk taking behavior of individuals and to examine whether the domain in which these determinants are elicited influences our findings. Moreover, we analyze interactions among determinants of risk taking behavior. To accomplish this we have to elicit risk attitudes, risk perceptions and beliefs in several domains by using various methods. This can be only done in an experimental or questionnaire setup. Therefore, we conducted a questionnaire study that allows us to assess the respective variables using not only lottery questions and portfolio choice questions but also psychometric approaches. Using a questionnaire offers the advantage that we can directly measure determinants instead of using crude and questionable proxies for risk attitude and overconfidence such as age or gender. We believe that our study contributes to still a small number of existing empirical studies on determinants of risk taking behavior. In contrast to other studies, we analyze the effects of various determinants, on portfolio choice in one single study, using different methods of measurement.

Our main findings can be summarized as follows. Consistent with the descriptive literature on risk taking we find that portfolio choices, i.e. risk taking behavior can be predicted by individual risk attitudes, subjective perceptions of risk as well as beliefs such as optimism and confidence. We are able to show that less risk averse individuals and subjects that perceive the risk as higher take more risks. The same result holds for overly optimistic and overconfident subjects. However, the domain in which these variables are elicited is important. We find that risk attitude and risk perception elicited in an artificial lottery context are not related to portfolio choices. The same is true for overconfidence in a general knowledge context. On the contrary we find evidence that eliciting risk attitudes, risk perception and both belief measures in an investment related context allows us to predict portfolio choices of individuals. Hence, our results imply a domain specificity in all determinants of risk taking and thereby supplement the findings by Weber et al. (2002). The domain specificity result could explain why previous empirical studies on overconfidence and risk taking could not find the proposed relationship. Furthermore, we analyze the interaction between respective determinants and offer evidence for domain specificity. Risk perception in the stock domain is related to overconfidence measures in the financial domain but not to risk attitude and risk perception in the lottery domain. We believe that with respect to the implementation of the MiFID, investment firms can heavily benefit by incorporating some of our findings into their risk tolerance estimation methods.

The remainder of the paper is organized as follows. In section 2 we present an overview of the theoretical and empirical literature. Section 3 describes the design of the study and illustrates descriptive results. Section 4 contains the main results of the study, and section 5 provides a short summary and a conclusion.

2 Related Literature

In this section we examine the existing literature analyzing the link between risk attitude, risk perception, beliefs and risk taking i.e. portfolio choice more comprehensively.

Risk attitudes are argued to play a crucial role in determining the risk taking behavior of investors. Standard finance literature assumes that risk attitudes determine the ratio of risk free assets to risky market portfolio in an investor's portfolio. According to expected utility theory different methods of eliciting risk attitudes should produce the same results and indicate risk taking behavior, i.e. portfolio composition. Hence, to predict investors' risk taking behavior should not depend on the way their risk attitudes are elicited. In contrast to this MacCrimmon and Wehrung (1990) and Güth et al. (1997) show that different elicitation methods need not yield identical risk attitudes. This finding may be one reason why many empirical studies cannot confirm the theoretical proposition that risk attitudes should predict risk taking behavior. Amongst others, Fellner and Maciejovsky (2007) report that the explanatory power of risk attitudes depends on the way these risk attitudes are elicited. Kapteyn and Teppa (2002) and Klos and Weber (2003) provide evidence that intuitive subjective measures of risk seem to be better predictors of portfolio choice than more sophisticated methods such as lottery questions. Thus, our hypothesis that more risk averse individuals are going to take less risky portfolio choices should be validated more vigorously for risk attitudes elicited in a financial decision making context.

There is a growing number of studies arguing that not only risk attitudes but also the way that individuals subjectively perceive the risk of a risky investment such as stocks might impact the risk taking behavior of individuals. Sitkin and Pablo (1992) and Sitkin and

Weingart (1995) are indicative of theoretical studies arguing that both risk attitudes (risk propensities) and risk perceptions have an impact on risk taking. Experimental studies analyzing this link find that risk perception indeed plays a major role in determining individuals' investment behavior (see e.g. Weber and Milliman (1997) and Weber and Hsee (1998b)). However, Weber et al. (2002) show that the domain is essential, in which risk perceptions are elicited. Hence, our hypothesis that individuals who perceive the risk of an investment to be low will take on more risks should be validated more strongly if risk perception and risk taking are elicited in the same domain.

We argue that beliefs like confidence or optimism impact investors' risk taking decisions and that excessively optimistic and accordingly overconfident investors are ceteris paribus going to take more risks. Whereas the link between overoptimism and risk taking is straightforward (see e.g. Coval and Thakor (2005)) the relationship between overconfidence and risk taking is not as straightforward. Therefore, we will illustrate this in the following section in a more detailed manner.

Many psychological studies show that individual decision makers are prone to the so-called overconfidence bias. Within psychological literature, overconfidence can manifest itself in various forms such as illusion of control (Langer (1975)), the better than average effect (Svenson (1981)) and miscalibration (Lichtenstein et al. (1982)). In finance literature the concept of overconfidence was adopted by researchers in the early 1990's (see e.g. DeLong et al. (1991) and Kyle and Wang (1997)). Most theoretical models in finance use miscalibration as a synonym for overconfidence and model overconfidence as the tendency of individuals to underestimate the volatility of stock prices, and to assign too tight confidence intervals for stock price forecasts (see Benos (1998), Odean (1998), Wang (1998), Daniel et al. (2001), Gervais and Odean (2001), Hirshleifer and Luo (2001), Wang (2001), Caballé and Sákovics (2003) and Peng and Xiong (2006)). Although there are considerable differences in the setup of these models, (e.g. risk averse vs. risk neutral market makers and static vs. dynamic modelling environment) they are all based on the assumption that overconfident investors overestimate the precision of a signal $\tilde{s} = \tilde{v} + c \cdot \tilde{e}$ for a risky asset v with realizations $\tilde{v} \sim N(0, \sigma_{\tilde{v}}^2)$. The variable c is an indicator for the level of overconfidence where $c = 1$ indicates that a person is perfectly rational, whereas $c = 0$ indicates that a person is highly overconfident and takes his private signal for granted.

This way of modelling allows us to calculate the conditional mean and variance estimates for each investor i given a signal s:

$$E_i[\tilde{v} \mid \tilde{s} = s] = E_i[\tilde{v}] + \frac{Cov_i[\tilde{v}, \tilde{s}]}{Var_i(\tilde{s})} \cdot (s - E_i[\tilde{s}]) = \frac{\sigma_v^2}{\sigma_v^2 + c_i^2 \cdot \sigma_e^2} \cdot s, \tag{1}$$

and

$$Var_i[\tilde{v} \mid \tilde{s} = s] = [\frac{1}{Var_i(\tilde{v})} + \frac{1}{Var_i(c_i \cdot \tilde{e})}]^{-1} = [\frac{1}{\sigma_v^2} + \frac{1}{c_i^2 \cdot \sigma_e^2}]^{-1} = \frac{\sigma_v^2 \cdot \sigma_e^2 \cdot c_i^2}{\sigma_v^2 + c_i^2 \cdot \sigma_e^2}. \tag{2}$$

From Equation 2 it is straightforward that overconfident investors ($c < 1$) underestimate the variance of the risky asset conditional on the observed signal:

$$\frac{\partial Var_i[\tilde{v} \mid \tilde{s} = s]}{\partial c_i} > 0. \tag{3}$$

Assuming normality and investors maximizing their exponential utility function $U(w_i) = -e^{-\gamma_i \cdot \tilde{w}_i}$ with risk aversion coefficient γ_i and overall wealth $\tilde{w}_i$ implies that investors are in a mean-variance framework (cf. Hirshleifer and Luo (2001)). Hence, they maximize their expected utility $E_i[\tilde{w}_i \mid \tilde{s} = s] - \frac{\gamma_i}{2} \cdot Var_i[\tilde{w}_i \mid \tilde{s} = s]$ subject to their budget constraint $\tilde{w}_i = w + d_i \cdot (\tilde{v} - p)$, i.e. given the constraint that overall wealth equals initial wealth plus gains from trade. Taking the first order condition it is possible to calculate investor *i's* demand function d_i for the risky asset:

$$d_i = \frac{E_i[\tilde{v} \mid \tilde{s} = s] - p}{\gamma_i \cdot Var_i[\tilde{v} \mid \tilde{s} = s]} = \frac{\frac{\sigma_v^2}{\sigma_v^2 + c_i^2 \cdot \sigma_e^2} \cdot s - p}{\gamma_i \cdot \frac{\sigma_v^2 \cdot \sigma_e^2 \cdot c_i^2}{\sigma_v^2 + c_i^2 \cdot \sigma_e^2}}. \tag{4}$$

Equations 1 and 2 imply that overconfident investors have more extreme and in absolute values higher conditional expectation estimates and a lower conditional variance. Therefore, we can easily see in Equation 4 that this results in overconfident traders taking larger long or short positions in the risky asset. For example, overconfident investors take more risk than rational investors. Since all finance studies model overconfidence in a similar framework, they all predict that overconfident investors take more risks, because they perceive the riskiness (=volatility) of the asset given a certain signal to be lower than rational investors.[1]

However, theoretical predictions and empirical findings need not coincide as results of the very few empirical studies in this area show. Dorn and Huberman (2005) and Glaser and Weber (2007) combine questionnaire data with actual portfolio holdings of online broker customers and find that overconfidence elicited within the questionnaire study is not related to actual portfolio choice. In addition, Sautner and Weber (2006 and 2007) analyze in two studies the exercise behavior of managers in executive stock options programs. Both studies combine questionnaire data with real transaction data. Again, both studies cannot find the aforementioned relationship between overconfidence, risk attitude and risk taking. In a pure survey study Menkhoff et al. (2006) analyze the relationship of risk taking and overconfidence among German fund managers. They do not find any significant effects between the two distinct concepts either. Simon et al. (1999) is indicative of a study in another field of economics analyzing the effect of overconfidence on the decision to start a venture. The authors distinguish between overconfidence (miscalibration) and some sort of illusion of control, and they observe mixed results. On the one hand, illusion of control seems to be related to risk taking. On the other hand, overconfidence in terms of miscalibration (as modelled in most theoretical studies) seems to be unrelated to risk taking entirely. Lin (2005) and Barber and Odean (2001) are two studies that do not measure overconfidence directly but proxy for it by using gender or prior outcomes as proxy variables. Whereas Lin (2005) is not able to confirm the hypothesis that more overconfident traders invest in more risky assets, Barber and Odean (2001) are the only researchers we are aware of who find support for the proposed effect in an empirical study by proxying for overconfidence with gender. They find that women, who are generally assumed to be less overconfident take less risks than men.

Overall, table 1 summarizes the main findings in the literature on overconfidence and risk

[1] The relationship between risk taking and overconfidence is also present in other fields of economics. Kahneman and Lovallo (1993), Kahneman and Riepe (1998), Simon et al. (1999) and Bernardo and Welch (2001) are indicative of studies in related fields arguing that overconfidence is related to risk taking.

taking. Theoretical studies predict that higher levels of overconfidence can be associated with higher levels of risk taking whereas empirical studies are mainly not able to detect the proposed relationship. A possible explanation for these differing results could be that most empirical studies do not measure risk taking and overconfidence in the same domain. Thus, we hypothesize that the more (over)confident an individual is in the financial domain, the more risky investments he is going to choose.

Insert table 1 here

In addition, there is inconclusive evidence that besides beliefs, risk attitudes and risk perceptions, other variables such as gender (see e.g. Schubert et al. (1999) and Eckel and Grossman (forthcoming)), age, experience or knowledge (see for example Barsky et al. (1997) and Donkers et al. (2001)) might influence risk taking behavior of individuals. To account for this, we will control for these factors in our analysis.

Altogether, the main objectives of our study are (i) to investigate the determinants influencing the risk taking behavior of investors, (ii) to evaluate whether our results are domain specific and (iii) to analyze how various determinants of risk taking behavior are related to each other. In line with the existing literature, we predict that both risk perception and risk attitude will influence risk taking behavior. Moreover, we assume that consistent with various models on overconfidence more overconfident, i.e. more miscalibrated investors are going to take more risks. We also hypothesize that the same argument will hold for optimism: the more optimistic an investor is, the more risks he will take. However, we argue that all proposed relationships will only hold if the respective determinant is also elicited in a financial or investment related context.

3 Design and Descriptives

3.1 Questionnaire

In this section, we present a detailed overview of the variables and measures employed throughout our analysis. 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. In part 1 we measured risk perception and risk attitude both in a lottery context and in a general context. The second part of the questionnaire was used to elicit various overconfidence scores in a broader context. In part 3 subjects were shown 5 stock price charts, displaying the stock price development over the last 5 years. This part was designed to measure both beliefs (overconfidence and optimism), risk perception of the subjects about each of the price charts and the resulting portfolio choice. Part 4 was used to measure investment experience, knowledge and various demographic variables. Table 2 summarizes and defines all variables used in the study and presents the method used to measure the respective variable.

Insert table 2 here

In part 1 we used a binary lottery that paid 10,000 Euro with probability 1/2 and 0 Euro otherwise to elicit risk perception and risk attitude in a lottery context. *Risk Perception (Lottery)* 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 the common procedure in the literature (see for example Weber and Hsee (1998a) and Pennings and Wansink (2004)). We elicited *Risk Attitude (Lottery)* with the certainty equivalence method by repeatedly asking subjects whether they prefer a sure payment of x or the lottery, with x ranging from 1000 to 9000. The last question in part 1 (*Subjective Risk Attitude*) asked participants to rate their willingness to take financial risks on a scale from 1 to 5 with the endpoints "1 = very low willingness" and "5 = high willingness". This easy and quick classification method is quite common in investment advice.

In the second part of the questionnaire, participants first had to state 90% confidence intervals to 10 general knowledge questions, such as "How long is Tower Bridge in London". 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 answers less than 9 questions correctly, i.e. the lower the *Miscalibration (General Knowledge)* score, the more overconfident the subject is. 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 respectively the average participant correctly answered for the general knowledge task. The relating variable *Better Than Average (General Knowledge)* is calculated as the margin between these two answers and takes positive values for subjects that think they have answered more questions correct 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 statement: "I am able to identify stocks that will beat the market", "My stock forecasts are always correct" and "Losses and gains in stock markets are just a matter of chance". To get an overall illusion of control score we aggregated the answers to the three questions, standardized them and calculated an illusion of control score ranging between 0 and 1. Subjects prone to the illusion of control bias, have scores close to 1.

In part 3, subjects were shown charts illustrating the stock price development of the following 5 DAX companies over the course of the last five years: DaimlerChrysler, Infineon Technologies, Continental, Münchener Rück and Adidas. To construct the 5 stock charts we used daily closing prices for the time period November 2001 to November 2006 obtained from Thomson Financial Datastream. The stock charts were constructed with great care to avoid any undesirable effects. Similar to Glaser et al. (2007) we included firms with stable, upward and downward stock price trends. Furthermore, we standardized the limits and the area in which the stock graphs were displayed according to the method proposed by Lawrence and O'Connor (1993). Figure 2 illustrates the stock price chart of Adidas which was shown to subjects in the depicted way.

Insert figure 2 here

For each of the 5 stocks we elicited the following variables:

- *Risk Perception (Stocks)*
- *Risk Taking (Stocks)*

- *Miscalibration (Stocks)*
- *Optimism (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 Euros between the particular stock and a risk free asset that yields a yearly return of 3%, assuming an investment horizon of 1 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).

To measure the degree of miscalibration and optimism in the stock domain we asked individuals to state a median stock price forecast as well as upper and lower bounds for 90% confidence intervals for the stock price in 1 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 1 year will be below the lower bound and a 5% chance that it will be higher than the upper bound. We transformed all 3 stock price estimates for each subject and for all 5 stock charts into return estimates.[2] The median return estimate allows us to calculate a measure of optimism concerning each stock. The corresponding variable *Optimism (Stocks)* is therefore simply the median return estimate for each stock. Using the median forecast and both the upper and the lower bound allows us to get a measure of miscalibration in the stock domain by using the methodology suggested in Keefer and Bodily (1983). This method transforms stated confidence intervals into volatility estimates[3] and has been widely used in the empirical literature (e.g. Graham and Harvey

[2]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: $\mathrm{r(s)}_i^j = \ln(\frac{\mathrm{p(s)}_i^j}{\overline{value_i}})$, with $\overline{value_i}$ indicating the price of stock i in November 2006.

[3]Keefer and Bodily (1983) propose that an extended Pearson-Turkey approximation is a widely applicable approximation for continuous probability distributions if one has information on the upper bound r(0.95), the lower bound r(0.05) and the median r(0.5). Since we collected exactly these three point estimates for every stock, we can use their proposed method to recover each respondents' probability distribution for each stock i by using the following formula: $\mathrm{Volatility}_i = \sqrt{[0.185 * \mathrm{r}(0.05)_i^2 + 0.63 * \mathrm{r}(0.5)_i^2 + 0.185 * \mathrm{r}(0.95)_i^2] - [0.63 * \mathrm{r}(0.5)_i + 0.185 * \mathrm{r}(0.05)_i + 0.185 * \mathrm{r}(0.95)_i]^2}$. To get an easily interpretable and standardized measure of miscalibration in the stock domain, we divided the estimated 1 year volatility by the historical volatility to get our overconfidence measure: $\mathrm{Miscalibration} = \frac{\text{Estimated volatility}}{\text{Historical volatility}}$. This yields

(2005), Ben-David (2006) and Glaser et al. (2007)). This *Miscalibration (Stocks)* measures an individual's miscalibration of his volatility forecast for each stock and is easily interpretable. A score of 1 indicates that an individual is well-calibrated whereas a score of less than 1 indicates that an individual sets too tight intervals, i.e. is overconfident. Hence, lower values of *Miscalibration (Stocks)* indicate higher levels of overconfidence. Furthermore, we also asked individuals to assess their own performance and the performance of the average subject respectively. 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.

Within part 4 we elicited demographic variables, knowledge and investment experience. Demographics include age, gender, field of study and terms studied. We proxied for investment experience by asking the subjects to indicate the number of investment products they have owned within the last year. In the end, we measured both financial and statistical knowledge using simple self-assessment questions. Subjects had to indicate their knowledge in each field on a scale from 1 to 5, with 1 indicating very good knowledge and 5 indicating bad knowledge in the respective field.

3.2 Descriptive Statistics

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

a miscalibration measure which is close to 0 for excessively overconfident subjects and equal to 1 for perfectly calibrated subjects. We calculated 1 year volatilities for each stock by using daily returns for the last 5 years, exactly the same time period subjects were given in the questionnaire. To check for robustness, we computed historical 1 year volatility using non overlapping monthly and quarterly returns. The results are essentially the same and since the division is only a standardization we will in the following only report results with respect to 1 year volatilities on the basis of daily returns.

prices we chose to pay out fixed amounts to avoid strategic behavior.[4]

The mean and median scores for all demographic and risk variables are presented in table 3. The average age of the participants is 24 years, with 32% of the respondents being female. Approximately 90% of the students in our sample study business administration or economics and are within their fourth year on average (6.8 semesters studied). Over 44% of all respondents have not held stocks or any other assets within the last year and only 8% have held more than 10 investment products over the course of the last year. The self-reported statistical knowledge score is approximately 2.7 and the one for financial knowledge is 3.3 indicating that students were slightly more confident in their statistical knowledge. Table 3 further documents that participants stated an average subjective risk attitude of 2.6 on a scale from 1 to 5. The risk of participating in a two outcome lottery was perceived as higher (7.1) than the average risk for all 5 stocks (5.4). Moreover, the table shows that subjects invest on average 43.6% of their funds into the risky asset.

Insert table 3 here

With regards to the different overconfidence measures we have elicited, we do find substantial degrees of overconfidence among subjects for most of our measures. However, the degree of overconfidence varies substantially, being relatively low for better than average questions and being substantially high for miscalibration. Summary statistics on the different degrees of overconfidence can be found in table 4. For our 10 general knowledge questions, we asked subjects to submit bounds that they are 90% sure that the true answer is going to be within these bounds. Hence, properly calibrated subjects should answer 9 out of 10 questions correctly whereas miscalibrated, i.e. overconfident subjects will tend to give wide enough confidence intervals on less than 9 questions. We can observe that the average subject is well calibrated on less than 6 questions, which indicates a substantial level of miscalibration. A Wilcoxon matched-pairs signed-ranks test shows that subjects are significantly miscalibrated (p-value < 0.0001). A similar picture arises when we look at miscalibration in the stock domain. For each stock, by comparing the implicit estimated

[4] 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.

volatilities with historical volatilities, we can calculate whether a subject is miscalibrated for the respective stock. Miscalibrated subjects will fail to indicate wide enough intervals for at least one or even more stocks. The miscalibration score in table 4 takes the value 5 if the person has stated wide enough confidence intervals for each stock question. The lower the score, the more often subjects stated confidence intervals which are too narrow. The mean score of 1.8 indicates that there is substantial miscalibration in the stock domain (p-value < 0.0001). Table 4 also indicates that we find substantial levels of illusion of control in our sample. Regarding the better than average effect, the findings are not as clear-cut. We find a significant positive effect in the general knowledge domain indicating a better than average effect yet no significant effect in the stock domain. However, the better than average effects in both domains have a median score of 0 and are on average very close to 0 and hence of very low economic significance.

Insert table 4 here

4 Results

4.1 The Relationship between Determinants of Risk Taking Behavior

This section investigates the extent to which various determinants of risk taking behavior are related with one another. More specifically, we evaluate the bivariate interactions between risk attitudes, risk perceptions, optimism and overconfidence. To get single scores of risk perception, optimism and overconfidence in the stock domain we have to aggregate these variables for each subject over all 5 stocks. We make use of three aggregation methods: firstly we take the mean over all 5 questions, secondly we take the median over all 5 questions and thirdly we use a dummy variables method for the belief measures. This dummy method assigns in each case a value of 1 to individuals who are overoptimistic or overconfident and a value of 0 otherwise. Since all three measures essentially yield the same results, subsequently we will only report the results for the aggregation rule using the mean score.[5] These results using Spearman's rank correlation coefficients

[5]The three scores using the mean as an aggregation rule are calculated the following way. 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)

are illustrated in table 5.

Insert table 5 here

We show that all risk attitude and risk perception variables elicited in the first part (1-3) of the questionnaire are significantly correlated. The higher an individual perceives the risk, the more risk averse he is. However, with respect to risk perception (4) in the stock domain this clear-cut pattern disappears. Neither subjective risk attitude nor risk perception and risk attitude in the lottery domain are related to risk perception in the stock domain. The results supplement findings by Weber et al. 2002 who show that risk perceptions and risk attitudes are domain specific.

To evaluate the question whether our belief measures are related to either risk perceptions or risk attitudes we calculate spearman's rank correlation coefficients again (see table 5). As measures of overconfidence we take only methods for which we can find statistical and economic significance. Hence we exclude *Better Than Average (General Knowledge)* and *Better Than Average (Stocks)* from our bivariate analysis (see table 4). Our findings indicate that more optimistic individuals (8), i.e. individuals that have higher return expectations, are not less risk averse and do not perceive risks as lower. Table 4 documents that none of our risk measures is related to miscalibration in a general knowledge context (5). However, for miscalibration in the stock domain (6) we find that individuals who perceive the risk of an investment in stocks as higher will be less miscalibrated. For our illusion of control score in the finance context we find that subjective financial risk attitudes, risk perception in the stock domain and risk attitude in the lottery domain are related to illusion of control. *Risk Perception (Lottery)* is not correlated with any of our overconfidence measures. Overall, our results are consistent with our main prediction that more overconfident individuals will show the tendency to (i) be less risk averse and (ii) perceive the risks of an investment as lower. In addition, our results seem to confirm our hypothesis regarding domain specificity at least to some extent since most of the significant correlations are found between risk and overconfidence variables from the investment domain.

$= [\sum_{i=1}^{5} \text{Optimism}_i]/5.$

4.2 Factors Influencing Risk Taking Behavior

Both investment advisors and researchers are eager to learn more about factors that allow them to predict risk taking behavior of investors from a descriptive point of view. We have illustrated that there are many variables that are believed to have an influence on risk taking behavior of investors. However, it is unclear which variables actually influence risk taking behavior, and more specifically to what degree. Hence, the main objective of the following section is to investigate factors that influence risk taking behavior of investors, i.e. portfolio choices. To do this, we will regress individuals' risk taking behavior for each stock on a wide range of variables. However, it is possible that risk taking behavior and overconfidence scores between the 5 stocks may be correlated within individuals. Thus, 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 clustering our observations over subjects and analyzing the relationship between risk and overconfidence using clustered ordinary least squares regressions. Clustering the data over subjects allows us to examine the individual effects on risk taking for all stocks.

Investment advisors mostly use simple subjective risk attitudes to measure their customers preferences. Measures of their customers' beliefs and risk perceptions are not common in practice. Hence, we first evaluate whether this simple measure of eliciting risk attitudes can help investment advisors to predict their customers risk taking behavior (see column 1 in table 6). Our simple clustered OLS regression with subjective risk attitudes as the only explanatory variable generates a highly significant positive coefficient indicating that less risk averse individuals are going to invest more heavily into the risky stock. In a similar manner MacCrimmon and Wehrung (1986) show that subjective self-ratings of managers are related to their risk taking behavior. However, the adjusted R^2 of our regression is 0.111 and suggests that the simple model does not fit the data exceptionally well.

Insert table 6 here

In part 2 we argued that there are other determinants of risk taking behavior besides risk attitude, and that these determinants should show some sort of domain specificity. To assess the validity of these arguments we include in our second regression in table 6 all investment related determinants of risk taking behavior. We find that subjective financial risk attitudes, risk perception, optimism and miscalibration in the stock domain have a significant effect on portfolio choices. The less risk averse an individual is, and the less he perceives risk, the higher is the amount invested into the risky stock. In addition, we find that more optimistic individuals tend to buy a larger amount of risky stocks. The negative coefficient (-7.684) for *Miscalibration (Stocks)* indicates that a perfectly calibrated subject (overconfidence-score = 1) invests exactly 768.4 Euro less into the risky asset than a completely overconfident subject (overconfidence-score = 0). With respect to illusion of control in a finance related context, we cannot find a significant effect in our data. However, this is consistent with the evidence in Dorn and Huberman (2005) and Glaser and Weber (2007) who use a similar measure and also cannot find a significant effect. Overall, the goodness of fit of this extended model more than doubles in comparison to the first model with an adjusted R^2 value of 0.246.

To analyze whether past portfolio returns, demographics and belief and preference measures not related to the financial domain influence our level of risk taking, we conduct the third and fourth regression in table 6. In the third regression we add historical stock return and historical stock volatility as well as all remaining overconfidence measures and risk perception and risk attitude in the lottery context to our regression. Adding historical risk and return measures allows us to analyze if objective, subjective or both kinds of risk and return measures drive risk taking decisions of subjects. Column 4 in table 6 shows that the risk taking decision is driven by both subjective and objective measures of risk. The previously included risk related variables (*Subjective Risk Attitude, Risk Perception (Stocks) and Miscalibration (Stocks)*) remain significant and the newly added variable *Stock Volatility (historical)* has a highly significant negative coefficient indicating that subjects tend to invest less into stocks that have been more volatile in the past. With respect to objective and subjective return measures we find that subjective return expectations (*Optimism (Stocks)*) can explain risk taking behavior whereas historical stock returns are not able to do so. In the same regression we also include risk attitude and risk perception in an artificial lottery context and overconfidence measures that are not related to the investment domain to analyze if these factors influence risk taking behavior of subjects. We cannot find a significant effect on risk taking which strengthens our hypothesis that there exists a domain specificity for all determinants of risk taking behavior.

Furthermore, in section 2 we have presented various studies arguing that risk taking behavior is influenced by demographic variables, knowledge or experience. To analyze these points we run an additional regression where we control for these effects (see column 4 in table 6). In line with Schubert et al. (1999) we find no significant gender effect in our data. For example, controlling for risk attitudes, risk perception and beliefs we find that women do not take significantly less risk in their portfolio choices than men. In contrast to large scale survey studies analyzing the whole population (see Donkers et al. (2001)), we cannot find a significant effect of age and the number of terms studied in our data on risk taking. The coefficients of *Statistical Knowledge* and *Financial Knowledge* are highly insignificant indicating that subjective assessments of knowledge do not influence risk taking. Moreover, we cannot find that subjects that have invested into stocks (*Investment Experience*) and are more familiar with these kind of investments are going to take more risks. Given the homogeneity of our sample with students being of approximately the same age and having similar levels of experience and knowledge these results seem not too surprising. Interestingly, the inclusion of these control variables does not alter our previous results with regard to risk preferences and beliefs. In addition, the inclusion of these additional variables did not dramatically increase the goodness of fit for our model with adjusted R^2 in the range of our second regression. To test whether multicollinearity might cause problems in our analyses, we conduct a variance inflation factor test. However, all variance inflation factor scores are way below the critical threshold of 2.5, indicating a low degree of multicollinearity, if any.

5 Conclusions

The main goal of this study was to analyze determinants of risk taking behavior of investors. We present evidence that risk attitudes, risk perceptions and beliefs are three important determinants of risk taking. However, we show that the way or more specifically the domain in which all of these variables are elicited is crucial in determining whether the variable can predict risk taking behavior or not. Our domain specificity result for all determinants of risk taking adds to the results of Weber et al. (2002). In line with our domain specificity result we find that simple subjective financial risk attitudes and risk perception in the stock domain are able to predict risk taking behavior whereas risk perception and risk attitude elicited in the lottery domain are not able to do so. Our results also indicate that subjects who are more optimistic about future stock price developments tend to make more risky investment decisions. Furthermore, our results are able to confirm the prediction made in all theoretical models on overconfidence. More overconfident subjects are going to invest a higher amount of their wealth into risky assets. However, this result again depends on the way and the domain in which we elicit overconfidence. Whereas we document highly insignificant effects for overconfidence measures not related to the finance domain, we find significant effects for finance related overconfidence measures.

We think that our results have implications for both researchers and practitioners. For practitioners it is certainly interesting to know that not only simple subjective risk attitudes but also risk perception and belief measures are able to predict risk taking behavior of investors. In particular, the implementation of the MiFID will urge financial institutions to know more about the risk profile of their customers and the way these customers make decisions. To be in line with these still very vague regulations, practitioners should take into account that the predictive power of a regression with risk taking as the dependent variable is more than twice as high if they would include finance related risk perception and beliefs. Since our measures of eliciting these measures are pretty simple and straightforward, some of them could certainly be utilized in practice. But what type of questions should financial institutions ask investors to elicit their risk attitude, risk perception and beliefs? In our view, it is important for practitioners to understand that only eliciting risk attitudes, risk perceptions or belief measures in a financial context is useful for predicting investors' risk taking behavior. However, the exact wording of these questions relating to the risk taking behavior of investors requires further and thorough analysis in future studies.

For researchers it is certainly interesting to analyze which factors different from risk attitude, risk perception and beliefs in the finance domain drive the risk taking behavior of investors. In our view, risk taking behavior could be influenced by events such as obtaining a university degree or having children or by investors' financial literacy level. Future research should study this issue in more detail. We think that research could also contribute to the implementation of regulations such as the MiFID by suggesting guidelines about how financial institutions should measure the various determinants of the risk taking process. For example, it could be interesting to develop new and reliable techniques for eliciting risk preferences in the financial domain. Furthermore, it might also be interesting to analyze how loss aversion in a finance related context affects risk taking behavior of investors.

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Table 1: Studies on the relationship between overconfidence and risk

This table reports theoretical and empirical studies analyzing the relationship between overconfidence and risk taking behavior. Relationship between risk and overconfidence indicates that the study predicts/finds that more overconfident subjects tend to take more risk. No relationship indicates that the study does not predict/find unambiguous support for the prediction that more overconfident subjects do take more risks. OC describes how overconfidence is modelled and respectively measured in the particular study. The following abbreviation are used: BTA stands for Better Than Average Effect, Misc for Miscalibration and IC for Illusion of Control.

	Theoretical Studies	OC	Empirical Studies	OC
Relationship between risk and overconfidence	De Long et al.(1991)	Misc		
	Kahneman and Lovallo (1993)	IC		
	Benos (1998)	Misc		
	Kahneman and Riepe (1998)	Misc		
	Odean (1998)	Misc		
	Wang (1998)	Misc		
	Simon et al. (1999)	Misc/IC		
	Bernardo and Welch (2001)	Misc		
	Daniel et al. (2001)	Misc		
	Gervais and Odean (2001)	Misc/IC		
	Hirshleifer and Luo (2001)	Misc		
	Wang (2001)	Misc		
	Caballé and Sákovics (2003)	Misc		
	Dubra (2004)	Misc	Barber and Odean (2001)	Gender as proxy for OC
	Peng and Xiong (2006)	Misc		
No Relationship between risk and overconfidence			Simon et al. (1999)	Misc/IC
			Lin (2005)	Prior outcomes as proxy for OC
			Dorn and Huberman (2005)	BTA/IC
			Menkhoff et al. (2006)	BTA/IC/Misc
			Sautner and Weber (2006)	Misc
			Glaser and Weber (2007)	BTA/IC/Misc
			Sautner and Weber (2007)	Misc

Table 2: 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 Perception (Lottery)	Scale (0-10)	Measures an individual's subjective risk perception for a lottery with the endpoints "0 = no risk at all" and "10 = very high risk".
Risk Attitude (Lottery)	Certainty Equivalent	Measures an individual's risk attitude in the lottery domain by eliciting the certainty equivalent for a stock. A higher certainty equivalent indicates a lower level of risk aversion.
Subjective Risk Attitude	Scale (1-5)	Measures an individual's subjective risk attitude using the most common elicitation method in investment advice. A score of 1 indicates a high level of risk aversion and a score of 5 a low level.
Part 2		
Miscalibration (General Knowledge)	Confidence Intervals	Measures an individual's degree of miscalibration with respect to 10 questions concerning general knowledge.
Better Than Average (General Knowledge)	Self assessment vs assessment of others	Measures overconfidence based on the comparison between the assessment of one's own performance and the assessment of the performance of the average subject in the general knowledge task.
Illusion of Control	Scale (0-1)	Based on answers to three statements, this variable measures the extent to which an individual thinks he 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 the 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 respectively and is used as a proxy for portfolio choice.
Optimism (Stocks)	Point Estimate	Measures an individual's degree of optimism about future returns of 5 stocks.
Miscalibration (Stocks)	Confidence Intervals	Measures an individual's degree of miscalibration with respect to 5 questions concerning confidence intervals of 5 stocks.
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.
Investment Experience		Reflects the number of investment products an individual has owned within the last year and proxies for investment experience.
Financial Knowledge	Scale (1-5)	Measures self assessed financial knowledge of subjects with the endpoints "1 = very good" and "5 = bad".
Statistical Knowledge	Scale (1-5)	Measures self assessed statistical knowledge of subjects with the endpoints "1 = very good" and "5 = bad".

Table 3: 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	5.317
Semester	6.808	7	1.761
Investment Experience	3.507	3	0.911
Statistical Knowledge (1-5)	2.776	3	0.842
Financial Knowledge (1-5)	3.342	3	1.014
Subjective Risk Attitude (1-5)	2.592	2.5	0.882
Risk Perception (Lottery) (1-10)	7.118	7	1.673
Certainty Equivalent (Lottery) (1000-9000)	4144.737	4000	1207.796
Risk Perception (Stocks) (1-10)	5.426	5.4	1.172
Risk Taking (Stocks) (0-100)	43.639	40	21.449

Table 4: Descriptive Statistics on Various Overconfidence Measures

This table reports descriptive statistics on various overconfidence measures. The Miscalibration General Knowledge score is calculated by adding up the number of questions a subject has answered correctly. A perfectly calibrated subject should have answered 9 questions correctly. Overconfident subjects will have answered less than 9 questions correctly. Both Better than Average Knowledge and Better than Average Stocks indicate whether a subject thinks he has answered more questions correctly than the average subject (score $>$ 0). Miscalibration Stocks shows for how many of the 5 stock price chart questions the subject actually submitted confidence intervals that were wide enough. Lower values of this score point towards higher overconfidence. The Illusion of Control score takes the value 1 if a subject thinks he can manipulate random events and the value 0 if the subject perfectly anticipates that he cannot influence these random events. The last column contains p-values of a Wilcoxon matched-pairs signed-rank test. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Sort of Overconfidence	Mean Score	Median Score	Overconfidence significant (p-values)
Miscalibration General Knowledge (Overconfident if score $<$ 9)	5.868	6	0.0000***
Better than Average Knowledge (Overconfident if score $>$ 0)	0.075	0	0.0026***
Aggregate Miscalibration Stocks (Overconfident if score $<$ 5)	1.829	1	0.0000***
Better than Average Stocks (Overconfident if score $>$ 0)	0.046	0	0.2274
Illusion of Control (Overconfident if score $>$ 0)	0.408	0.417	0.0000***

Table 5: Correlation Coefficients

This table reports spearman rank correlation coefficients between individual overconfidence and risk perception, risk attitude and risk taking in the stock domain, as well as the significance level as indicated by stars. * 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)	(7)	(8)
(1) *Subjective Risk Attitude*	1							
(2) *Risk Perception (Lottery)*	-0.23**	1						
(3) *Risk Attitude (Lottery)*	0.44***	-0.50***	1					
(4) *Mean Risk Perception (Stocks)*	-0.01	0.05	-0.03	1				
(5) *Miscalibration (General Knowledge)*	0.11	0.02	-0.02	0.12	1			
(6) *Mean Miscalibration (Stocks)*	0.04	-0.02	0.13	0.30***	0.27**	1		
(7) *Illusion of Control*	0.43***	0.10	0.23*	-0.20*	0.07	-0.04	1	
(8) *Mean Optimism (Stocks)*	0.15	0.02	0.10	-0.07	0.11	-0.02	0.15	1

Table 6: Regression Results

This table presents regression results between the level of risk taking in stocks and demographics, risk variables, optimism factors and confidence. The regressions are clustered over subjects. As dependent variable we use the degree of risk taking for each subject for each stock. 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 Taking (stocks)	*Risk Taking (stocks)*	*Risk Taking (stocks)*	*Risk Taking (stocks)*
Subjective Risk Attitude	10.087	8.528	9.158	9.259
	(0.000)***	(0.002)***	(0.001)***	(0.003)***
Risk Perception (Stocks)		-3.868	-3.731	-3.259
		(0.000)***	(0.000)***	(0.003)***
Optimism (Stocks)		15.694	26.656	28.239
		(0.074)*	(0.007)***	(0.006)***
Miscalibration (Stocks)		-7.685	-8.162	-9.808
		(0.024)**	(0.013)**	(0.012)**
Illusion of Control		13.113	14.582	15.32
		(0.288)	(0.288)	(0.281)
Stock Return (Historical)			3.36	3.677
			(0.481)	(0.465)
Stock Volatility (Historical)			-58.101	-58.359
			(0.001)***	(0.002)***
Risk Perception (Lottery)			-0.176	-1.103
			(0.895)	(0.461)
Risk Attitude (Lottery)			-0.001	-0.003
			(0.547)	(0.103)
Miscalibration General Knowledge			-0.901	-0.279
			(0.398)	(0.822)
Better than Average Knowledge			9.759	9.731
			(0.454)	(0.507)
Better than Average Stocks			-12.686	-8.862
			(0.313)	(0.57)
Female				-0.27
				(0.966)
Age				0.69
				(0.618)
Semesters				0.044
				(0.98)
Investment Experience				4.417
				(0.242)
Decision Analysis Course				5.553
				(0.304)
Statistical Knowledge				2.972
				(0.369)
Finance Knowledge				2.057
				(0.522)
Constant	17.493	43.605	71.546	42.834
	(0.015)**	(0.000)***	(0.000)***	(0.223)
Observations	380	377	362	352
R-squared	0.113	0.26	0.291	0.283

Figure 1: Determinants of Risk Taking Behavior

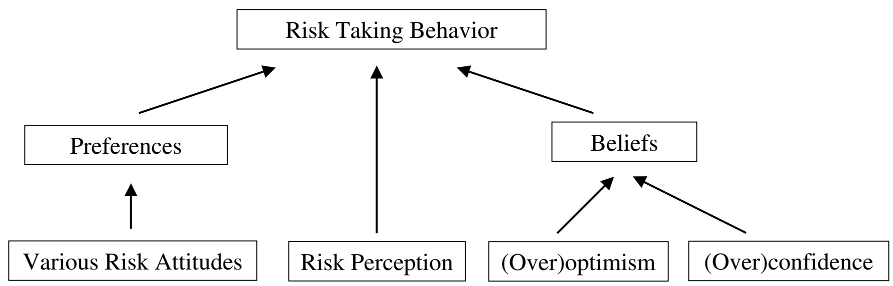

Figure 2: Exemplary Stock Chart