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The Influence of Information Presentation, Psychological Mechanisms, and Personal Characteristics on Households' Financial Decision Making

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Für Mama und Papa

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1 GENERAL INTRODUCTION

1.1 IMPORTANCE OF HOUSEHOLD FINANCE

"Experience is a hard teacher because she gives the test first, the lesson afterwards."

– Vernon Law, U.S. baseball player –

There are some decisions in day to day life in which a lesson will be harder than in others. In financial decision making, regarding for example the decision of how to save for retirement, people often do not have the time for experience – it is a one-shot game. Financial decision making in a broader sense is a task every person has to deal with; the outcome of these decisions has a strong impact on the near future as well as the long term overall life situation and often does not only affect the decision maker himself but also his family, his children and the relatives he is responsible for. Financial decisions are, however, often associated with great complexity, as the decision maker has to deal with risk, ambiguity, complicated contracts and choice overload; this is challenging for financial professionals and even more complicated for the ordinary private household. It is hence an important question for politicians as well as for researchers how to help households with their financial decisions. To improve financial behavior it is, however, necessary in a first step to analyze households' actual behavior as compared to what they should do according to normative theory. This thesis focuses on the analysis and evaluation of investment decisions and risk taking behavior of private households by observing their actual behavior with the intention to explore and explain potential reasons for the discrepancy from normatively optimal behavior.

One reason why actual behavior differs from normative theory when it comes to financial decision making, is the great complexity of information. A potential way to help people would hence be to simplify information. Before financial decision making can be improved, it is, however, important to understand, which underlying factors (e.g., the way information is provided) determine the quality of households' financial decision making. Since the presidential address of John Campbell on Household Finance at the American Finance Association Meeting in 2006, the analysis of households' financial decision making has gained increasing attention. Various financial decisions have been observed, analyzed and explained with the help of demographic, economic, psychological and behavioral factors. This thesis sheds further light on the question which personal and behavioral characteristics explain households' financial behavior and whether there are possibilities to improve financial decision making by varying the way the necessary information is presented.

According to Campbell (2006) *"household finance asks how households use financial instruments to attain their objectives"*. One reason for the increasing interest in this topic is the structural change in society. Due to demographic change, private households can no longer rely exclusively on the public pensions system. According to a study published by the social protection network of the World Bank in 2007, most European countries belong to the group of countries with the highest life expectancy and simultaneously the lowest fertility worldwide. The median age within the EU27 will be 48 in 2050 (Muenz 2007). There are two possibilities to overcome the gap between what one will receive out of the public pensions system and what one is accustomed to (Börsch-Supan 2004): private households need to either save more or to work longer. In many European countries, private savings for retirement are incentivized by the government, mostly through tax deferrals. To benefit from these pension reforms private households need a certain degree of financial knowledge. In a study published by the Deutsche Bundesbank, Le Blanc (2011) analyzes the participation rate in private retirement savings across several European countries; she shows that, among the working population, the participation rate in the private pension systems differs up to 20% between groups with higher and lower education.

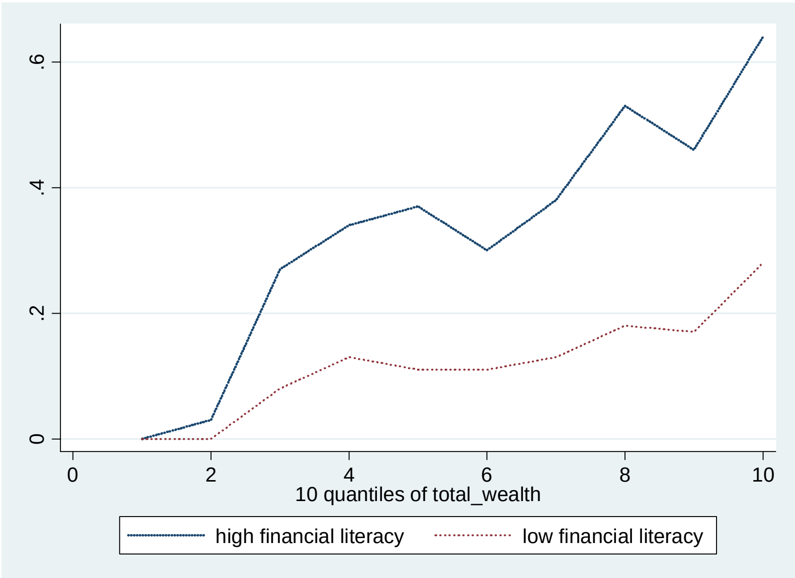
There are factors influencing financial decision making which are difficult to change. Households with a higher income, a lower number of dependent children or a higher level of outstanding credit are, for example, less likely to face financial distress (e.g., McCarthy 2011, Hilgert et al. 2003); households with a higher wealth level are far more likely to participate in the stock market (e.g., van Rooij 2011). There is nevertheless one factor which has been discussed a lot, as it pertains to something one might be able to influence, namely the level of financial literacy. Research has shown that people with high financial literacy diversify more (e.g., Kimball and Shumway 2010, Guiso and Jappelli 2009) and are more likely to invest into the stock market (van Rooij et al. 2011, Calvet et al. 2007). Figure 1-1 displays the stock market participation of German households by financial literacy over financial wealth deciles.[1] The figure shows that stock market participation increases with financial wealth and is higher for people with financial literacy. The causal relationship has been studied in the

[1]Own calculations based on data from the 2009 wave of the SAVE survey; the panel study is conducted by the former Mannheim Institute of Retirement and Aging (MEA); for further information on the panel see Börsch-Supan et al. (2009).

literature and results show that it is indeed a higher degree of financial literacy causing an increase in the probability to participate in the stock market (e.g., van Rooij et al. 2011).

Figure 1-1: Stock Market Participation by Financial Literacy over Financial Wealth Deciles

This figure displays the average stock market participation of households with a high and low amount of financial literacy over deciles of wealth (including real estate). Financial literacy is measured by an index of correct answers to questions adapted from van Rooij (2011). A high amount of financial literacy refers, based on a median split of participants, to 2 or more out of 4 questions answered correctly.
Own calculations based on data from SAVE 2009; N= 2,222.



There is an ongoing discussion among politicians, practitioners as well as researchers how to help people to avoid mistakes and biases and whether to educate people in financial decision making. One idea is to increase the general financial knowledge by financial education programs, e.g., by including a mandatory financial education class at school or by offering a voluntary financial education program at work.

According to the Organisation for Economic Co-operation and Development (OECD) financial education is defined as *"the process by which financial consumers/investors improve their understanding of financial products and concepts, and through information, instruction, and/or objective advice, develop the skills and confidence to become more aware of financial risks and opportunities, to make informed choices, to know where to go for help, and to take other effective actions to improve their financial well-being."* (OECD 2005)

There are several financial education programs provided by a quite diversified group, namely the military and community colleges as well as commercial banks and employers (Braunstein and Welch 2002). The information and lectures provided within those programs have a broad range, from providing an overall course and comprehensive information on credit and savings to being tailored to a specific goal, e.g., mortgage decisions or a target group, e.g., military personnel or youth (Braunstein and Welch 2002). Evidence on the effectiveness of such programs is mixed. Bernheim and Garrett (2003) find, for example, that financial education can improve financial decision making especially with regard to savings behavior among low and moderate savers. In contrast, Cole and Shastry (2009) find a significant influence of financial knowledge itself, but no influence of education programs such as a financial education classes at school. Braunstein and Welch (2002) analyze the effectiveness of different programs and find that some of them, namely those with discrete objectives, can indeed improve certain aspects of decision making, e.g., participation in employers' benefit plans or increasing savings. According to the authors it is nevertheless not quite clear, whether the improved decision making is caused by an increase in financial literacy or other factors like format and timing of the program or reducing participants' aversion to change. The real impact of financial education programs is discussed controversially in research and needs to be investigated further. Nevertheless, before discussing how to improve financial decision making, it is important to know, which biases and failures have been observed so far.

In this thesis, different financial decisions are analyzed – from whether households are able to manage their income to how they decide about their risk taking in investment decisions. It is shown how the quality (further explained in 1.3) of these decisions is determined by the decision context (framing) as well as demographical (e.g., income, age, gender), personal (e.g., risk attitude, financial literacy) and behavioral (e.g., self control, propensity to plan) characteristics. To analyze and evaluate financial behavior of households it is important to know what they *should* decide on versus how they *do* decide. Therefore, the next section gives an overview of the differences between research on the "should", namely traditional finance, and research on the "do", namely behavioral finance.

1.2 TRADITIONAL FINANCE VERSUS BEHAVIORAL FINANCE

The literature distinguishes between the behavioral and traditional approaches in research in various domains and fields. Positive household finance (Campbell 2006), or behavioral finance, describes what households actually do in contrast to what they should do as suggested by classical or traditional finance theory. Bloomfield (2010) simplifies the differences and similarities between traditional and behavioral finance by classifying the two research fields by the institution (topic of the study), the method (economic modeling, econometric modeling and experimental analysis) and the theory (e.g., theories from economics like the theory of efficient markets or theories from psychology like behavioral theories of cognition or affect). According to the author, the main differences between the two research approaches are their "theoretical underpinnings" (Bloomfield 2010). Traditional finance usually does rarely include psychological elements whereas behavioral finance *often* does not base the research or, at least primarily, on economic theory. But is that really the case?

Richard Thaler subsumed the conflict between behavioral finance, the discipline he is famous for, and traditional finance while talking to Robert Barro, who works in the latter field:

"The difference between us is that you assume people are as smart as you are, while I assume people are as dumb as I am" (Richard Thaler cited by Bloomfield 2010).

There are a lot of studies that have proven that people do often not behave in accordance with traditional finance models and that these models are often not able to predict behavior. To mention only some examples: people tend to concentrate their stock holdings on equity of their domestic stock market and do not diversify sufficiently referred to as the home bias (e.g., Graham and Harvey 2009, Lewis 1999, French and Poterba 1991); investor trade too much and tend to hold losers and sell winners known as the disposition effect (Barber and Odean 2000; Odean 1999) and show a certain degree of under-diversification by not investing in stocks at all and therefore do not diversify over asset classes (e.g., Christelis et al. 2010; Goetzmann and Kumar 2008; Blume and Friend 1975). Taken several findings on investment mistakes together, the science journalist Sam McNerney (2011) writes in his blog called whywereason.com:

"I hate behavioral economics. Not because I disagree with its' theories or findings, but because it consistently reminds me of how stupid I am. I think I choose optimally – nope. I think I weigh all the options equally – nope. I think I am rational – nope. You get the idea, and if you're familiar with behavioral economics, then perhaps you feel my pain."(McNerny 2011).

Nevertheless, this does not mean that people behave randomly – the deviations from rational behavior are often systematic and predictable. Does this mean that traditional finance and experimental or behavioral finance are an "either or"? Will these two research fields exist side by side or even complement each other? In a behavioral economics panel discussion at the Nobel Laureates Meeting in Lindau in 2011, the nobel laureate Robert J. Aumann suggested the following way of looking at the problem:

"the thesis is classical economics (people behave rationally) ... the antithesis is that (behavioral economics) people behave irrationally ... I suggest a synthesis ... people do not act rationally, but they choose rules ... heuristics ... choose mechanisms of behavior which usually are optimal but if you put them into unfamiliar situations these can indeed lead to severe and systematic biases." (Aumann 2011)

His perspective seems more in favor for a side by side. The development in the literature during the last years, however, makes it often difficult to distinguish exactly between the two. In his article on the end of behavioral finance, Richard Thaler subsumes his perspective on the future of the two research fields the following way:

Behavioral finance is no longer as controversial a subject as it once was. As financial economists become accustomed to thinking about the role of human behavior in driving stock prices, people will look back at the articles published in the past 15 years and wonder what the fuss was about. I predict that in the not-too-distant future, the term "behavioral finance" will be correctly viewed as a redundant phrase. What other kind of finance is there? In their enlightenment, economists will routinely incorporate as much "behavior" into their models as they observe in the real world. After all, to do otherwise would be irrational. (Thaler, 1999a, p.17)

To include behavior into the models, it is necessary to describe and observe it and to find a pattern in it. This thesis analyses financial decision making and risk taking behavior of private households. One key element to predict and understand behavior is to know how it is influenced by personal characteristics and the way the decision itself is presented. This is an important question for politicians as well as for practitioners, as the way information itself is presented might influence the outcome and is an element which can cause harm to people as well as help them dependent on the way it is (un-)intentionally used. The following section gives an overview of behavior observed in the literature in the context of risk taking and presentation format, which is the essential for the thesis. The section focuses especially on investigating situations in which households have found to make errors and to be prone to biases.

1.3 OVERVIEW OF HOUSEHOLD FINANCIAL DECISION MAKING

The underlying idea is to show whether households make good financial decisions and what determines whether they do so; but, what is a good financial decision? Is it a rational decision in the sense of the traditional finance literature? Is it the decision resulting in the highest expected return over the lifecycle or the highest satisfaction? According to Kahneman et al. (2006) it is not the absolute amount of money resulting in the highest satisfaction; it is more the relative income influencing people's happiness (Frank 2010), as people compare themselves to their peer group.

A good decision is referred to as a decision, in which mistakes and biases have been avoided from an ex ante perspective. This does not necessarily mean that the outcome will be optimal as well. In an asset allocation decision, for example, an ex ante "good" decision could be to divide the amount to invest between a broad diversified fund and a risk-free asset in accordance with one's risk preferences: nevertheless, the final wealth out of this investment can be lower than expected and therefore the decision might be judged as bad even if it was not. In contrast, an investor could put "all eggs into one basket"; thousands of private German investors, for example, had bought "supposedly safe" Lehman certificates and lost all their money, when the US bank Lehman Brothers declared bankruptcy in September 2008, as they neglected the counterparty risk; it is true, that the risk was supposed to be small, however, even small risks can be reduced by diversification. Such an under-diversification is an example for an obvious investment mistake. An investor A investing all his money into one stock could, however, at the end of the day gain a better asset performance from an ex post point of view compared to an investor B who has diversified broadly; nevertheless, investor B made an ex ante better decision than investor A referred to the definition used in this thesis. There are several mistakes like under-diversification, which can be made in asset allocation decisions. With risk taking in investment decisions being the main focus of the thesis, the next paragraphs provide an overview of the determinants of risk taking behavior.

1.3.1 Determinants of Risk Taking Behavior

Results of behavioral research have shown that individuals' risk taking behavior is a function of *subjective* measures such as risk attitude, risk perception and perceived return (see Nosić and Weber 2010, Jia et al. 1999, Sarin and Weber 1993). The behavioral model of risk taking suggests:

$$Risk\ Taking = f\{Perceived\ Return;\ Risk\ Attitude;\ Perceived\ Risk\}$$

These subjective measures often result in excellent predictive validity: as the following studies have shown; risk taking itself is often measured as how much risk a subject invests into a risky prospect as compared to a risk-free possibility or as the general participation rate in the stock market; this is true for survey studies as well as for experiments (e.g., Buecher-Koenen and Ziegelmeyer 2011, van Rooij et al. 2011, Nosić and Weber 2010).

The influence of return perceptions plays a minor role for the analyses conducted in this thesis. Nevertheless, as changes in risk taking behavior have found to be mainly driven by changes in return expectations or risk perception, experimental evidence will be briefly described here. Return expectations do generally not seem to be stable over time (Dominitz and Manski 2005, Vissing-Jorgensen 2003). In a panel survey with data from online brokers, Weber et al. (2010) show that return expectations substantially change over time and that these changes in return expectations, and not changes in past performance, primarily attribute to changes in risk taking.

Risk attitude seems to be a quite stable construct, independently of being measured through survey questions or in experiments (Nosić and Weber 2010, Andersen et al. 2008, Klos 2011, Sahm 2007). According to classical theory risk attitude is simply expressed by the shape of the utility function (Arrow 1965 and Pratt 1964) with a concave function describing a risk averse person and a convex function describing preferences of a risk seeking person. In experimental economics or survey studies, risk attitude is often measured via a self assessment question on how willing investors are to take financial risk in order to end up with a higher expected return (e.g., Bucher-Koenen and Ziegelmeyer 2011, Merkle and Weber 2011). The assessment of risk attitude has also practical relevance as the Markets in Financial Instruments Directive (MiFID) of the European Union instructs banks to elicit "*the customers' preferences regarding risk taking, his risk profile and the purpose of the investment*" (Article 19, 4). The Securities and Exchange Commission in the US also claims that banks inform their clients about past performance of investment products and their special risks. But nevertheless, there is no information or instruction how this risk preferences should be measured and therefore, policy makers and financial professionals have a great discretion about how to present and assess the according information. Aside from that, it has to be taken into account that risk attitude has found to be domain specific (e.g., Weber et al. 2002; Rettinger and Hastie 2001). Results show that a person, taking for example high health risks can be very risk averse regarding financial decision making. Nosić and Weber (2010) demonstrate in addition that risk behavior even varies within the financial domain: risk taking in lottery decisions differs from risk taking behavior in asset allocation decisions.

In contrast to risk attitude, risk perception (for the same domain) does not seem to be stable over time, but instead varies tremendously with regard to the decision context[2] (Mellers et al. 1997, Weber and Miliman 1997). Risk perception is a strong predictor of risk taking, despite its weak relationship to more objective measures, such as standard deviation (Klos et al. 2005, Keller et al. 1986). Risk perception can be defined as "*an individual's assessment of how risky a situation is in terms of probabilistic estimates of the degree of situational uncertainty, how controllable that uncertainty is*" (Sitkin and Weingart 1995). Most of empirical evidence suggests that subjective perception will be influenced by the manner in which risk is communicated (findings on the influence of framing and presentation format on risk perception will be provided in the next section). The risk of an investment option is for example perceived differently dependent on whether it follows from a series of gains or losses (Weber and Milliman 1997).

Aside from the elicitation of risk preferences the MiFID also requires that advisors provide appropriate information about "*financial instruments and proposed investment strategies; this should include appropriate guidance on and warnings of the risks associated with investments in those instruments or in respect of particular investment strategies, ... so that they are reasonably able to understand the nature and risks of the investment service and*

[2] The influence of decision frames will be discussed in the next section.

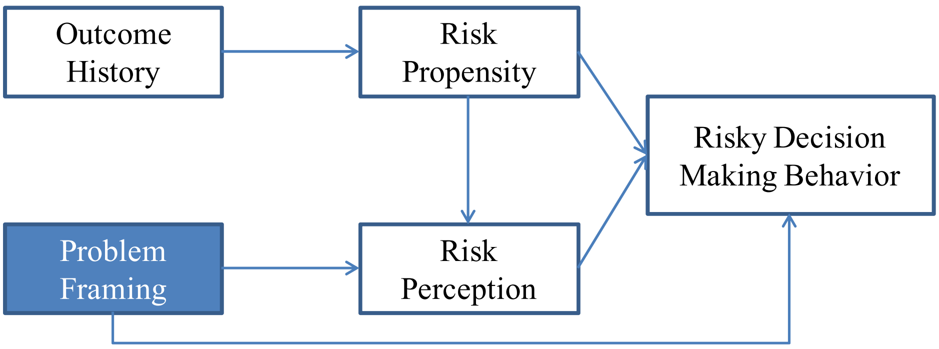
of the specific type of financial instrument that is being offered and, consequently, to take investment decisions on an informed basis" (Article 19, (3)). To provide appropriate information it is, however, important to know, how investors react to different types of information. Findings on that will be discussed in the next paragraph.

1.3.2 The Influence of Information Frames and Presentation Formats on Financial Decision Making

Subjects are generally prone to framing effects. According to Tversky and Kahneman (1981) the effect of framing is described as "*the decision-maker's conception of the acts, outcomes, and contingencies associated with a particular choice*". Framing the same decision problem differently can hence influence preferences and behavior; Tversky and Kahneman (1981) document for example that people behave risk averse if outcomes are framed as gains and risk seeking if the outcomes are framed as losses. A decision maker needs information if he wants to decide between different options, e.g., choosing the optimal mortgage rate, credit contract or asset allocation. According to classical finance theory, framing should not matter. In financial decision making, however, framing plays a major role for instance regarding the presentation of risk information in asset allocation decisions. Therefore, the influence of framing should be mentioned when talking about a behavioral model of risk taking and its determinants, as it has been suggested by Sitkin and Weingart 1995 based on Sitkin and Pablo 1992 (see figure 1-2).

Figure 1-2: Determinants of Risky Decision Making Behavior

This figure displays the determinants of risky decision making behavior.
Source: Sitkin and Weingart 1995 based on Sitkin and Pablo 1992.



Sitkin and Weingart (1995) have tested the behavioral model of Sitkin and Pablo (1992) with the help of experiments. They also find (in line with other risk value models like in Sarin/Weber 2003) that risk propensity (in the sense of risk attitude) and risk perception are the key mediators influencing risky decisions. Aside from that they show a direct as well as indirect influence of framing (in the sense of, for example, highlighting losses versus highlighting gains) on risk taking.

Several studies have shown that the format of how investment risk, past returns and their volatility are "framed" influences risk perception and preferences. There are numerous ways to graphically present information about historical returns – density functions, index of value over time, bar charts of percent annual yields, etc. These presentation variations yield differences in risk perception and risk taking propensities; (e.g., Vrecko et al. 2009, Diacon and Hasseldine 2007, Weber, E.U. et al. 2005). In addition to variations in graphical displays, information can differ regarding the information period. Benartzi and Thaler (1999) show for example, that varying the time horizon of past performance between one year and 30 years has a strong influence on the level of risk taking.

Kühberger (1998) differentiates between strict framing, which is referred to as a re-description of the same situation by semantic manipulations, and loose frames, which describe a problem where the situation is still equivalent from the perspective of economic theory. Such a loose framing might be a variation in the degree of information. One example for the context of asset allocation is the inclusion of asset names. E.U. Weber et al. (2005) find in their study that participants increase their risk taking if asset names are included. Economically, participants face the same situation, no matter whether they know the asset names or not. The provision of asset names, however, results in significantly higher return expectations and lower risk perception. Another way the degree of information can be framed is by varying the time in the sense of how often information is provided. The effect is referred to as myopic loss aversion, namely the increase in investors' willingness to invest into a risky prospect if performance feedback is given less frequently. Based on experimental results, the myopic loss aversion literature predicts higher allocations over the five year time horizon compared to the one year horizon (e.g., Langer and Weber 2008, Bellemare et al. 2005, Gneezy et al. 2003; Gneezy and Potters 1997; Thaler et al. 1997).

More recent research describes another way of decision frames, namely whether risk information is communicated in the form of explicit numerical descriptions (of outcomes and probabilities) or whether it is learned through repeated experiences. Hertwig et al. (2004) show that decisions based on numerical descriptions, which explicitly give information about outcomes and probabilities, differ significantly from decisions based on experience where probabilities are learned through sampling. In their study, participants push two buttons to sample two options and then decide which option to accept. In contrast to the overweighting of small probabilities that occurs with numerical descriptions (described by the probability weighting function of Prospect Theory (Kahneman and Tversky 1979)), results suggest that people underweight small probabilities if they experience the risk through sampling. For example, in the descriptive condition 36% chose to gamble on a .8 chance to win 4 points (0 points with a probability of .2) over a sure gain of 3 points, while in the experience condition, 88% chose to gamble. Even if the authors do not agree on the underlying mechanisms causing the effect, these findings have been replicated by several other studies (e.g., Abdellaoui et al. 2011, Rakow et al. 2008, Fox and Hadar 2006) and will be tested in this thesis in an asset allocation context.

The overview of recent literature on framing has shown that several the ways of how information is presented affect risk taking behavior. Nevertheless, until now most of the studies have analyzed the influence on risk taking, but not whether different formats improve financial decision making, by increasing for example investors confidence or commitment to the decision. This thesis will shed more light on this question.

1.4 OUTLINE OF THE THESIS

The data for most parts of the thesis have been gained via online experiments, except for chapter 2, in which the analysis is based on data from a German household survey. Based on these data the following research questions are addressed:

1. Which demographical, behavioral and psychological factors determine the financial well being of households? (Chapter 2)
2. What is the best way to present information about the risk of investment products to private investors? (Chapter 3)
3. Does simplifying information by aggregating performance information over asset returns influence risk taking? (Chapter 4)

4. Do private investors see a relationship between risk attitude and the amount invested risky at all and do they adjust their investments if provided with different risk levels of the risky asset? (Chapter 5)

Chapter 2 of this thesis investigates which demographical, behavioral and psychological characteristics determine how households get along with their income; more precisely, it is investigated who is in financial difficulties, how these difficulties are handled and who is able to get out of them. The financial situation, defined as how much of the income is left at the end of the month, a household faces influences several other upcoming financial decisions; households in a bad financial situation reduce their stock market participation, are more likely to be financially constrained in the future, whereas households with in a good financial situation are more likely to make good credit and investment decisions. Indeed, it is a lot more than economic factors influencing private households' day to day financial decision making. Even if factors like income, wealth and outstanding credit are strong predictors of how well households get along, I find an important influence of financial literacy and cognitive abilities as well as psychological factors like the propensity to plan on the current financial situation as well as on the ability to handle and solve financial difficulties once they occur.

In chapter 3 (joint work with Emily Haisley and Martin Weber) we investigate the question of how risk presentation format influences investing. This question is important as financial professionals have a great deal of discretion concerning how to relay this information about the risk of financial products to their clients. We examine how different risk presentation modes influence how well investors understand the risk-return profile of financial products and how much risk they are willing to accept. We analyze four different ways of communicating risk: (i) numerical descriptions, (ii) experience sampling, (iii) graphical displays and (iv) a combination of these formats in a 'risk simulation'. Participants receive information about a risky and a risk-free fund and make an allocation between the two in an experimental investment portfolio. We find that risky allocations are elevated in both the risk simulation and experience sampling conditions. Greater risky allocations are associated with decreased risk perception, increased confidence in the risky fund and a lower estimation of the probability of a loss. Despite these favorable perceptions the risky fund, participants in the risk simulation underestimate the probability of a high gain and are more accurate on comprehension questions regarding the expected return and the probability of a loss. We find no evidence of greater dissatisfaction with returns in these conditions and observe a willingness to take on similar levels of risk in subsequent allocations. The results have important implications for the current debate surrounding how financial advisors assess the suitability of investment products for their clients.

Chapter 4 (joint work with Martin Weber) deals with information aggregation as one way to simplify complexity in asset allocation decisions. Former research has shown that the degree of information aggregation has an influence on decision making resulting in a higher risk taking. Information in the financial context can be aggregated over asset returns, e.g., on an account balance sheet, where investors can look at each asset or their portfolio as a whole. In this paper we analyze the underlying mechanisms which cause higher risk taking in the case of aggregated information. Additionally, we explore the ex post decision evaluation of participants who take on more risk and also explore the effects of different risk presentation formats. We conducted three experiments, in which we ask subjects to allocate an endowment between a risky and a risk-free fund and use three treatments to test the effects of information aggregation. In line with former studies we find a higher level of risk taking for a higher degree of information aggregation over different investment amounts, different cultural background and different risky assets. The higher risk taking is accompanied by lower risk perception, more accurate estimation of the probability of a loss and by participants' feeling more informed. Additionally, a higher degree of information aggregations result in consistent subsequent allocation decisions and a higher decision satisfaction for participants receiving a loss (outcome below the expected value). In other words, people take into account that a well considered ex ante decision might ex post have a negative outcome.

In Chapter 5 (joint work with Christian Ehm and Martin Weber), we analyze investors ability to deal with risk in investment decisions. Following the classical portfolio theory all an investor has to do for an optimal investment is to determine his risk attitude. This allows him to find his point on the capital market line by combining a risk-free asset with the market portfolio. We investigate the following research questions in an experimental set-up: do private investors see a relationship between risk attitude and the amount invested risky at all and do they adjust their investments if provided with different risk levels of the risky asset? To answer these questions we ask subjects in a between subject design to allocate a certain amount between a risky and a risk-free asset. Risky assets differed between conditions, but could be transferred into each other by combining them with the risk-free asset. We find that mainly investors' risk attitude, but also their risk perception and the investment horizon are good predictors for risk taking. Indeed, investors do not appear to be naïve, but they do something sensible. Nevertheless, we observe a strong framing effect: investors choose almost the same allocation to the risky asset independently of changes in its risk-return-profile thus ending up with significantly different volatilities. Feedback does not mitigate the framing effect. The effect is somewhat smaller for investors with a high financial literacy. Overall, people seem to use two mental accounts – one for the risk-free and one for the risky investment with the risk attitude determining the percentage allocation, and not the overall volatility of the investment.

2 What I Am and What I Know – Determinants of Households' Financial Situation

2.1 Introduction

Since the presidential address of John Campbell on *Household Finance* at the American Finance Association Meeting in 2006, the analysis of households' financial decision making has gained increasing attention; various types of financial decisions (e.g., asset allocation, stock market participation, mortgage selection or credit card usage) have been analyzed. However, the decisions that have been investigated are often quite sophisticated. Studies on investment behavior analyze whether households participate in stock markets (e.g., van Rooij et al. 2011, Christelis et al. 2010, Calvet et al. 2009), whether they hold passively or actively managed funds (e.g., Müller and Weber 2010) or how they diversify (e.g., Guiso and Jappelli 2009). Research on credit behavior explains mortgage decisions (e.g., Campbell 2006, Moore 2003), credit contract decisions, extreme forms of financial distress (e.g., households not being able to pay any bills) or credit default. The current study investigates, by going one step back, how financial households handle decisions every household has to deal with, namely how to get along with the income one does (not) have. In that context, getting along refers to the question, whether a household on average has money left at the end of the month during a certain time period. In a more simple way it compares income to expenditures. With this in mind, it is possible to categorize households into a group with no financial difficulties, referring to households who always or often have something left, opposed to a group with financial difficulties. The financial situation a household faces is such an important one, as it influences most of the other upcoming, perhaps more sophisticated financial decisions: households in a bad financial situation reduce their stock market participation (Guiso et al. 1996) and are more likely to be financially constrained in the future (Böheim and Taylor 2000), whereas households in a good financial situation are more likely to make good credit and investment decisions (Hilgert et al. 2003).

Several studies have been conducted to analyze the influence of personal characteristics like financial literacy and cognitive abilities as well as behavioral traits like the propensity to plan or self control on financial decision making. Research has for example shown that people with high financial literacy diversify more (e.g., Kimball and Shumway 2010, Guiso and Jappelli 2009) or are more likely to invest into the stock market (van Rooij et al. 2011, Calvet et al. 2009); people with high cognitive abilities are more patient and less risk averse (Sunde et al. 2010, Benjamin et al. 2006, Frederick 2005) and more likely to invest into the stock market (Christelis et al. 2010). Behavioral traits like higher self control increase people's willingness to save (Lea et al. 1995, Groenland and Nyhus 1994) opposed to people with low self control who tend to over-spend money and hence are more likely to get into financial distress (McCarthy 2011, Bernheim and Rangel 2004, Thaler and Shefrin 1981). Furthermore, studies reveal that financial planning results in higher wealth accumulation (Ameriks et al. 2003) and higher savings for retirement (Lusardi and Mitchell 2007).

In this paper, I want to analyze how these personal characteristics and traits influence financial decisions every household, no matter whether rich or poor, has to deal with every day. In more detail, I investigate the following questions:

1. What determines how households get along with their income?
2. If households do not get along, what are the causes for financial difficulties?
3. What determines how these financial difficulties are handled?
4. Which factors influence whether households are able to improve their financial situation?

To answer these research questions, I use microeconomic data of 2,222 households in the 2009 and 2007 wave of the SAVE survey, which is a representative German household panel designed to analyze savings behavior, retirement planning and formation of wealth of German households (for further information on the panel see Börsch-Supan et al. 2009). These data provide the opportunity to relate financial management of households to economic and demographic variables, personal characteristics, behavioral traits as well as educational factors. Besides the factors, which have been analyzed in the literature until today (propensity to plan, self control, financial literacy and cognitive abilities), an additional factor, namely the openness for change, is included into the analysis. The idea behind that is that participants who are more willing to change their behavior might be able to cut down their expenses more easily and therefore, are more likely to handle financial difficulties. Last but not least the current study analyses the influence of educational factors. There is an ongoing discussion in the literature about causal relationships. Do people get along better because they have higher self control or do they control themselves because they have experienced not to get along?

With given information about the financial situation in participants' adolescence on whether they received allowance on a regular basis and whether they immediately spend it, it is possible to investigate whether there is a significant relationship between today's financial situation and behavior in the childhood.

Results show that it is a lot more than economic and demographic factors influencing private households' day to day financial decision making and therefore their financial well being. While factors like income, wealth and outstanding credit are, as expected, strong predictors of household financial management, I also find a strong influence of ability and knowledge, behavioral traits and educational factors. The most important of those explanatory factors are a combination of cognitive ability and financial literacy and a high propensity to plan. For people with high financial literacy and high cognitive abilities (high propensity to plan) the probability of being in financial difficulties decreases by 10% (8%) and they are in addition 14% (9%) more likely to handle those difficulties in a sensible way (reduce savings instead of increasing credit) once they face financial problems; furthermore, they are 12 % (9%) more likely to get out of these problems two years after. People with a high financial self control (not spending all their pocket money immediately during their adolescence) are 8% less likely to be in financial difficulties and have a 9% higher chance not to be worse off after two years, whereas participants with a higher openness for change are 7% less likely to be in financial difficulties.

The paper contributes to the literature by analyzing the influence of several economic, behavioral and personal factors in a representative data set for one of the most important financial decisions, namely how people get along with their income, and, in addition to existing studies (e.g., McCarthy 2011, Gathergood 2011), how difficulties are handled once households are facing them. The decision is important as it influences other financial decisions like stock market participation (Guiso et al. 1996) or credit decisions (Hilgert et al. 2003). If there is no money left close to the end of the month, people are not able to save and therefore will get into trouble with their retirement planning; they will either need loans or they will not be able to repay their loans and are, in the current situation as well as later on, more likely to get into financial distress or indebtedness (Böheim and Taylor 2000).

An additional contribution to the existing literature is the analysis of the combined influence of financial literacy and cognitive abilities in financial decision making. It is discussed controversially, whether financial education programs are able to improve financial decision making (e.g., Cole and Shastry 2009). Nevertheless, results of this study reveal that it is not only cognition improving financial decision making, but it is a combination of knowledge and abilities. It is hence necessary to think about a way financial knowledge can be improved somehow.

With this in mind the answers to the research questions have major policy implications. There is an ongoing discussion among politicians, researchers and practitioners how to help private households in managing the financial decision process, especially as the outcome of the decision does often not only affect the decision maker himself, but the whole family he has to take care of. However, to predict the outcome of financial decisions of private households, it is important to know the determinants of how well households manage their financial tasks. Identifying these factors has, besides educational interest, also implications for the credit risk management of banks in the retail banking sector. There are several demographic characteristics and economic factors influencing the quality of financial decision making like income, wealth, education and age. Until today, mainly those factors are included into credit models to determine the creditworthiness of retail banking customers (see e.g., Puri et al. 2011; Norden and Weber 2010). Gathering more insights into additional factors explaining household financial management could thus help to improve the credit rating system and to not overburden customers with additional credit they are not able to afford.

The study is organized as follows: section 2.2 provides a literature review; section 2.3 describes the SAVE panel including the measurement of the main dependent and explanatory variables and gives an overview of descriptive statistics within the sample. The empirical results are presented in section 2.4; finally, section 2.5 provides a discussion of the findings.

2.2 Literature Review

There are some studies underlining the importance of understanding the determinants of households' day to day financial decision making by relating the outcomes of those decisions to other financial domains influenced by them: Research has shown that households who are in a good financial situation are also more likely to make good credit and investment decisions; households are not able to participate in the stock market or at least reduce their holdings of risky assets when facing financial problems in the sense of liquidity constraints or a bad cash management (Hilgert et al. 2003, Guiso et al. 1996); aside from that, previous experience of milder forms of financial difficulties (e.g., not paying bills on time) is significantly related to the current financial situation (Böheim and Taylor 2000); Norden and Weber (2010) show for example that there is an abnormal pattern of credit lines usage, which is likely to increase when facing liquidity constraints, approximately 12 months before default events. These studies give an intuition why the understanding of day to day financial decision making is important and what severe consequences the financial situation has on other domains of financial decision making.

The determinants of households' everyday financial management have only been analyzed by some studies. According to Hilgert et al. (2003), who use data from the Survey of Consumers of the University of Michigan, a better cash management (e.g., paying bills on time) is related to higher income and higher financial literacy. McCarthy (2011) supports the finding of an influence of financial literacy on the household's financial situation by showing that people with higher financial literacy are less likely to face mild and severe forms of financial distress. Aside from this, financial literacy has found to be an important predictor of good financial decision making in other domains like stock market participation, diversification, fund choice and refinancing of mortgages (e.g., van Rooij et al. 2011, Calvet et al. 2009, Guiso and Jappelli 2009, Müller and Weber 2010; Moore 2003). A measure for financial literacy is hence included into the following analysis.

Another personal characteristic which seems to be related to a better household financial situation is the degree of cognitive abilities[3]. Zagorsky (2007) shows that people with high cognitive abilities are less likely to get into financial difficulties. This goes in line with Cole and Shastry (2009) who find that increasing cognitive abilities are related to a higher tendency to save. Nevertheless, to my knowledge, there are no studies, which simultaneously analyze the influence of both characteristics, namely cognitive abilities and financial literacy, on households` financial situation.

There are only some studies linking household financial situation to behavioral traits. Thaler and Shefrin (1981) explain, that a lower level of self control might induce a lower level of savings, as they regard "*saving behavior primarily as a set of self-imposed rules of thumb*". In following studies, the authors' idea has been confirmed empirically; people with

[3]In general, cognitive abilities are referred to as the ability, which enables an individual to perform a cognitive task. Grinblatt et al. (2011) use cognitive abilities as a synonym for IQ, whereas Agarwal and Mazumder (2011) differentiate between certain domains like mathematical and verbal abilities. The main difference to literacy is that abilities cannot be learned, however, they can be trained. Further information on our cognitive ability measure is given in section 3.

higher level of self control tend to save more (Lea et al. 1995, Groenland and Nyhus 1994). Gathergood (2011) investigates the influence of self control and financial literacy on over-indebtedness and self reported distress level (on a five item scale ranging from "keeping up with all bills without any difficulties" to "real financial problems, fallen behind with many bills") using the DebtTrack household survey from the UK. Results reveal that higher financial literacy and higher self control are negatively related to over-indebtedness and a problem of self control increases self reported financial distress. McCarthy (2011) investigates the influence of self-control and the propensity to plan on mild and extreme forms of financial distress using the UK Financial Capability Survey. She finds that both traits, controlling for economic and socio-demographic factors, significantly predict financial distress and have a stronger impact than financial literacy or education. Ameriks et al. (2003) confirms these results showing that people with a higher propensity to plan tend to save more. In the current study both described variables, namely self control and the propensity to plan, are included into the analysis.

It is, however, not obvious whether self control is an exogenous or and endogenous variable; people might get along better because they have a higher self control and are able to only spend the money they have; on the other side people might need to self control themselves once they have no money left. To overcome this problem, educational factors are included to the analysis. Webley and Nyhus (2006) show, for example, a weak, but clear impact of parental behavior, e.g., talking about financial matters, on economic behavior in the childhood as well as in adulthood. To investigate a causal relationship between self control and the financial situation, an additional question of SAVE is included into the analysis, where participants have been asked about how they had spent their allowance during their childhood.

2.3 Data Set

The SAVE Panel

SAVE is a representative annual panel study designed to analyze savings behavior, retirement planning and formation of wealth of German households; it contains information about the general financial situation, personal characteristics and demographics, as well as special information about financial decision making and psychological traits (for further information see Börsch-Supan et al. 2009). The survey is in paper and pencil format and was first conducted in 2001 by the Mannheim Research Institute for the Economics of Aging (MEA) in Germany. Participants receive €20 cash as well as other presents (for details see Schunk 2006) independent of whether they really participate or not and the participation rate has been very stable over the years; the retention rate[4] was 87% on average between 2005 and 2009 (Börsch-Supan et al. 2009). The person answering the survey is generally involved into financial decision making in the household, only 3% of respondents of the 2009 wave have stated that it's mainly their partner alone, who is in charge for financial decision making.

I use the panel data of 2009 and 2007, both conducted in the early summer of the respective year. The SAVE Panel is an imputed data set; missing information is generated based on iterative multiple imputation procedure (Schunk 2008; Ziegelmeyer 2011) with the aim to reduce the non-item response bias. Additionally, efficiency of the results can be increased due to a larger number of observations. Based on this method five imputed data sets are generated and used for the analysis with the results being derived with the help of Rubin's method (Rubin1987, 1996). However, for all main effects the analysis was also performed with non imputed values for the dependent as well as the main explanatory variables (cognitive abilities and financial literacy) as a robustness check (not reported due to space limits). Results do not differ qualitatively from the results for the imputed data set.

The sample consists of 2,222 subjects, who have participated in 2007 and 2009. 47% of participants are male and the mean age is 53, ranging from 22 to 91. Participants on average report a net household income of €2,200 (median €1,900) and a mean total wealth, including real estate, of €150,000 (median €69,000). All descriptive statistics are weighted with the German Mikrozensus as a reference statistic (see Börsch-Supan et al. 2009) and results are representative for the German population. Weights for multivariate analysis are not used with reference to Deaton[5] (1997).

Household Financial Situation

The households' financial situation is measured in SAVE by asking participants directly about the financial circumstances they live in.[6] The question used to analyze how

[4] Retention rate = suitable interviews/sample$_{(t-1)}$; suitable is net of the non evaluable interview, e.g., due to a different person in the household answering the questionnaire (Börsch-Supan et al. 2009).
[5] Deaton (1997) argues in his paper that "when the sectors [the sub-groups] are homogeneous, OLS is more efficient, and when they are not, both estimators are inconsistent. In neither case is there an argument for weighting." (p. 70).
[6] For an overview of all questions in the 2009 wave see Börsch-Supan et al. (2009).

households get along with their income was phrased the following way (in 2009 as well as in 2007):

If you think back, how you and your partner on average got along with your income during the last year: What fits best for you? There was enough money left at the end of the month. / There was some money left at the end of the month. / There was only money left, if there was additional one-time income. / There was often too little money at the end of the month. / At the end of the month there was never enough money left.

For the main analysis I use the response of 2009 (always referred to if not stated otherwise); the responses of 2007 are used to analyze whether certain characteristics determine the changes in financial circumstances over time.

Participants on average report that they got along quite well and often had something left during the last year (47% of participants), 9% of participants even had always enough left at the end of the month. Nevertheless, also 8% state that the money has never been enough, 21% that the money often has not been enough, or only if they received an additional one-time income (15%). Table 2-1 relates the degree of getting along with the income to summary statistics for households in the sample. These uni-variate results suggest that financial well being – in the sense of having on average more money left at the end of the month – increases with being male, having less credit outstanding, a higher net income and a higher total wealth.

Table 2-1: Demographics by Households' Financial Situation

Table 2-1 reports summary statistics for overall 2,222 respondents in SAVE 2009 dependent on their reported level on how well they get along with their income. Data is weighted.

	FINANCIAL DIFFICULTIES			NO FIN. DIFFICULTIES	
	never anything n = 172	often not enough n = 467	only if add. income n = 337	often something n = 1,050	always enough n = 196
gender (male)	40%	40%	43%	50%	62%
age	51	53	50	55	53
net income in € (median)	1,600 (1,100)	1,800 (1,500)	2,200 (2,000)	2,200 (2,000)	3,300 (2,900)
mean total wealth in € (median)	67,000 (200)	92,000 (20,000)	140,000 (56,000)	164,000 (95,000)	370,000 (207,000)
outst. (CS) credit (1=yes, 0=no)	46% (22%)	51% (24%)	50% (22%)	35% (14%)	30% (6%)

The aim of the study is to explain, which households get along well and which households do not, dependent on various explanatory factors. Hence, I construct a dummy variable equal to one for all households reporting some degree of financial difficulties, and zero otherwise. There are also other measures which could be used to describe financial difficulties. One question in SAVE asks, for example, about the subjective (whether households did not apply for a credit because they were afraid of being rejected) and objective (whether a credit application was rejected or only granted partially) access to credit. These two measures reflect, nevertheless, real credit constraints, which are more severe financial difficulties compared to the measure used in this study; aside from that, only 8% of the participants in the whole sample are concerned by subjective limits to credit, which does not allow to gain broader insights about the ordinary household.

To compare the financial difficulties measure to other studies I use a report (Ollrog 2011) published by the German external credit bureau SCHUFA showing that those German households complaining about a general lack of money are remarkably often characterized by having three or more children and a low net income (less than €1,000). In the SAVE sample 66% (61%) out of those households, which have three or more children (and an income below €1,000), report to be in financial difficulties.

Financial Literacy and Cognitive Abilities

Financial literacy is measured with the help of four questions adapted from the advanced literacy score of van Rooij et al. (2011). The questions ask for the meaning of diversification, the concept of mutual funds, the function of the stock market and volatility over asset classes. The financial literacy score is constructed as an index taking values between 0 and 4 dependent on the number of participants' correct answers. A factor analysis on these four questions results in one factor with a meaningful interpretation. The mean number of correct answers in the sample is 2.29, the median 3 (for the exact wording of questions and an overview of participants' responses, see table 2-2). The score is significantly correlated to the basic literacy score[7] (Pearson correlation coefficient of 0.52, $p<0.01$) as well as to the self assessed financial knowledge[8] (Pearson correlation coefficient of 0.19, $p<0.01$).

[7]Basic literacy is measured through three numeracy, interest compounding and inflation questions. We construct a basic financial literacy index taking values between 0 and 3 dependent on the number of participants' correct answers. If we perform a factor analysis on these three questions, we retain, in line with van Rooij et al. (2011), one factor with a meaningful interpretation. Overall, 58% of our participants are able to answer all questions correctly; 9% of our participants got none of these correctly.
[8]Exact wording of the question: "How would you assess your personal financial knowledge?".

Van Rooij et al. (2011) report that the majority of participants who report a low score (1, 2 or 3 out of 7) for self-assessed economic knowledge, are in the lowest quartile of the advanced literacy score, whereas more than 50% of participants reporting high levels of knowledge are located in the top two quartiles. This is in line with the SAVE data: 43% of those reporting a low financial knowledge are in the lowest quartile and the majority reporting high knowledge are in the highest two quartiles as well. The advanced financial literacy score was first collected in 2009. In the 2007 wave, the questionnaire only involved the basic financial literacy questions. The correlation between the basic score in 2007 and 2009 is 0.82 and significant at the 1%-level.

Table 2-2:(In)correct Answers to the Financial Literacy and Cognitive Abilities Questions

These tables report the proportion of respondents who were (not) able to answer the questions of the financial literacy and the cognitive ability task respectively. The proportion of participants out of those who did not answer the respective cognitive ability question correctly, but gave the intuitive answer is reported in brackets. Data is weighted.

Financial Literacy Score	Correct	Incorrect	Don't know
Normally, which asset displays the highest fluctuations over time? (i) Savings accounts; (ii) Bonds; (iii) Stocks; (iv) Do not know.	70.31	10.11	19.58
Which of the following statements describes the main function of the stock market? (i) The stock market helps to predict stock earnings; (ii) The stock market results in an increase in the price of stocks; (iii)The stock market brings people who want to buy stocks together with those who want to sell stocks; (iv) None of the above; (v) Do not know.	50.81	17.03	32.16
Buying a company stock usually provides a safer return than a stock mutual fund. True or false? (i) True; (ii) False; (iii) Do not know.	63.52	4.56	31.92
Which of the following statements is correct? (i) Once one invests in a mutual fund, one cannot withdraw the money in the first year; (ii) Mutual funds can invest in several assets, for example invest in both stocks and bonds; (iii) Mutual funds pay a guaranteed rate of return which depends on their past performance; (iv) None of the above; (v) Do not know.	43.99	7.53	48.48
Financial Literacy Score, all (no) answers correct	28.99 (18.63)		

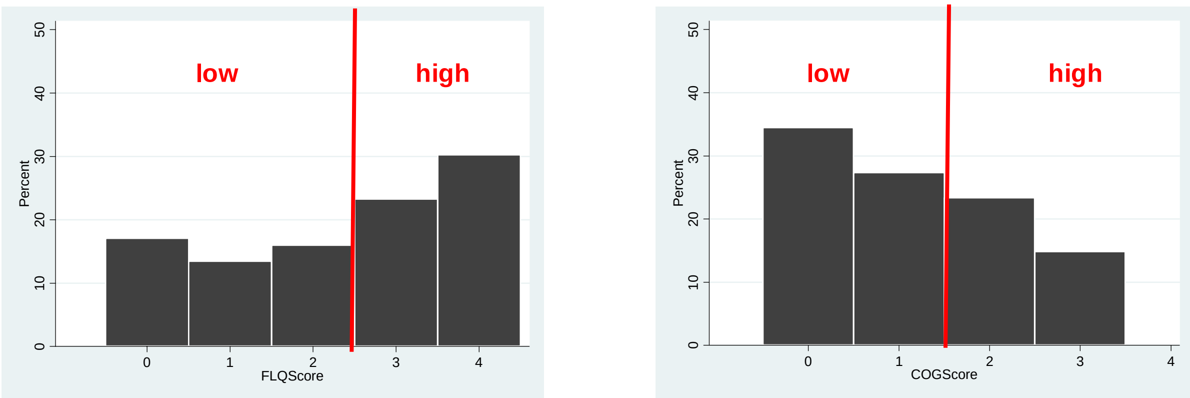
Cognitive Ability Score	Correct	Incorrect (intuitive)
A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? _____ cents	21.17	78.83 (95.46)
If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? _____ minutes	45.15	54.85 (74.01)
In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days	48.75	51.25 (84.05)
Cognitive Ability Score, all (no) answers correct	14.54 (36.15)	

In the questionnaire, cognitive abilities are measured with the help of the Cognitive Reflection Test (CRT), developed by Frederick (2005). According to Frederick's empirical analysis, the test scores correlate significantly with intelligence tests like the SAT (coefficient of 0.44) and the Wonderlic Personnel Test (coefficient of 0.43). The test was found to be a good predictor for time and risk preferences (Frederick 2005). The test consists of three questions like *a bat and a ball cost 110 Cents in total. The bat costs 100 Cents more than the ball. How much does the ball cost?* The intuitive answer to this question is ten Cents; however, the right answer is five Cents. In this sample, over 95% of those participants who did not answer this question correctly, stated the intuitive answer of "ten Cents". I construct a cognitive ability score as an index taking values between 0 and 3 dependent on the number of participants' correct answers (for an overview of all questions and participants' responses see table 2-2). A factor analysis on the three questions, results in one factor with a meaningful interpretation Overall, 15% of participants answered all, 36% none of the questions correctly (see table 2-2). The CRT seems to measure more than just numeracy, as the correlation to the first question of the basic literacy score, which measures numeracy, is only 0.21. The score is positively and significantly correlated to self assessed financial knowledge (Pearson correlation coefficient of 0.07, $p<0.01$), to self assessed math knowledge (Pearson correlation coefficient of 0.22, $p<0.01$), and the basic literacy score (Pearson correlation coefficient of 0.29, $p<0.01$).

Cognitive abilities and financial literacy are significantly and positively correlated (Pearson correlation coefficient of 0.35, $p<0.01$). Financial literacy increases with ability. Participants with very high abilities (all answers correct) have on average a financial literacy score of 3.11 whereas people with very low abilities (no answer correct) have on average a financial literacy score of 1.71 and the difference is significant at the 1%-level. The distribution of abilities and literacy in the sample is plotted in figure 2-1.

Figure 2-1: Stock Market Participation by Financial Literacy over Wealth Deciles

This figure shows the distribution of the financial literacy score (0-4 scale) and the cognitive ability score (0-3 scale) in the data set. The line in the middle of each graph reflects the median split, participants on the left are in the subsample with low financial literacy or cognitive abilities, participants in the right in the high financial literacy or cognitive ability group respectively.



For further analyses the sample is divided in four subsamples using a median split for both score indices: participants with high financial literacy and high abilities (604 participants), with high knowledge and low abilities (584 participants), with low knowledge and high abilities (245 participants) and a fourth group with low abilities and low knowledge (798 participants). High literacy means that participants answered three or four of the questions correctly; high ability means that they answered two or three of the respective questions correctly. For each group a dummy variable is constructed taking the value one if a participant belongs to the respective subsample and zero otherwise. The four groups show similar characteristics with regard to age, but differ in gender, education, net income and total wealth. In the high knowledge and high ability group the average monthly household net income is €2,900 (median: €2,600) and 34% of respondents have an A-level degree; in the low knowledge and low ability group participants on average report a monthly household net income of 1,700 (median: €1,400) and only 10% have an A-level degree.

Behavioral Traits and Educational Factors

There were several behavioral trait measures included in the 2007 wave of the SAVE panel. The reason for including these questions was to infer individual preferences on financial planning out of several respondents' characteristics and to investigate how these affect investment and saving decisions; additionally SAVE reports answers to a set of questions focusing on individual's attitudes in the past to analyze how these may have influenced actual preferences (Börsch-Supan et al. 2009).

I include three behavioral traits in the analysis, propensity to plan, self control and openness for change; two of which (propensity to plan and self control) are included, as they have been found to be strong predictors of financial decision making (e.g., McCarthy 2011; Lea et al. 1995). The third variable, openness for change, is included with the idea in mind that people who are open to change might be better able to cut down expenses or to handle a difficult situation and thus get out of financial difficulties more easily.

To measure the propensity to plan participants have been asked to place themselves on a scale from zero to ten in terms of two different personality types with zero meaning "*I live for the moment and take live as the case may be. I do not think a lot about the future and I am not worried about it*." and ten being "*I care a lot about the future and I know quite exactly who I want to be and what I want to do*." I construct a dummy variable *planner* taking the value of one if participants have placed themselves higher than five, zero otherwise. For the self control variable I use the answer to the following question, where participants have again have been asked to place themselves on a scale from zero to ten in terms of two different personality types with zero being "*I usually decide impulsively. I rather immediately want to have the things I like*." and ten being "*I am tentative and considerate and I need a lot of time to decide.*". I construct a dummy variable *self control* taking the value of 1 if participants have placed themselves higher "five", and zero otherwise. As a third variable I use participants answer on how strongly they (dis)agree to the following statement "*I am open for change.*" with zero being strongly disagree and ten being strongly agree. Again, a dummy variable, namely *openness for change*, is constructed taking the value of one if participants have placed themselves higher "five", and zero otherwise.

In the data set, participants show on average a tendency to plan (mean score of 6.6) and to be more self controlled than impulsive (mean score of 5.8). High self control and being a planner are positively correlated (Pearson correlation coefficient of 0.20, $p<0.01$). Participant report on average a tendency to be open for change (mean score of 6.4) and the openness for change is positively correlated with being a planer (Pearson correlation coefficient of 0.09, $p<0.01$) and negatively correlated with self control (Pearson correlation coefficient of -0.11, $p<0.01$); this negative correlation means that participants with a higher openness for change also have a tendency to be more impulsive. In a bi-variate setting all dummy variables of behavioral traits (results for the scores are similar) are related to households' financial situation: the degree of getting along with the income is positively correlated to self control (Pearson correlation coefficient of 0.05, $p<0.01$), being a planner (Pearson correlation coefficient of 0.12, $p<0.01$) as well as being open for change (Pearson correlation coefficient of 0.04, $p<0.01$).

The educational factors that are included into the analysis focus on participants' attitudes in the past. This provides the opportunity to analyze how past impact factors influence actual behavior and hence to investigate a causal relationship. If participants with a high self control are better able to overcome financial difficulties, I do not know whether they control themselves more in the current situation, because they have money constraints or whether they improve their situation because they are in general able to control themselves. For these measures participants are asked *whether they in their adolescence used to receive allowance on a regular basis* and whether *they immediately spend the money they had been given* (again zero being strongly disagree and ten being strongly agree). On average participants did not receive allowance on a regular basis (mean score of 4.60) and did not spend everything they got immediately (mean score of 2.91). I construct a dummy variable "financial self control" taking the value of one if participants placed themselves lower than five with regard to the question on how immediate they used to spend their allowance. In a bi-variate setting, getting along with the income is positively correlated to whether participants received allowance (Pearson correlation coefficient of 0.03, $p=0.02$) and negatively correlated to their spending behavior (Pearson correlation coefficient of 0.06, $p<0.01$).

2.4 EMPIRICAL RESULTS

What determines how people get along with their income – who faces financial difficulties?

Descriptive statistics reveal that the probability to be in a good financial situation is influenced by economic and demographic factors (income, wealth, gender, outstanding debt), increases with higher literacy and abilities and is correlated with certain behavioral traits (being a planner, open for change and having a higher level of self control) as well as with educational factors (receiving allowance and the way spending it during the adolescence). These uni-variate results are now tested in a multivariate setting using a probit regression model with *financial difficulties*[9] as the dependent variable. Marginal effects and standard errors are reported in table 2-3.

As expected, being in financial difficulties is significantly and negative related to income[10] as well as wealth and positively related to the number of children living in the household; the probability of being in difficulties additionally increases strongly with having debt outstanding (compared to no debt outstanding), namely by 28%. Results are comparable to former results found by McCarthy (2011) or Hilgert et al. (2003).[11] We include age and the squared age into the regression analyses, as the literature suggests a u-shaped influence of age, namely younger and older people are less likely to be in a bad financial situation as compared to middle-aged people (e.g., McCarthy 2011, Ollrog 2011).

While those findings underline the importance of economic factors, results in table 2-3 also show that it is more than just demographic and economic factors that are important for being in a good financial situation. Literacy and knowledge matter: for people with high abilities and high knowledge the probability of being in difficulties decreases by 10%. If I include both variables without the interaction term, only literacy is significant. However, people with high financial literacy and low cognitive abilities do not seem to have a higher probability to be better off. It might be that financial literacy matters on how good somebody is, if that person is good anyhow.[12]

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[9]As explained earlier the financial difficulties measure is constructed using the answer to the get along with the income question – a dummy taking the value of one for participants reporting some degree of financial difficulties (answers 1-3), zero otherwise (answer 4 and 5).

[10]We use the net income interval to control for income. Participants have been provided with eleven different income intervals to help them in case they are not aware of the exact household income. Results do not change in a meaningful way if we use reported income.

[11] If regressions are repeated (results are not reported due to space concerns) with dummy variables for one, two or three and more children as explanatory variables and "no children" as the omitted category, I find that the probability of being in difficulties increases by 7% having one child and by 30% having three children and more. If I include dummy variables for the income (instead of one general variable for income) as explanatory variables, I find that the probability of being in financial difficulties increases by 22% for a household with a net income of less than €1,000 and by 8% for a household with an net income between €1,000 and €1,500 compared to a household with an income between €1,500 and €2,000. The results are in line with the findings of the German external credit bureau (Schufa) report cited earlier in this paper, that mainly those households with a low net income and having three or more children complain about a lack of money (Ollrog 2011).

[12]This can be tested with a probit regression (not reported due to space concerns) limited to people who are not in financial difficulties. The dependent variable is a dummy variable indicating whether a participant has always as opposed to often something left; and indeed, the probability to have always something left increases by 5% (p=0.05) for participants with high literacy and low abilities, by 9% (p=0.07) for participants with high abilities and low literacy and by 7% (p=0.01) for participants having both.

Table 2-3: Financial Difficulties

Table 2-3 reports the effect of different explanatory variables on being in financial difficulties. The dependent variable is a dummy variable indicating whether a household is in financial difficulties (never something left, often nothing left, only something left if additional income). The table reports marginal effects (ME) and standard errors (Std. Err.) in parentheses. For the ability and knowledge dummies, having a low financial literacy and low abilities is the omitted category. Model 2 excludes participants reporting "extreme" financial difficulties (never something left at the end of the month). Regression 3 reports probit regression analysis of household in more severe difficulties, with a dummy as a dependent variable taking the value 1 if people reported to have never something or often nothing left at the end of the month and zero otherwise. Coefficients and standard errors are calculated with the help of five imputed data sets according to Rubin's Rule (Rubin 1987 and 1996).

* indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

	Financial Difficulties Probit Regression	**(1)**	**(2)**	**(3)**	**(4) less severe**	**(5) more severe**
		ME (Std. Err.)	**ME (Std. Err.)**	**ME (Std. Err.)**	**ME (Std. Err.)**	**ME (Std. Err.)**
Economic & demographic factors	**Male**	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.00 (0.02)
	Partner	0.00 (0.03)	0.01 (0.03)	0.01 (0.03)	0.03 (0.03)	-0.01 (0.03)
	Age	0.03*** (0.01)	0.03*** (0.01)	0.03*** (0.01)	0.03*** (0.01)	0.03*** (0.01)
	Age squared	-0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)
	Education	0.01 (0.01)	0.02* (0.01)	0.02 (0.01)	0.02** (0.01)	0.00 (0.01)
	Children @ home	0.10*** (0.02)	0.10*** (0.02)	0.10*** (0.02)	0.10*** (0.02)	0.07*** (0.01)
	Net Income Interval	-0.05*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	-0.04*** (0.01)
	Log Total Wealth	-0.04*** (0.01)	-0.04*** (0.01)	-0.03*** (0.01)	-0.03*** (0.01)	-0.03*** (0.01)
	Outstanding Credit	0.28*** (0.03)	0.28*** (0.02)	0.28*** (0.03)	0.25*** (0.02)	0.23*** (0.02)
Ability & Knowledge	**low FL, high COG**	0.00 (0.04)	0.00 (0.04)	0.00 (0.05)	0.01 (0.05)	-0.02 (0.05)
	high FL, low COG	-0.05 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.06** (0.03)
	high FL, high COG	-0.10*** (0.03)	-0.10*** (0.03)	-0.10*** (0.03)	-0.08** (0.03)	-0.11** (0.03)
Behavioral Traits	**Planner**		-0.09*** (0.03)	-0.08*** (0.03)	-0.09*** (0.03)	-0.04 (0.03)
	Self Control		-0.01 (0.03)	-0.00 (0.03)	-0.00 (0.03)	-0.02 (0.02)
	Open for change		-0.07*** (0.03)	-0.07*** (0.03)	-0.07*** (0.03)	-0.03 (0.03)
Educational Factors	**Self Control – allowance**			-0.08*** (0.03)	-0.09*** (0.03)	-0.05** (0.02)
	Regular allowance			-0.00 (0.03)	-0.03 (0.03)	-0.02 (0.02)
	N	2,222	2,222	2,222	2,051	2,222

In table 2-3 column 2, the behavioral traits are included into the regression model with financial difficulties as the dependent variable. Behavioral traits also play an important role; a higher propensity to plan and being open for change both decrease the probability of getting into financial trouble by 8% and 7% respectively. Self control has a negative coefficient, but is, in contrast to former findings (e.g., Garthergood 2011), not significant. If educational factors (table 2-3 column 3) are included, financial self control shows a similar pattern in statistical and economical terms as the propensity to plan or the openness for change: people who did not spend all their allowance immediately during their childhood face an 8% lower probability to be in a bad financial situation today.

As a robustness check I vary the degree of financial difficulties. In column 4 (table 2-3) participants who reported "extreme" financial difficulties (never something left at the end of the month) are excluded, as it might be that those people do not have any options open to get along better. However, results do not change in a significant way. In regression 5 (table 2-3) I define a dummy variable taking the value 1 if people reported to have never something or often nothing left at the end of the month and zero otherwise. I therefore compare people in more severe difficulties to the rest of participants. Results only differ for the financial literacy dummy. This is again an indication that financial literacy plays a role if the situation is extreme – may it be good or bad. With regard to behavioral traits, being a planner and open for change does no longer significantly explain behavior when it comes to severe difficulties. The reason might be that when it comes to severe problems, it is not a question of attitudes, but a question of knowledge how to get along. This has to be tested in future research. One possibility to get an intuition about the importance of knowledge, once a problem is there is to investigate what households do if they do not get along with their income and are in financial difficulties.

How do people handle financial difficulties?

Results suggest that certain personal traits decrease the likelihood of getting into financial difficulties. In the following, I take a closer look at those participants in financial difficulties to determine whether these traits only have an influence on how people handle financial problems once they are facing them. In the SAVE panel, participants have been asked

If there was not enough money left at the end of the month, did you and your partner then … i) overdraft your current account or increasing your credit line[13] *usage? ii) draw on your savings? iii) take out a bank loan? iv) borrow something from friends or family? v) get along somehow?*

Multiple responses to that question were allowed. Out of those participants who have been in financial difficulties 44% reduce their savings to overcome the present financial situation, 55% increase their credit line, 8% take an additional consumer credit and 20% take additional credit from friends. Out of those participants, who face a more severe situation (never anything left or often nothing left), however, 36% reduce their savings, 58% increase their credit line, 8% take an additional consumer credit and 23% take additional credit from friends. The increase in borrowing from friends and family might be explained with the fact that 33% of those participants report that they have not applied for a bank loan because they expected to be rejected (for all participants in financial difficulties 16% of participants have not applied for a bank loan for that reason).

As increasing the credit line usage and reduce savings are the most frequently mentioned response options, I will investigate those in more detail. Karlan and Zinman (2011) state in their research on nudging people to improve their debt management: "Pay down debt is the highest save return a private investor can get". From this interrelation one can infer that, in case of cash resources or risk free savings, it would be more rational to reduce those instead of increasing the credit line or overdraft the current account.

[13]With the help of a credit line people are able to overcome temporary income shortages. They are used to be, dependent on the bank, twice or three times the net monthly income and are - in contrast to an overdraft of the current account – charged with a lower interest rate. Nevertheless, the interest rate is still around three times as high as the interest rate for a consumer credit. Therefore, it does not make sense to refinance with a help of a credit line for a longer time. 78% of the constrained participants have a credit line with an average amount of €2,700 (median of €2,000).

Table 2-4: Handling of Financial Difficulties

Table 2-4 reports the effect of different explanatory variables on how people handle financial difficulties. The table reports marginal effects (ME) and standard errors (Std. Err.) derived from probit regression models. In Model 1 the dependent variable is a dummy variable indicating whether a household in financial difficulties draws savings to overcome them. In Model 2 the dependent variable is a dummy variable indicating whether a household in financial difficulties overdrafts the current account or increases the credit line usage to overcome them. In Model 3 the dependent variable is a dummy taking the value 1 if a household draws savings (and does not overdraft the account) and 0 if a household overdrafts the account (and does not draw savings). Households doing both or neither of the two possibilities are excluded. Marginal effects and standard errors are calculated with the help of five imputed data sets according to Rubin's Rule (Rubin 1987 and 1996).

* indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

	Handle Fin. Difficulties Probit Regression	**(1) Red. Savings**	**(2) Overdraft**	**(3) Sav. versus CL**
		Marg. Eff. (Std. Err.)	**Marg. Eff. (Std. Err.)**	**Marg. Eff. (Std. Err.)**
Economic & demographic factors	**Male**	0.02	0.05	-0.04
		(0.04)	(0.04)	(0.05)
	Partner	0.05	-0.00	0.05
		(0.04)	(0.04)	(0.06)
	Age	-0.01	-0.01	-0.00
		(0.01)	(0.04)	(0.01)
	Age squared	0.00*	0.00	0.00
		(0.05)	(0.00)	(0.00)
	Education	0.01	-0.00	0.01
		(0.01)	(0.02)	(0.02)
	Children @ home	-0.01	-0.02	0.01
		(0.02)	(0.02)	(0.03)
	Net Income Interval	0.01	0.03***	-0.01
		(0.01)	(0.01)	(0.01)
	Outstanding Credit	-0.08**	0.18***	-0.20***
		(0.04)	(0.04)	(0.05)
	Savings/1000	0.01***	-0.01***	0.02***
		(0.00)	(0.00)	(0.01)
	Credit Line	0.08**	0.50***	-0.37
		(0.04)	(0.04)	(0.06)
Ability & Knowledge	**low FL, high COG**	0.08	0.08	-0.01
		(0.06)	(0.06)	(0.08)
	high FL, low COG	0.09**	-0.02	0.09
		(0.05)	(0.05)	(0.06)
	high FL, high COG	0.17***	-0.00	0.14**
		(0.05)	(0.05)	(0.07)
Behavioral Traits	**Planner**	0.08**	-0.03	0.09*
		(0.04)	(0.04)	(0.05)
	Self Control	0.03	-0.01	0.04
		(0.04)	(0.03)	(0.05)
	Open for change	-0.04*	0.01	-0.05
		(0.04)	(0.01)	(0.05)
Educational Factors	**Self C. – allowance**	0.03	0.01	0.04
		(0.04)	(0.04)	(0.05)
	Regular allowance	0.06	0.02	-0.00
		(0.04)	(0.04)	(0.06)
	N	980	980	613

Using a probit model to calculate marginal effects, I first analyze the determinants of both possibilities separately (see table 2-4 columns (1) and (2)). Reduction of savings is a dummy variable taking the value of one if the respondent reduced his savings to overcome the financial shortage (notice again, that multiple responses were allowed) and the regression is limited to those participants in financial difficulties. People are more likely to draw their savings to overcome their financial difficulties in case they have risk free savings[14], possess a credit line (which is often related to income and creditworthiness) and have lower outstanding credit. With regard to ability and knowledge, even people with low cognitive abilities have 9% higher probability to reduce their savings if they are financially literate; people with high financial literacy and abilities are even 17% more likely to reduce their savings. Regarding the personal traits – having a high planning propensity increases the probability to reduce savings by 8% and being open for change reduces it by 4%. These results underline former findings that the influence o f knowledge is stronger compared to the influence of attitudes once one is in financial difficulties.

The behavioral trait "openness for change" significantly decreases the probability of being in financial difficulties. However, it also decreases the probability that participants reduce their savings in case they have financial problems; one reason might be that participants do not need to reduce their savings, as they try to change their behavior in order to get along. To follow up on this idea I analyze participants who have stated that they "got along somehow" to the above mentioned question, what participants did in case the money was not enough. Participants who responded "we got along somehow" were able to write down free text; among those typical explanations are "spending less", "cutting down expenses", formulated in the following way: "I am cooking different things, less meat", "I am not going out or shopping the respective months", "I am selling things on ebay or yard sale" or "We are cutting down expenses for beer and cigarettes". These responses show that those people really tried to change their behavior. The average response score for "openness for change" in the sample is 6.24 for people in financial difficulties. For those of them who have reported that they got along somehow the average score is 6.22 and hence not different. However, if I limit the analysis to those people who really have the choice to either increase their credit line, reduce savings or change behavior, as they possess a credit line or risk free savings, the score is 6.94 and the difference is significant on the 1% level. This indicates that

[14]The average of risk free savings (including savings deposits and time deposits) for households in financial difficulties is €4,300, the median €0).

participants with a higher openness to change try to change their behavior once they face financial problems. As these results are only uni-variate and only for a small proportion of the sample, the idea has to be tested in future research.

When it comes to credit line usage (table 2-4, column 2) it is not quite obvious, what determines participants' behavior. An obvious issue is that having a credit line increases the probability to use it by a large percentage of 50%. Additionally, I again find a relationship to savings – people with lower savings are more likely to overdraft their account. Interesting from a behavioral view is, who chooses which of the two options. To investigate this question, table 2-4 column 3 shows results of a probit regression with savings versus (credit) line as a dependent variable taking the value of one if a participant reduces his savings (and does not overdraft his account) and taking a value of zero if a participant uses the credit line (and does not reduce savings).[15] The probability of handling financial difficulties by a reduction of savings opposed to an overdraft increases, not surprisingly, with higher savings and decreases with outstanding credit. For people who have high abilities and high literacy the probability of "doing the rationale thing" increases by 14% and having a high propensity to plan increases the probability by 9% (only marginally significant on the 10%-level). However, handling the difficulties does not mean getting out of them. In the next section I analyze who is able to resolve financial difficulties over a two year time horizon.

Who overcomes financial difficulties?

To get insights on what determines the ability to resolve financial difficulties, I additionally regard how people responded to the question on how they get along with their income in the 2007 wave of the survey and compare the response to those stated in 2009. There is, in general, a positive and significant correlation on whether participants have been in financial difficulties or not (Pearson correlation coefficient of 0.53, $p<0.01$) in 2007 compared to 2009; 21% get along better in 2009 compared to 2007, 25% of participants get along worse, for 54% the financial situation has not changed (a transition matrix with detailed information is given in table 2-5).

[15] Sample size decreases as we excluded participants who report to have used both options.

Table 2-5: Transition Matrix – Get along Income 2007 and 2009

Table 2-5 reports the change in how people get along with their income from 2007 to 2009 using a transitions matrix. Example (second row of table 2-5): Out of 170 people, who had never something left in 2007, 74 still have never had something left in 2009, 63 have often not had enough, 16 only have had enough if there was additional income and so on.

	never something left n = 172	often not enough n = 467	only if add. income n = 337	often something left n = 1,050	always enough n = 196
never sth. left n = 170	74	63	16	16	1
often not enough n = 538	72	236	89	136	5
only if add. inc. n = 361	11	74	124	145	7
often sth. left n = 959	15	88	99	673	84
always enough n = 194	0	6	9	80	99

The first question to analyze is what determines whether a person is better or worse off after these two years. The analysis is done with the help of a probit regression model (see table 2-6). The dependent variable getting worse is a dummy variable taking a value of one if a person gets along worse in 2009 compared to 2007 and zero if the financial situation has not changed; participants who are better off in 2009 are excluded from the analysis. Vice versa the dependent variable getting better is a dummy variable taking a value of one if a person gets along better in 2009 compared to 2007 and zero if the financial situation has not changed; participants who are worse off in 2009 are excluded from that analysis.

Across all participants, results reveal a marginally significant and negative influence of financial literacy and a significant, negative influence of financial self control on getting along worse in 2009 compared to 2007: the chance of being worse off (compared to being in the same situation) decreases by 5% for people with a higher literacy and by 8% for people who had a higher financial self control in their adolescence (see table 2-6 column 1). In an additional regression, participants who have stated that there was never anything left are excluded, as they are by definition not able to get into a worse situation; besides that, participants who state to always have something left are excluded, as I want to analyze participants who get into financial difficulties.

Table 2-6: Change in Financial Difficulties Wave 2007 Compared to Wave 2009

Table 2-6 reports the effect of different explanatory variables on whether households change their financial situation to the better or the worse. The table reports marginal effects (ME) and standard errors (Std. Err.) derived from probit regression models. In Model 1 the dependent variable is a dummy variable indicating whether a household faces a worse (compared to nothing has changed) situation in 2009 opposed to 2007; Model 2 excludes participants always as well as never having something left. In Model 3 the dependent variable is a dummy variable indicating whether a household faces a better (compared to nothing has changed) situation in 2009 opposed to 2007. In Model 4 and 5 the dependent variable is a dummy variable indicating whether a household in financial difficulties 2007 is out of them in 2009. Analysis is limited to participants in financial difficulties in 2007. Marginal effects and standard errors are calculated with the help of five imputed data sets according to Rubin's Rule (Rubin 1987 and 1996).

* indicates significance at the 10% level, ** at the 5% level and *** at the 1% level;

	Probit Regression	**(1) Getting worse**	**(2) Getting worse (in fin. diff.)**	**(3) Getting better if fin. diff 2007**	**(4) Resolve fin. diff. of 2007**	**(5) Resolve fin. diff. of 2007**
		ME (Std. Err.)	**ME. (Std. Err.)**	**ME (Std. Err.)**	**ME (Std. Err.)**	**ME (Std. Err.)**
Economic & demographic factors	**Male**	-0.02	-0.01	-0.04	0.02	0.02
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
	Partner	-0.05	-0.04	-0.01	-0.03	-0.03
		(0.03)	(0.04)	(0.05)	(0.05)	(0.05)
	Age	0.00	0.01	-0.03***	-0.03	-0.03
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Age squared	-0.00	-0.00	0.00***	0.00***	0.00***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	Education	-0.00	0.00	-0.01	-0.02	-0.02
		(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
	Children @ home	0.03**	0.05***	-0.04	-0.06***	-0.06***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
	Net Income Interval	-0.00	-0.01	0.03**	0.03**	0.04***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Outstanding Credit	0.06**	0.13***	-0.11**	-0.22***	-0.20***
		(0.03)	(0.03)	(0.05)	(0.04)	(0.04)
	Log Total Wealth	-0.00	-0.01*	0.01	0.02**	0.02**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ability & Knowledge	**low FL, high COG**	-0.06	-0.05	0.00	0.01	0.01
		(0.04)	(0.04)	(0.07)	(0.06)	(0.06)
	high FL, low COG	-0.05*	-0.06**	0.04	0.06	0.06
		(0.03)	(0.03)	(0.05)	(0.05)	(0.05)
	high FL, high COG	-0.05	-0.08***	0.11**	0.12**	0.13**
		(0.05)	(0.03)	(0.06)	(0.06)	(0.06)
Behavioral Traits	**Planner**	-0.00	-0.03	0.01	0.09**	0.10***
		(0.01)	(0.03)	(0.05)	(0.04)	(0.04)
	Self Control	-0.03	-0.01	0.01	0.00	0.00
		(0.03)	(0.03)	(0.04)	(0.01)	(0.01)
	Open for change	0.04	-0.04	-0.01	0.02	0.02
		(0.03)	(0.03)	(0.05)	(0.04)	(0.04)
Educational factors	**Self C. – allowance**	-0.08***	-0.09***	0.00	0.02	0.02
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
	Regular allowance	-0.03	-0.04**	-0.05	-0.03	-0.03
		(0.03)	(0.03)	(0.05)	(0.04)	(0.04)
	Increase CL in 2007					-0.12***
						(0.05)
	Reduce Savings in 2007					-0.05
						(0.04)
	N	1,665	1,398	910	1,069	1,069

For those participants, results again show a significant influence of financial literacy and financial self control and, additionally, a significant influence of the interaction of financial literacy and cognitive abilities (see table 2-6 column 2). Results suggest that financial literacy and cognitive abilities especially play a role for whether participants at all get into financial difficulties or not. In both regressions the number of children and whether the household has outstanding credit significantly increase the chance of being worse off two years after.

After analyzing what determines whether someone is worse off, the following analysis describes the other side of the coin – which person got along better in 2009. The analysis is limited to those people facing difficulties in 2007. Results reveal that an improvement of the financial situation is positively related to the interaction of high cognitive abilities and high financial literacy; additionally, being better off is positively and significantly related to not being middle aged as well as to higher income and no outstanding credit.

By now I have analyzed what determines whether one is better or worse off in general. In the two last regressions I am now interested in, who ultimately resolves his financial difficulties and is able to get out of them. Therefore I use a dummy variable "resolved", which takes the value of one if a person is not in financial difficulties in 2009 and zero otherwise and limit the analysis to participants being constrained in 2007. Results show that the variables with the strongest influence are outstanding credit and the interaction of high abilities and literacy: for a person without any outstanding credit the chance of resolving the difficulties increases by 21%, for a person with high financial literacy and high cognitive abilities the chance increases by 12%. Results do not change in a meaningful way if I limit the regression to people in more severe financial difficulties ("never anything left" or "often nothing left"). I additionally include two variables on how participants have handled their difficulties in 2007 (table 2-6 column (5)). For those participants using their credit line or overdrafting the account, the probability to resolve their financial problems decreases by 12%.

2.5 DISCUSSION

Results reveal that the quality of households' financial situation is influenced by far more than income or wealth status. Ability and knowledge as well as behavioral traits, especially the propensity to plan, are comparably statistical significant and economically important in determining how well households get along with their income and how they handle and resolve financial difficulties once they got into them.

Demographic factors, which are for example used by banks to determine the creditworthiness of customer, are easy to assess and are important predictors for consumer behavior; however, they cannot be changed, at least in most of the cases. If researchers or politicians want to find a way to help people to improve their financial behavior, it is necessary to investigate other important factors. Results show a significant relationship between financial literacy, cognitive abilities and the current financial situation; people who have a certain degree of financial literacy get better along with their income and are more likely to get out of financial problems once they have any.

It has been discussed in the literature whether financial literacy really plays such an important role in financial decision making. Cole and Shastry 2009, for example, show that an additional year of schooling has a much higher effect on savings and stock market participation than one year of financial education. In the SAVE sample, the effect of financial literacy is stronger opposed to cognitive abilities. One reason for this difference might be that participants in the SAVE panel might have gained their knowledge voluntarily as opposed to people who participated in an financial education program which was mandatory. Nevertheless, even if there were consensus on an important influence of financial literacy on financial decision making, it is not known how a higher level of knowledge can be obtained.

Research for example controversially discusses the impact of financial education programs. Bernheim et al (2001) find an increase of savings after participating in a financial education program, whereas Cole and Shastry show a negligible effect of financial education at school on financial decision making. One reason might be that education does not help if people do not want to be educated. It might be rather meaningful to convince people to be interested in gaining financial knowledge or how to explain them the necessity for it opposed to providing mandatory education programs. One experiment that has shown that drawing interest might be a promising idea has been conducted by Hershfield et al. 2011. It is generally known from the literature that people save too little for retirement (e.g., Thaler and Benartzi 2004). According to Hershfield et al. (2011) one reason for this is the lack of imagining the future. Therefore, the authors increased the ability to identify the current self with the future self by letting them interact with realistic computer renderings of themselves in the future. With this setup, the authors were able to increase the participants' retirement savings rate. Another study on investment allocation decisions conducted by Haisley et al. (2011) shows that participants increase their risky asset accompanied by an increase in confidence and understanding, if they are informed in an interactive simulation.

Overall, there are several research studies, showing that financial literacy matters. People with higher financial knowledge make better financial decisions. Until today, it is however not known how to improve financial decision making with that knowledge. Further research need to be done in that field. One suggestion therefore is to go one step back by finding a way to gain people's interest to concern themselves with their financial matters before providing education programs.

3 The Role of Experience Sampling and Graphical Displays on one's Investment Risk Appetite

3.1 Introduction

One of the most important financial decisions is how much risk to bear in one's investment portfolio. The behavioral finance literature shows that people find it extremely difficult to choose portfolios that match their preferences and may be easily influenced by non-normative features of the decision making environment. Financial professionals should provide clients with tools that are most likely to produce decisions in line with underlying preferences. One obvious step in the right direction is to use tools that result in stable decisions and comprehension about the risk-return profile of the chosen portfolio. The manner in which people acquire knowledge about risk of investment products may affect how well they comprehend risk and have a dramatic influence on the risk they are willing to accept. The decision making literature distinguishes between two fundamentally distinct ways in which people learn about risk: *description* vs. *experience.* Decisions from *description* are based on explicitly stated probabilities associated with outcomes. Decisions from *experience* are based on sampling possible outcomes, meaning that the underlying probabilities must be judged or inferred based on the observed evidence. In an investment context, risk can be *described* in summary form, e.g., historical returns or factsheets. Alternatively, knowledge about risk can be acquired through *experience,* through feedback about the outcomes of previous decisions or observing outcomes in the market.

The literature on the 'experience-description gap' documents situations in which these two decision modes lead to different decisions. These findings raise the issue of what is the best way to present information about the risk of investment products. As empirical researchers, it may seem intuitive to us that risk should be described in summary statistical form. However, this is not obvious from this literature. Decision making from experience can reduce or reverse decision-making biases, such as overweighting of rare events as described by prospect theory (Barron and Erev 2003).

We extend research on the experience-description gap to the domain of investment decision making. Since investment outcomes are continuous, this is a more complex decision making task than what has been examined so far in the literature. The question of how risk presentation format influences investing is important as financial professionals have a great deal of discretion concerning how to relay this information to their clients. At worst they do not assess risk preferences at all or ask irrelevant questions about risk-seeing in other domains, such as “Are you a bungee jumper?”[16]. Often, they assess willingness to take financial risks using psychometric scales.

Our research question has important implications for policy making. In the EU, advisors are legally obliged to assess customers’ risk preferences and issue “*appropriate guidance on and warnings of the risks associated with investments”* during the advisory process.[17] Similarly, the Securities and Exchange Commission in the US instructs banks to inform their clients about past performance of investment products and their special risks. Nevertheless, there is little instruction about how risk information should be presented. Research is needed to elucidate the implications of risk presentation format on willingness to accept and comprehend risk.

To further this objective, we developed a ‘risk simulation’ to more completely inform investors about the risk of investment products. The risk simulation incorporates both experience sampling and a graphical display of the full historical distribution of the MSCI USA. The simulation forces participants to sample possible outcomes for a five-year investment in a stock fund – the “risky fund”. Each sampled outcome is used to build up the distribution and then the entire distribution is displayed. Participants are also shown the expected five-year return of a risk-free fund. Finally, participants make an allocation between the risky fund and the risk-free fund. We contrast this simulation with a numerical *description* of the expected value and variance of the risky fund. Further, we break-down the simulation into its constituent parts with a pure experience sampling and a pure distribution condition to determine their relative contributions. These different risk presentation modes are tested in an incentive compatible experimental investment portfolio, conducted online

[16] This was an item in a risk tolerance assessment of an European bank, which we will keep anonymous. Hanoch et al. (2006) showed in their study on domain specificity in risk taking that those individuals with high levels of risk taking in one domain (e.g., bungee jumpers) are sometimes very risk averse in other domains (e.g., financial decisions).

[17] See Article 19 of the Markets in Financial Instruments Directive (MiFID) of the European Union (The European Parliament and the European Council, 2004).

with participants drawn from a German university and the general population in the United States.

We find that the risk simulation increases the propensity to take financial risks in that participants invest a higher fraction of their endowment in the risky asset. This effect appears to be driven more by experience sampling than the displays of historical distributions. Thus, a main contribution of this paper is an extension of the literature on the experience-description gap to show that experience sampling leads to greater risk taking in the context of investing. We document three potential psychological mechanisms that vary with risk presentation format and may underlie this effect: reduced *over*estimation of the small probability of a loss, lower risk perception and higher confidence about investing in the risky fund.

A second major contribution of this paper is improving risk communication to give investors a greater appreciation for potential benefits and the risks of investment products. We asses participants' comprehension of the risk-return profile of the risky investment product with both a subjective measure of how informed they feel and with objective measures that require them to estimate the expected return and probabilities associated with different outcomes. The risk simulation enhances comprehension of the stock fund along several dimensions: the expected return, the perceived probability of a loss and how informed they feel.

Another potential benefit of the risk simulation is that it leads participants to be less reactive when they receive a return that falls below expectations. Instead of accepting lower risk in a subsequent allocation decision, akin to pulling out of the market after a downturn, participants in the risk simulation condition are more likely to "stay the course" and make a consistent subsequent allocation decision.

The remainder of this study proceeds as follows: in Section 3.2 we provide a literature review and formulate our hypotheses. Section 3.3 describes our experimental paradigm. Our main results are presented in Section 3.4. We describe how four different types of presentation formats influence people's investment allocation decisions: i) numerical description, ii) experience sampling, iii) graphical displays of distributions and iv) a combination of these with the risk simulation. Section 3.5 explores comprehension and underlying psychological factors that affect the allocation decision. Section 3.6 examines whether the increased risk taking with the risk simulation leads to decision regret by analyzing satisfaction with returns and a subsequent allocation decision. Section 3.7 provides a discussion of our findings.

3.2 LITERATURE REVIEW AND HYPOTHESES

Research on risk presentation format addresses the question of whether risk taking behavior varies depending on whether the risk is experienced instead of simply described. When information about risk is acquired through *experience,* the probabilities associated with outcomes are not known or explicitly stated. They must be learned either through feedback from previous decisions or through experience-sampling, i.e. allowing people to sample possible outcomes before making a choice. This mirrors many decisions in everyday life in which people often do not have access to statistical probabilities and have to estimate risk based on personal experience and external information. For example, people draw on their own and other's past experiences when deciding whether to back up their hard drive, purchase insurance, or how cautiously to drive. The decision to invest in the stock market is not made based on the probability that the S&P 500 will go up over the next year. Rather, their intuition about the attractiveness of the stock market derives from their appreciation of how it has performed in the past.

Given identical underlying probability distributions, decisions based on description and experience can be substantially different, particularly for decisions that involve rare events. Hertwig et al. (2004) demonstrate that decisions based on numerical descriptions of outcomes and their associated probabilities differ significantly from decisions based on experience, in which probabilities are learned through pushing buttons to sample possible outcomes. Decisions based on numerical decisions are consistent with the overweighting of small probabilities, described by the probability weighting function of prospect theory (Kahneman and Tversky 1979). However, decisions based on experience show do not reflect a pattern consistent with overweighting. For example, in the descriptive condition of Hertwig et al. (2004), 36% choose to gamble on a .8 chance to win 4 points (.2 chance of 0 points) over a sure gain of 3 points, while in the experience condition 88% chose to gamble.

Numerous studies find that experience sampling choices are consistent with a reduced weight placed on rare effects, despite little consensus about the underlying mechanisms behind the effect (Barron and Erev 2003, Weber, E.U. et al. 2004, Fox and Hadar 2006, Hadar and Fox 2009, Hau et al. 2008, see Rakow and Newell 2010 for review). Fox and

Hadar (2006) and Hadar and Fox (2009) challenge whether the apparent reduced underweighting of rare events is truly a change in the psychological weight assigned to rare probability events. They argue the effect can be accounted for by sampling error that results in information asymmetry between the two conditions and leads people to underestimate the probability associated with the rare event in the experience condition. The empirical evidence is equivocal on this point. In favor of a sampling error explanation, the prospect theory weighting function applied to the *sampled* rather than *objective* probability can account for observed choices (Fox and Hadar 2006) and the experience-description gap is not observed when the experience condition is yoked to a description condition that provides the probabilities of what was actually sampled (Rawkow et al. 2008). However, using a similar strategy to remove the sampling error confound, the reverse was found. Consistent with reduced psychological weighting, the experience-description gap persisted when participants in the experience condition observed a completely representative sample of events and this resulted in accurate explicit probability judgments (Ungemach et al. 2009).

We remain open to the possibility that the experience-description gap may be more than an artifact of sampling error and that experience sampling may affect judgments about possible outcomes. The literature is clear on the point that experience sampling leads to greater risk taking among experimental lotteries that have a small probability of a loss. However, this has not been tested whether this phenomena also occurs in more contextualized domains. The decision we analyze – to invest in an equity fund over a multi-year time horizon – fits the risk profile of a small probability of a loss. For example, over a five-year time horizon, the probability of a loss is < 20%.[18] In this context experience sampling is expected to increase risky allocations.

Thus, we hypothesized that riskier allocations would be made in the risk simulation condition compared to the description condition (Hypothesis I).

In addition to experience sampling, the risk simulation displays return distributions. Previous research in the myopic loss aversion literature suggests that distributions may also increase risk taking. Benarzti and Thaler (1999) offered participants 100 repeated plays of a gamble with a positive expected value, allowed them to make a decision and later showed them the distribution of returns graphically. Many who initially decline the gamble

[18] Based on the historical returns of the MSCI USA (1973-2008) the probability of a five-year return less than the capital invested is 16%.

subsequently accept it after seeing the return distribution. Using a different graphical presentation format**,** Beshears et al. (2011) also found that distributions can increase risk taking. The graphs they used showed the historical percentage returns of equity funds over a 30 year time horizon, ordered by lowest return to highest return. These displays increased allocation to equities by 11-12%. These results also lead us to hypothesize greater risk taking in the risk simulation (*Hypothesis 1).* In order to disentangle the relative effect of experience sampling and distribution displays, Experiments II and III compare a pure experience sampling and a pure distribution condition.

It is imperative that a decision aid which results in an increase risk taking should not be used unless it also leads to a similar or greater level of comprehension. We expected the risk simulation to increase comprehension of the risk-return profile of the risk fund. Lejarraga (2010) demonstrated that experience sampling can increase comprehension, as measured by frequency judgments of potential outcomes. In Lejarraga's description condition, participants viewed the probability of rain in four cities. In the experience condition, participants were allowed to sample whether there was sun or rain on a given day in each of the four cities. Following a delay period, participants estimated the number of days it would rain in a ten-day period in each of the cities. Frequency estimates were more accurate in the experience than in the description condition. Fox and Hadar (2006) asked participants to estimate the probabilities associated with outcome following experience sampling. They found a high degree of accuracy - the medium correlation between judged and experienced probabilities was .97 and the medium absolute error was .06. Ungemach et al. (2009) document a similarly impressive level of accuracy. Based on these findings, we expected experience sampling to increase comprehension regarding the risk-return profile of the risky fund.

We hypothesized that the experience sampling and richer provision of information in the risk simulation condition would be associated with more accurate estimates of expected returns and probabilities associated with outcomes (Hypothesis II).

Another criterion for assessing the merits of a decision aid is post-outcome evaluation. We wanted to ensure that increased risk taking was not associated with dissatisfaction with outcomes or second guessing about the validity of one's initial decision after receiving an unfavorable return (a tendency documented by research on the outcome bias (Baron and Hershey 1988)). In order to assess whether they experienced decision regret which lead them to re-evaluate their initial risk exposure, after receiving their return participants reported satisfaction with the return and were asked to make a subsequent allocation decision.

3.3 EXPERIMENTAL DESIGN AND DATA

3.3.1 EXPERIMENTAL TASK

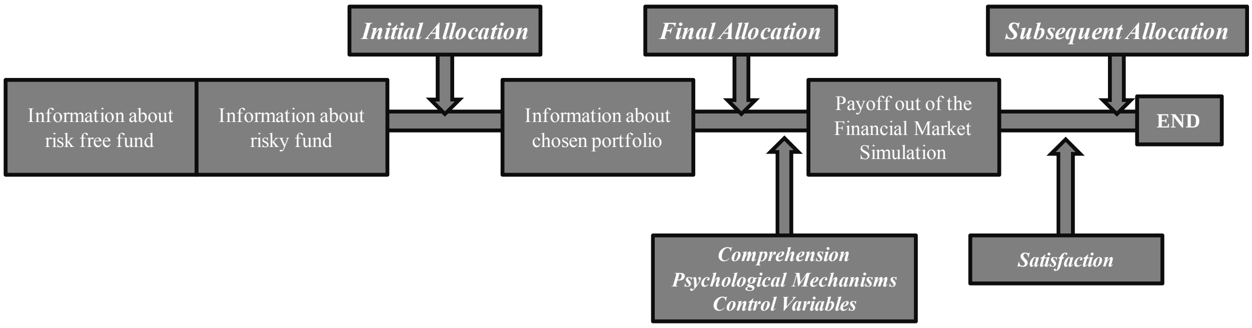
In each of the three experiments, participants were asked to allocate an endowment between two funds. Fund A was a risk-free fund and fund B was a risky fund whose payoff was based on the historical returns off the MSCI US (which was not made explicit to participants).[19] Participants first received information about the five year risk-return-profile of the risk-free fund and the risky fund separately. The manner in which this information was presented varied between conditions (described further in Section 3.2).

Next participants made an *initial allocation*, which allowed them to view the diversified risk-return profile of this initial allocation over a five year time horizon in their assigned risk presentation mode. They could adjust their allocation via a scroll bar and observe how the risk-return profile of the portfolio as a whole changed as many times as they wanted before deciding on their *final allocation*. Only the final allocation was assessed in an incentive compatible manner. Participants were informed that at the end of the experiment a "financial market simulation" would be run to determine the five year return on their *final allocation* decision. It was explained that this simulation randomly generated a return based on the underlying distribution of allocation decision that they chose. Participants had the chance to win Amazon.com gift cards for their simulated return.[20] Figure 3-1 gives an overview of the experimental flow.

[19]For the return on the MSCI US, we calculated the average return based on the historical returns from 1973 to 2008 of 8.95%. To calculate final wealth we assumed normally distributed continuous returns. Note that due to the underlying continuous-time framework, the final value of the portfolio's risky fraction follows a lognormal distribution. For the risk-free return, we assumed an interest rate of 3.35%, which was based on the actual five year interest rate on time deposits in a bank account. The difference between the two returns corresponds to the standard characterization of the equity premium.

[20] Consistent with the existing procedures of the subject pool, we used gift cards instead of real money. Gift cards have several advantages – they can be sent via email and precluded the need for subjects to provide a name and mailing address, which helps ensure anonymity.

Figure 3-1: Overview of Experimental Flow



Experiment III only then assessed psychological measures regarding the risky fund: perceived risk, confidence and the comprehension questions. One comprehension question was subjective: how informed they felt about the risky fund. Several other comprehension questions assessed the objective accuracy of their knowledge about the risky fund by asking them to estimate the expected return, probability of a loss of investment capital and probability of a return of 50% or greater. For further information about the differences between experiments see Appendix Chapter 3.1. Appendix Chapter 3.2 provides an overview of the variables and measures.

In all experiments, before the financial market simulation participants reported control variables: risk attitude, financial literacy (adapted from van Rooij et al 2011), stock ownership and demographics. The financial market simulation was run and participants then reported their satisfaction with their outcome on a 7-point scale. Finally, they reported how they would hypothetically allocate their endowment between the risk-free and the risky fund if they could make the same investment decision again.

3.3.2 STIMULI

All three experiments included a description condition and the risk simulation condition. The risk simulation was developed to use experience sampling and graphical displays to communicate the asset risk in contrast to the way it is usually done in banks – by presenting return expectations with stated information about historical returns (reflected by the description condition).

In the description condition participants were given the expected return as a percentage and additionally as the expected amount of final wealth for each of the funds. The variance of the risky fund was explained in terms of frequencies (in 70 out of 100 cases your final wealth will be between X and Y, in 95 out of 100 cases your final wealth will be between U and Z, see Appendix Chapter 3.3). They entered an initial asset allocation and saw the effects on return and variance of the diversified portfolio numerically. Next, they could adjust the allocation and see the corresponding effects on the return and variance until they decided on a final allocation.

In the risk simulation condition participants saw the expected returns and potential outcomes of their investment on a graphical interface.[21] They were first shown what the return would be if they were to invest the total amount in the risk-free Fund A on a graphical display with a single line. The next step illustrated the expected return and variance of investing the total amount in the risky Fund B. To simulate experience sampling, the program drew potential returns out of the distribution at random and each draw contributed to a distribution function on the screen (see Appendix 3.3). Participants were allowed to sample for as long as they wanted but were required to sample at least eight draws. After sampling, the simulation rapidly displayed another eight draws and then rapidly built up the entire distribution. After watching the simulation for the risky fund, participants entered an initial asset allocation between Fund A and Fund B and went through the simulation again, which now reflected the underlying distribution of their chosen diversified portfolio. They were able to adjust this allocation and repeat the simulation until they decided on a final allocation.

Experiments II and III attempted to deconstruct the risk simulation condition by examining two additional conditions: a pure experience sampling condition and a pure distribution condition. In the experience condition participants first drew returns from the distribution of the two funds separately, in a manner similar to the sampling procedure in Hertwig et al. (2004). Participants had to sample at least three times from the risk-free fund (which was always an outcome of $118) and at least eight times from the risky fund[22] and then entered in an initial allocation. Next they sampled from the diversified portfolio of their

[21]Goldstein et al. (2008) introduce a similar interactive tool that uses distributions to aid decision making in the context of retirement portfolio selection. This tool elicits risk preferences by enabling people to choose the outcome distribution that they would like to determine their income in retirement, within cost constraints. This tool estimates parameters of risk aversion and loss aversion with reliability and validity. In contrast to the current paper, they do not compare how risk preferences differ between different modes of risk presentation, but compare different ways of informing customers about risk.

[22]On average participants drew 14.48 times, with a range from 8 to 109 draws. The number of draws did not influence final allocations significantly.

initial allocation and were able to adjust their allocation and continue to sample until they decided on a final allocation.

In the distribution condition participants viewed the return of the risk-free fund on a graphical display (as a single line) and the distribution graph of returns for the risky Fund B and made their initial allocation. Next they could change this allocation and see how the distribution graph changed before deciding on their final allocation (see Appendix Chapter 3.3).

3.3.3 DATA AND PARTICIPANTS

Experiment I was run at the University of Mannheim with one hundred and thirty-three undergraduates[23] (eighty-two male). The mean age was 22 with a range from 18 to 50 years. Approximately thirty percent of the students reported owning stocks. It took participants on average nineteen minutes to complete the experiment online, for which they were compensated with the chance to earn money in an incentive-compatible manner, based on the outcome of the financial market simulation of their final allocation decision. Participants allocated €1,000 and we randomly selected 10 students to receive an Amazon gift card for the amount of the financial market simulation divided by 100 (which resulted in payments between €10 and €18).

Experiment II recruited one hundred and eighty-eight participants[24] (sixty-six male) from the general population using the subject pool of the Yale School of Management. The mean age was 34 with a range from 18 to 70 years. Participants were predominantly Caucasian with an median income of $40,000 (range from $0 to $199,000). Fifty percent were college educated and approximately forty-five percent owned stocks. Participants again completed the experiment online and were offered a $5 Amazon.com gift certificate for their participation plus a 1 in 20 chance to earn additional performance-based money dependent on the outcome of their final allocation decision. Participants allocated an endowment of $100 and earnings ranged from $96 to $144.

[23] Ten participants were dropped from the original sample of 188 because they participated more than once. Five participants were excluded because they failed an attention-check question which asked what the experiment was about. Nine endorsed just clicking through the experiment or being very distracted. Thirty-one did not complete the experiment. In all experiments, the point at which participants dropped out did not vary between conditions.

[24] Thirty-seven observations were dropped from the original sample of 237 because the participant completed the experiment more than once, as identified by a duplicate IP address. Four participants were excluded because they failed to correctly respond to the attention check. One endorsed just clicking through the experiment. Seven did not complete the experiment.

Experiment III assessed comprehension and potential underlying psychological mechanisms so the sample size was increased to three hundred sixty-two participants[25] (one hundred twenty-two male), again using the subject distribution list of the Yale School of Management. Demographics were similar to those in Experiment II. The mean age was 35 with a range from 18 to 75 years. Participants were overwhelmingly Caucasian with a median income of $39,000 (range from $0 to $145,000). Fifty-three percent were college educated and approximately forty percent owned stocks. Participants again completed the experiment online in exchange for a 50% chance to earn a $5 Amazon.com gift certificate and a one in 40 chance to earn additional performance-based pay based on the outcome of their final allocation decision.

3.4 INFORMATION PRESENTATION AND ALLOCATION DECISIONS

We find that the manner in which people acquire knowledge about risk does affect their allocation decisions. In line with Hypothesis I, the final allocation was significantly higher in the risk simulation condition in all three experiments. Table 3-1 shows the means of the initial and final allocation to the risky fund. In all experiments the final allocation to the risky fund was significantly greater in the risk simulation condition compared to the experience condition.

[25] Thirty-tree observations were dropped from the original sample of 429 because they participated more than once. Nine participants were excluded because they failed the attention-check. Fourteen endorsed just clicking through the experiment or being very distracted. Eleven did not complete the experiment.

Table 3-1: Allocation to the Risky Fund

Table 3-1 reports the results mean allocations, standard deviations and median allocations to the risky fund expressed in percent of total endowment. There was a €1,000 endowment in Experiment I a $100 endowment in Experiment II and III.

	Experiment I (Students) Allocation			Experiment II (General Population) Allocation			Experiment III (General Population) Allocation		
	n	**Initial**	**Final**	**N**	**Initial**	**Final**	**n**	**Initial**	**Final**
Description	75			44			99		
Mean		43.56	**60.42**		52.68	**54.39**		47.95	**57.71**
Std. Dev.		30.85	26.34		28.44	26.04		31.84	27.85
Median		45.00	60.00		50.00	50.00		50.00	60.00
Risk Simulation	58			45			93		
Mean		44.54	**74.15**		52.27	**66.53**		47.16	**70.59**
Std. Dev.		31.68	23.60		25.77	25.50		31.29	26.31
Median		37.50	81.00		50.00	65.00		50.00	75.00
t-test description vs. risk simulation			$t_{(131)}=3.12$ $p<0.01$			$t_{(87)}=2.22$ $p=0.03$			$t_{(190)}=3.38$ $p<0.01$
Distribution				50			81		
Mean					58.32	59.52		50.04	62.46
Std. Dev.					24.03	27.48		27.67	27.33
Median					50.00	60.00		50.00	65.00
Experience				51			88		
Mean					52.61	61.00		41.72	66.65
Std. Dev.					25.46	24.64		31.04	26.62
Median					50.00	65.00		50.00	70.00

The increased risky allocations in the risk simulation condition remains significant when we include control variables using OLS regression analysis[26] in table 3-2. Consistent with previous literature (Hong et al. 2004, van Rooij et al. 2011, Nosić and Weber 2010), self-reported risk attitude is highly significant in all three experiments. The control variables financial literacy, stock ownership, age, education and income were generally insignificant. Education and income were not collected from the student population since education is relatively constant in the sample and it is difficult to meaningfully assess income in a student sample. See Chapter 3.2 for an explanation of the variables used in this and all other analyses. There was no difference in the initial allocation between conditions.

[26] Results also hold using Tobit regression analysis censored by €0 and €1,000 for Experiment I and $0 and $100 for Experiments II and III.

Table 3-2: Final Allocation to the Risky Fund

This table reports OLS regression analysis of final allocations to the risky fund. See Appendix C for an overview of control variables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level, income expressed in ten thousands, standard errors in parentheses.

	Experiment I	**Experiment II**		**Experiment III**	
	Description vs. Risk Simulation	Description vs. Risk Simulation	Experience and Distribution vs. Description	Description vs. Risk Simulation	Experience and Distribution vs. Description
Risk Simulation	132.72***	13.83***		11.92***	
	(38.42)	(5.24)		(3.64)	
Experience			7.61		9.78***
			(5.09)		(3.80)
Distribution			7.75		4.74
			(5.16)		(3.87)
Risk Attitude	137.69***	9.72***	8.81***	10.37***	7.46***
	(22.63)	(2.93)	(2.39)	(2.00)	(1.76)
Financial Literacy	7.19	1.65	1.47	-1.11	-0.44
	(7.99)	(1.25)	(1.05)	(0.86)	(0.65)
Stock Ownership	-48.85	12.03**	5.34	1.77	0.61
	(44.72)	(5.69)	(4.99)	(4.16)	(3.81)
Age	16.04**	0.05	-0.37*	0.001	0.08
	(6.23)	(0.23)	(0.20)	(1.16)	(0.14)
Gender	31.70	3.49	-0.63	1.14	6.54*
	(40.92)	(5.92)	(4.72)	(4.19)	(3.55)
Education		1.97	-3.61	4.39**	1.62
		(2.85)	(2.35)	(2.15)	(1.82)
Income		-1.22	0.07	-0.21	-0.00
		(1.03)	(0.07)	(0.17)	(0.00)
Constant	-189.03	1.96	31.15***	20.70**	29.11***
	(156.06)	(14.21)	(12.17)	(9.91)	(8.32)
Observations	133	89	145	192	268
R-squared	0.33	0.30	0.18	0.21	0.13

Results suggest that adding information through the use of experience sampling and a distribution function leads to more risky asset allocations. This raises the question of whether it is the presence of one or both of these features that results in riskier allocations. This is explored in Experiments II and III by adding a pure experience sampling and a pure distribution condition.

Table 3-2 analyses the results including control variables in an OLS regression, we find in Experiments II that risky allocations are elevated in the experience and distribution conditions compared to the description condition, but are not significantly different (see table

3-2, column (3)). With the increased sample size in Experiment III, the difference between experience and description is significant (see table 3-2, Column (5)).

This evidence of the experience-description gap[27] suggests that the increased risk taking in the risk simulation is driven more by experience sampling rather than by the presentation of the distribution function. Nevertheless, it does not explain the whole effect, as the difference between the description and combination risk simulation condition is greater than the difference between description and experience conditions. There were no significant differences between the description and distribution conditions (table 3-2, Columns (3) and (5)).

3.5 COMPREHENSION AND UNDERLYING PSYCHOLOGICAL MECHANISMS

3.5.1 COMPREHENSION

We analyze whether the manner in which people acquire information about risk affects their comprehension, as measured in several ways. Three comprehension questions had objectively correct responses and required them to estimate aspects of the underlying risk-return profile of the risky fund: expected return, probability of a loss (downside) probability of a high gain (upside potential). Two subjective questions assessed how informed they felt regarding the risky and risk-free fund. See Table 3-3 for comprehension results.

The first question assessed the expected return of the risky fund after five years with an initial investment of \$100. Note that in all conditions except the experience condition, participants were explicitly given the return of the risky fund and only had to recall it correctly. The correct answer based on historical returns is \$153 and participants choose from among five intervals. The highest percentage of right answers was in the risk simulation condition (57%), though this is not significantly higher than any of the other conditions. In the experience condition, where the exact expected return was not stated, correct responses (47%) were similar to the description condition (46%). In order to understand the direction and

[27] Hertwig et al. 2004 and Fox and Hadar 2006 invoke two mechanisms to explain the experience-description-gap: reliance on relatively small samples of information due to limited search (*sampling error*) and overweighting of recently sampled information due to memory constraints (*recency effects*). After controlling for these variables, we continue to find a significant difference between experience and description. It seems that the effect cannot be fully explained by the sampled outcomes. Results are available on request.

magnitude of incorrect answers, we created a new variable to reflect overestimation by assigning the value -1 to the \$100-\$140 interval (the interval that underestimated the return), 0 to \$141-\$180 (the correct interval), 1 to \$181-\$220, 2 to \$220-\$260 and 3 to >\$260. Using ordered probit analysis with control variables, there is significantly less overestimation of the return in the risk simulation condition compared to the description condition ($z= 2.28$, $p= .02$), in line with Hypothesis II. Using the midpoint of each interval to estimate the magnitude of overestimation in each condition, the expected return in the risk simulation condition is overestimated by \$13 in the risk simulation condition and \$24 in the description condition (see columns 3 and 4 of table 3-3).

Table 3-3: Comprehension about the Risky Fund

This table reports the mean deviation from corrects answers to comprehension questions about the risky fund and the mean of feeling informed about the risky fund on a seven-point scale.

Condition	n	Correct return interval	Overestimation of the return+	Overestimation of the probability of a loss	Underestimation of the probability of a gain > \$150	Feeling Informed
Description	99	46%	\$24	0.21	0.15	4.60
Distribution	81	54%	\$27	0.23	0.19	4.39
Experience	88	47%	\$26	0.15	0.12	4.37
Risk Simulation	93	57%	\$13	0.05	0.21	4.99

+Overestimation of return is estimated from the return intervals by averaging the midpoint of the intervals.

Participants estimated the probability that the five year return of a \$100 allocation to the risky fund would fall below \$100 (correct answer 16%) or exceed \$150 (correct answer 54%). Note that the correct responses to these questions were not explicitly stated; participants had to have a sense of the risk-return distribution in order to give a correct answer. Across conditions, participants do not display consistent over- or underestimation regarding the variance of the return. Overall, there is an overestimation of the chance of receiving a loss (overall mean 29%) but an underestimation of a return higher than 150 (overall mean 36%).

Participants were asked to estimate the probability of a loss with the question: "If we put \$100 in the riskier fund, in how many cases out of 100 will final wealth fall below \$100 after five years?" (column 5, table 3-3).[28] Estimations in the risk simulation were significantly more accurate compared to the description condition using OLS regression analysis with

[28] One observation was dropped because it exceeded 100 (180).

control variables (β=-15.37.91, t= 4.97, $p < 0.01$), in line with Hypothesis II. In the experience condition participants were also significantly more accurate about the probability of a loss compared to the description condition (β =-6.77, t= 3.13, p=0.03), suggesting that experience sampling, not the presentation of the distribution function, drives the effects we see in the risk simulation condition. This is consistent with the experience-description gap literature, which documents very high calibration between judged and sampled probabilities.

Though participants in the risk simulation condition overestimate the probability of a loss to a lesser extent and are willing to accept more risk, they do not have unrealistically optimistic expectations. They are most accurate about the perceived return and underestimate the probability of a gain to a higher degree than in all other conditions, though this effect is not significant (Column 6 of 3-3). Again, participants in the experience sampling condition are highly calibrated at judging probabilities, demonstrating significantly more accuracy compared to all other conditions ($t_{(358)}$=2.12, p=0.04).

It is especially important to identify strategies for those with low financial literacy to understand the underlying risk-return profile of their investments. We divide our sample into high and low financial literacy by splitting participants at median financial literacy score (which is equal to the mean). Across conditions, those with low financial literacy are less accurate about the estimated expected return ($t_{(359)}$= 1.71, p= 0.09) and the estimated probability of a loss ($t_{(358)}$= 2.50, p= 0.01). However, participants with low financial knowledge in the risk simulation condition are significantly more accurate about the probability of a loss compared to people with high financial knowledge in other conditions ($t_{(183)}$=2.09, p=0.04). This suggests that the risk simulation holds promise as a tool for financial education.

It may be that participants in the risk simulation give more accurate estimations (aside from estimations of upside potential), but do not feel more informed since the risk simulation might have been perceived as overly complicated. We asked participants how informed they feel about the risky and the risk-free fund on a 7-point scale. For the risk-free fund we find no significant difference in “feeling informed” (mean answers ranged from 5.38 in the experience condition to 5.65 in the risk simulation condition). With regard to the risky fund, which is more complex to understand, participants felt significantly more informed in the risk simulation condition compared to all other conditions $t_{(359)}$=2.84, $p<0.01$) (column 7 of table 3-3).

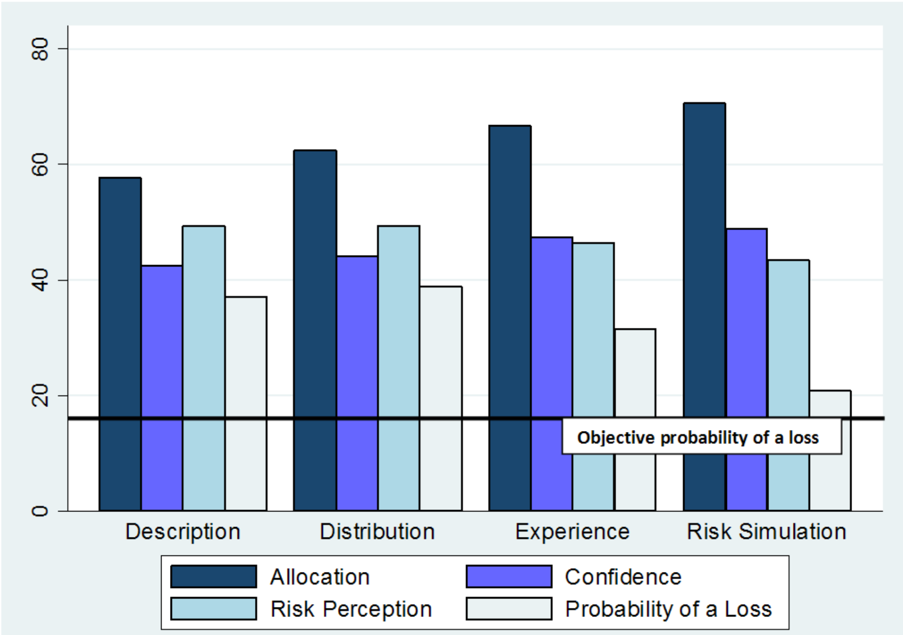
3.5.2 Risk Perception and Confidence

In Experiment III we sought to better understand the psychological drivers that are associated with increased risk taking in the risk simulation. In an exploratory fashion, we examined possible psychological perceptions that could be induced by different presentation formats and drive risk taking. The behavioral model of risk taking posits that risk taking is a function of risk attitude, perceived return and perceived risk, which can be influenced by the decision making context. As discussed in the comprehension section, perceived return was lowest in the risk simulation, making it an unlikely candidate as psychological driver of risk taking. Attitude towards risk, always a significant control variable, behaves like a stable personality trait and does not vary based on risk presentation format. In contrast, perceived risk is associated with risk taking in a manner that varies with presentation format.

After making their allocation decision, participants were asked to report how risky they perceived the risky fund to be on a seven-point scale (anchored at “not risky at all” and “very risky”). Risk perception is significantly lower in the risk simulation (M=4.34) compared to description (M=4.93; $t_{(190)}$= 3.10, p<0.01). It may be that the risk simulation reduces risk perception, which in turn increases risky allocations. The perceived probability of a loss can be considered an indicator of risk perception. Across conditions, both the subjective report of risk perception and the judged probability of a loss closely track risky allocations (see figure 3-2)

Figure 3-2: Graphical Overview of Main Results of Experiment III

This figure displays the pattern of increased confidence, decreased risk perception and decreased perceived probability of a loss associated with investment allocations to the risky fund in the risk tool compared to the other conditions. Perceived risk and confidence, originally measured on a 7-point scale, are multiplied by 10 to facilitate comparisons with allocation decisions.



In addition to the factors of the behavioral model we assessed confidence about investing in the risky fund. Confidence is significantly higher in the risk simulation (M= 4.89) compared to confidence in the description condition (M= 4.25; $t_{(190)}$=3.32, p<0.01). This coupled with the finding that participants in the risk simulation condition feel more informed about their decision is a positive indicator that the risk simulation leads to positive subjective feelings regarding the allocation decision. Across conditions, confidence also closely tracks risky allocations (see figure 3-2).[29]

3.6 Post-Return Decision Evaluation

Does the manner in which people acquire information about risk influence their satisfaction with their outcomes? Those in the risk simulation condition might only be temporarily convinced to accept greater risk and later come to regret their decision, especially if they receive a loss or a return that does not meet their expectations.

[29] Mediation analysis for these measures indicates that risky allocations in the tool conditions are mediated by decreased risk perception, increased confidence in the risky fund, and a lower estimation of the probability of a loss. Results are available on request.

After receiving the outcome of their decisions from the financial market simulation, participants reported satisfaction with their return. We find no evidence that people in the risk simulation condition regret their relatively high allocations to the risky fund. In all three experiments participants in the risk simulation condition were not less satisfied with the outcomes than in the description condition (see table 3-4). Even for people whose return fell below the expected value of their allocation decision, satisfaction was not reduced for those in the risk simulation condition.

Table 3-4: Satisfaction with Returns

This table reports the mean of overall self assessed return satisfaction (7 point scale) and return satisfaction for a subsample of participants - those who received a return below the expected value of their chosen portfolio. Standard deviations are in parentheses. The n in brackets reflect the subsample with luck < 0.

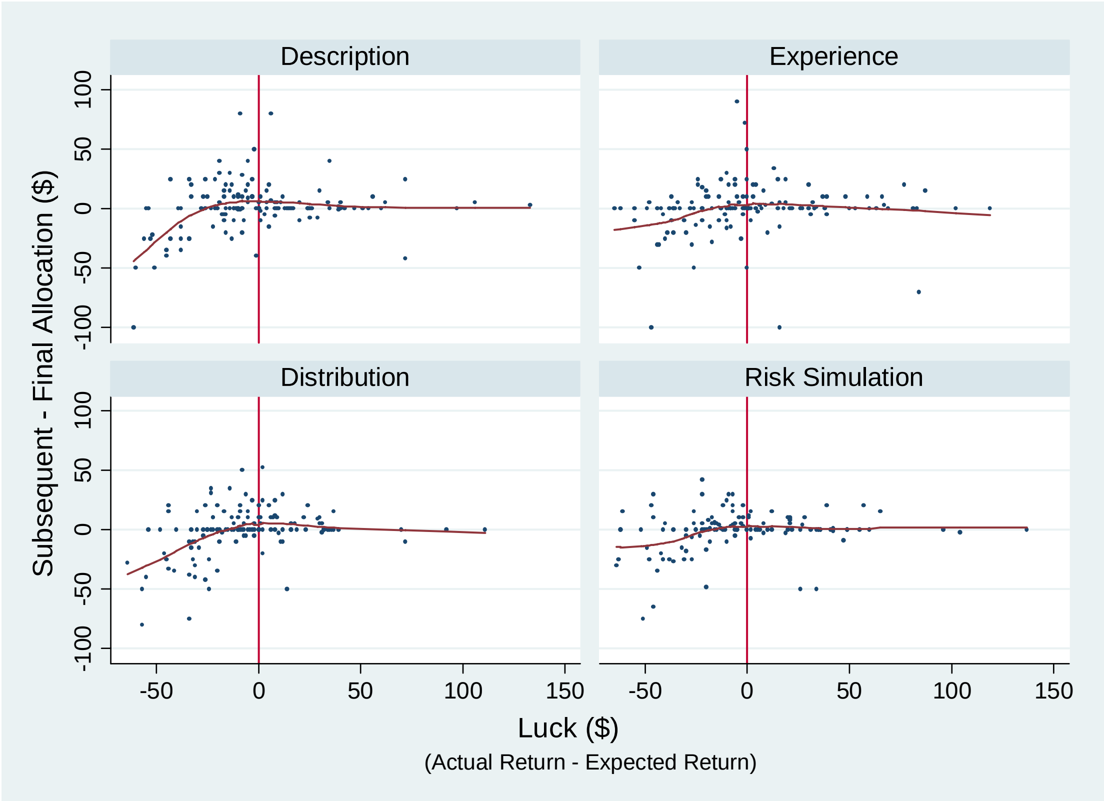
	Experiment I (Students)			Experiment II (General Population)			Experiment III (General Population)		
Condition	**n**		**luck < 0**	**N**		**luck < 0**	**N**		**luck < 0**
Description	65	4.25	3.03	44	5.41	4.70	99	5.25	4.72
	[37]	(2.02)	(1.66)	(23)	(1.59)	(1.43)	(60)	(1.58)	(1.63)
Risk Simulation	54[2]	4.10	3.28	44	5.12	4.54	93	5.31	4.75
	[29]	(1.90)	(1.94)	(26)	(1.59)	(1.70)	(55)	(1.62)	(1.64)

Another indicator of how people evaluate their allocation decision after receiving their return is their subsequent (hypothetical) allocation decision. Across conditions, there are high correlations between the allocation and subsequent allocation (r_{Exp1}= .52, r_{Exp2}=.70, r_{Exp3}=.72). All t-tests comparing subsequent allocation in the tool simulation and the description condition are highly significant, consistent with the pattern of results we see for the final allocation. Participants' willingness to subsequently take on a similar level of risk in the risk simulation suggests that they do not regret their previous allocation decision.

Another way to address the issue of decision regret is to analyze the difference between the first and the subsequent allocation to gain a better understanding of the subjects' reactivity to returns between conditions. Figure 3-3 plots the subsequent minus the first allocation against the variable luck, which reflects whether subjects earned more or less than their expected return in their final outcome. For example, if a participant invested the total \$100 endowment in the risky fund and received an outcome of 160 in the financial market simulation, the variable luck is calculated as 160 – 153 (the expected return) = 7. We combine the data from Experiments II and III, in which participants allocated a \$100 endowment.

Figure 3-3: Subsequent Allocation as a Function of Investment Success (Luck)

This figure reports the subsequent allocation minus final allocation dependent on luck (outcome of the market simulation minus the expected return), in Experiment II and III combined across all conditions.



Across conditions, participants are reactive to losses but not gains. They reduce their allocation to the risky fund in reaction to a return less than the expected value of their allocation (i.e., luck <0). This tendency appears less pronounced in the risk simulation and experience conditions compared to the description and distribution conditions (see figure 3-3). In order to assess this pattern more formally, we focus on the subsample of participants where the expected value falls short of the realized return (i.e. luck<0) and regress the difference between subsequent and final allocation on the interaction terms of the dummy variables for the condition and luck. A higher coefficient suggests that participants reduce their risky allocation in a hypothetical subsequent allocation as a result of a more negative difference between expected and realized return. We find evidence of a lower reactivity to losses in the risk simulation condition. Participants are significantly less reactive in the risk simulation condition compared to distribution ($F_{(1,314)}$ = 6.59, p= 0.01) and in the experience condition compared to distribution ($F_{(1,314)}$ = 4.26, p= 0.04). Participants are more reactive to losses than participants in the experience and the risk simulation condition in the description condition; however this effect is not significant.

3.7 DISCUSSION

Research to date had not examined the optimal way to inform investors about the riskiness of investment products in a manner that maximizes comprehension and does not diminish satisfaction with returns. The results of the current paper suggest that a risk presentation format which incorporates experience sampling and distributions of returns may help achieve this objective. With this increased comprehension comes an increased willingness accept risk in one's portfolio. We do not wish to imply that research should aim to bolster people's willingness to take on investment risk, but rather that it is essential to understand how the information provided in the context of this decision influences the propensity to accept risk and comprehension regarding return expectations. We examine risk taking in an experimental paradigm that models a common investment decision: allocating assets between the risk-free return and a diversified equity fund. The risk simulation may have a different effect on risk taking in an alternative paradigm, such as one that pits a diversified stock fund versus an asset with a high probability of a loss.

Our main result is that information presentation format reliably affects allocation to a stock fund over the risk-free rate. Across three experiments, when the presentation format both includes experience sampling and displays the distribution of returns, risky allocations are higher compared to stating the expected return and standard deviation. Experiments II and III suggest that experience sampling is the more powerful driver of the riskier allocations compared to displays of return distributions. However, experience sampling does not entirely explain the increased risk taking in the risk simulation since risk taking in the distribution condition was consistently (though non-significantly) elevated compared to the description condition. Presentation of the distribution function may have some additive effect. Future research should further explore different graphical presentation formats. For example, displays that contrast annual historic returns of bond and stock funds have been found to increase allocations to the stock fund (Beshears et al. 2011).

We examined whether there are negative repercussions to accepting more risk in the risk simulation. Increased risk taking in the risk simulation does not compromise comprehension. Participants in the risk simulation condition were most accurate about the expected return and the probability of a loss and felt significantly more informed about their decision. We do not observe any evidence of greater decision regret or unrealistic expectations about the risky fund. Participants in the risk simulation conditions are no less satisfied with the return they receive and maintain the same or greater risk level when they are asked how they would allocate their money if they could make a subsequent allocation decision. In conditions that included sampling subsequent allocation decisions tend to be less reactive to variance in returns. Experience sampling seems to prepare participants for the possibility of a loss, resulting in a decreased tendency to react to losses by taking on less risk in a subsequent decision. If we extrapolate from the current findings, we would predict that experience sampling could assist people in sticking to a long term investment plan in the face of market volatility. However, the current paper is an experimental paradigm intended to model decision-making that would occur over the course of years compressed into the short time span of the experiment. Further research should examine the role of experience sampling in actual investment decision with feedback and ongoing decision making extended in time.

Across conditions, risky allocations are associated with a pattern of lower perceived probability of a loss, lower risk perception and greater confidence in the risky fund. Consistent with the behavioral model of risk taking, these findings suggest that subjective perceptions can be powerful determinants of risk taking. Risk presentation format may act on these perceptions to drive risk taking. To test this proposition, further research should explore whether these perceptions vary by risk presentation mode prior to choice (which then could determine risk taking) or are simply after-effects of making riskier choices.

Future research should examine the effect of the risk simulation for other types of financial decisions. As discussed above, we do not expect the risk simulation to uniformly increase risk-taking. Future research could examine allocations among funds of various risk levels, foreign vs. domestic funds, more than two funds, etc. Further, a limitation of this paper is that we examine a single time horizon: five years. As described by the research on myopic loss aversion, extending the time horizon is likely to increase risk taking. It may be that the effect of information presentation format will interact with this effect. Specifically, the effect of the risk simulation on increased risk taking is likely to diminish with longer time horizons. Future research could also look beyond investment decisions. Risk simulations could also be used to inform home buyers about the risks associated with the real estate market, such as home prices and fluctuations in interest rates.

This research contributes to the objective of helping people understand the risk that they face in their investment decisions. Instead of simply using psychometric scales to assess willingness to accept risk, financial providers could provide tools to further clients' understanding of the implications of portfolios with different risk profiles and ensure suitability. The use of experience sampling in financial simulations may be a fruitful strategy for banks to improve the quality of the information they provide about their investment products to ensure that clients understand both the risks they take and the amount of risk they are prepared to take.

4 SOMETIMES LESS IS MORE – THE INFLUENCE OF INFORMATION AGGREGATION ON INVESTMENT DECISIONS

4.1 INTRODUCTION

During the last years we have observed an increasing individual involvement in financial decision making, especially in investment decisions. Bank customers use online banking not only for money transfers, but also for their asset allocation within their home bank accounts or open new accounts at online brokers. As a result, they decide on their own how to invest their money. The financial crisis has shown that many investors are overburdened with that decision, as they often do not understand the risks they have taken or have incorporated a risk level that does not fit their preferences. So, what makes financial decisions so difficult and error-prone for private investors? Investment decisions are associated with risk, ambiguity, choice overload and therefore great complexity. Investors deciding about their level of risk taking need to think about return expectations and have millions of investment options to choose from. This is a challenge even for financial professionals and experienced investors and much more complicated for the ordinary private household.

Different policy regulations intend to simplify financial decision making and protect consumers taking the well documented lack of financial literacy (e.g., van Rooij et al. 2011, Calvet et al. 2009, Guiso and Jappelli 2009) into account. One example is the key investor information document (KIID) within the European Union[30], which is a mandatory two pages document for each mutual fund. The aim is to make different investment funds comparable by providing predefined simplified indicators for each of the funds. Before making investment options comparable it is, however, important to know, what kind of information is understandable for the customer and how this information can be provided as complex as necessary, but as simple as possible. There are numerous ways to graphically present information about historical returns – density functions, index of value over time, bar charts of percent annual yields, etc. These presentation variations yield differences in risk perception

[30]For further information see Markets in Financial Instruments Directive 2004/39/ec.

and risk taking propensities (e.g., Vrecko et al. 2010, Diacon and Hasseldine 2007; Benartzi and Thaler 1999). The literature has shown that bar graphs of returns induce, for example, a lower risk perception compared to a continuous density distribution (Weber, E.U. et al. 2005), or that simulated risk information opposed to descriptive information is related to higher decision confidence and a better risk understanding (Haisley et al. 2011). The key question is hence how to simplify information without losing necessary content.

One way to simplify complexity is to aggregate information. This can be done in several ways; information can be aggregated over time by providing information less often (e.g., quarterly instead of monthly); or, information can be aggregated cross sectional by providing information less detailed (e.g., fund returns instead of returns of every single holding within the fund). The way how given information is aggregated has indeed an influence on decision making. Studies show that a higher degree of information aggregation under temporal aspects, also referred to as myopic loss aversion, leads to higher risk taking (e.g., Fellner and Sutter 2009; Langer and Weber 2008; Haigh and List 2005; Gneezy and Potters 1997, Thaler et al. 1997). Evidence for the influence of information aggregation over asset returns on risk taking is not consentaneous until now; while Anagol and Gamble (2011) find an increase in risk taking if feedback on the whole portfolio is given instead of asset wise returns in an experimental setup, Beshears et al. (2011) do not find that effect in their field study.

In this paper, we want to shed further light on the influence of cross sectional information aggregation with the intention to explain the different findings in the literature. In general, cross sectional information aggregation can be given externally. One example are mutual funds where different assets, and hence asset returns, are aggregated into one product. Besides that, information aggregation can be self selected, as investors are able to choose whether they observe the performance of each of their assets separately or, aggregated, namely of their portfolio as a whole.

We analyze the influence of cross sectional information aggregation in a simple, but also very important investment decision – the allocation between a risky and a risk free asset. According to basic financial theory, the efficient frontier of investment opportunities in a mean-variance-framework is defined by the capital market line, the line through the risk-free rate forming a tangent to the set of risky investments. Following this classical finance theory all an investor has to do for an optimal investment is to finds his point on that capital market line (Tobin 1958) allocating his money between a risky market portfolio and a risk free asset.

The following example reflects, how information can be aggregated while making that decision: In the process of allocating money between a risky and a risk-free option an investor gets information about historical returns of risky investment opportunities (one diversified fund in our setting), often stated in percent or in standardized forms starting from a 100 units investment; he then has to decide about how much to invest risky as compared to a risk free alternative. He needs to apply (and therefore aggregate this information on his own) the given risk-return information to his personal circumstances (his personal investment amount and time horizon). Afterwards he needs to incorporate all the information given, namely about one diversified risky asset and one risk-free asset, into one outcome estimation for the whole portfolio (second step where information needs to be aggregated). In other words, the customer should based on the given information be able to estimate the risk return profile of his portfolio. In our setup, we manipulate these two ways of aggregating information.

We conducted three experiments, where subjects had to allocate an endowment between a diversified risky and a risk free fund. In Experiment I and II we test the effects of information aggregation by providing risk information in an interactive format, where participants sampled information. In Experiment II we used a different risky asset and a different subject pool compared to Experiment I to analyze the robustness of our results and assessed additional explanatory measures. In Experiment III we use a descriptive way to present risk information to analyze whether the presentation format itself influences the effects of information aggregation.

In each of the experiments, individuals were randomly assigned to one of three treatments differing only in the degree of information aggregation. In our first treatment participants get standardized information about the two assets and decide about their allocation (*control group*). In a second treatment we introduce a small level of aggregation. Instead of a standardized risk-return profile (in the sense of "if an investor were to invest $100"), participants are provided with the risk-return profile for the risky and the risk free asset based on the amounts they have chosen to invest into each of them (*separation group*). In a third group participants get the information on a portfolio level (which means that they observe one return instead of two separate estimates), which reflects the most aggregated level (*aggregation group*).

Our results suggest that the extent of information aggregation affects asset allocation in our interactive presentation framework. We find the highest level of risk taking in the aggregation group, followed by the separation group and the control group. Getting more aggregated information about potential consequences of a chosen portfolio encourages people to increase their risk level. We underline the robustness of this effect by using continuous distributed assets for the risky option (in contrast to binary prospects frequently used in the decision making literature, e.g., Steul 2006, Langer and Weber 2001) as well as replicating the effects in a second experiments with different investment amounts ($100 versus €10,000), different cultural background (U.S. and Germany) and different underlyings for the risky asset (historical returns of the MSCI USA in Experiment I and a worldwide diversified fund in Experiment II).

In Experiment I we additionally explore how participants evaluate their decision ex post, namely after receiving one simulated outcome based on their chosen allocation. In addition to former studies, which evaluate ex post decision satisfaction based on the subsequent allocation decisions (e.g., Anagol and Gamble 2011; Langer and Weber 2001), we add subjective measures of decision satisfaction. We find that participants in the aggregation treatment 'stay the course' and do not lower their risk in a second choice. Participants show a similar level of satisfaction over all treatments. However, if we limit the analysis to participants, who receive a loss (outcome below the expected value of their chosen portfolio), we find significantly lower dissatisfaction in the aggregation treatment. It seems that presenting potential outcomes as a portfolio reduces dissatisfaction with a negative outcome. In other words, people are more aware of the overall portfolio risk and take into account that a well considered ex ante decision might ex post have a negative outcome.

In Experiment II we additionally ask which underlying mechanisms cause this higher risk taking in case of information aggregation. We find that the higher risk taking is accompanied by a lower risk perception as well as a more accurate estimation of the probability of an overall loss.

Our findings of Experiment I and II revealed a robust effect of higher risk taking in case of higher information aggregation. However, findings in the literature are quite contradictive. One reason for the robustness of our results might be the general risk presentation format, namely the interactive sampling of risk information. Therefore, we run an additional Experiment III to test the effect of a different risk presentation format, a descriptive format. In that case we do not find a higher risk taking in the aggregation treatment. In contrast, participants seem to bear less risk compared to the separation treatment if they do not get informed about the distribution as a whole. The effect disappears for participants who take on more time for the allocation decision. Looking at the ex post decision behavior, we find that participants in the aggregation treatment are again more committed to their decision in a subsequent allocation and are less dissatisfied in the loss domain, whereas participants in the separation treatment significantly reduce their risk taking in a subsequent allocation.

Overall, we find that information aggregation has an important influence on risk taking. It significantly increases risk taking if information about the risk-return profile is provided in an interactive way. The effect in a descriptive format is not quite clear, which is in line with former research (e.g., Beshears et al. 2011).

We contribute to the existing literature of cross sectional information aggregation by further decomposing the degree of information aggregation by comparing the separation treatment, which already has a small degree of aggregation, to a control group, where no aggregation takes place. Additionally, we test different risk presentation formats, namely an interactive presentation format where participants were shown the full distribution of asset returns and a descriptive presentation format, where participants were shown the expected return and quantiles of the distribution of historical returns. With the help of these two presentation modes, we are able to explain, why some studies in the literature might find an effect and others don't as the effect of information aggregation strongly depends on the way the risk information itself is presented. Besides that, we contribute to the literature by showing, that, even if information aggregation might not always influence risk taking itself, it robustly influences people's satisfaction with the outcome of their decision. It has a positive and robust influence on ex post decision evaluation independently of whether the information in general is presented in an interactive or a descriptive way.

4.2 LITERATURE REVIEW AND HYPOTHESES

Research on information aggregation addresses the question of whether risk taking behavior varies depending on how often or how detailed information is provided. There are different possibilities to aggregate risk information in a financial context. Investors could observe the performance of the assets they have in their account very frequently or rarely – an aggregation under temporal aspects known as "myopic loss aversion": investors' willingness to invest into a risky asset increases if feedback about returns is given less frequently (e.g., Haigh and List 2005, Langer and Weber 2001, Gneezy and Potters 1997).

In this study we focus on another possibility to aggregate information, namely over asset returns. Steul (2006) observes that participants appear to be less risk averse in aggregated conditions if ambiguity[31] is induced; she does not find an influence of information aggregation on risk taking if binary prospects (which were mostly provided in the study as investment opportunities) can be associated with definite outcomes and probabilities. This result is interesting for portfolio decisions, where future returns can only be estimated and returns are ambiguous in case investors haven't built subjective probabilities for the assets' performance. However, the results for the ambiguous and non ambiguous group can also be explained with complexity instead of ambiguity; in the ambiguous condition decisions were more complex, as ambiguity was introduced by providing probability estimations of "experts". So if outcomes are segregated participants need to take more information into account (experts' opinion plus different assets) and therefore might take on more risk in the aggregated condition. A study which introduces a wider and therefore more complex range of potential outcomes was conducted by Anagol and Gamble (2011). They show that providing feedback about the performance of chosen assets on a portfolio level instead of asset by asset increases risk taking. And the effect could not be explained with higher diversification as a driver for lower risk in the segregated treatment, as they also faced lower expected returns. Kumar and Lim (2008) analyze a dataset of individual investors' trades and portfolio positions. They find that investors who frame narrowly (for an overview of narrow framing see Kahneman 2003, Kahneman and Lovallo 1993), which is in line with more segregated information, face a stronger tendency to sell winners and hold loser (disposition effect, see Odean 1999; Weber and Camerer 1998) and exhibit weaker diversification skills. In contrast, Beshears et. al. 2011, could not replicate this effect in their field study; they do not find any effect of cross sectional information aggregation on risk taking. The authors have found different potential reasons for that, namely that they label the assets, have larger investment amounts, take real mutual funds and accompany participants for a long time horizon and have a different subject pool.

In our current study we analyze how much risk investors take in their portfolio dependent on the degree of information aggregation. Building up on the results of the literature we suppose that higher risk taking can be observed if the information about the potential outcomes is presented in a more consolidated way. Nevertheless, a presentation of separated returns already incorporates a certain degree of information aggregation, as the return information is already shown for the amount participants want to invest. Therefore, we introduce a third group where nothing is aggregated and participants get standardized return

[31] Ambiguity is induced by providing expert information about potential environmental states making associated probabilities uncertain.

information, namely an investment of 100 units in the respective asset. We expect that even this small degree of aggregation in the separation groups already leads to a higher risk taking in comparison to a treatment, where nothing is aggregated. We summarize this in hypothesis I:

Risk taking increases if risk-return information (a) is provided on a portfolio level instead of asset by asset and if the information is provided (b) based on subjects' chosen investment amounts compared to a standardized format (Hypothesis I).

Haisley et al. (2011) show that a better understanding of the given information in a asset allocation context leads to a better ex post decision evaluation, especially if the outcome of a decision does not meet the expectations. As we expect participants to better understand the underlying risk if information is more aggregated, we suppose that they are more committed to their decision and evaluate their decision ex post more positive even if the outcome does not meet their ex ante expectations. This leads us to our hypothesis II:

People are (a) more satisfied with the outcome of their decision and (b) less dissatisfied when facing a loss if information has been presented in a more aggregated manner. Additionally they (c) accept the same level of risk in a subsequent allocation decision (Hypothesis II).

An apparent reason for the higher risk taking itself might be that investors do not observe the variance of each asset, but of the portfolio as a whole and therefore perceive the risk to be lower. This effect was also found in studies on information aggregation under temporal aspects; Benartzi and Thaler (1995) show for example that investors are not willing to accept return variability, which is more obvious under shorter time frames. There are various studies in the literature showing that risk taking is more determined by subjective risk measures like risk perception (see e.g., Nosić and Weber 2010, Jia et al. 1999, Mellers et al. 1997, Sarin and Weber 1993) than by objective measures like variance (which is constant between treatments in our experiment). In an experiment from the decision making literature (Benartzi and Thaler 1999) participants have been offered 100 repeated plays of a gamble with a positive expected value; in a second step, the distribution of returns has been shown graphically. Many who initially decline the gamble subsequently accept it after seeing the return distribution. The authors hypothesize that the reversal in preferences is caused by the tendency of subjects to overestimate the probability of a loss if they do not view the overall return distribution. They recommend that investors should be presented with aggregated distributions that reflect the range of possible outcomes of their investment decisions because people seem unable to comprehend the characteristics of this distribution based on numerically stated probabilities. We summarize that in hypothesis III:

People perceive the risk to be lower (a) and are more accurate in estimating the downside risk of an investment (b) if the return distribution is shown in an aggregated format. People additionally feel more informed (c) if the return distribution is shown in an aggregated format (Hypothesis III).

4.3 EXPERIMENT I

4.3.1 METHOD

Participants, Procedure and Payment

178 participants (78 male) we recruited using the subject pool of the elab[32] of the Yale School of Management in July 2010. The mean age was 35 with a range from 18 to 74 years. Participants were overwhelmingly Caucasian with a median yearly income of $45,000 (range from $0 to $8,000,000). Around sixty percent were college educated and approximately fifty-five percent owned stocks. After completing the study, participants could provide their e-mail address to take part in the lottery. Participants are told that a "financial market simulation" will be run at the end of the experiment to determine the five year return of their investment. It is explained that this return will be randomly drawn out of the distribution of returns they choose with their allocation and that they have the chance to win Amazon.com gift cards for their simulated return. Participants allocated $100 and completed the experiment online in exchange for a 50% chance to earn a $5 Amazon.com gift certificate and a one in 40 chance to earn additional money based on the outcome of their allocation decision.

Experimental Task

At the beginning of the experiment participants are informed that the main task will be to allocate a certain endowment between a risky and a risk free fund for a five year time horizon. The risk free fund has a guaranteed return with an interest rate of 3.35% p.a. The payoff of the risky fund has an expected annual return of 8.9% and an annual standard deviation of 15.89% (returns are based on the historical returns of the MSCI USA, what, however, was not known by participants). The risk-return information of the risk free and the

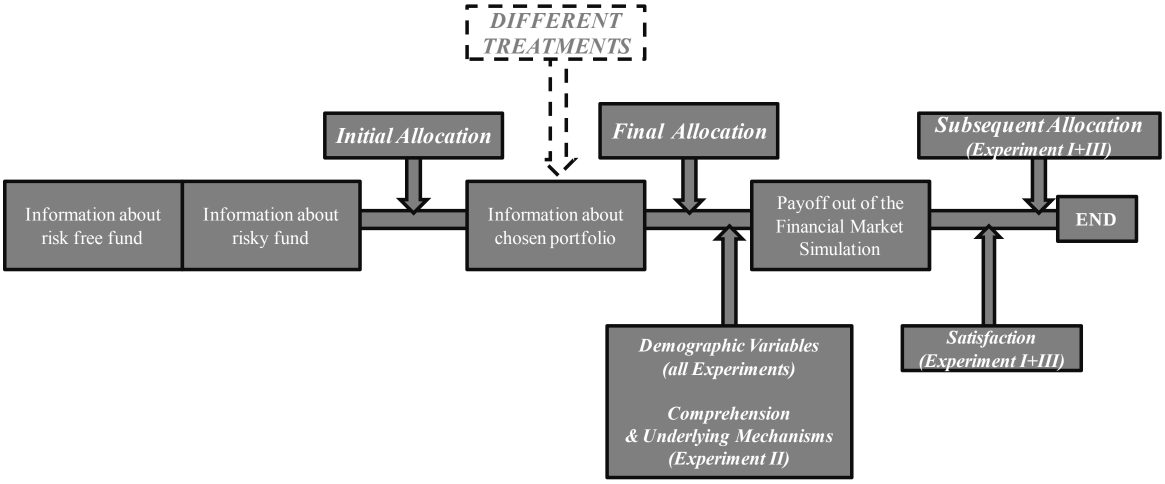
[32]The researchers using the elab subject pool at Yale School of Management are conducting research that examines consumer behavior. For further information see https://elab.som.yale.edu.

risky fund is provided by a risk simulation tool, which has been introduced in a study conducted by Haisley et al. (2011). The risk tool uses experience sampling and graphical displays to communicate the asset risk. Haisley et al. (2011) show that using the risk tool in comparison to other methods of presenting asset risk (description, distribution graphs and pure experience sampling) leads to a greater comprehension, a higher risk taking without any increase in decision regret and less reactivity to either positive or negative variations in returns. The risk tool works as follows: participants observe the expected returns and potential outcomes of their investment on a graphical interface. They are first shown what the return will be if they are to invest the total amount into the risk free fund on a graphical display with a single line indicating that the return is guaranteed without any variance (see Appendix Chapter 4.1 for an overview of the single steps). The next step illustrates the expected return and variance of investing the total amount into the risky fund. To simulate sampling, the program draws potential returns out of the distribution at random and each draw contributes to a distribution function on the screen. Participants are allowed to sample for as long as they want to (until the entire distribution is built up) but are required to sample at least eight draws shown as a bar graph (comparing the endowment and the outcome) and eight draws just seeing the outcome. After deciding about an initial allocation, participants could adjust this allocation and also see their risk-return information with the help of quantiles (in how many out of 70 cases their final wealth will be between X and Y, see Appendix Chapter 4.1). They are additionally able to watch the risk simulation again.

As mentioned before, the first decision subjects are asked for is to enter an initial asset allocation between the risk free and the risky fund, after they have watched the presentation of the two funds separately with the help of the risk tool described above. This initial allocation reflects the starting portfolio. To test how different degrees of information aggregation influence asset allocation participants are randomly assigned to one of three different treatment groups (described further below) in a between-subjects design.

In all treatments participants get further information about their chosen allocation and are able to adjust the initial allocation and see how adjustments change the risk-return profile (dependent on the treatment). They can watch the quantiles and the simulations and change their allocations as long as they want to until they are able to decide about a final allocation.

Figure 4-1: Overview of Experimental Flow



After the final allocation decision subjects are asked to fill out a questionnaire (described further below) and the financial market simulation for the payment of participants is conducted. Figure 4-1 gives a graphical overview of the experimental flow.

Treatments

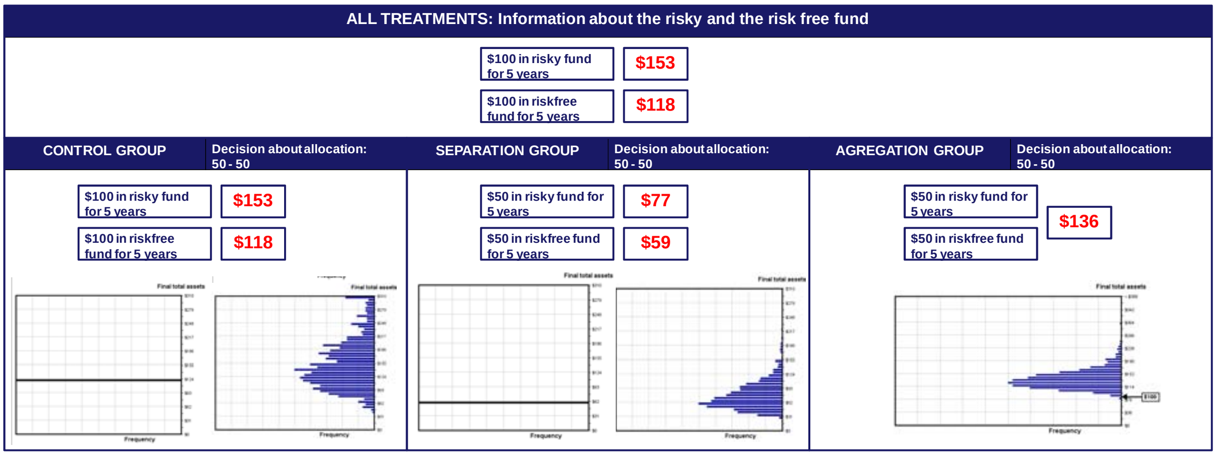
The three treatments differ in the degree of information aggregation. Figure 4-2 displays differences between treatments giving a numerical example for each treatment, exemplarily for an investor $50 in the risk free and $50 in the risky asset.

In the *control group* treatment participants view the simulation for the two assets separately one after another for a second time, namely the same way as the two assets have been introduced at the beginning of the experiment. They receive the information for each of the two assets based on a hypothetical $100 investment, independently of their chosen allocation. Given quantiles and the provided simulation do hence not change if participants change their allocation and they have to calculate the respective expected returns for their portfolio on their own in case they need that information for their decision.

In the *separation* group participants view again two graphical interfaces with the quantiles and *two* simulations, one for the risky and one for the risk free asset, *but with the respective amounts* they have chosen as an initial investment.

In the *aggregation* treatment participants are watching the quantiles for the whole portfolio they have chosen. Afterwards, they view one simulation of their potential returns after a five year investment horizon, which now reflects the underlying distribution of their chosen diversified portfolio (see figure 4-2).

Figure 4-2: Overview of Differences between Treatments



In the example depicted in figure 4-2, participants in the separation group, who face an expected return for the risky asset of $77 and a sure outcome for the risk free asset of $59, can easily calculate the aggregated portfolio return of $136 (by adding up), that a person in the aggregation treatment would have been provided with.

Questions on Ex Post Decision Evaluation – Satisfaction and Subsequent Allocation

To analyze how participants evaluate their decision on an ex post basis, we assess different measures of decision evaluation after participants have received the information about the outcome of their decision made (see figure 4-1). The first indicator for ex post decision evaluation is satisfaction with participants' return (assessed on a 1-7 scale) out of the financial market simulation, which is conducted to determine the payoff of the participants winning the lottery. This simulation draws one outcome out of the distribution of returns determined by the subjects chosen *final allocation*.

We conduct the satisfaction with a hypothetical loss, namely the 5^{th}% quantile of their chosen portfolio, as a second measure of decision evaluation to analyze whether participants evaluate an ex ante decision good even if the ex post outcome does not meet their expectations differently between treatments; if a participant has for example invested $100 in the risky asset over five years he is asked, how satisfied he would be with a return of $80. To further test participants commitment to their decision we ask them, how they would allocate their endowment again, if they had a second chance, referred to as the *subsequent allocation*.

Questions on Demographics

Participants are also asked to provide the following demographic information, which we use as control variables: age, gender, income, and the degree of education. We additionally assess their risk attitude asking how willing they are to take financial risks on a 1-7 scale and their financial literacy score (adapted from van Rooij et al. 2011).

4.3.2 Results

Patterns of Asset Allocation

To examine the effect of information aggregation on risk taking, we use the *marginal allocation*, the difference between the investor's *initial* and *final allocation* to the risky fund, as our main dependent variable (see Appendix Chapter 4.2 for an explanation of the variables used in this and all other analyses). The differences between treatments can only be observed if participants somehow allocate their money between the risky and the risk free fund: participants, who have invested everything in the risk free or the risky asset respectively, do not see any difference between the treatments and cannot be influenced by the treatment itself. Consequently, they need to be excluded from the analysis. We drop nine participants investing nothing and thirty-eight investing everything into the risky asset. Later in the results section we analyze different initial allocation intervals, e.g., only participants investing between 15 and 85 percent to the risky asset, to test whether the degree of portfolio building has an influence on the differences between treatments.

We find that the degree of information aggregation, or in other words, the way in which potential outcomes are consolidated, does affect risk taking. The mean *marginal allocation*[33] is higher in the aggregation group compared to the separation group and the control group (see table 4-1) and the effect is significant for the difference between the aggregation and the control group (t_{110}=2.25, p= 0.03). The marginal allocation in the separation group is also higher compared to the control group, which indicates that helping people to apply the information they get to their personal circumstances has an influence on risk taking.

[33]Again the marginal allocation is defined as the difference between initial and final allocation, where the aggregation manipulation took place. The initial allocation is by definition not influenced by treatments, as participants in all treatments got the same information before this decision is made.

Table 4-1: Overview of Initial and Marginal Allocation to the Risky Fund

This table reports the results mean (standard deviation) initial allocations and marginal allocation (difference between final and initial allocation) to the risky fund out of a possible $100 allocation by treatments.

Treatment	**Asset Allocation**		
	N	**Initial in %**	**Marginal Allocation in %**
Control Group	57	54.79 (17.38)	4.11 (9.45)
Separation	63	58.56 (18.35)	6.92 (14.93)
Aggregation	55	55.27 (18.82)	8.87 (12.76)

For further analysis we perform an OLS regression analysis including demographic and personal characteristics as control variables. Consistent with H_I we find that risk taking increases significantly for participants in the aggregation group (see table 4-2, column 1).[34] Providing participants risk information based on their personal investment amounts (separation group) has a positive, marginal significant influence on risk taking if controls are included. Confidence, namely how confident participants feel with their allocation, and decision time (described further below) are additional significant predictors of marginal allocation. People, who feel more confident, are more likely to increase their initial risk taking. Confidence is strongly and significantly correlated with risk attitude (ρ=0.60, p=0.00). We do not find a significant influence of risk attitude, which is a robust predictor of risk taking in the literature (e.g., Hong et al. 2004, van Rooij et al. 2011, Nosić and Weber 2010) on marginal allocation. However, this finding does not contradict the literature. Results of an OLS regression analysis with the absolute level of risk taking (initial allocation instead of the marginal allocation as a dependent variable) reveal a significant influence of risk attitude (regression coefficient $\beta = 4.36$, $p < 0.01$) as well as financial literacy ($\beta = 1.54$, $p < 0.01$, results not reported due to space concerns).

Due the experimental design, the differences in what participants observe in the treatments get more obvious if participants distribute their money more equally over the two assets (as participants need to aggregate more information on their own if they are in the

[34]Results stay significant using Tobit regression analysis. We also test for multicollinearity using the variance inflation factor. The maximum VIF of any of the explanatory variables is 1.91. In other words, multicollinearity appears to be less of a concern in our setting.

control group). Therefore, we want to explore whether the effects of information aggregation differ for those participants. We narrow the defined interval of participants who initially allocate between 1% and 99% to the risky fund in additional regressions to participants who initially allocate between 15% and 85% and between 30% and 70% to the risky fund (see table 4-2, column 2 and 3). The coefficient dummies for the aggregation treatment as well as for the separation treatment increase if the analyzed interval is scaled down to participants who observe more obvious portfolio effects. We conclude from that information aggregation especially influences risk taking when the information is more complex; when for example only a small fraction of the risky asset is included in the portfolio the portfolio looks quite similar to the risk free asset and participants can use information for the risk free asset only as an indicator how their final portfolio looks like. This gets more complicated if the money is for example distributed 30-70 across the two assets.

Besides the effect of treatments, we also observe a significant influence of *decision time.* Decision time is defined as the time a participant spends between his initial and his final allocation (the time where the different treatments take place) divided by the median decision time within that treatment (aggregation, separation or control group).[35] Decision time does not differ significantly between treatments and a longer time spent seems to generally convince subjects to increase their risk level. One reason might be that the decision context feels more familiar if people pay attention for a longer time.

[35]We standardize decision time to relate the effect of spending more (less) time as the average participant increases risk taking.

Table 4-2: Marginal Allocation to the Risky Fund

This table reports results of OLS regression analysis of marginal allocations to the risky fund comparing the three treatments (control group is omitted) in Experiment I and Experiment II. Column 1 reports results of all participants investing between 1 and 99% into the risky assets, whereas column 2 and 3 are restricted to participants investing between 15% and 85% as well as 30% and 70% respectively.

* indicates significance at the 10% level, ** at the 5% level and *** at the 1% level, standard errors in parentheses.

Marginal Allocation	**(1) All**	**(2) 15-85**	**(3) 30-70**
Aggregation	7.39***	7.95***	9.40***
	(2.65)	(2.75)	(3.27)
Separation	5.49*	6.00**	6.22**
	(2.52)	(2.64)	(3.21)
Risk Attitude	-0.80	-0.69	-0.24
	(1.29)	(1.34)	(1.70)
Gender	-2.05	-2.57	-2.52
	(2.22)	(2.34)	(2.90)
Age	-0.15	-0.19*	-0.20
	(0.09)	(0.10)	(0.12)
College	-3.20	-3.59	-6.85**
	(2.09)	(2.21)	(2.87)
Log (Income)	-0.25	-0.26	0.05
	(0.36)	(0.37)	(0.44)
Financial Literacy	0.28	0.40	0.63
	(0.41)	(0.44)	(0.57)
Confidence	2.20**	2.50**	3.08**
	(0.97)	(1.02)	(1.25)
Decision Time	1.99**	2.21**	2.90**
	(1.01)	(1.06)	(1.31)
Constant	-0.10	-1.01	-8.15
	(5.92)	(6.22)	(8.15)
Observations	175	166	123
R-squared	0.10	0.11	0.16

Ex post decision evaluation

The effect of different aggregation formats on self assessed satisfaction is analyzed in an ordered probit regression model (see table 4-3). Results show a positive, but not significant effect of the aggregation treatment on satisfaction (see table 4-3, column 1). Satisfaction is significantly influenced by the *outcome*, calculated as the return of the financial market simulation divided by the expected value of the participants' chosen portfolio. There is a significant and negative effect of income on decision satisfaction; participants with a higher income might have higher expectations or are quite more used to additional income compared to participants with lower income.

Aside from measuring overall satisfaction, one could analyze satisfaction dependent on whether participants receive a gain or a loss; according to Haisley et al. (2011) participants are less reactive to a negative outcome if risk information is simulated (in the risk tool) compared to other presentation formats. To investigate whether the degree of information aggregation also influences (dis)satisfaction in the loss domain, regression model (2) is limited to participants, who received an outcome from the financial market simulation below the expected value of their chosen portfolio; results reveal that presenting potential outcomes as a portfolio reduces dissatisfaction with a negative outcome (see table 4-3, column 2).[36] To further explore this effect, *every* participant was asked about his *hypothetical satisfaction* receiving a loss. Results show, in line with our $H_{II(b)}$, that participants receiving a hypothetical loss report a significantly higher satisfaction in the aggregation treatment (see table 4-3, column 3). In other words, especially participants, who receive a loss or a return that does not meet their expectations, show less dissatisfaction if assets are displayed in an aggregated way. For participants in the separation treatment we only find a positive, but not significant influence on satisfaction. The satisfaction with a hypothetical loss is also significantly and negatively predicted by financial literacy. A reason might be that people with higher financial literacy are better prepared of what might happen and are hence less disappointed in case in really happens.

[36]We do not find significant differences between treatments in the gain domain.

Table 4-3: Satisfaction with the Outcome

This table reports the result of an ordered Probit regressions of decision satisfaction and hypothetical decision satisfaction with returns (both reported on a 1-7 scale). (1) analyzes satisfaction over all outcomes (2) is limited to outcomes falling below the expected value of participants' chosen final allocation (3) analyzes satisfaction with a hypothetical loss, which was calculated as the 5th quantile of the return distribution of participants chosen final allocation. Payoff and Expected Value are expressed in % of the amount invested.

* indicates significance at the 10% level, ** at the 5% level and *** at the 1% level, standard errors in parentheses.

	(1) Satisfaction	(2) Satisfaction payoff < exp. Return	(3) Satisfaction hypothetical loss
Outcome	2.04***	4.64***	0.71***
	(0.38)	(1.01)	(0.33)
Aggregation	0.27	0.59**	0.48***
	(0.21)	(0.29)	(0.21)
Separation	0.14	0.26	0.03
	(0.20)	(0.28)	(0.19)
Risk Attitude	0.16	0.19	0.13
	(0.16)	(0.15)	(0.11)
Gender	0.12	0.40	0.25
	(0.19)	(0.26)	(0.19)
Age	-0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)
College	0.16	0.20	0.26
	(0.18)	(0.24)	(0.17)
Log (Income)	-0.12***	-0.13***	-0.00
	(0.03)	(0.05)	(0.03)
Financial Literacy	0.01	-0.02	-0.15***
	(0.04)	(0.04)	(0.03)
Confidence	0.08	0.07	0.04
	(0.08)	(0.12)	(0.08)
Observations	175	95	175

The second measure of ex post decision evaluation is *subsequent allocation* to the risky fund, which is highest in the aggregation treatment (64.07), followed by the separation (62.92) and the control group (58.42). Difference between treatments are, however, only marginal significant if we include control variables (comparable to table 4-3, column 1): the coefficients for the aggregation dummy ($\beta = 7.59$, $p = 0.06$) as well as for the separation dummy ($\beta = 6.60$, $p = 0.08$) are positive. The difference between the subsequent and the final allocation, the *marginal subsequent allocation*, is negative, which means that the risk level is reduced, in the separation treatment (-2.55 % on average), close to zero in the other two treatments, and overall, not significantly different in none of the treatments ($H_{III(c)}$).

4.3.3 DISCUSSION

Results suggest that the extent of information aggregation affects risk taking. We find the highest level of risk taking (highest percentage allocation to the risky asset) in the aggregation group, followed by the separation group and, at last, the control group. Getting more aggregated information about potential consequences of a chosen portfolio encourages people to increase their risk level. The results are derived in an asset allocation environment, namely the allocation of an endowment between a diversified "real" risky asset with continuous distributed returns and a risk free asset (in contrast to binary prospects or artificial assets frequently used in the decision making literature, e.g., Steul 2006, Gneezy and Potters 1997). We additionally find a strong influence of decision time on risk taking. People spending more time for their decision increase their risk level. Anagol and Gamble (2011) find economically large differences in risk taking between the segregation group and the aggregation group limiting their analysis to participants who spend more than the average time with the historical return information; it might be that aggregation effects increase if participants pay more attention (in the sense of spending a longer time with that information). To further explore these findings we manipulate the decision time in Experiment II by doubling the required simulation time randomly for half of the participants.

An additional finding of Experiment I is that participants seem to evaluate losses differently if information was given in a more aggregate way. A reason for this behavior could be that participants perceive the risk differently or are more aware of the risk and therefore are able to better get along with an ex post negative outcome. To further examine whether the degree of information aggregation influences risk perception or perceived loss probabilities influence the decision, we added survey questions in Experiment II.

4.4 EXPERIMENT II

4.4.1 METHOD

Participants, Procedure and Payment

138 subjects (113 male) were recruited using an email distribution list[37] of the University of Mannheim. Subjects were told that the experiment has the intention to gain further insights as to which personal characteristics determine people's risk taking behavior in financial decision making. Prospective participants could follow a link to a Behavioral Finance website. The mean age was 49 with a range from 21 to 78 years. Seventy-three percent of the participants are college educated and approximately eighty percent report owning stocks (stock funds included). As in Experiment I, they were compensated with the chance to earn money based on the outcome of the financial market simulation of their allocation decision. In this experiment, we randomly selected 20 participants to receive an Amazon gift card for the amount of the financial market simulation divided by 100 (as the amount to allocate was €1,000).[38]

Experimental Task

The experimental task itself was only changed slightly in comparison to the set up in Experiment I. Participants also had to allocate an endowment between a risky and a risk-free fund over a five year time horizon, and the steps of the decision and information process were the same as in Experiment I (see figure 4-1). Instead of investing $100 we asked participants to allocate an amount of €1,000. Additionally, we did not use the historical returns of the MSCI USA, but the historical returns of a World Portfolio (annual expected return of 11.6%, annual volatility of 11.4%) – an index consisting of stocks, bonds, and commodities (invented by Jacobs et al. 2009).[39]

The risk-return information was again presented with the help of the risk tool. However, we manipulated the sampling time this time. In Experiment I participants had been allowed to

[37] The distribution list was established during former studies conducted at the University of Mannheim, where participants were asked whether they would be willing to participate in ongoing experiments.

[38] The payment scheme between the two experiments differ because of different habits with reference to the subjects pools. For participants in Germany we use the same payoff scheme we had at the former study they had participated in (a lottery of 20 amazon gift cards whose amount was performance based). Subjects from the elab in the U.S. are used to earn show up fees and the chance to win additional money, which we also pay in a performance based manner.

[39] Again, participants were only given the risk-return profile an no additional information about the underlying asset.

sample for as long as they want to and were required to sample at least eight draws shown as a bar graph (comparing the endowment to the outcome). This time we had an additional condition where people were required to sample at least 16 draws shown as a bar graph. The number of required draws was assigned randomly to participants.

Treatments

There was no change in treatments in comparison to Experiment I; our three treatments again differ in the degree of information aggregation while presenting the quantiles and the simulation in the risk tool.

Survey Questions

To better understand the underlying mechanisms of asset allocation decisions we ask participants on a 1-7 scale how *informed* they feel based on the information they have been given, and how risky they perceive their chosen allocation to be (*risk perception*). Additionally, we ask them to estimate in how many out of 100 cases their final wealth will fall below their invested amount, which we call *probability of a loss*. Assessed control variables were the same as in Experiment I.

4.4.2 RESULTS

Patterns of Asset Allocation

For the same reason as in Experiment I, participants allocating nothing (one participant) and participants allocating everything (twelve participants) into the risky asset in their initial allocation were excluded from all analyses. Results show the same pattern as in Experiment I; the mean *marginal allocation* is higher in the aggregation group compared to the separation group and the control group (see table 4-4). The marginal allocation in the separation group is also higher compared to the control group. If we include control variables (the same as in table 4-2 in Experiment II) in an OLS regression analysis, we get a significant effect for the aggregation dummy ($\beta = 7.11$, $p = 0.03$), but not for the separation dummy.

Table 4-4: Overview of Initial and Marginal Allocation by Sampling Time

This table reports the results mean (standard deviation) *initial* allocations and *marginal allocation* (difference between final and initial allocation) to the risky fund out of a possible €10,000 allocation in Experiment I and a $100 allocation in Experiment II by treatments. This table reports the results mean (standard deviation) *initial* allocations and *marginal allocation* (difference between final and initial allocation) to the risky fund out of a possible €10,000 allocation in Experiment I and a $100 allocation in Experiment II by treatments.

	All Participants			**Standard Sampl. Time**			**Doubled Sampl. Time**		
	N	**Initial in %**	**Marginal Alloc. in %**	**N**	**Initial in %**	**Marginal Alloc. in %**	**N**	**Initial in %**	**Marginal Alloc. in %**
Control Group	47	54.03 (22.02)	-0.07 (22.02)	23	49.78 (19.80)	0.13 (9.02)	24	58.09 (23.66)	-0.26 (19.00)
Sep. Group	45	50.55 (21.43)	2.02 (7.98)	19	51.32 (18.32)	0.47 (7.06)	26	50.00 (23.79)	3.16 (8.55)
Agg. Group	47	54.46 (23.37)	5.27 (19.93)	26	55.37 (23.37)	2.10 (16.94)	21	53.33 (23.89)	9.19 (22.93)

In Experiment II sampling time within the risk tool simulation was manipulated. Results show a higher marginal allocation if participants view information about their chosen portfolio for a longer time, namely doubled sampling time (see table 4-4); differences in marginal allocation between the standard and the double sampling in each of the treatments are, however, not significant. If OLS regressions are performed separately for the group with the double time sampling and the standard time sampling, the coefficient for the aggregation dummy changes from 13.10 to 1.75 respectively; results hence indicate that paying more attention to the simulation seems to convince subjects to bear more risk and also influences the differences between treatments.

Underlying Mechanisms of Asset Allocation

One reason for differences in asset allocation between treatments might be that the degree of information aggregation influences participants' perception of the riskiness of their selected portfolio. To ensure that participants perception does not in generally differ between treatments, we have asked participants how risky they perceive the risky asset to be after the introduction of the risky asset (the information has been provided in the same way for all treatments); the perception does not differ significantly between treatments.

Comparing the mean risk perception (see table 4-5) shows that participants perceive the risk of their chosen allocation to be lower if asset returns are presented on a portfolio level as compared to the other two treatments; the difference is significant for differences between the aggregation and the separation group (a one-way anova regression results in a significant influence of the degree of information aggregation on portfolio risk perception; a bonferroni post-hoc pair wise comparison test shows a significant difference for the separation group opposed to the aggregation group on the 5% level). It might be that the differences in portfolio risk perception can be explained by different portfolio allocations and therefore differently distributed underlying 'objective' risk between treatments and participants. Therefore, we use a second variable limited to participants who invest between 40% and 60% to the risky fund (see table 4-5); those participants objectively face a similar risk; participants still perceive the risk to be lower in the aggregation group compared to the other groups (again a pair wise post hoc comparison test results in a significant difference between the separation and the aggregation group).

Table 4-5: Underlying Mechanisms of Asset Allocation Decisions

This table reports the results mean (standard deviation) risk perception, risk perception weighted by the allocation to the risky fund (calculated as (risk perception/final allocation)*100), overestimation of the probability of a loss (Overestimation = Estimation of the probability of a loss – objective probability of a loss), and feeling informed (How informed do you feel about the investment?; 1-7 scale) conducted in Experiment I.

	N	Risk Perception	Risk Perception 40-60 allocation	Overestimation of the prob. of a loss	Feeling informed
Aggregation	47	3.80 (1.15)	3.30 (0.67)	5.20 (7.93)	4.81 (1.53)
Separation	45	4.44 (1.22)	4.56 (1.01)	9.58 (12.14)	4.84 (1.93)
Control	47	4.14 (1.33)	4.09 (1.38)	15.00 (16.87)	4.34 (1.68)

Another reason for the differences in risk taking might be that participants perceive the probability of a loss differently between treatments (as suggested by Benarzti and Thaler, 1999). Results reveal, in line with $H_{II(a)}$, that a more aggregated return distribution indeed results in a lower overestimation of the probability of a loss; participants in the aggregation treatment are significantly more accurate compared to participants in the separation treatment ($t_{(89)} = 2.04$, $p=0.04$) as well as participants in the control treatment ($t_{(91)} = 3.57$, $p<.01$), see table 4-5. The difference between participants in the separation treatment and the control treatment is marginally significant ($t_{(90)} = 1.76$, $p=0.08$) indicating that providing people a simple calculation of their investment amount based personal outcomes significantly reduces the bias to overestimate rare events. These results confirm $H_{III(b)}$.

Next, we test whether people take on more risk, because they feel more informed about the assets they are able to invest in. Participants in the aggregation treatment and the separation treatment feel slightly more informed about the investment alternatives compared to the control group (see table 4-3). The differences are, however, not significant.

4.4.3 DISCUSSION

Overall, we find that a higher marginal allocation is accompanied by a lower risk perception for participants who get information on a portfolio level and that a higher degree of information aggregation in general helps people to better understand the underlying downside risk associated with their investment. In the last two experiments, we have underlined the robustness of the effects of information aggregation on risk taking by using continuous distributed assets, different investment amounts, different subject pools and different historical return distributions for the risky asset. The results are in line with findings in the literature (e.g., Anagol and Gamble 2011). However, there are also studies, which did not find an effect (e.g., Beshears et al. 2011) or only under certain circumstances (e.g., Steul 2006). Due to our experimental setup we do not think that these different results are due to different investment amounts or underlying risky assets, as our results are robust to differing those. Another idea is that the way the risk itself is communicated influences the effects of information aggregation. In our analysis, we have used an interactive risk simulation tool. Haisley et al. (2011) find a strong influence of the risk presentation format itself on risk taking. To get an intuition whether the information aggregation effects are dependent on the way information is given in general, we also conduct a third experiment, where participants do not sample information via the risk tool, but receive information about the potential outcomes in a descriptive way.

4.5 EXPERIMENT III

4.5.1 METHOD

Participants, Procedure and Payment

177 subjects participated in Experiment III, now referred to as the *description condition* in contrast to the *risk tool condition*. The subjects were recruited via the same subject list as in Experiment I (the elab of Yale University) and are comparable to those; the mean age is 34, around forty-five percent are male, around sixty percent college educated with a median income of $40,000 and around 50 percent own stocks. Participants are again told that a "financial market simulation" will be run at the end of the experiment to determine the five year return of their investment, allocated $100 and completed the experiment online in exchange for a 50% chance to earn a $5 Amazon.com gift certificate and a one in 40 chance to earn additional performance-based money based on the outcome of their allocation decision.

Experimental Task

In the description condition participants do not sample information via the risk tool, but get information about the potential outcomes in a descriptive way; subjects receive information about the expected return for each of the two funds. The variance of the risky fund was explained in terms of frequencies in the following way:

Fund A is a risk free asset. It has a guaranteed annual return of 3.35%. If you invest $100 in Fund A, you will have an outcome of $118 in 5 years.

Fund B is a risky asset. It has an expected annual return of 8.92% with an annual standard deviation of 15.89%. If you invest the full $100 in that asset, you will have an expected final outcome of $153 in 5 years. However, the actual outcome is not known. It could be higher or lower. In 70 out of 100 cases your final wealth will be between $100 and $208 and in 95 out of 100 cases between $72 and $289.

Participants entered an initial asset allocation, were provided with additional information numerically (dependent on the treatment, explained in the next paragraph), could adjust the allocation and see the corresponding effects on the return and variance until they decided on a final allocation. Other features of the experimental task (investment horizon, risk-return profiles, etc.) as well as the payment scheme were held constant with regard to Experiment I.

Treatments

In line with Experiment I and II, participants first got information about the two assets separately and then, dependent on the treatment they were randomly assigned to, in a separated, aggregated or control information treatment. In the *control* treatment participants were shown the same information as before, no matter what allocation they selected. In the *separation* treatment a participant who has chosen to invest 50-50 was told the following:

Given your chosen portfolio allocation ($50 risk free and $50 risky) you guaranteed outcome for the risk free asset will be $58.96, your expected outcome for the risky asset $76.63 after five years. In 70 out of 100 cases your final wealth for the risky asset will be between $50 and $104 and in 95 out of 100 cases between $36 and $144.

In the *aggregation* treatment, a participant who has chosen to invest 50-50 was told the following:

Based on your chosen portfolio allocation ($50 risk free and $50 risky) your expected outcome after five years is $136. In 70 out of 100 cases your final wealth for the risky asset will be between $109 and $163 and in 95 out of 100 cases between $95 and $203.

4.5.2 Results

Patterns of Asset Allocation

The observed pattern in Experiment III differs from Experiment I and II; the marginal allocation is the highest in the separation group, followed by the control group and the aggregation group (see table 4-6) and the difference between participants in the separation and the aggregation treatment is significant ($t_{(130)} = -2.15$, $p=0.03$). The effect of information aggregation is reversed compared to the risk tool condition. This might be evidence for a combined effect of risk presentation mode (risk tool versus description) and degree of information aggregation on risk taking and is in line with the picture given by the literature – that the effect of information aggregation in a descriptive set up is not quite clear.

Table 4-6: Initial and Marginal Allocation to the Risky Fund – Description Condition

This table reports the results mean (standard deviation) *initial* allocation, *marginal allocation* (difference between final and initial allocation), and *marginal subsequent allocation* (difference between subsequent allocation and final allocation) to the risky fund out of a possible $100 allocation in Experiment III by treatments.

	N	Initial Allocation	Marginal Allocation
Aggregation	62	50.81 (20.33)	2.10 (7.51)
Separation	70	50.01 (18.87)	6.13 (12.95)
Control Group	45	49.69 (20.92)	3.78 (10.67)

In Experiment I and II, we found an important role of decision time plays in explaining risk taking. If we limit the uni-variate analysis in Experiment III to participants, who spend a longer time than average for their decision, marginal allocation in the separation treatment is still higher opposed to the aggregation treatment, but the effect is no longer significant ($t_{(77)}$ = 1.05, p=0.30). All in all, a higher aggregation level only seems to play a role for risk taking if information for participants is provided in an interactive way and does not matter or reverses if returns are presented in a descriptive way.

Beside the influence of information aggregation on risk taking itself, results in Experiment I and II have also shown an influence on ex post decision evaluation. Similar to Experiment I, there is no significant effect of the treatment on the overall satisfaction (see table 4-7, column 1). In line with former results (Experiment I), the outcome of the financial market simulation significantly predicts satisfaction. In Experiment I we have found a significant influence of information aggregation on satisfaction in the loss domain. If the regression is limited to participants who receive a loss (again defined as an outcome below the portfolio's expected value), the aggregation dummy shows a positive and significant influence on decision satisfaction (see table 4-7, column 2). As in Experiment I, participants were also asked about their satisfaction with a hypothetical loss and results again show, in line with Experiment I, a lower dissatisfaction of participants in the aggregation group (see table 4-7, column 3). Overall, results reveal that, independently of how the risk information itself is presented, aggregation returns results in a higher decision satisfaction if the ex post outcome does not meet ex ante expectations.

Table 4-7: Ex Post Decision Evaluation: Satisfaction with Returns – Description

This table reports the result of an ordered Probit regressions of decision satisfaction and hypothetical decision satisfaction with returns (both reported on a 1-7 scale). (1) analyzes satisfaction over all outcomes (2) is limited to outcomes falling below the expected value of participants' chosen final allocation (3) analyzes satisfaction with a hypothetical loss, which was calculated as the 5th quantile of the return distribution of participants chosen final allocation.
* indicates significance at the 10% level, ** at the 5% level and *** at the 1% level, standard errors in parentheses.

	(1) Satisfaction	**(2) Satisfaction payoff < exp. Return**	**(3) Satisfaction hypothetical loss**
Outcome	1.67***	3.18***	0.48
	(0.37)	(0.93)	(0.35)
Aggregation	0.00	0.70***	0.48**
	(0.05)	(0.28)	(0.21)
Separation	0.05	0.22	-0.05
	(0.21)	(0.28)	(0.20)
Risk Attitude	-0.11	-0.16	-0.06
	(0.10)	(0.13)	(0.10)
Gender	0.12	0.12	0.12
	(0.17)	(0.22)	(0.17)
Age	-0.02**	-0.02**	0.01
	(0.01)	(0.01)	(0.01)
College	0.09	0.27	0.15
	(0.17)	(0.23)	(0.17)
Log (Income)	-0.01	-0.07	-0.00
	(0.03)	(0.06)	(0.03)
Fin. Literacy	0.01	-0.05	-0.12***
	(0.02)	(0.05)	(0.03)
Confidence	0.06	0.13	0.02
	(0.07)	(0.09)	(0.07)
Observations	177	107	177

Results for our second measure of ex post decision evaluation are similar to those in Experiment I. Participants on average invest 52.2% into the risky asset in the control group, 53.6% in the separation treatment and 53.1% in the aggregation treatment This means that participants reduce their risk taking in the separation treatment (-2.56 percentage points on average). And we find a small increase for a subsequent allocation in the aggregation group (+0.2%). If we now compare risk taking in the separation and the aggregation treatment we do not find a significant difference.

4.5.3 Discussion

Results of Experiment III suggest that the influence of information aggregation strongly depends on the way risk information is presented (interactively versus descriptively). Results might explain, why the effect can be found in most of the studies in the literature, but not in all of them. If we take our findings on a subsequent allocation into account it does not seem that, as at first supposed, the effect of information aggregation might reverse in a descriptive presentation format. It might be that there is no difference between treatments (as suggested by Beshears et al. 2011) or that it takes a certain time till the effect of information aggregation occurs (Anagol and Gamble 2011). Aside from that, information aggregation seems to help people to be more committed to their decision and more aware of potential losses, as they show a stable decision evaluation and this effect holds independently of the risk presentation format.

4.6 General Discussion

Research to date has not examined the optimal way to inform customers about the riskiness of investment alternatives in a manner that maximizes satisfaction and helps customers to find the allocation that optimally fits to their risk preferences. With the current research we try to shed light on the question how investors perceive information about risk and incorporate those in their allocation decisions dependent on the degree of information aggregation. Overall, a higher degree of information aggregation encourages people to bare more risk if risk information is presented in an interactive way. The effect is accompanied by a lower risk perception and a more accurate estimation of the probability of a loss, which means that participants' decision to increase risk taking is not based on an underestimation of it. It might be the other way round: participants take on less risk in the other treatments groups because of a lack of knowledge, as they overestimate the probability of a loss.

The finding that the provision of a more aggregated information results in higher decision satisfaction and commitment to the decision in the loss domain is also evidence that results are driven by a lack of knowledge or by being overwhelmed by too much information. Information aggregation seems to have a strong influence on decision satisfaction if an ex post outcome does not meet ex ante expectations, which is an indicator that participants had been aware of the according risks. The effect holds even for different risk presentation formats. Kroll et al. (1988) analyzed in their experiment, whether participants are able to incorporate information about correlations between assets into their decision and found out that they were not. As an explanation they assumed a certain degree of cognitive overload resulting in an ignorance of certain information. By aggregation information in our experiment we reduce the information people have to take into account by aggregating it; findings hence might be explained by the fact that people incorporate all given information in an aggregated treatment and are not able to do so if information is given more separately. Further research needs to be done to analyze the relationship between the degree of information aggregation and cognitive (over-)load.

There are some studies that do not find an effect of information aggregation on risk taking (e.g., Beshears et al., 2011). Our results are robust to different investment amounts, subject pools, and underlying risky assets if we use an interactive presentation format. However, the effect on risk taking does not occur if we present the information in a descriptive way. One reason might be that participants are better able to process information in an interactive presentation format (in line with Haisely et al. 2011). Besides that, our study is based on one investment decision and does not analyze several follow up decisions like the studies of Beshears et al. (2011) and Anagol and Gamble (2011). Nevertheless, we asked our participants about one hypothetical subsequent allocation. We find in the descriptive decision format that participants start with a higher allocation in the separation treatment but reduce the risk level in a subsequent allocation in the separation treatment while increasing it in the aggregation treatment. So it might be that the risk level evens out throughout all treatments in a descriptive presentation format at some point in time as it has been found by Beshears et al. (2011).

5 INVESTORS CARE ABOUT RISK BUT CAN'T COPE WITH VOLATILITY.

5.1 INTRODUCTION

One of the central questions in investing is how much risk to take; theoretically, this question is easy to answer. According to basic financial theory, the efficient frontier of investment opportunities in a mean-variance-framework is defined by the capital market line (Tobin 1958), the line through the risk-free rate forming a tangent to the set of risky investments. The capital market line offers some central insights (Sharpe 1964; Lintner 1965; Mossin 1966; Treynor 1962):

- more expected return requires the investor to take on more risk, which is defined as standard deviation (volatility),
- risk and return are linearly related,
- there is one risky asset (market portfolio) for all investors - independent of the investor's risk attitude.

All an investor has to do to find the optimal investment alternative is to assess his risk attitude. Risk attitude directly leads to the allocation between the risk-free asset and the risky asset: higher risk aversion will result in a higher proportion invested into the risk-free asset.[40]

This paradigm is relevant not only from a theoretical perspective, but also has large practical implications. According to the European MiFID directive (European Parliament and European Council, 2004; European Parliament and European Council, 2006), the risk attitude of each European investor seeking investment advice needs to be assessed and the investment alternative recommended has to be in accordance with this risk attitude. More recently, the new European UCITS directive (European Parliament and European Council, 2009) requires a key investor information document (KIID) for a large class of investment alternatives: in this two page flyer risk and return have to be described, with risk defined as standard

[40]Note, that the central role of risk attitude to determine the optimal portfolio is also true in other models than the mean-variance model (see e.g., Merton, 1969).

deviation[41] just as in the Markowitz model. All banks and investment advisers in Europe are required to fulfill these requirements. Two questions follow immediately:

1. Do investors see a relation between their stated risk attitude and an amount invested into a risky portfolio?
2. In choosing a simple portfolio, are investors subject to framing effects when given portfolios with different riskiness (i.e. volatilities)?

Let us explain the idea using a simple example: an important question in real life is how much sugar to take in one's coffee. In case we like to know more about people's capability to determine the subjectively "right" amount of sugar, we could first ask if people understand the relationship between "I want to have my coffee sweeter" and "putting more sugar into it" (similar to question 1). Next, we would be interested in determining the extent to which the concentration of sweetness is related to the amount chosen, e.g., if you take sweetener (where the same amount has a higher concentration of sweetness) instead of crystal sugar. Of course, we should be able to adjust the amount of sugar, thus independently finding the optimal sweetness for the coffee. Another analogy would be the question to what extent the size of the spoon is related to the amount of sugar taken. In this case we should be able to end up with the same amount of sugar and adjust for the size of the spoon. This should be the case especially if we have the possibility of tasting the coffee during the procedure.

To answer these two research questions, we use a standard design often employed in the analysis of financial decision making under risk (Gneezy and Potters 1997; Frijns et al. 2008; Nosić and Weber 2010). Borrowing from the idea of the capital market line, we ask subjects to allocate a stated amount of money between a risk-free and a risky asset, whereas subjects were able to choose between three amounts and investment horizons to set the investment context close to their personal circumstances. The risk- return profile of the risky asset as well as the chosen portfolio provided to the subjects by means of an interactive computer simulation which allows them to experiencing the return distributions (cf. Haisley et al. 2011). In addition, we ask subjects to state their risk attitude allowing us to analyze our first research question. To answer our second research question we vary the risky asset subjects could invest into in a between-subject design. One group of subjects was asked to invest into a "market portfolio", a second and a third another one to invest into a risky asset (about) twice or half as risky as the market portfolio. As the assets could have been transformed into each

[41] The volatility of returns is presented as a simplified risk indicator with seven categories to which the products are assigned to based on their historical volatility.

other by combining them with the risk-free asset, we are able to measure the influence of framing an asset more or less risky on risk taking and risk judgment.

Our study is related to different fields of research. Research on risk judgments until now has provided several insights with regard to the influence of risk preferences on risk taking. We know that risk attitude is domain-specific (e.g., E.U. Weber et al. (2002); Vlaev et al. (2009); Nosić and Weber (2010)), that is to say a risk attitude measured in one domain (e.g., sports) is not necessarily related to a risk attitude in another domain (e.g., the financial domain). Even within the financial domain risk attitude measured through means of lottery decisions has been found to be less predictive for investment decisions than a simple question about the willingness to take on financial risk on a Likert Scale (e.g., Dorn and Hubermann 2005, 2010), which we hence use in our experiment. This question not only allows us to link preferences to behavior, but also to investigate whether investors do something sensible. Research has shown that participants often use simple heuristics, when decisions get more complex. One famous example is known as the 1/n heuristic - participants distribute their investments equally over the set of available assets, no matter whether those consist mainly of stock funds or of bonds funds, resulting in vastly different risk-return profiles in the overall portfolio (Benartzi and Thaler 2001). Apart from using heuristics, subjects are also very prone to general framing effects (e.g., Tversky and Kahneman 1981) in financial decision making. People perceive assets to be less risky if names are included (E.U. Weber et al. (2005)) and risk perceptions differ if the riskiness is presented in different formats (e.g., Haisley et al. 2011; Diacon and Hasseldine 2007), e.g., in bar charts versus distributions. In our setting we are able to link the different findings on risk judgments and perceptions to a framing effect on objective risk measures, namely volatility, and analyze subjects' behavior in more detail. We focus on individual differences in risk taking behavior and analyze its variation between subjects, taking into account different personal traits (risk attitude or financial literacy).

Subjects were recruited from the general population through newspaper articles and radio station reports in a joint campaign with the German Consumer Protection Agency ("Verbraucherzentrale Bundesverband"). Overall, 1,958 people participated in our online experiments; subjects had a 25% chance of being paid proportionally to their performance.

We find that people are able to state their risk attitude and that this risk attitude is strongly related to the percentage amount invested into the risky asset. Our participants on average invest 60% into the risky asset but individually vary their allocation widely in accordance with their stated risk attitude; in addition, people act in a sensible way. We replicate results from the previous literature: a longer time horizon leads to riskier investments (Klos et al. 2005; Siebenmorgen and Weber 2004), lower volatility and lower perceived risk also result in a higher allocation to the risky asset (Nosić and Weber (2010), E.U. Weber et al. (2002)).

The answer to our second research question is rather astonishing: we find a perfect framing effect. Subjects on average did not adjust for the volatility of the risky investment at all, i.e. they take the same amount of sugar independently of its sweetness or the size of the spoon. This is even more surprising as we interactively simulate the distribution of the risky asset as well as the chosen portfolio, i.e. we let them taste the sweetness of the coffee. We also ask subjects for the riskiness of the risky asset and cannot observe any significant difference even if the volatility differs by a factor of two or four. If we only consider participants who are more knowledgeable (higher financial literacy or employed in financial industry) we find significant adjustments; these adjustments are, nevertheless still far away from resulting in portfolios with the same risk-return profile.

As a further test, we give to one additional group of participants another risky asset that dominates the basic asset. The results are similar; people seem to have risk preferences for their investments. However, they seem to use two mental accounts (see e.g., Thaler 1999b) when deciding on their allocation; they divide their portfolio into "risk-free investment" and "risky investment" and do not adjust their investment decision for the riskiness (volatility) of the second account; results hold although we let people experience the return distribution of their investment.

Our contribution to the literature is threefold; first, we combine the flood of details that is known about risk attitude and risk-taking. While most papers investigate details on the relationship between stated risk preferences, personal traits, demographics and the chosen asset allocation, we combine these details enabling us to extend findings of other studies like Benartzi and Thaler (2001) to an analysis on an individual level. Second, we document a very strong framing effect and are able to analyze risk preferences and risk taking behavior as well as its changes by changes in riskiness simultaneously. Our framing does not stem from manipulations that should only affect subjective perceptions but results from framing of objective numbers, namely the volatility: we set different anchors in the sense of different risk levels provided. However, the manipulation still reflects framing as the results of the decisions can be economically the same - by moving them up and down the capital line, the portfolios we provide can be transformed into each other. We find that investors are not able to fulfill this task, even if it is central for investing. Third, we obtained these results although subjects were given frequent feedback in an easily understandable form. In the words of our example: Investors taste their coffee, but they don't adjust the amount of sugar when providing it with a higher concentration or volume of sweetness.

Our results have major policy implications. It seems that people either do not understand the information provided or have another risk concept in mind when deciding on their asset allocation. The concepts of randomness and probability seem to be more difficult than researchers and regulators think so far. Even when provided with a simulation, subjects are not able to independently evaluate the riskiness of an investment. One possibility for solving this problem is to educate or patronize people even more: Participants could be shown different distribution functions or could be helped by being provided with easier understandable risk indicators in the way the EU regulation is currently suggesting. We discuss these implications as well as ideas for future research in the discussion section.

The remainder of the paper is organized as follows. After a short literature review (section 2) we present the design of our study (section 3). In Section 4 we address the relationship between risk attitude and risk taking (question 1) whereas Section 5 focuses on the influence of riskiness of the risky asset provided on risk taking (question 2). Section 6 summarizes and discusses policy implications and ideas for future research.

5.2 LITERATURE REVIEW

There is a large literature on how investors *should* choose their preferred portfolio out of the universe of available assets versus how they *do* choose it. With regard to classical portfolio theory following Markowitz (1952), investors differ only with respect to the extent that they are trading off return against volatility. According to the two-fund separation theorem of Tobin (1958) all investors should hold a combination of the *same* risky efficient market portfolio and a risk-free asset, whereas the actual split is determined by the individual's risk attitude. Empirical findings show, however, that investors' behavior in practice is different. A phenomenon known as the equity premium puzzle (Mehra and Prescott 1985; Benartzi and Thaler 1995) describes that the low participation rate in stocks markets cannot be explained by investors' risk aversion taking the strong outperformance of stocks over bonds into account. Canner et al. (1997) find in their study that investors additionally are not advised to allocate their money between a risky and a risk-free fund, but instead to adjust their bond to stock ratio dependent on their risk attitude; this contradicts classical finance theory, as they vary the composition of the risky asset and not the allocation between the risky and the risk-free asset)[42]. In our study, an asset-allocation decision in line with the fund separation theorem is presented. Subjects face a trade-off between risk and return by having to allocate an endowment between a risky and a risk-free asset. We then analyze how investors in general determine their point on the capital market line as well as the effect of setting different starting points on this line by providing different risky assets.

The literature shows that people do not always act in accordance with classical finance theory; this does not mean, however, that they behave randomly. Risk taking can be explained and predicted by various factors (Frijns et al. 2008). The literature has shown that these factors are driven more by subjective beliefs and expectations than by objective risk indicators (see, e.g., Jia et al. 1999, Sarin and Weber 1993). Two of the key explanatory variables in those behavioral models are risk attitude and risk perception. The influence of these traits varies tremendously dependent on the situational context and the domains they are assessed in. Risk attitude itself has been found to be a quite stable construct over time (Klos 2011, Baucells and Villasís 2010, Nosić and Weber 2010, Sahm 2007); however, it varies across domains (E.U. et al. (2002)). Even within the financial domain, risk attitude changes, as evidenced for instance by the fact that preferences elicited with the help of lotteries differ from those elicited in a portfolio choice setting (Nosić and Weber 2010, Vlaev et al. 2009). We hence use self-assessed risk attitude measured by a simple question asking for the willingness to take financial risk; simple questions have been shown to be predictive for financial risk taking (Dorn and Huberman 2010, Kapteyn and Teppa 2009). Risk perception, on the other hand, is not a stable trait, but instead influenced by various factors and seems to mediate the relationship between risk taking and contextual factors (e.g., Sitkin and Weingart 1995; Sitkin and Pablo 1992). Studies have shown that measuring risk perception and risk attitude results in greater cross-situational stability of risk preferences (E.U. Weber et al. 2002, E.U. Weber and Milliman 1997) and therefore improves explanatory power. In this study, both variables are used to address the first research question.

Apart from the influence of personal traits and preferences, risk taking depends on the decision context. There are two phenomena documented in the literature which can serve as an explanation for our results: the first is known as anchoring and adjustment, the second is known as framing. Anchoring and adjustment means that subjects start with an initial value

[42]Apart from that it has been known for some time, that investors do not construct their market portfolio optimally when provided with multiple assets (Kroll et al. (1988b,a); however the construction of the market portfolio is not the focus of our study.

(anchor) and come to their final decision by means of an adjustment in either direction, based on additional information and further thinking. However, this adjustment is mostly insufficient and the final decision depends strongly on the anchor which has been set, for example by a certain presentation format, the formulation mode, or the elicitation mode (Tversky and Kahneman 1974). Anderson and Settle (1996) analyze portfolio choice decisions and find that anchoring is one possible reason for the final choice; they provide both annualized returns and ten-year returns for a ten-year investment horizon and find that the adjustment for the different returns (yearly vs. ten-year) is insufficient. This is different from our experiment as we use another form of anchor: subjects start with different risky assets.

A decision frame is described as *"the decision-maker's conception of the acts, outcomes, and contingencies associated with a particular choice"* (Tversky and Kahneman 1981). A different framing of the same decision problem can have an influence on preferences and behaviour. Inconsistent reactions to different decision frames have been observed in several studies. Diacon and Hasseldine (2007) for instance show for example that risk perception is influenced by the presentation format (past return information as fund values versus percentage yields). In our experiment three risky assets are considered, all of which could be transferred into each other by the participants; subjects are hence in a similar decision context. The assets are each a combination of the risky and the risk-free asset, with only the part already invested into the risky asset differing.

Our analysis is also related to the literature on heuristics in decision making. Naïve diversification (Benartzi and Thaler 2001) describes investors' allocations in retirement plans. The authors show that, on average, investors divide their contributions evenly between the different funds offered in the plan. As a consequence, the riskiness of the portfolio depends strongly on the riskiness of the products offered - a higher fraction of equity funds compared to bond funds for instance results in a higher portfolio risk: investors investing in a stock and a bond fund (not labeled as such) on average allocate 54 percent to the stock fund; investors investing in a balanced fund (with substantial lower volatility compared to the stock fund) and a bond fund allocate 57 percent to the balanced fund. In our study, a simpler decision context (the choice between a risky and a risk-free investment) is analyzed; furthermore, instead of the group level, the individual level is analyzed in our study.

We additionally investigate whether the effects found are mitigated by financial knowledge. Kaustia et al. (2008) find that students are more prone to anchoring than professionals and that this effect is diminished for students with stock market experience that have taken finance courses. While the authors show that the anchor effect can be attenuated by experience, the effect itself is observed across all groups of participants. In accordance with these results, Müller and Weber (2010), Campbell (2006), Calvet et al. (2007) find that more financially sophisticated households and individuals invest more efficiently. We control for financial literacy, for stock market experience and for whether participants work in the financial industry.

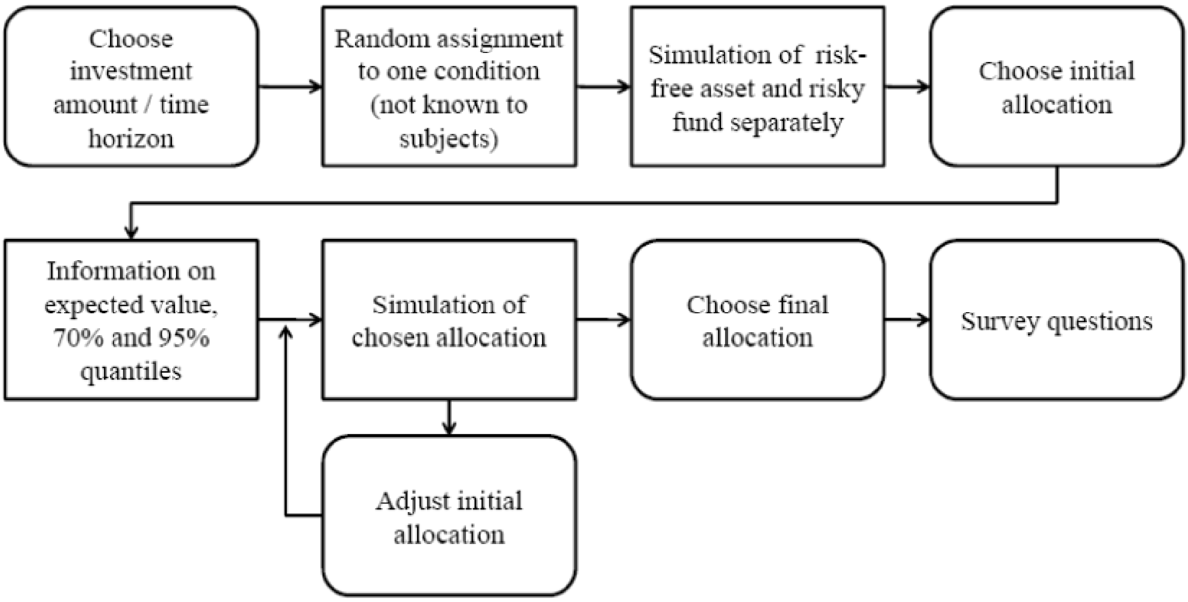
5.3 DATA

5.3.1 EXPERIMENTAL TASK

In our study, participants were asked to allocate a certain investment amount between a risk-free asset and a risky asset. Figure 5-1 gives a graphical overview of the experimental design.

Figure 5-1: Experimental Flow

This figure gives a graphical overview of the experimental design. Decisions which participants have to take are in round boxes, the information they are provided with is in square-cut boxes.



At the beginning of the experiment, participants had to choose an investment amount (either €5,000, €50,000, or €100,000) and a time horizon (either one, five, or ten years). When pre-testing the design with a fixed investment environment, several participants reported that the investment context was not familiar as the investment amount was too high or too low or the investment horizon was too long or too short. Consequently, participants were allowed to choose a decision context that was as close as possible to individual circumstances. All participants choosing the same time horizon received the same risk-free asset, whose return was based on the actual interest rates for time deposits in July 2010 when the experiment was conducted (see table 5-1).

Table 5-1: Interest Rates for Different Investment Horizons

This table reports the interest rates for different investment horizons. The respective investment horizon can be chosen by the participants.

Investment horizon	Return
One year	1.0%
Five years	2.5%
Ten years	3.4%

Subjects were randomly assigned to one of six different treatment conditions. The conditions presented differed in the risk-return profile of the risky asset; the different risk-return combinations are summarized in table 5-2.

Table 5-2: Return and Standard Deviation of the Risky Assets

This table reports characteristics of the different risky assets. The three main conditions are based on returns of the German stock index DAX. The ancillary conditions include dominating and named assets. Conditions are randomly assigned.

Main Conditions	Return	Risk (st.d.)
De-levered asset	7.4%	11.4%
Basic asset	8.9%	20.0%
Levered market portfolio	11.6%	29.1%
Ancillary Conditions	**Return**	**Risk (st.d.)**
Dominating asset	11.6%	11.4%
World portfolio (named)	11.6%	11.4%
DAX (named)	8.9%	20.0%

The focus of the analysis is on the first three conditions (referred to as the "*main conditions*") whose risky assets are easily comparable. The three remaining risky assets are used for additional ancillary analyses and robustness checks ("*ancillary conditions*"). The risky assets in the main conditions all approximately lie on the same line in a μ-σ-diagram which means that they can theoretically be transformed into one another by combining them with a risk-free asset. The first risky asset is based on historical monthly returns of the

German stock index DAX from 1973 to 2009. Subjects are not told that they face the DAX but instead only about a diversified fund. The no-name DAX condition is referred to as the "*basic condition*" or as the "*basic asset*".

The second and third assets are also based on the returns of the DAX; they nearly lie on the same line in the μ-σ-diagram; their return distributions are constructed from the DAX returns by combining the DAX with a risk-free asset. As compared to the *basic asset*, the second asset's return and risk are reduced by replacing some of the DAX's share with this risk-free asset; the resulting condition is referred to as the "*de-levered condition*" or the "*de-levered asset*". The third condition's return and risk are increased by lending at the respective risk-free rate and increasing the DAX's share above 100% ("*levered asset*" or the "*levered condition*").

We decided to use the historical Frankfurt Interbank Offered Rates (FIBOR) as the risk-free asset[43]. For every month, a new return is computed by combining the historical FIBOR with the historical DAX return. There are three possibilities: an arbitrary percentage combination (e.g., 50% DAX and 50% FIBOR), a target volatility for the resulting asset that implicitly determines the percentages, and a target return for the resulting asset that determines the percentages. Note that the exact standard deviation and the exact return of the resulting market portfolios do not matter as long as they differ sufficiently from the ones of the basic asset. The standard deviation of the dominating asset described later has been chosen as the target value for the *de-levered asset* and its return has been chosen as the target value for the *levered asset*. Both of the assets constructed are comparable to the *basic asset* as they share a common distribution of stock returns. Subjects can approximately transform one into the other by combining it with the risk-free asset they are provided with.

The three *ancillary conditions* (see table 5-2 for an overview) are used to test the robustness of our results and to investigate interactions with known phenomena. The first of these additional risky assets dominates the three assets described above as it has a lower risk and/or a higher return than the *main assets*. We refer to this asset as the "*dominating asset*" or the "*dominating condition*"; it's risk-return-profile is based on historical returns of "the *world portfolio*" described by Jacobs et al. (2010). The second *ancillary condition* shares the return distribution of the *dominating asset* but participants receive additional information on the

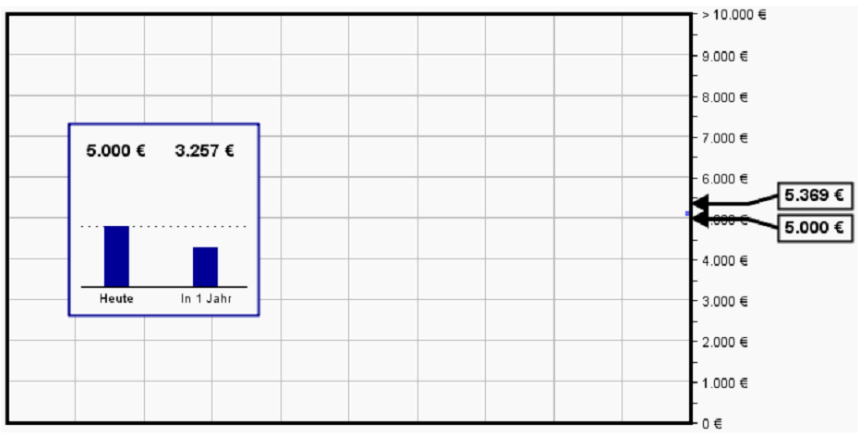
[43]For the return of the risk-free asset used, one has to decide between a fixed rate and historical risk-free returns that fluctuate over time. Historical interest rate fluctuations may not be independent from historical DAX returns, e.g., both risk-free returns and stock returns were very high after the reunification of Western and Eastern Germany. Additionally historical returns are more realistic as investors could really have faced these returns.

asset; they are told that they face a world index invested into common stock (60%), bonds (25%), and commodities (15%). It can be inferred from this information that the asset is broadly diversified. The third ancillary condition shares the return distribution with the basic condition. Additionally, participants in the "*DAX (name) condition*" are told that they face the DAX and that the DAX is a pure stock index which contains the 30 largest German companies according to market capitalization.

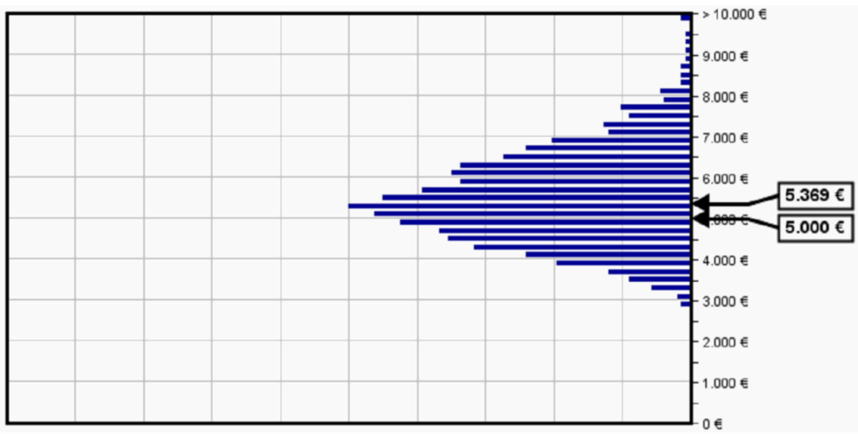
Having been assigned to one of the six conditions, subjects were informed about the return of the risk-free asset and about the risk-return-profile of the risky asset separately before taking an allocation decision. Information about the potential returns of the assets was provided via a risk simulation tool.

Figure 5-2: The Risk Simulation Tool

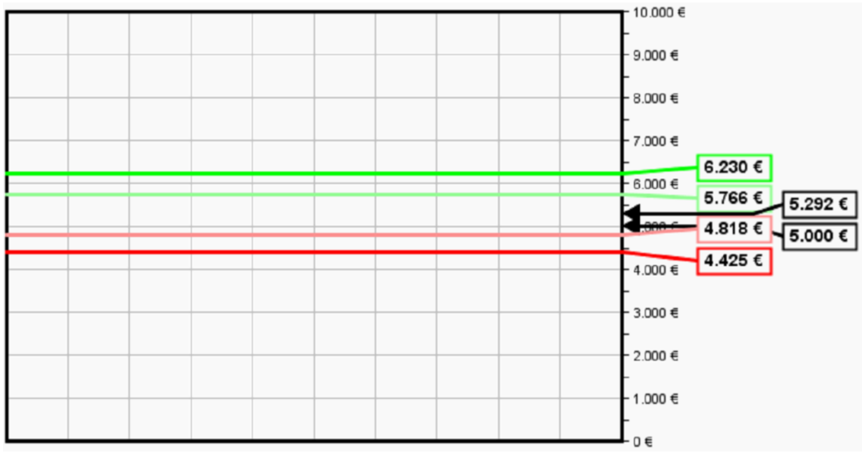
These figures illustrate the simulation tool. Figure 5-2(a) shows how single outcomes are drawn during the simulation process, figure 5-2(b) shows how the full distribution looks like when the simulation is completed, and figure 5-2(c) shows the lines indicating important intervals of the respective distribution.



(a) Simulation



(b) Compete distribution after simulation



(c) Lines indicating 70% and 95% intervals

This risk tool has been introduced in a study conducted by Haisley et al. (2011) and has been developed to communicate asset risk with the help of experience sampling and graphical displays. Haisley et al. (2011) show that the use of the risk tool in comparison to the use of other methods for presenting asset risk (description, distribution graphs, and pure experience sampling) leads to greater recall abilities and subjective comprehension, higher risk taking without any increase in decision regret, and less reactivity to either positive or negative variations in returns. The risk tool works as follows: Participants see the expected returns and potential outcomes of their investment on a graphical interface. With a single line indicating that the return is guaranteed without any variance, they are first shown the return of the risk-free asset before they are shown the expected return and variance of the risky asset. The program randomly draws potential returns out of the underlying distribution (see figure 5-2(a)). The whole distribution is built up bit by bit with each draw contributing to a distribution function on the screen. It is explained that a higher bar in the distribution reflects a higher probability for the respective outcome. Participants are allowed to sample for as long as they want (at most until the entire distribution is built up), but they are required to sample at least sixteen draws (eight in a slow mode, eight in a fast mode). The picture of the full distribution that is shown at the end of the simulation includes markers at the amount invested and at the expected outcome highlighting this key data (see figure 5-2(b)). The return scale shown in the distribution diagram is the *same* for all conditions with the same investment amount and the same time horizon, meaning that a person assigned to a condition with a riskier asset will also see a more widespread distribution function.

After the illustration of the two assets, participants are asked to choose an initial allocation between the two assets; they are told that they will have the possibility to adjust this allocation afterwards. The percentage allocation can be chosen from the range of 0% to 100%; lending, which would lead to an allocation above 100%, is not allowed. Most private investors have the possibility to take on credits and loans, so it might make sense to allow this; however, as subjects already face a complex decision, we have decided not to complicate it any further by adding a lending possibility. Additionally, investors are often advised against buying risky assets on loan; for that reason, even subjects that would have understood the design, might have been reluctant to take out loan, thus affecting the results. While these problems are circumvented by omitting a lending possibility, the results do not lose generality (this issue is considered in more detail in sections 4 and 5).

To give subjects a feeling for the riskiness of their choice, they also see the expected value and quantiles of the portfolio profile based on their chosen allocation. The two lines incorporated into the graphical interface enclose 70% of all possible outcomes; additionally, two lines that enclose 95% of all possible outcomes are added (see figure 5-2(c))[44]. Analogously to the presentation of the risky asset, the portfolio resulting from the initial allocation decision is then simulated using the risk tool. Afterwards, subjects can change their allocation and try as many different allocations as they want. When they fell that they have seen enough information, they are asked to give their final allocation decision. The participants are incentivized to state their real preferences: they are told that 500 participants will win an amazon.com gift card whose amount depends on the chosen allocation to the risky asset. It is explained that a "financial market simulation" will be run at the end of the experiment to determine the return of their investment after the chosen investment period. It is explained that this return will be drawn randomly from the distribution of returns and that they determine this distribution with their allocation decision.

Subsequently, participants are asked for some personal characteristics. Participants first provide their self-reported risk attitude on a 1-7 scale and answer questions on their age, gender, education, and income.

Questions measuring subjects' knowledge, abilities, and familiarity with portfolio allocation decisions then follow. A direct measure for knowledge is financial literacy;

[44]If the historical returns were normally distributed, the first two lines would indicate the expected outcome plus around one standard deviation and the expected outcome minus around one standard deviation while the second two lines would indicate plus/minus two standard deviations.

consequently, the set of advanced literacy questions from van Rooij et al. (2011) is used to control for this effect. Stock market participation and employment in the financial industry are also elicited.

5.3.2 PARTICIPANTS AND DESCRIPTIVES

Participants are recruited from the German population via articles in various German newspapers (nationwide ones like Tagesspiegel or Börse Online as well as regional newspapers), reports on various German radio stations (e.g., Deutschlandfunk), and information from a behavioral finance e-mail newsletter. The articles have been published following a press release which includes a link to our on-line-experiment. The press release explains new EU regulation on mutual funds and the description of fund risk herein. People are offered a summary of their results and a classification of their chosen portfolio in terms of the seven risk buckets that are also used by the EU key investor information document. Journalists are explicitly asked not to describe the experiment in more detail so as not to influence the results. Newspaper articles and reports on the radio have been screened for information that exceeds the information given in the press release but no further information has been found. Overall, 2,105 participants have completed the survey. Data points that appear to result from a person's repeated participation are manually deleted. The resulting dataset consists of 1958 participants.

The median income range is €30,000 - €50,000, which fits the German average (€33,700 (see table 5-3(a)). Around fifty-two percent are college educated (graduate-level and Ph.D.-level), which is clearly above the German average of nearly 14% (see 5- 3(b)). The remaining summary statistics can be found in table 5-3(c). The average of the stated risk attitude is also higher than the German average. Participants have high financial knowledge on average and over eighty percent own stocks (German average: 25%). The participants are significantly younger than the average German, there is a high number of male participants, and financial professionals seem to be overrepresented. While this indicates that the sample is not representative for the German population, it does not mean that the results lose generality; all relevant variables indicate that participants in the sample are more familiar with financial decision making. If there is a selection bias, it will only lead to subjects' decisions appearing to be better/more rational. Results indicate that even participants in this sample (who should perform better) are not able to take consistent decisions. Nevertheless, the sample is split controlling for such effects when performing analyses.

Table 5-3: Descriptive Statistics

Table 5-3(a) shows the number of participants in a certain income range. The German average is taken from DESTATIS (2006). Table 5-3(b) reports the education level of participants. There is no equivalent school in the English system for some German school types. Hauptschule and Realschule enable to begin an apprenticeship; Realschule makes it easier to switch to Gymnasium later. Gymnasium directly enables to attend a university. The average German percentages are calculated from DESTATIS (2010). Table 5-3(c) reports summary statistics for other variables. The German averages for risk attitude (measured on a 1-10 scale), age, and stock market participation are taken from the German SAVE study (Börsch-Supan et al., 2009); the German average for gender is taken from DESTATIS (2010).

(a) Income

Income	N	German average
less than €12,000	179	€33,700
€12,000 to €30,000	410	
€30,000 to €50,000	648	
€50,000 to €100,000	402	
more than €100,000	125	
no answer	194	
N	1,958	

(b) Education

Education	N	Percentage Sample	Percentage Germany
Still in school	19	0.97%	3.25%
Hauptschule	107	5.46%	38.43%
Realschule	398	20.33%	21.42%
Gymnasium	424	21.65%	11.69%
University	864	44.13%	12.50%
Ph.D.	146	7.46%	1.07%
No response/Other	0	0.00%	11.64%
N	1,958	100.00%	100.00%

(c) Other variables

Variable	Mean	St.D.	Min.	Max.	German average
Risk attitude	4.23	1.37	1	7	2.24
Financial literacy	8.19	1.16	0	9	-
Age	42.17	16.99	11	109	55.44
Male gender	0.87	0.33	0	1	0.49
Stock market participation	0.81	0.39	0	1	0.25
Financial professional	0.31	0.46	0	1	-
N	1,958				

Investment amounts are almost equally distributed across participants (see 5- 4(a)). The investment amount chosen increases with age, male gender, income, education, financial knowledge, and a preference for saving (regressions not reported). Across all conditions almost fifty percent of participants choose a time horizon of five years for their investment (see table 5-4(b)). The chosen time horizon increases with education, employment in the financial industry, lower risk aversion, participation in the stock market, financial knowledge, and a preference for saving (regressions not reported). The selection issue for investment amount and investment horizon is addressed in more detail in the following sections.

Table 5-4: Self-Selected Decision Context

Table 5-4(a) reports the number of participants who choose a certain investment amount and table 5-4(b) reports the number of participants who choose a certain investment horizon.

(a) Investment amount

Investment amount	**N**
€5,000	771
€50,000	734
€100,000	453
	1,958

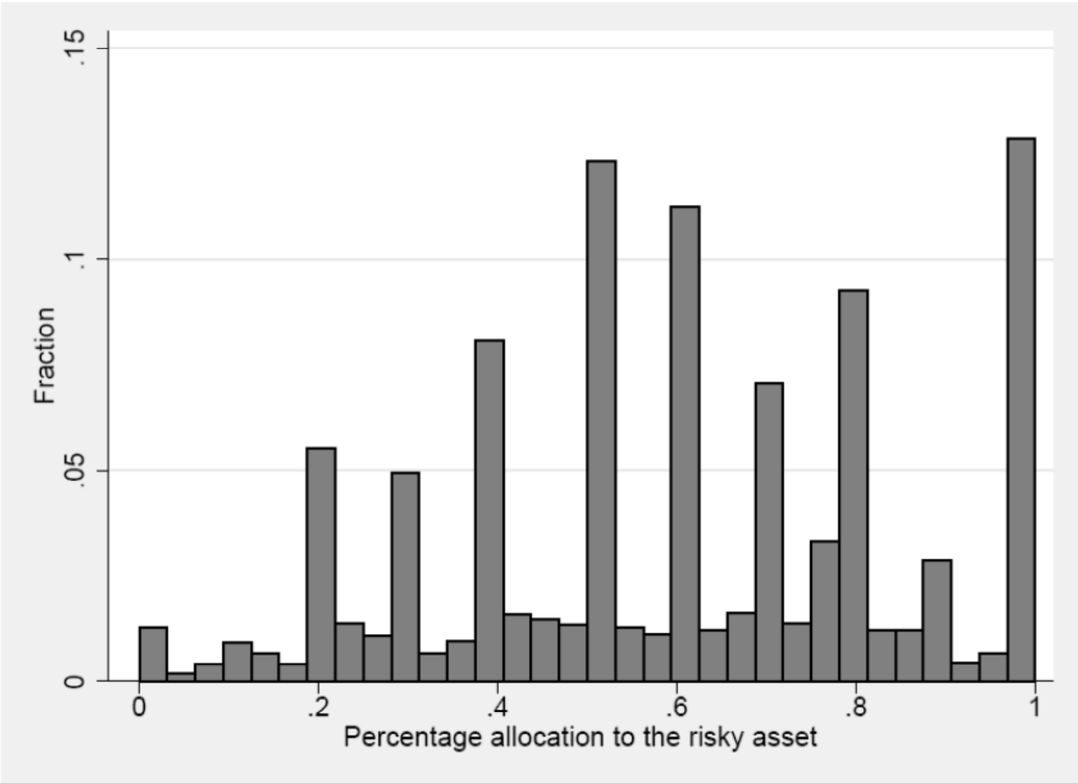
(b) Investment horizon

Investment horizon	**N**
1 year	521
5 years	939
10 years	498
	1,958

5.4 The Relationship between Risk Attitude and Risk Taking

Across all conditions, participants on average allocate 59.8% to the risky asset. The distribution of percentage *allocations* seems to be wide spread and does not look unusually distributed (see figure 5-3). Participants show a preference for rounding to the nearest ten percent: 25% of the participants use multiples of ten for their allocation. Similar effects have been shown in the literature (e.g., Huberman and Jiang 2006). The high fraction of participants investing 100% into the risky asset is due to the experimental design; whenever a participant were to prefer an allocation above 100%, he should choose exactly 100%. Overall, the distribution pattern does not give the impression that subjects were using naïve diversification by simply investing 50:50 - only 11% of the participants choose an allocation consistent with this kind of strategy, while Benartzi and Thaler (2001) report numbers between 21% and 34%. Reasons for this considerable difference may be found in the different experimental designs: While Benartzi and Thaler (2001) offer a choice between a bond fund and a risky fund, we offer a choice between a risk-**free** asset and a risky fund, and while Benartzi and Thaler (2001) use fixed graphical displays, we simulate the assets in more detail. Another reason might be the fact that our subjects are quite financially literate (the effects of financial literacy will be discussed in more detail later).

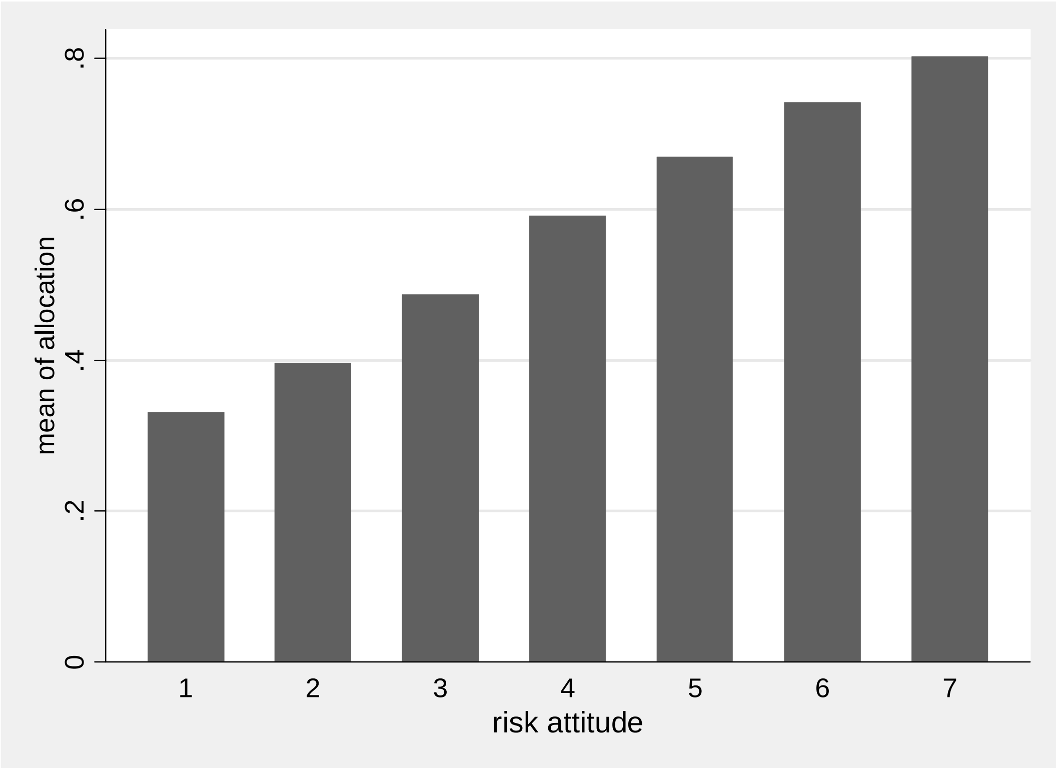
Figure 5-3: Histogram of Percentage Allocations to the Risky Asset



Having considered risk taking itself, we shall now focus on risk attitude as its main explanatory variable. Participants on average report a risk attitude of 4.23 on a scale of one to seven (1= not willing to accept any risk; 7=willing to accept substantial risk). The mean allocation to the risky asset (i.e. actual risk taking) is monotonically increasing in the risk attitude (see figure 5-4): for instance, participants reporting a risk attitude of 2 (n=189) allocate an average of 39.6% to the risky asset, whereas participants reporting a risk attitude of 6 (n=281) on average allocate 74.1% to the risky asset. This difference is significant ($t_{(468)} = 15.99$, $p = 0.00$). Out of 21 pair wise differences, nineteen differences are statistically significant (p = 0.00).[45] We find an increasing allocation for higher risk attitudes.[46] Differences between risk attitudes are highly significant in almost all cases.[47] The correlation between *allocation* and *risk attitude* is equal to 0.455 and is highly significant ($p<0.01$), also implying a strong relation between these two variables. At first glance, these univariate results hence support the notion that an investor's risk attitude is strongly related to the percentage he chooses to invest into the risky asset.

Figure 5-4: Mean Allocation to the Risky Asset by Risk Attitude

This figure reports the mean allocation to the risky asset over all participants dependent on the their self assessed risk attitude (with 1 being the least risky).



[45]The difference between allocations for risk attitude 6 and 7 is significant with $p < 0.05$ and the difference for risk attitude 1 and 2 is not significant (p = 0.158), which is due to the small number of participants with a risk attitude of 1.

[46]Except for risk attitudes 1 and 7 in the de-levered condition. The inconsistent values are driven by outliers together with small sample sizes (5 and 14 observations respectively). Differences between conditions are analyzed in more depth in the next section.

[47]Only when sample sizes are low and risk attitudes are close at the same time, significance vanishes. Let's take the basic condition as an example: the difference in allocation for participants with the risk attitude 1 (7 subjects) and those with risk attitude 2 (33 subjects) is not significant. However, the difference for risk attitude 1 (7 subjects) vs. 3 (55 subjects) is significant again (p = 0.01).

In order to formally test this relationship in a multivariate setting, an OLS regression with *allocation* to the risky asset as the dependent variable is used.[48] The results confirm the findings of the univariate analysis and show that participants behave in accordance with their stated preferences: risk attitude significantly predicts risk taking (see table 5-5); a one level increase on the risk attitude scale results in an increase of 7% in the allocation to the risky asset (which is in line with previous findings, e.g., Dorn and Huberman 2005, 2010). Additionally, investors tend to reduce their allocation to the risky asset with a higher *perceived risk*, which is also in line with the literature (Sitkin and Pablo 1992; E.U. Weber and Milliman 1997; Nosić and Weber 2010): a one level increase in risk perception of the risky asset results in an allocation decrease of 4%.

An increase in *investment horizon*[49] or in *investment amount* leads to higher risk taking, which also shows that participants do something sensible: facing a ten year time horizon instead of a one year time horizon, the probability of receiving an outcome below the amount invested decreases from 36.5% to 16%. The probability of receiving a return below the risk-free return decreases from 38.5% to 31.5%.[50] The free choice of investment horizon and investment amount should not lead to endogeneity as they are both chosen before participants have any information on the assets and before they make their allocation decisions.[51]

As they differ between conditions, the *annual expected return* and *volatility* of the risky assets are added as further control variables; both are significant predictors of risk taking. Consistent with previous results (e.g., Croson and Gneezy 2009; Nosić et al. 2011), women appear to be more risk averse than men, albeit this relationship is significant only at the 10%-level. Participation in the stock market and education are also controlled for, but these variables have no significant effect on risk taking.[52]

[48]As *allocation* is limited to the interval from 0 to 1, a Tobit regression model is used to conform the results. Results do not qualitatively differ in the Tobit model; consequently only the results of the OLS model are described.

[49]Results do not change if the risk-free return is used as a control variable instead of the investment horizon as the investment horizon determines the risk-free rate.

[50]Calculations are based on the historical monthly return distribution and are exemplarily calculated for an investment of 100% to the risky asset in the basic condition.

[51]Nevertheless, the endogeneity issue is addressed by correlating the residuals of the regression models on the investment amount and the investment horizon. Both correlations have a value of 0.00, which indicates that there is no endogeneity problem.

[52]Regressions are checked for multicollinearity using variance inflation factors. The maximum variance inflation factor of any of the explanatory variables is 1.31. This indicates that multicollinearity is not a problem.

Table 5-5: Allocation to the Risky Asset

This table reports results of an OLS regression explaining *allocation* with the stated *risk attitude*. Perceived risk, investment amount, and investment horizon also influence the allocation to the risky asset in the predicted way. Standard errors are in parentheses. * indicates significance at the 10%-level, ** at the 5%-level, and *** at the 1%-level.

	(1) allocation to the risky asset
Risk Attitude	0.074***
	(0.004)
Perceived Risk of the asset provided	-0.042***
	(0.004)
Investment Horizon	0.007***
	(0.002)
log(Investment Amount)	-0.013***
	(0.004)
Stock market participation	-0.009
	(0.014)
Male Gender	0.027*
	(0.015)
Age	-0.000
	(0.000)
Education	0.001
	(0.005)
annually return of the portfolio provided	0.756**
	(0.298)
annually std of the portfolio provided	-0.379***
	(0.077)
Constant	0.543***
	(0.060)
Observations	1,958
Adjusted R^2	0.265

As the dependent variable is not normally distributed (due to the number of participants who invest 100% into the risky asset) Tobit and OLS regressions excluding these observations are run (but not reported here due to space constraints); the results do not differ qualitatively from the results described above in any meaningful way. Overall, the findings enable us to give an answer to our first research question: Investors do a sensible thing, they invest more into the risky asset when they are less risk averse and when they perceive the risk to be lower.

5.5 EFFECTS OF THE RISK-RETURN-PROFILE GIVEN ON RISK TAKING

Framing should not matter: participants can and should choose the same risk-return profile for their portfolio across conditions by varying their respective allocations to the risky asset. However, participants change their percentage-allocations only slightly: they on average invest 59% into the risky asset in the de-levered condition, compared to 57% in the basic and 55% in the levered condition (see table 5-6) and only the difference between the allocation in the de-levered and the levered condition is significant ($t_{(633)} = 2.24$; $p = 0.03$); results are comparable for median instead of mean allocations. Table 5-6 gives a descriptive overview of the chosen allocations by condition and self selected time horizon. While the allocation to the risky asset increases with the time horizon (compare Klos et al. 2005; Siebenmorgen and Weber 2004), differences between conditions do not change significantly.[53]

Table 5-6: Percentage Allocations to the Risky Assets over Different Time Horizons

This table reports the resulting mean and median allocations to the risky fund divided by the total endowment. Results are reported for the three main conditions across and between self-selected time horizons. These numbers are descriptive, see table 5-7 for regressions controlling for other influences.

	De-levered asset			**Basic asset**			**Levered asset**		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
All horizons	0.593	0.6	323	0.574	0.6	331	0.547	0.5	312
One year	0.55	0.55	72	0.599	0.6	79	0.48	0.5	99
Five years	0.563	0.545	160	0.517	0.5	164	0.548	0.5	137
Ten years	0.679	0.73	91	0.658	0.625	88	0.633	0.63	76

An analysis of mean allocations shows that participants slightly (but not significantly) adjust their percentage allocations. Nevertheless, it might be that even these small adjustments between conditions lead to similar portfolios in terms of risk and return. Figure 5-5 shows the different risky assets given as well as the risk-return profiles chosen in a μ-σ-diagram, exemplarily for the five year horizon.[54] The risky assets provided differ in the risk-return-

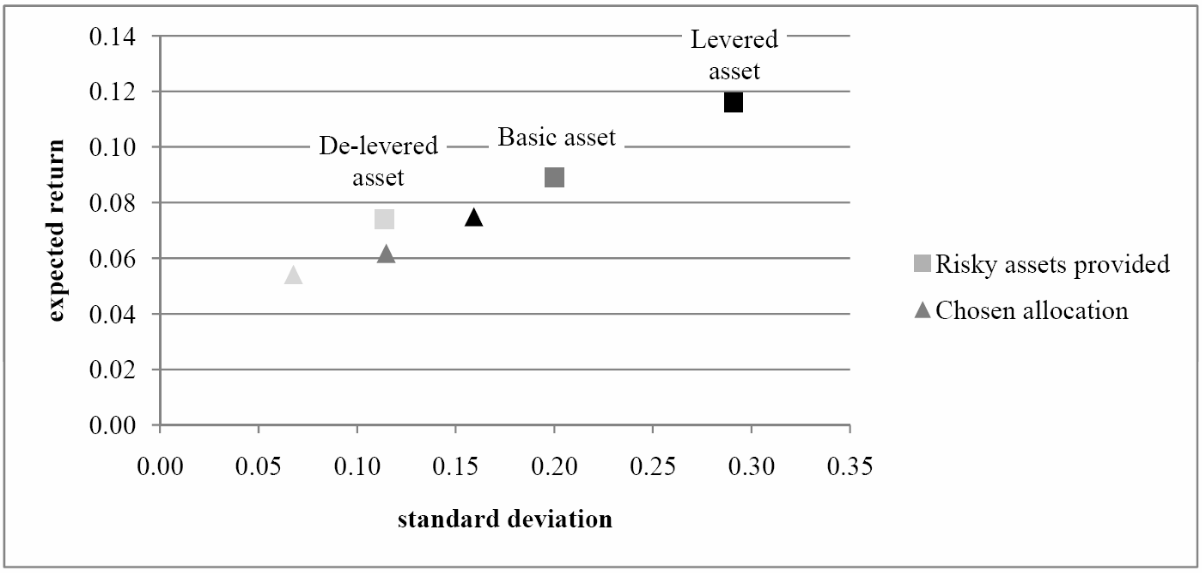
[53] Differences between the levered and the de-levered condition are only marginally significant for the one year time horizon and not at all significant for the other time horizons; as time horizon is self- selected, it might be that we find a selection bias in the data, e.g., that less risk averse participants choose longer time horizons and therefore allocate a higher fraction to the risky asset. We therefore later on control for risk attitude as well as other personal traits and demographics in a multivariate setting.

[54] Results look similar for the one year as well as the ten year time horizon.

profile, but are approximately[55] located on the same capital market line. It is therefore possible to end up with a similar risk-return-profile between conditions by combining the risky asset with a certain fraction of the risk-free asset. If framing did not matter, subjects would end up at the same point in the diagram by changing their percentage allocation dependent on the condition they face. The graph shows that the mean allocation in the de-levered condition of 56.3% for the five year time horizon results in an annual expected return of 5.2% and a volatility of 6.4%. An investor desiring this could end up with the same portfolio by investing 40% to the risky asset in the basic condition or by investing 30% to the risky asset in the levered condition.

Figure 5-5: μ-σ-Diagram of the Risky Assets Provided and the Chosen Allocations

This figure displays the annual expected return and the annual standard deviation of the he risky assets provided in the main conditions, exemplarily for the five year time horizon. The respective triangles reflect the average risk-return-profile of the portfolios chosen by the subjects within the respective condition. The portfolio returns are calculated by the percentage invested into the risky asset multiplied with its return plus the percentage invested into the risk-free asset multiplied with the annual five year interest rate of 2.5%.



The graph shows a different picture, however: the mean percentage allocations chosen by our participants (51.7% in the basic condition, 54.8% in the levered condition) result in economically and statistically meaningful differences between conditions in terms of both expected return and standard deviation. The comparatively small differences in percentage

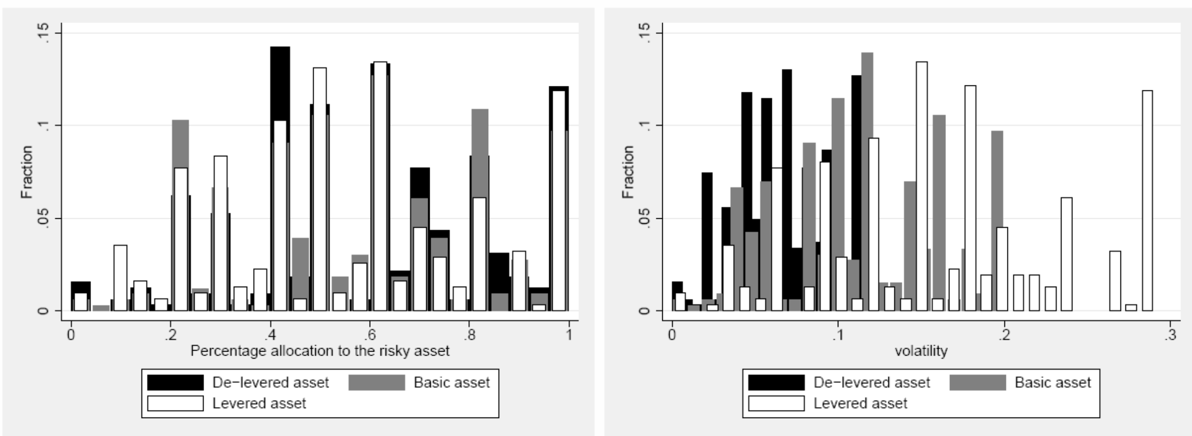
[55] The assets are not exactly on the same line, as we constructed the levered and the de-levered by combining them with the historical and not a fixed risk-free rate (for further explanations, see section 3). However, changes are only marginal and the constructed portfolios differ by far stronger from each other than the difference with regard to the interest rates could explain.

allocation to the risky fund between conditions are far from being sufficient to result in similar risk-return-profiles for the portfolios. To put things into numbers, these allocations on average result in significantly different portfolio volatility of 6.4% for participants in the de-levered, 11.5% in the basic and 15.9% in the levered condition respectively ($p < 0.01$ for all pair wise t-tests as well as for the bonferroni post-hoc pair wise comparison tests). In line with the findings of Benartzi and Thaler (2001), the risk of the chosen allocation increases significantly with the riskiness of the risky asset. Results for the mean %-allocations suggest the existence of a severe framing effect.

On an individual level, allocations to the risky assets are distributed over the whole possible range in each of the conditions. Comparing the distributions between conditions (see figure 5-6(a)), there is no evidence that similar mean allocations in the de-levered, the basic, and the levered market portfolio can be explained by extreme values or abnormal distribution in one or more of the conditions. Figure 5-6(b) shows the distributions of volatilities[56] that correspond to the chosen percentage allocations.

Figure 5-6: Distributions of Chosen Portfolios across Conditions

Figure 5-6(a) displays the distribution of allocation to the risky asset in % of participants over conditions. Figure 5-6(b) displays the distribution of the resulting chosen volatility to the risky asset in % of participants over conditions. As the maximum volatility differs between conditions, participants in the levered condition could choose from a broader volatility range (0-29%) as compared to participants in the de-levered condition (0-11.4%)



(a) Percentage Allocations

(b) Resulting volatilities

Figure 5-6(b) shows that the distribution of selected volatilities becomes broader if the provided risky asset is made riskier. In general, a broader distribution is sensible, as

[56] The results stay the same if we plot return distributions.

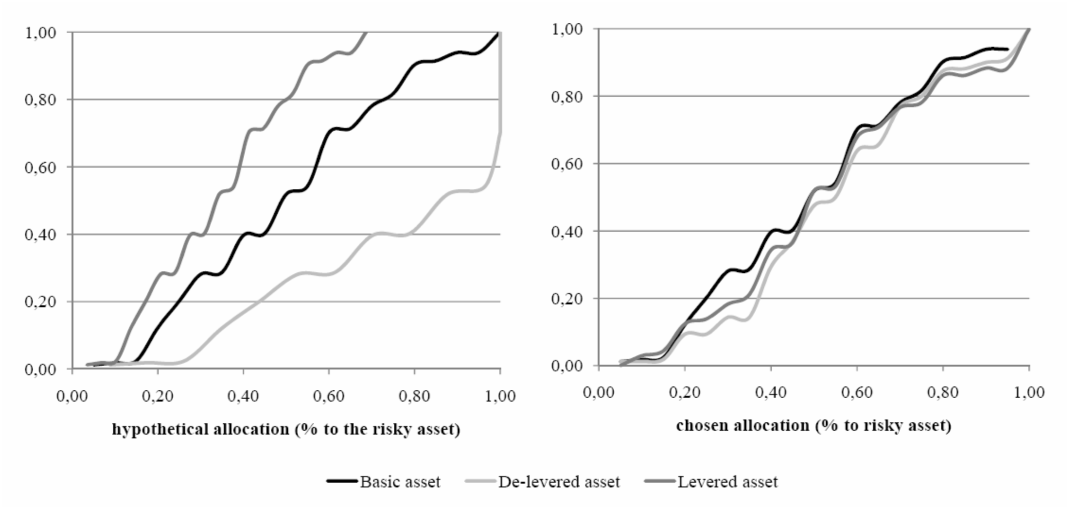
participants get a broader range of possible volatilities that can be chosen in the levered condition as for example compared to the de-levered condition.

Keeping this in mind, there should be more participants investing 100% into the risky asset in the de-levered condition than in the basic condition, as well as more in the basic condition than in the levered condition. However, 11% of participants invest 100% into the risky asset in the de-levered condition, compared to 9% in the basic and 11% in the levered condition. Looking at the chosen volatility the framing effect becomes even more obvious: In the de-levered condition 11% take the highest possible risk - resulting in a volatility of 11.4%. In the basic condition 52% take on a volatility of 11.4% or higher and in the levered condition as much as 72% do so. Participants distribute their allocation to the risky fund over the potential range independently of changes in the risk-return-profile of the given risky asset.

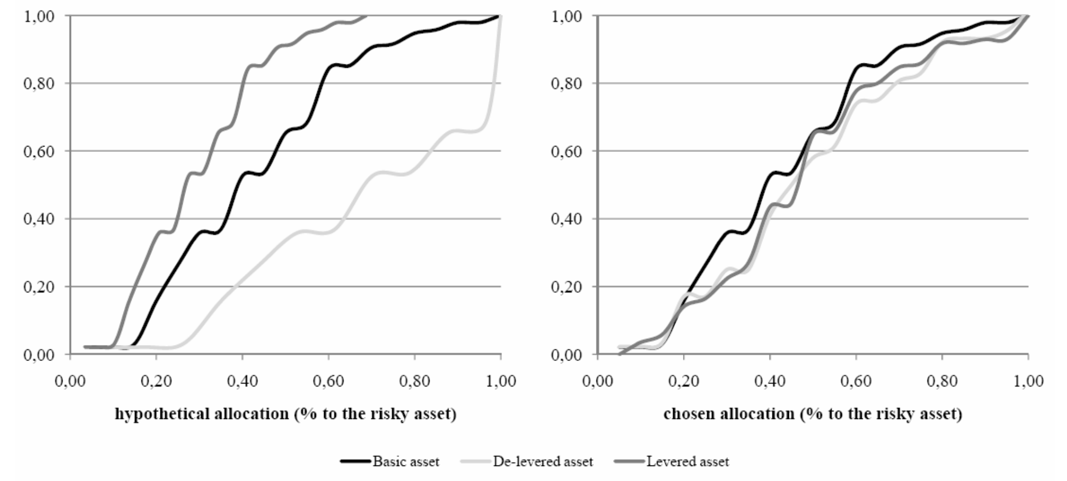
A comparison of the cumulative distribution of the observed percentage allocations with a hypothetical distribution that would be consistent across our conditions gives further evidence for the strength of the framing effect: with the basic portfolio as the reference curve it is possible to calculate what the cumulative distribution should be in the de-levered or the levered conditions respectively if participants wanted to obtain the same final allocation on the capital market line, e.g., a participant investing 60% to the risky asset in the basic condition would need to invest around 90% in the de-levered condition and around 35% in the levered condition to get to the same risk-return profile in his portfolio. The difference between the hypothetical, "rational" distributions and the realized distributions is plotted in figure 5-7(a).

Figure 5-7: CDFs of Percentage Allocations to the Risky Asset

The left part of figure 5-7(a) displays the hypothetical cumulative distribution functions (CDFs) of allocations to the risky asset. The hypothetical CDFs are calculated based on the chosen allocations to the basic asset and reflect how the distribution of allocations to the de-levered or the levered conditions respectively would look like if participants chose the same portfolios (in terms of risk and return) as in the basic condition. The right part of figure 5-7(a) shows the empirical allocation - what participants really have chosen - for all three conditions. Figure 5-7(b) also shows hypothetical and empirical CDFs for a subgroup of participants with risk attitude between 1 and 4 (on a 1-7 scale, where a higher number indicates a lower risk aversion).



(a) Full sample



(b) Risk attitude 1-4 only

The left part of figure 5-7(a) illustrates what the cumulative distribution functions (CDFs) of the de-levered and the levered conditions *should look like* if participants behaved in accordance with the observed behavior in the basic condition. The right part of figure 5-7(a) illustrates how the distribution of the chosen allocations in our experiment *actually looks like*: People do not change their percentage allocation to the risky fund if the asset gets more risky -

and this is the case not only for high percentage allocations (which could be explained by a ceiling effect), but for the whole distribution of allocations. A Kolmogorov-Smirnov test shows that there are no measurable differences in distributions between conditions.

As an additional robustness check, figure 5-7(b) shows the CDFs for participants with a risk attitude between 1 and 4. The maximum volatility that can be chosen ranges between 11.4% in the de-levered condition to 29% in the levered condition. Among the participants with a risk attitude between 1 and 4, three quarters have chosen a volatility below 11.4% and over 80% have allocated less than 75% to the risky asset. The graphs in figure 5-7(b) show that even participants with a low risk attitude between 1 and 4 (who are able to choose the same risk-return-profile within all conditions) select similar allocations resulting in significantly different risk-return profiles. An example in numbers: a person with a risk attitude of 2 on average chooses a volatility of 4.5% (resulting from an allocation of 40% to the risky asset) in the de-levered condition, 7.5% in the basic condition (37% to the risky asset) and 10.9% in the levered condition (37% to the risky asset).

The results hold in a multivariate OLS regression analysis with *allocation* as well as *chosen volatility* as a dependent variable. Column 2 of table 5-7 shows that there is no significant change in percentage allocations induced by providing different risky assets. An even more precise measure of the framing effect may be obtained from a regression with chosen volatility as a dependent variable. If framing did not matter, the dummy variables for the de-levered and the levered conditions (the basic condition is omitted) should not have a significant influence; however, we find that both condition dummies (see table 5-7, column 2) significantly predict the chosen volatility.

As a robustness check, results can be replicated in a sub-sample regression of participants with a risk attitude between 1 and 4 (table 5-7, column 3, the same sub-sample we used in figure 5-7(b)). Overall, an analysis on the individual level strengthens the evidence that participants do not base their allocation decision on the riskiness of the provided risky asset; the results of the multivariate analysis indicate that there are other objective and subjective variables which influence the allocation decision.

These main explanatory variables are risk attitude, investment horizon, and risk perception. Risk attitude is an exogenous variable and said to be a stable personality trait. It significantly predicts allocation as well as chosen volatility (see table 5-7). Risk perception, however, is likely to be influenced by the given risky asset. If we compare risk perception of the risky asset between conditions, we do not find any significant differences: participants on average reported a risk perception of 4.5 in the de-levered condition, of 4.6 in the baseline condition, and of 4.5 in the levered condition. This is in line with the framing effect - a risky asset is perceived risky independently of changes in riskiness (i.e. volatility).

We additionally asked participants about the portfolio risk perception of their chosen allocation instead of the risky asset itself; results support former findings: portfolio risk perception of participants who take on the same percentage allocation (e.g., allocating between 45% and 55% to the risky asset) are not significantly different: 3.4 in the de-levered condition, 3.5 in the baseline condition, and 3.5 in the levered condition. However, the portfolio risk perceptions of participants who choose the same volatility, e.g., between 0.04 and 0.08 (and therefore face the same objective risk level), differ between conditions with an average of 3.34 in the de-levered condition, 3.14 in the baseline condition and 2.82 in the levered condition. The difference is significant for the pair wise t-tests between the levered and the de-levered condition and marginally significant for the difference between the de-levered and the baseline condition; the bonferroni post-hoc pair wise comparison test shows a significant difference between the levered and the de-levered condition; to put it simple: portfolio risk perception depends on the percentage allocated to the risky asset and not on the objective riskiness/volatility.

Table 5-7: Chosen Allocation and Volatility

This table reports OLS regressions analyzing differences between conditions. The basic condition is omitted in all three regressions. The dummies for the de-levered and the levered asset show the respective difference to the basic asset. Regression (1) analyzes the effects on final allocations to the risky fund measured as a percentage of the initial endowment as dependent variable; (2) reports the effects on chosen volatility. In (3) the same regression as in (2) is performed for a sub-sample of participants with a risk attitude between 1 and 4 (on a 1-7 scale, where a higher number indicates a lower risk aversion). Standard errors are in parentheses. * indicates significance at the 10%-level, ** at the 5%-level, and *** at the 1%-level.

	(1) allocation	(2) volatility	(3) vola, risk-attitude 1-4
De-levered asset	0.013	-0.048***	-0.041***
	(0.018)	(0.004)	(0.005)
Levered asset	-0.020	0.046***	0.041***
	(0.018)	(0.004)	(0.005)
Risk Attitude	0.069***	0.014***	0.014***
	(0.006)	(0.001)	(0.003)
Perc. Risk (asset given)	-0.034***	-0.007***	-0.008***
	(0.006)	(0.001)	(0.002)
Investment Horizon	0.005**	0.001**	0.001
	(0.002)	(0.001)	(0.001)
log(Investment Amount)	-0.008	-0.003*	-0.003
	(0.006)	(0.001)	(0.002)
Stock Market Particip.	0.001	-0.000	0.003
	(0.020)	(0.004)	(0.005)
Male Gender	0.030	0.009*	0.009*
	(0.022)	(0.005)	(0.005)
Age	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)
Education	0.002	-0.001	-0.001
	(0.006)	(0.001)	(0.002)
Constant	0.475***	0.106***	0.114***
	(0.075)	(0.016)	(0.022)
Observations	966	966	529
Adjusted R^2	0.222	0.451	0.384

Overall, investors indeed do something sensible: they base their risk taking decision on their risk preferences and their time horizon. However, the decision variable "risk" seems to be driven by the question "what absolute amount do I wish to invest riskily" instead of "what risk level (how much volatility) do I wish to take". In the remainder of this section, we will analyze the robustness of the observed framing effect by testing two variations. 1. We find an abundance of evidence in the literature that a higher degree of financial literacy improves financial decision making; therefore, the interaction of financial knowledge and framing will be explored (Campbell 2006; Calvet et al. 2007). 2. The framing of riskiness can be induced subjectively and objectively. For the objective variation, an additional condition with a dominating asset is included so we can see whether participants adjust their allocation if differences in risk-return profiles become more obvious. For the subjective variation we include asset names for the basic and the dominating asset to determine whether the framing effect interacts with more subjective information.

Financial Literacy and Asset Allocation

To test for the framing effect for different degrees of financial knowledge, the sample is split into two sub-samples relative to the median financial literacy score, resulting in sub-samples with relatively high and low financial literacy. Participants with a higher financial literacy in general tend to invest a higher fraction into the risky asset, with a mean allocation of 60.34% versus 53.36% for participants with lower financial literacy. This is not surprising as financial literacy is significantly positive correlated with risk attitude (ρ = 0.30; p < 0.00). Table 5-8 reports the chosen allocation for the different conditions by financial literacy groups: participants with high financial literacy significantly adjust their allocation in the de-levered condition. The bonferroni post-hoc pair wise comparison test shows a significant difference between the levered and the de-levered condition as well as between the de-levered and basic condition on the 5% significance level. Nevertheless the resulting portfolios of the high financial literacy group still differ economically: a mean allocation of 65% in the de-levered condition results in a annual volatility of 7.4%, whereas the 58% invested in the basic and the levered condition result in an annual volatility of 11.8% and 17.1% respectively. In the low financial literacy group, a bonferroni post-hoc pair wise comparison test shows no differences between conditions at all.

Table 5-8: Percentage Allocations to the Risky Assets across Financial Literacy Groups

This table reports the mean and median allocations to the risky fund divided by the total endowment. Results are reported for the three main conditions across and between financial literacy groups. High (low) financial literacy refers to the group of participants with a financial literacy above (below) the median financial literacy score in the whole sample. These numbers are descriptive, see table 5-9 for regressions controlling for other influences.

	De-levered asset			**Basic asset**			**Levered asset**		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
Full sample	0.593	0.6	323	0.574	0.6	331	0.547	0.5	312
Low Fin. Lit.	0.524	0.5	149	0.568	0.6	155	0.516	0.5	154
High Fin. Lit.	0.651	0.675	174	0.579	0.57	176	0.578	0.6	158

The uni-variate results are confirmed in an OLS regression with allocation as the dependent variable: the dummy for the de-levered condition (the basic condition is omitted) is positive as well as significant in the high financial literacy group (see 9 (2)) and not significant in the low financial literacy group (9 (1)). However, an OLS regression model with chosen volatility as a dependent variable[57] shows that the changes in allocation are still far from resulting in similar portfolios in terms of volatility. The framing effect still persists in both financial literacy groups (compare table 5-9, column 3 and 4). The results are similar if we compare participants with stock market experience to participants without stock market experience (correlation to financial literacy 0.20) or participants working in the financial industry to those not working in the financial industry (correlation to financial literacy 0.31).

An additional effect we observe in the regressions is that the influence of investment horizon is only significant in the high financial literacy group and that the effect of risk perception seems to be stronger in the low financial literacy group, indicating that people with higher financial literacy at least to a certain extent take into account objective risk measures. If we include the volatility and the annual expected return into the regression (comparable to table 5-5, not reported) the results support this idea: standard deviation of the provided risky asset, investment amount and investment horizon significantly predict asset allocation in the high financial literacy group, while only standard deviation has a significant influence in the low financial literacy group.

[57] Again, results do not differ using a Tobit model.

Table 5-9: Chosen Allocation and Volatility for Different Financial Literacy Groups

This table reports OLS regressions of the chosen allocation and chosen volatility for different financial literacy groups. The basic condition is omitted in all three regressions. The dummies for the de-levered and the levered asset show the respective difference to the basic asset. Regression (1) analyzes the effects on final allocations to the risky fund in percent for the low financial literacy group (participants with a financial literacy score below the median); (2) reports the effects for the high financial literacy group (participants with a financial literacy score above the median). (3) analyzes the effects on chosen volatility for the same sub-sample as in (1), and (4) analyzes the effects on chosen volatility for the same sub-sample as in (2). Standard errors are in parentheses. * indicates significance at the 10%-level, ** at the 5%-level, and *** at the 1%-level.

	(1) alloc. low FL	(2) alloc. high FL	(3) vola low FL	(4) vola high FL
De-levered asset	-0.031	0.054**	-0.051***	-0.045***
	(0.025)	(0.024)	(0.006)	(0.005)
Levered asset	-0.031	-0.009	0.041***	0.051***
	(0.025)	(0.025)	(0.006)	(0.005)
Risk Attitude	0.073***	0.063***	0.015***	0.013***
	(0.008)	(0.009)	(0.002)	(0.002)
Perc. Risk (asset given)	-0.047***	-0.020**	-0.009***	-0.005**
	(0.009)	(0.009)	(0.002)	(0.002)
Investment Horizon	0.001	0.010***	0.000	0.002***
	(0.003)	(0.003)	(0.001)	(0.001)
log(Investment Amount)	-0.002	-0.014	-0.002	-0.003
	(0.009)	(0.009)	(0.002)	(0.002)
Stock market participation	-0.006	0.008	-0.001	0.002
	(0.025)	(0.032)	(0.006)	(0.007)
Male Gender	0.031	0.032	0.009	0.009
	(0.026)	(0.038)	(0.006)	(0.008)
Age	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Education	-0.005	0.011	-0.002	0.001
	(0.009)	(0.010)	(0.002)	(0.002)
Constant	0.543***	0.394***	0.122***	0.085***
	(0.103)	(0.112)	(0.023)	(0.025)
Observations	458	508	458	508
Adjusted R^2	0.252	0.178	0.461	0.436

Objective Persistence of the Framing Effect: Dominating Asset

One reason for the overall small adjustment might be that differences in risk-return profiles are not obvious enough. We therefore analyze differences in allocations between the basic asset and a dominating asset, which offers a higher return combined with a lower risk. As an asset with a higher Sharpe-ratio is now provided, investors should invest significantly more into that dominating asset compared to the basic asset. We find an adjustment in the data: participants on average invest 57% into the risky asset in the basic condition and 62% in the dominating condition. This difference is significant ($t_{(642)} = 2.14$; $p = 0.03$).[58]

Results of an OLS regression model with allocation as a dependent variable, [59] show that the significant adjustment for the full sample is driven by the high financial literacy group (see table 5-10, column 2), whereas no differences in allocations between the basic and the dominating condition can be found in the low financial literacy group (see table 5-10, column 1). We do not analyze differences in volatility as these can be expected by construction: the dominating asset has a lower volatility and a higher return, thus making it sensible for participants to take on a higher or a lower volatility when compared to the basic asset. Differences in demographic variables between the two sub-sample regressions can be explained by the differences in participants between the two groups: in the high (low) financial literacy group 92% (82%) are male, 88% (72%) are invested into stocks and the mean risk attitude is 4.59 (3.83). Investors with high financial literacy overall seem to take large differences in risk-return-profiles into account, while participants with low financial literacy don't seem to do so on the same scale.

[58]Results are similar if we compare allocations to the levered or the de-levered asset with those to the dominating asset.
[59]Again, results do not differ using a Tobit model.

Table 5-10: Chosen Allocation for Basic and Dominating Asset

This table reports OLS regressions of the chosen allocation. The basic condition is omitted in both regressions. The dummy for the dominating asset shows the respective difference to the basic asset. Regression (1) analyzes the effects for the high financial literacy group, regression (2) the effect within the low financial literacy group. Regressions (3) and (4) show the same analysis for the named assets. Standard errors are in parentheses. * indicates significance at the 10%-level, ** at the 5%-level, and *** at the 1%-level.

	(1) alloc. low FL	(2) alloc. high FL	(3) alloc. low FL name	(4) alloc high FL name
Dominating asset	0.008	0.054**		
	(0.026)	(0.023)		
Dom. Asset named			0.022	0.072***
			(0.024)	(0.023)
Risk Attitude	0.092***	0.076***	0.094***	0.072***
	(0.011)	(0.009)	(0.011)	(0.009)
Perc. Risk (asset given)	-0.029**	-0.026**	-0.043***	-0.053***
	(0.011)	(0.010)	(0.010)	(0.010)
Investment Horizon	0.000	0.013***	0.003	0.014***
	(0.005)	(0.004)	(0.004)	(0.004)
log(Investment amount)	-0.011	-0.030***	-0.010	-0.012
	(0.011)	(0.010)	(0.010)	(0.010)
Stock market participation	-0.071**	-0.022	0.021	-0.033
	(0.034)	(0.041)	(0.030)	(0.038)
Male gender	0.047	0.119**	-0.032	0.048
	(0.035)	(0.048)	(0.032)	(0.041)
Age	-0.000	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Education	0.011	0.030**	-0.007	-0.002
	(0.011)	(0.012)	(0.010)	(0.012)
Constant	0.440***	0.421***	0.541***	0.536***
	(0.127)	(0.131)	(0.125)	(0.125)
Observations	296	348	335	344
Adjusted R^2	0.283	0.283	0.287	0.283

Subjective Persistence of Framing Effect

The information about the risky asset in the main conditions and the dominating asset condition was intentionally kept vague ("risky fund investing into capital markets") as we wanted subjects to focus on the return distribution. In two further conditions, an additional information about the risky asset was included - the asset name. The DAX condition has the exact same return distribution as the basic asset while the World Portfolio condition has the same return distribution as the dominating asset. In the DAX specification, participants are told that the risky asset is a fund replicating the German stock index (DAX), which represents the 30 largest (based on market capitalization) and most liquid German companies. In the World Portfolio specification, participants are informed that the risky asset is a fund replicating the performance of stocks (60%), bonds (25%) and commodities (15%) from all over the world (Jacobs et al. 2010). Consistent with the literature (e.g., Weber E.U. et al. 2005), participants take on higher risk if asset names are provided (see table 5-11): participants on average invest 57% into the basic asset as compared to 61% in the DAX asset and 62% in the dominating asset as opposed to 65% to the World Portfolio asset, however, the effect is only marginally significant for the difference between the basic asset and the DAX (p=0.09). Even if the influence on risk taking itself is not significant, results show a significant change in risk perception if asset names are included: reported risk perception in the basic condition is 4.63 in basic asset as compared to 4.40 in the DAX asset (t-test, p=0.01) and 4.59 in the dominating asset as opposed to 4.42 in World Portfolio asset (t-test, p=0.07). Interestingly, an objective variation in risk (different volatilities) does not change a subjective measure like risk perception while a subjective variation in the sense of information (asset names) does. One reason might be that the inclusion of asset names increases how familiar investors feel with their investment; while the absolute level of risk taking increases for both named asset, the relative difference between the dominating asset and the basic asset is equal to the relative difference between the two named assets. The objective risk adjustment is hence not influenced by the provision of asset names and results do not change if we include control variables in an OLS regression (not reported). Asset names seem to have an influence on the risk, but not on the riskiness. This finding also holds if we analyze our two sub-samples: participants with low financial literacy increase their risk taking by 4 percentage points on average for the DAX (61% instead of 57%) and the World Portfolio (again 61% instead of 57%) if asset names are included, but there are still no differences between the two assets. Participants with high financial literacy increase their risk taking by 3 percentage points for the DAX (61% instead of 58%) and the World Portfolio (68% instead of 65%) if asset names are included, and the difference between the two assets stays significant ($t_{(346)}$=2.93, p<0.01). The results suggest that the inclusion of subjective information (as the asset names) does not influence the behavior in a way that investors are able to judge differences in riskiness between the risky assets. They instead seem to generally increase risk taking, which is likely to be induced by a lower risk perception.

Table 5-11: Allocations to the Basic and the Dominating Asset (non-named and named)

This table reports the mean and median allocations to the risky fund divided by the total endowment. Results are reported for the ancillary conditions and the basic condition across and between self selected time horizons. These numbers are descriptive, see table 5-10 for regressions controlling for other influences.

	Basic asset		**Dominating asset**		**Dax (named)**		**Dominating asset (named)**	
	Mean	N	Mean	N	Mean	N	Mean	N
All horizons	0.574	331	0.617	313	0.607	321	0.645	358
One year	0.599	79	0.523	76	0.585	92	0.583	103
Five years	0.517	164	0.602	159	0.577	144	0.638	175
Ten years	0.658	88	0.739	78	0.68	85	0.743	80

5.6 Discussion

In the current paper we analyze two research questions which are highly relevant for private investors and have great policy implications. The good outcome of our analysis is: investors behave more rational than they are often said to; they base their decision on risk preferences like risk attitude and risk perception and, at least those with a high financial literacy, behave in accordance to personal circumstances like their invested amount or the planned investment horizon.

Nevertheless, we also find a strong framing effect when it comes to the overall portfolio risk: On average participants do not change their fraction invested risky as opposed to risk-free when the risk-return profile of the assets given changes. Our conclusion is that investors seem to have two mental accounts - one for their risk-free investment, another one for their risky investment - with a fixed percentage allocation to each of the two accounts in mind and disregarding the overall portfolio volatility. An adjustment seems to be non-existent for participants with low financial literacy; people with a higher financial literacy adjust when differences between risk-return profiles of given assets get more obvious, but their adjustment is still insufficient.

It does not seem that these findings can be explained by a lack in experimental validity; our sample size is by far larger than in comparable experiments and our participants are assigned randomly to our different conditions. As a consequence, characteristics across conditions do hardly differ. In the following we discuss different explanations for this behavior.

One explanation might be that investors use decision heuristics induced by the advisory process in banks. Generally, advisers elicit the risk preferences of their customers by asking them to state them on a scale (e.g., on a one to five scale ranging from "*not willing to accept any risk"* to "*willing to accept a substantial risk in order to have the chance to receive higher returns"*). This information is then used to recommend certain investment products to the customer. Some banks also use model portfolios in their advisory process where the percentage allocated risky differs for different risk attitudes. This percentage rate is not directly related to the overall volatility of the portfolio that is constructed for the investor. In this special case, customers are taught that the riskiness of their portfolio is determined by the amount they invest into risky assets, but neither their riskiness nor the overall portfolio volatility are taken into account in the first step. Furthermore this process reduces complexity for the investor; it is less complicated to decide how much to invest risk-free than to think about an overall portfolio volatility. In future research, different anchors like a maximum loss or percentage allocations suggested by investment advisers could be compared.

Another perspective on the observed behavior is to ask whether it indeed could be rational and is not induced by framing or anchoring - it just has the same consequences as one would expect from the manipulation. It might be that the private investor has another risk concept in mind. Riskiness for him is not risk measured by risk indicators, but in a first step everything which is not invested safely. When it comes to asset allocation people could think about the amount they need for sure after the investment period and this is the amount they allocate to the risk-free asset. Even if it is not realistic that participants lose all the money invested risky, they have only ambiguous statistics to rely on. We know that past returns work as an indicator, but we cannot use hindsight as foresight as it were a predictor (Taleb et al. 2009). The idea is supported by our findings that participants perceive the same percentage allocation to the safe (or the risky asset) across conditions as similarly risky - even if the objective risk in terms of volatility differs significantly. Additionally, we asked participants about the minimum amount they will need after the investment horizon (not reported in the results section), and this amount significantly predicts asset allocation decisions: when a small minimum amount is needed, participants invest a lot risky and still achieve their minimum for sure. A medium amount leads to a small allocation to the risky asset such that they still achieve the minimum amount for sure. If a large minimum amount is needed, investors gamble as this is the only way to achieve their minimum amount. With this in mind, it might be that we need a two-stage approach to elicit participants' risk preferences - first elicit the investment they need to have safe and secondly help them to allocate their risky invested money also taking the safe money into account. Investors may be more attentive to think about the "risky account" and realize differences between risky options once they are sure that the amount they need safe has been set aside. This is a question we want to investigate in future research. In line with that, it would be interesting whether these results hold for different investment purposes; it may be that investors use the mechanisms described above differently if they invest for retirement as opposed to future consumption they do not depend on.

Apart from their theoretical importance, our findings have important policy implications; they contribute to the current debate on the communication of investment risks to investors and on the measurement of investors' risk attitude. With the heuristics we describe, the choice of the risk-return profile used for the elicitation of risk preferences is crucial. A riskier asset will lead to a lower measured risk aversion. We know from the literature that standard deviation is a concept hardly understood by private investors, even quantitative analyst seem to fail by handling calculations correctly (Taleb et al. 2009). Even the use of a risk simulation - which does not state the volatility, but let's investors experience it - does not lead to major attention towards different risk levels. New EU regulations such as the *European Undertakings for Collective Investment in Transferable Securities Directives* (UCITS) and the *Key Investor Information Document* (KIID), request that mutual funds must be described in detail; together with other information, this document presents the volatility of returns as a simplified risk indicator with seven categories, which are calculated based on the historical volatility. In order to choose from these seven categories, investors would first have to find their personal category. Our findings show that the elicitation of a risk category depends crucially on the assets chosen for the elicitation process. If a riskier asset is chosen, the average investor will be categorized as more risk-seeking and funds from a higher category will be recommended. The measurement of an individual's risk preference has to be standardized in order to avoid conscious and unconscious manipulations resulting from the choice of different reference assets. Further research needs to investigate whether the indicator itself can help to better incorporate and understand information about the riskiness of an asset.

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APPENDICES

APPENDIX CHAPTER 3

3.1 OVERVIEW OF EXPERIMENTAL METHODS

	Experiment I	Experiment II	Experiment III
Conditions			
Description	*	*	*
Risk Simulation	*	*	*
Experience		*	*
Distribution		*	*
Measures			
Financial Literacy	*	*	*
Risk Perception			*
Confidence			*
Feeling Informed			*
Comprehension			*

3.2 Overview of Variables and Measures

Allocation Variables	
Initial	The first number participants typed in for the allocation to the risky fund after viewing information about the two funds separately. This could be adjusted before deciding on the Final Allocation.
Final	The allocation to the risky fund (out of €1,000 in Experiment I and \$100 in Experiment II and III) chosen after being informed about the diversified portfolio return and standard deviation of the initial allocation.
Subsequent	The hypothetical allocation made after seeing the results of the market simulation which determined their payoff (e.g., how they would choose again if they had another chance).
Control Variables	
Risk Attitude	Self reported: Please estimate your willingness to take financial risk (1= Not willing to accept any risk; 5=willing to accept substantial risk to potentially earn a greater return).
Financial Literacy	The score is the sum of the 11 financial literacy questions (highest score 11, lowest 0) adapted from van Rooij et al. 2011
Age	Age of the participant.
Gender	An indicator variable that equals one if the gender of the participant is male, zero otherwise.
Stock Ownership	An indicator variable that equals one if subjects own stocks or stock funds, zero otherwise.
Income	Self-reported income of participants in 1,000s of dollars / euros.
Education	0=some high school or no high school, 1=high school graduate, 2=specific (trade) school/ some college/ associate (2 year) degree, 3=college graduate, 4=advanced degree
Subjective Variables	
Risk Perception	How risky do you perceive Fund B (the risky fund) to be? (1=not risky at all, 7=very risky)
Confidence	How confident do you feel about investing in the risky fund? (Experiment III); How confident do you feel about your decision (Experiment I and II) 1= completely unconfident, 7=completely confident

Comprehension Variables	
Perceived Return	If we put \$100 in the riskier fund, what is the expected return of the \$100 after five years? (Give your best estimate.) Coded to reflect under- and overestimation: -1=\$100 - \$140, 0=\$141 - \$180 (correct interval), 1=\$181 - \$220, 2=\$221 - \$260, 3>\$260
Perceived Probability of a Loss	If we put \$100 in the riskier fund, in how man out of 100 cases will the return fall below \$100 after five years? In ________ out of 100 cases
Upside Potential	If we put \$100 in the riskier fund, in how man out of 100 cases will the return fall be above \$150 after five years? In ________ out of 100 cases
Informed	How informed do you feel about the funds? (1=completely uninformed, 7=completely informed)
Post-Return Decision Evaluation	
Satisfaction	Question asked after participants were shown their simulated return after five years: How satisfied are you with your return? (1=completely unsatisfied, 7=completely satisfied)
Luck	A variable measuring the outcome of the market simulation minus the expected return of the final allocation.

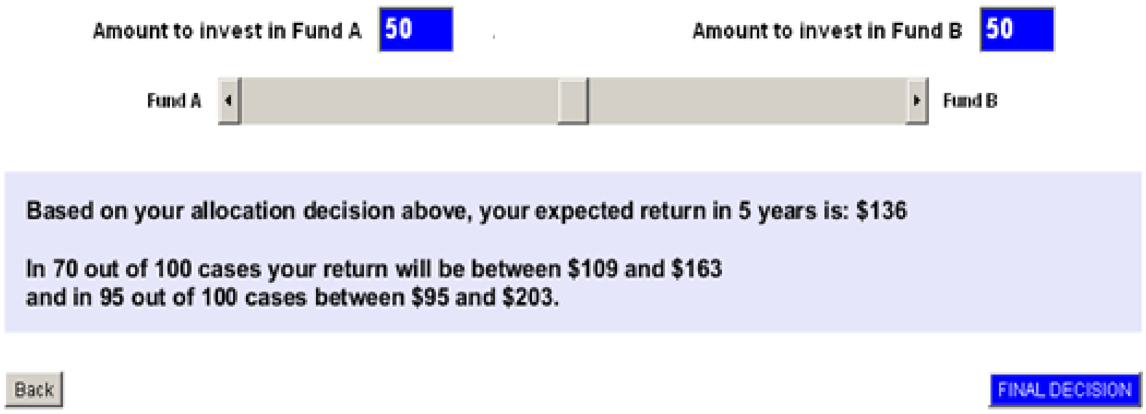
3.3 Overview of Different Conditions

DESCRIPTION CONDITION

Participants read descriptions of the risk free and the risky fund:

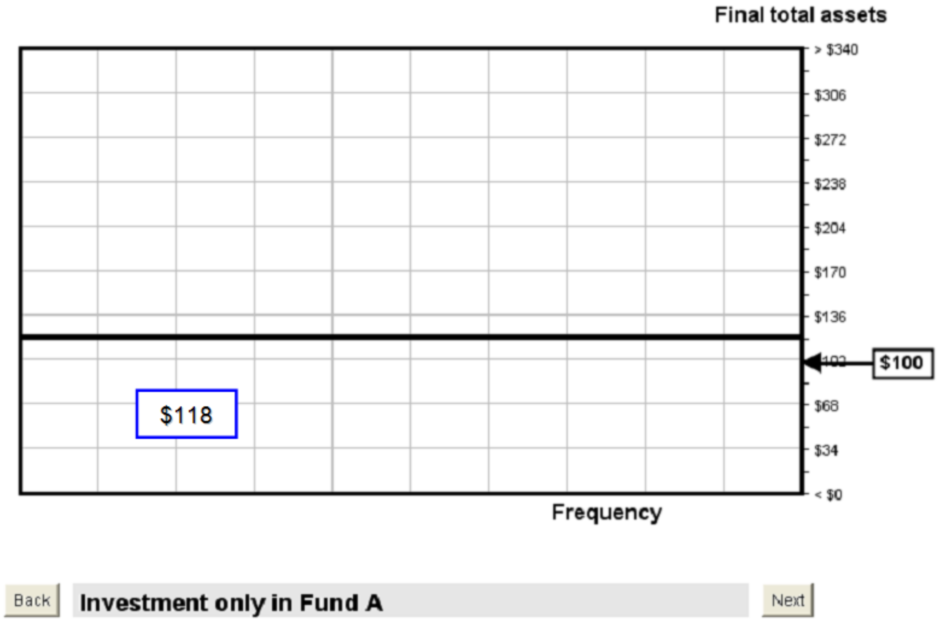
> You will choose how much to invest in a risk-free asset and how much to invest in a riskier asset.
>
> Fund A is a risk-free asset. It has a guaranteed annual return of 3.35% for sure. If you invest the full $100 in Fund A you will have a return of $118 in 5 years, net of fees.
>
> Fund B is a risky asset. It has an expected annual return of 8.92% with an annual standard deviation of 15.89%. If you invest the full $100 in that asset, you will have an expected final outcome of $153 in 5 years. However, the actual return is not known. It could be higher or lower. In 70 out of 100 cases your final wealth will be between $100 and $208 and in 95 out of 100 cases between $72 and $289.
> Now you will choose how to invest the $100.
>
> You can change the amounts you allocate to Fund A and Fund B by moving the scroll bar below and seeing how the expected return and the standard deviation of your total investment amount changes. When you have decided, click *final decision* below.

Next they made an initial allocation, which they could adjust using a slider and see how the expected return and variation changed before deciding on a final allocation:

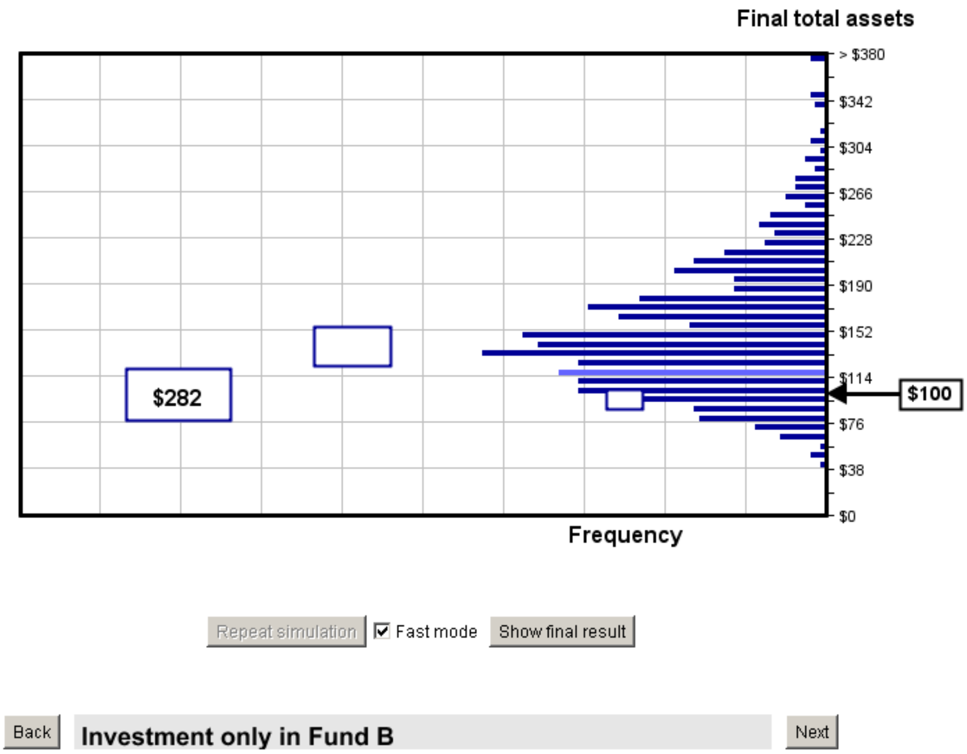


RISK SIMULATION CONDITION

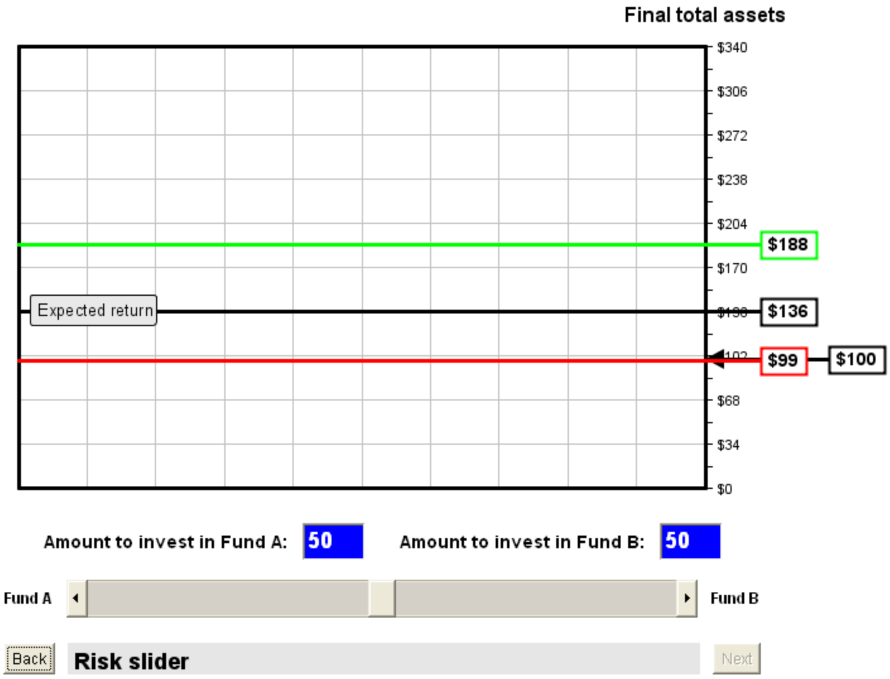
An experience sampling simulation draws the return of the risk free fund, resulting in a flat line:



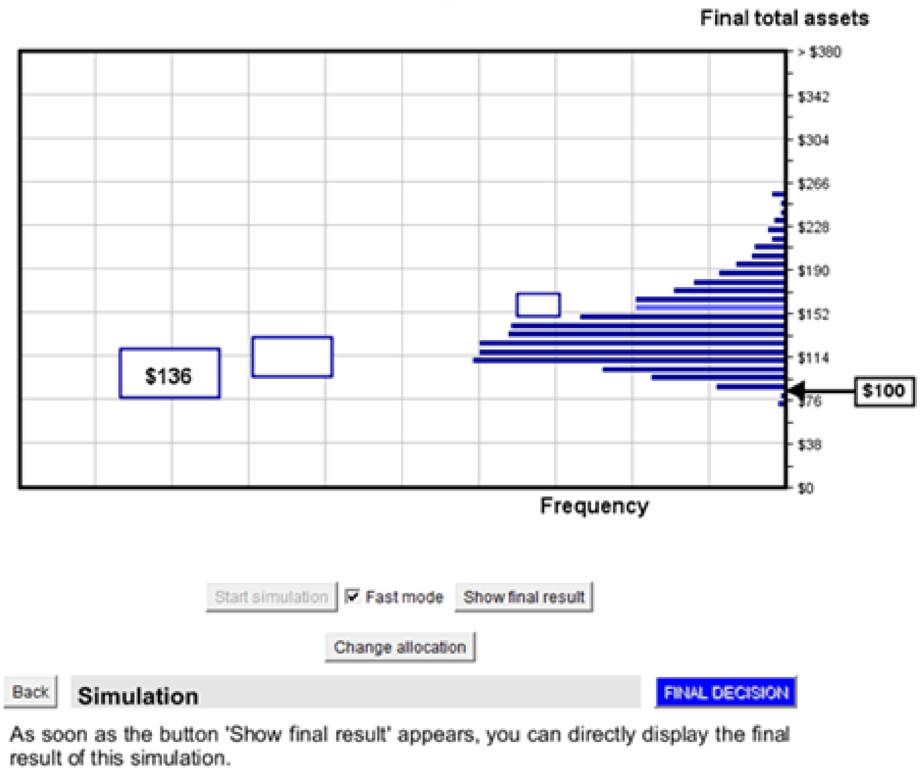
Experience sampling is used to build up the distribution of *the risky fund. Eight samples must be viewed before the simulation can go into "fast mode" to rapidly build up the distribution:*



Participants choose an initial allocation and could adjust it using a risk slider:



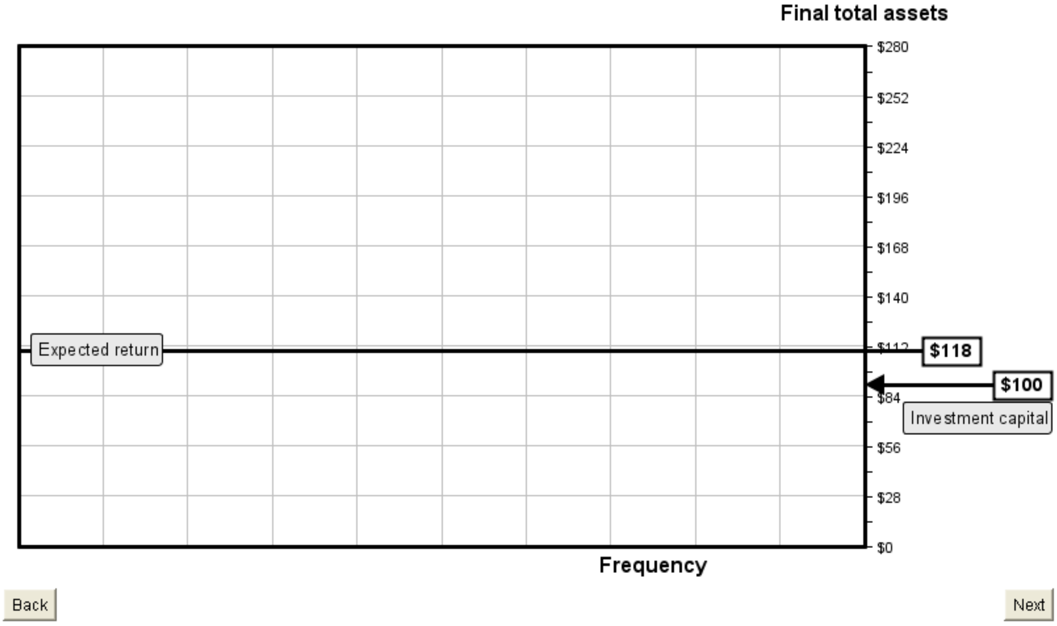
Experience sampling is used to build up the distribution of the risky fund based on the initial allocation:

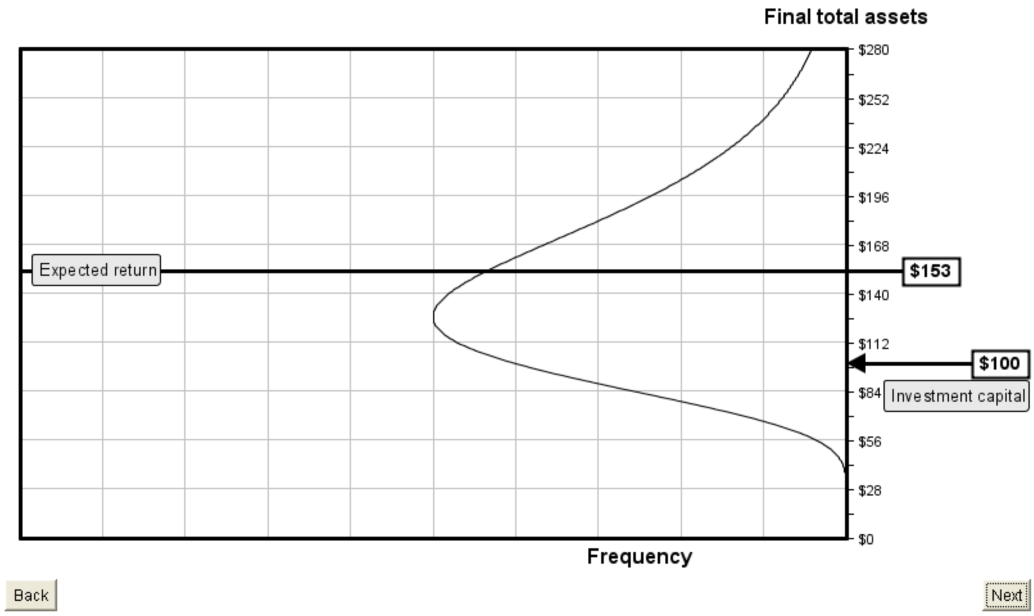


Participants can change their allocation and watch the simulation again as often as wanted until they decide on a final allocation.

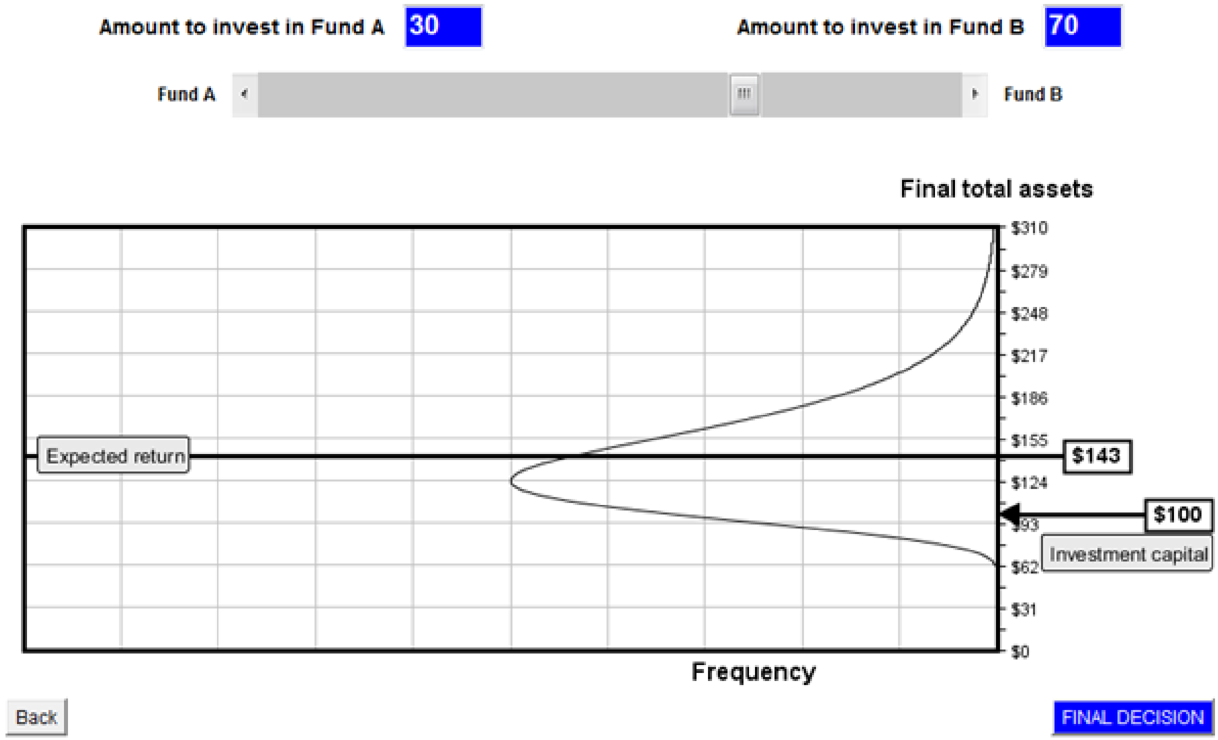
DISTRIBUTION CONDITION

A graphical display shows the return of the risk-free fund and then the risky funds:





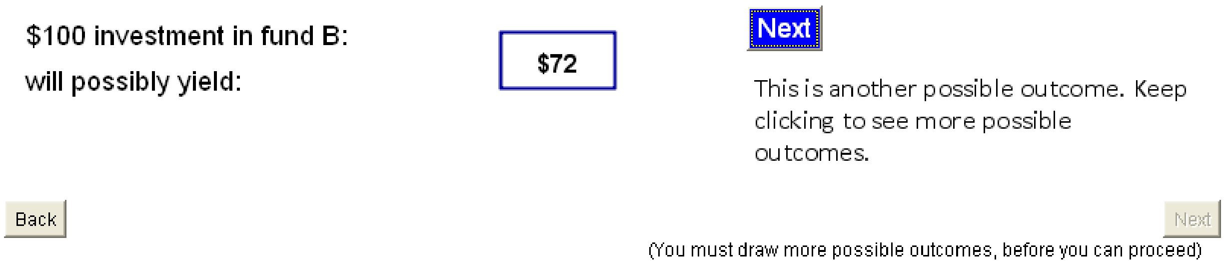
Participants choose an initial allocation that can be adjusted using a slider before making a final allocation decision:



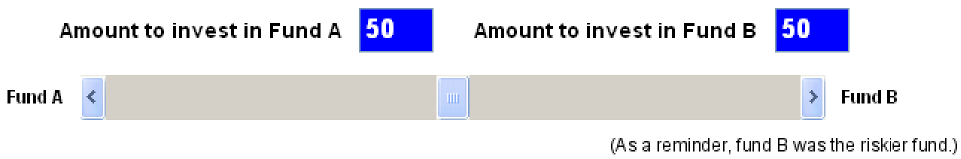
EXPERIENCE CONDITION

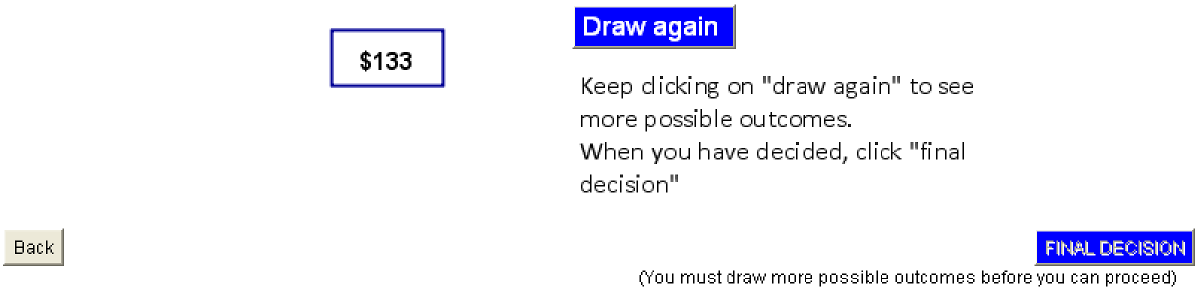
Participants draw possible returns for the risk free fund (at least 3 draws):

Participants draw possible returns for the risky fund (at least 8 draws):



The allocation can then be adjusted via a risk slider and the corresponding expected return is sampled (at least 8 draws):



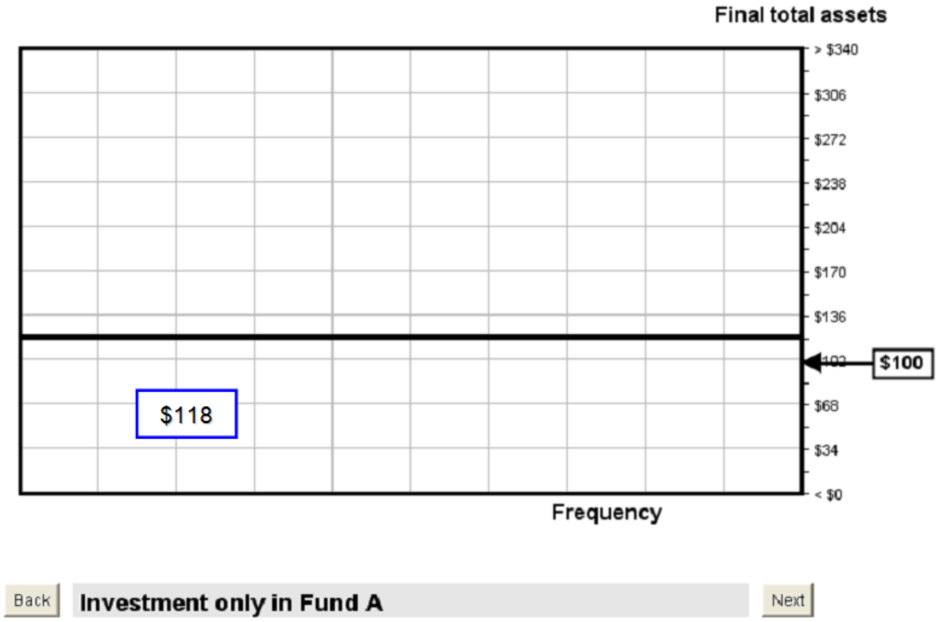


APPENDIX CHAPTER 4

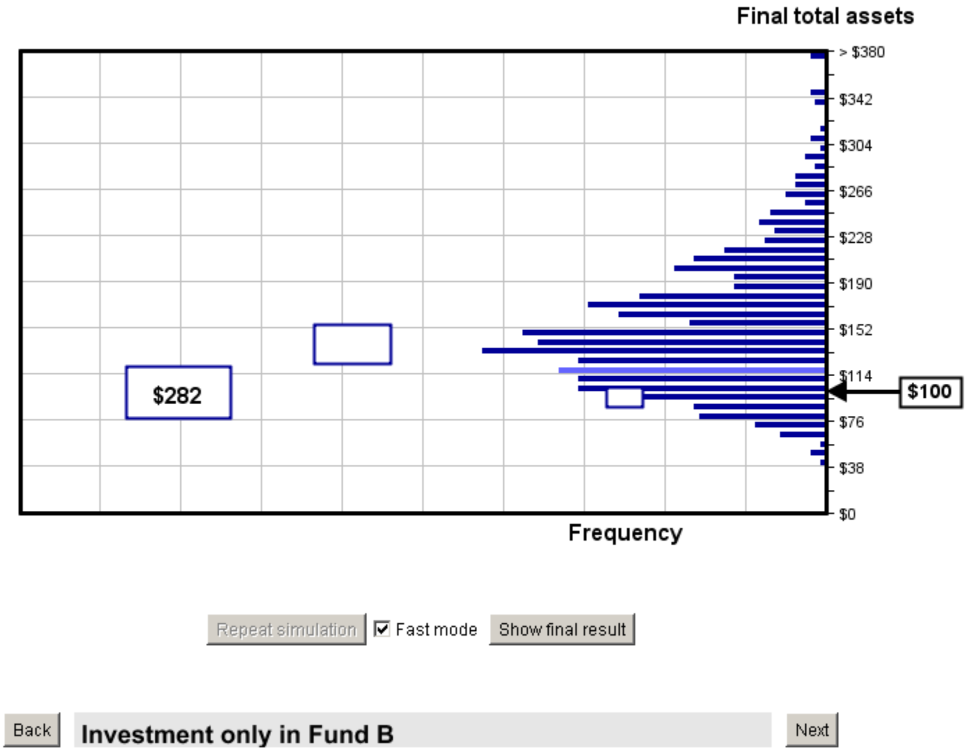
4.1 RISK COMMUNICATION VIA THE RISK TOOL

Experiment II taken as an example.

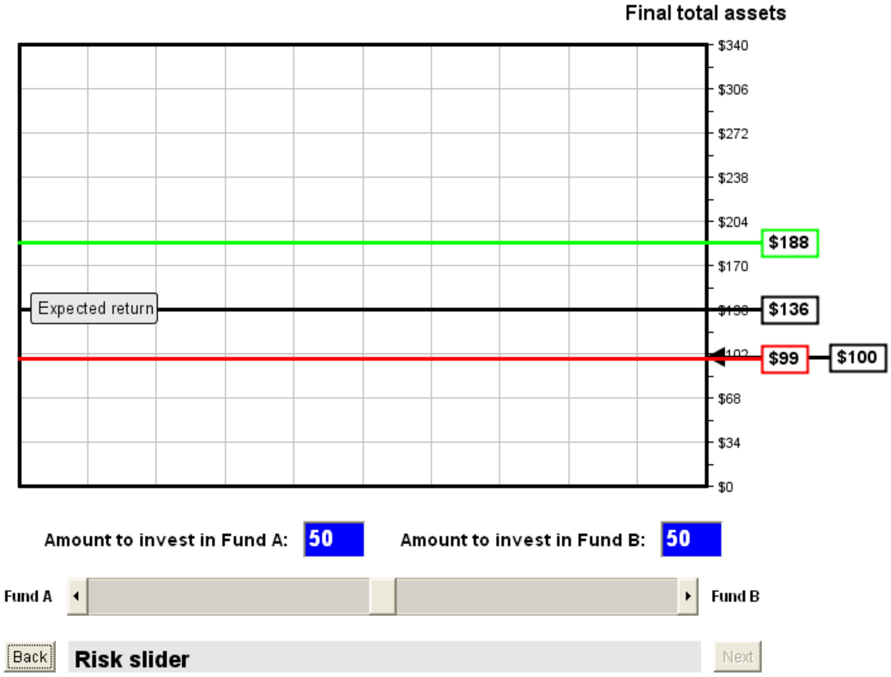
An experience sampling simulation draws the return of the risk free fund, resulting in a flat line:



Experience sampling is used to build up the distribution of *the risky fund. Eight samples must be viewed before the simulation can go into "fast mode" to rapidly build up the distribution:*



To give additional information about the risk-return profile without watching the full risk simulation while adjusting, people could change their allocation via a risk slider with the help of the following quantiles shown in the picture (in 70 out of 100 cases the final wealth will be between the two lines (this picture is exemplarily taken for the aggregation treatment).



4.2 VARIABLES AND MEASURES

Allocation Variables	
Initial	The first allocation (out of €10,000 in Experiment I and out of $100 in Experiment II) participants choose (for the allocation to the risky fund) after watching information about the two funds separately.
Final Allocation	The allocation to the risky fund (out of €10,000 in Experiment I and out of $100 in Experiment II) they select after being informed (dependent on treatment) about the potential returns of their chosen allocation
Marginal Allocation	Difference in Allocation and Initial
Subsequent	The subsequent (hypothetical) allocation they made after seeing the results of the market simulation which potentially determines their payoff (how they would choose again if they had the chance).
Marginal Subsequent Allocation	Differences in (hypothetical) subsequent allocation and allocation decision.
Decision Time	The decision time the participant took between the initial and the final allocation (where the information manipulation took place) divided by the mean decision time within that treatment (aggregation, separation or control group) and presentation mode (tool or description).
Treatment Dummies	
Control Group	An indicator variable that equals one if the participant was randomly assigned to the control group treatment, zero otherwise.
Separation	An indicator variable that equals one if the participant was randomly assigned to the separation treatment, zero otherwise.
Aggregation	An indicator variable that equals one if the participant was randomly assigned to the aggregation treatment, zero otherwise.
Control Variables	
Risk Attitude	Self reported: Please estimate your willingness to take financial risk (1= Not willing to take accept any risk; 5=willing to accept substantial risk to potentially earn a greater return).
Financial Literacy Score	The score is the sum of the 11 financial literacy questions (highest score 11, lowest 0) adapted from van Rooij et al. 2011, a right answer gives one point.
Age	Age of the participant

Gender	An indicator variable that equals one if the gender of the participant is male, zero otherwise.
Log_Income	The logarithm of the self assessed income of participants.
Confidence	How confident do you feel about investing in the risky fund? (Experiment III); How confident do you feel about your decision (Experiment 1 and 2); 1= completely unconfident, 7=completely confident
College	An indicator variable that equals one if the participant's education is college degree or higher, zero otherwise.
Ex-Post Decision Evaluation	
Satisfaction	Question asked after participants were shown their simulated return after five years: How satisfied are you with your return? (1=completely unsatisfied, 7=completely satisfied).
Hypothetical Satisfaction	Question asked after participants were shown their simulated return after five years: How satisfied would you be with a return of X (*5th quantile of the chosen distribution*)? (1=completely unsatisfied, 7=completely satisfied).
Luck	A variable measuring the outcome of the market simulation minus the expected return of the allocation.
Comprehension Variables to understand underlying mechanisms of Allocation	
Perceived Loss Probability	In how man out of 100 cases will the return of your chosen investment fall below $100 after five years? In ________ out of 100 cases
Informed	How informed do you feel about the funds? (1=completely uninformed, 7=completely informed).

Lebenslauf

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