Volatility inadaptability: Investors care about risk, but can't cope with volatility

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Abstract

Classical portfolio theory holds that the only requirement for an investor to make an optimal investment is to determine his risk attitude. This determination allows him to find his point on the capital market line by combining a risk-free asset with the market portfolio. Through an experiment, we investigate two research questions: Do private investors at all see a relationship between risk attitude and the amount invested in any risky asset? Further, do they adjust their investments if provided with risky assets with different volatilities? Using a between-subjects design, we ask investors to allocate a certain amount between a risky and a risk-free asset. We find that investors' risk attitude, their risk perception, and the investment horizon are strong predictors for risk taking. Investors are unable to adapt to risky assets with different volatilities; they choose almost the same allocation to the risky asset independently of its volatility, thus amassing significantly different portfolios. Feedback does not mitigate this volatility inadaptability. The effect is somewhat smaller for investors with high financial literacy. Overall, people seem to use two mental accounts, one for the risk-free investment and one for the risky investment, with the risk attitude determining the percentage allocation to the risky asset rather than the portfolio volatility.

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1 Introduction

On the central investment question of how much risk to take, economists and politicians agree on the answer: investors' risk attitude has to be assessed because it determines their portfolio choice, in terms of the risk return trade-off (i.e., chosen volatility). This paper shows that investors can perform the first step (assessing their risk attitude), but that they act inconsistently in the second step (choosing their portfolio). They exhibit an inability to adapt to volatility.

According to classical finance theory, an investor's risk attitude determines the optimal portfolio from the set of efficient portfolios, that is, from the capital market line (Tobin, 1958). The capital market line forms a tangent from the risk-free rate to the universe of risky investments. It shows that greater expected return requires the investor to take on more risk in terms of volatility (Sharpe, 1964; Lintner, 1965; Mossin, 1966; Treynor, 1962): starting with the lowest return at the risk-free rate, both expected return and volatility increase moving up the line. This idea suggests that an investor has only to assess his risk attitude, which will then lead to the allocation between the risk-free asset and the risky asset. A greater risk tolerance will result in the choice of higher volatility, which is compensated for by a higher expected return. This central role of the risk attitude can also be found in models other than the mean-variance model (see e.g. Merton, 1969).

Politicians have adapted this paradigm implementing the European MiFiD directive (European Parliament and European Council, 2004; European Parliament and European Council, 2006) and the UCITS directive (European Parliament and European Council, 2009). When an investor seeks investment advice, his risk attitude has to be elicited and the recommended asset has to be chosen in accordance with this risk attitude. To address this issue, mutual funds are accompanied by a compulsory key investor information document (KIID), which shows risk and return of the fund, with the risk described by seven categories that are based on their historical volatility. Note that these regulations affect all investors within the European Union (European Parliament and European Council, 2009).

We analyze in two steps whether this reasoning works in practice. First, does risk attitude determine the amount of money invested in the risky asset? Second, does risk attitude lead to the same portfolio (in terms of expected return and volatility) when investors are given different risky assets?

Let us explain the idea using a simple example:

> *A common question in real life is how much sugar to take in one's coffee. If we want to know more about people's ability to determine the subjectively "right" amount of sugar, we could first ask if people understand the relationship between wanting to have the coffee sweeter and putting more sugar into it (similar to question 1). Next, we would be interested in determining the extent to which different types of sugar or the spoon size influence this decision (similar to question 2). We should be able to adapt the amount of sugar, thus independently finding the optimal sweetness for the coffee. If instead of*

crystal sugar we take a sweetener where the same amount has a higher concentration of sweetness, we should adapt to that and take less. Alternatively, think about the size of the spoon should be with respect to the amount of sugar taken. A larger spoon obviously should be filled with less sugar than a smaller one.

To answer our two research questions, we adapt a standard design for financial decision making under risk (Gneezy and Potters, 1997; Frijns et al., 2008; Nosic and Weber, 2010): investors in our experiment have to split an amount between a risk-free and a risky asset. The risky assets differ across conditions. However, they are designed in a way that, in combination with the risk-free asset, they define the same capital market line. As this capital market line is identical across all conditions, the optimal allocation (risk-return trade-off) should be independent from the risky asset provided and depend only on the investor's risk attitude. This is what we investigate.

To ensure that subjects really understand the profiles of the assets provided, subjects are shown both the risky asset and the chosen allocation through an interactive computer simulation (Kaufmann et al., 2012). The simulation allows subjects to experience return distributions and volatilities, and leads to a better understanding of risk and return of an asset compared to alternative presentation formats like description (explicitly stated probabilities for certain outcomes) or pure experience sampling (repeated draws from the underlying distribution).

Our sample consists of 1,958 subjects from the general population, recruited through newspaper articles and radio station reports in a joint campaign with the German Consumer Protection Agency (Verbraucherzentrale Bundesverband). We chose both the sample size and the recruitment process to increase the generalizability and economic significance of our results (Dohmen et al., 2010; Levitt and List, 2007). For their participation, subjects received an incentive-compatible payment.

This paper is related to two research streams: the literature on financial risk-taking and the literature on investment biases. In the first stream, studies have demonstrated that stated risk aversion can predict risk taking. For example, data from the 1989 Survey of Consumer Finances show that households' stated willingness to take financial risks is a good predictor for the percentage of risky assets in their portfolio (Schooley and Worden, 1996). Similarly, an investigation of the influence of risk attitude on diversification revealed that risk-tolerant investors have more securities in their portfolio (Dorn and Huberman, 2005). Risk taking in paid lottery choices can also be predicted by risk attitude (Dohmen et al., 2011). As a final example, risk taking relates not only to risk aversion but also to cultural values (Breuer et al., 2011).

In the second research stream, investigators have found that investments are subject to certain biases. For example, some investors split their contributions evenly across different funds, independently of the risk of these funds (Benartzi and Thaler, 2001). Like our subjects, these investors end up with different portfolio volatilities even though they could achieve similar portfolios by varying the amount invested into each fund, depending on its volatility. For other investors, a behavior that is incompatible with classical finance theory should be expected (Shefrin and Statman, 2000), as a two-fund separation can fail in a behavioral portfolio theory based on prospect theory preferences (Kahneman and Tversky, 1979). Under behavioral portfolio theory (Shefrin and Statman, 2000)), investors build mental accounts for risky and risk-free assets, constructing their portfolios as pyramids of asset classes, and within that framework they vary the riskiness of the risky assets when taking on more risk instead of just decreasing the amount invested risk-free, and therefore end up with different market portfolios.

In accordance with previous studies, we find that investors' stated risk attitude is a good predictor for their allocation to the risky asset. Our participants on average allocate 60% to the risky asset, but individually their allocation varies widely depending on their risk attitude. Several aspects of their decision show that they act in a sensible way. A longer time horizon leads to riskier investments (cf. Klos et al., 2005; Siebenmorgen and Weber, 2004), and lower volatility and lower perceived risk also result in a higher allocation to the risky asset (cf. E. Weber et al., 2002; Nosic and Weber, 2010). However, when it comes to portfolio volatility, we find that investors are not able to adapt to different risky assets. They choose almost the same allocation independently of the risky asset. This volatility inadaptability holds on an individual level after controlling for various personal characteristics, and it persists even in the face of various robustness checks. This result is quite surprising, as we interactively simulate the distribution of the risky asset as well as the chosen portfolio. To refer back to our example, we let subjects taste the coffee while sweetening it but they still choose different levels of sweetness depending on the sweetness and the size of the spoon.

Our investigation makes a three-fold contribution to the literature. First, we combine the flood of details in what is known about risk attitude and risk taking. Most papers focus on single determinants of the chosen portfolio (like stated risk preferences, personal traits, or demographics), and we bring together these details and extend findings of other studies to an analysis on an individual level. Second, we document a very strong effect of different risky assets on the chosen volatility of the portfolio. While subjects could achieve portfolios that were economically the same, we find that they are unable to adapt to the different risky assets. Third, we obtain these results even though subjects were given frequent feedback in an easily understandable form. Feedback could not mitigate the effects of different risky assets, although for investors with high financial literacy, the effect is somewhat reduced.

Our results have major policy implications. Investors apparently do not use the information they receive about volatility (which is, however, a basic assumption for requiring the risk indicator for mutual funds within the KIID document). Two potential explanations may account for that. First, investors may be anchored by the investment advice provided by banks, which often categorize investors into different risk groups. An investor in a "balanced" category, for example, is told that he should invest between 40% and 60% of his portfolio amount in risky assets without consideration of the related volatility. Therefore, this investor could end up with various portfolios resulting in different portfolio volatilities. Second, investors may determine their allocation starting with the amount invested risk-free. As the investors in this experiment allocate their amount between a risk-free and a risky asset, the amount allocated to the risk-free asset would also determine the chosen volatility. We discuss the outcomes and consequences of the observed behavior further in the last section of the paper.

The remainder of the paper has the following organization. Section 2 explains the experimental design and the resulting dataset. Section 3 presents the analyses and the results, and section 4 summarizes and discusses policy implications and ideas for future research.

2 Data

2.1 Experimental Task

General idea and grouping of subjects

The experiment lets participants allocate a certain investment amount between a risk-free asset and a risky asset. The risky assets differ across conditions but together with the risk-free asset they all define the same capital market line.

Figure 1 gives a graphical overview of the course of the experiment, which was conducted in July 2010. First, participants choose an investment amount (either €5,000, €50,000, or €100,000) and a time horizon (either one, five, or ten years). When we pretested 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, we allowed participants to choose a decision context that was as close as possible to their individual circumstances. As we report in the next section, robustness checks assure that these choices do not lead to any problems. All participants choosing the same time horizon received the same risk-free asset, the return of which is based on the actual interest rates for time deposits in July 2010 (1%, 2.5%, and 3.4% for one, five, and ten years respectively).[1]

Insert Figure 1 here.

Subjects are then randomly assigned to a risky asset. The main risky assets consist of a *basic* asset and *levered* and *de-levered* versions of this basic asset. The main assets differ in volatility (and return), but they lie approximately on the same line in a μ-σ-diagram such that they can be transformed into one another by combining them with the risk-free asset. Three additional assets are used for robustness checks. The volatility–return combinations are summarized in Table 1 and details on the construction of the assets appear in Appendix A.

Insert Table 1 here.

Asset presentation and allocation with the risk tool

Having been assigned to an asset, subjects are separately informed about the return of the risk-free asset and about volatility and return of the risky asset. Information about the potential returns of the assets is provided via a risk tool (Kaufmann et al.

[1]In later analysis, it has to be controlled for either the risk-free rate or the investment horizon.

(2012)), which has been developed to communicate asset risk via experience sampling and graphical displays. Kaufmann et al. (2012) show that in comparison other methods for presenting asset risk (description, distribution graphs, and pure experience sampling), the risk tool 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 shows the expected returns and potential outcomes on a graphical interface. First, a single line shows subjects the guaranteed return of the risk-free asset. Then, they are shown the expected return and volatility of the risky asset. For all risky assets, the program randomly draws potential returns out of the underlying distribution (see Figure 2(a)). The whole distribution is built up bit by bit, with each draw contributing to a distribution function. Participants are informed that a higher bar in the distribution reflects a higher probability for the respective outcome. Participants are required to sample at least sixteen draws (eight in a slow mode, eight in a fast mode), but they are allowed to sample for as long as they want up to the point where the entire distribution is completed. When the simulation is stopped, the full distribution is shown. The full distribution includes markers at the amount invested and at the expected return (see Figure 2(b)). The return scale shown in the distribution diagram is the *same* for all assets with the same investment amount and the same time horizon, meaning that a person assigned to a riskier asset will also see a more widespread distribution function.

Insert figure 2 here.

After seeing the illustration of the two assets, participants rate how risky they perceive the risky asset to be on a seven-point scale. They then choose an initial allocation, which can be adjusted afterwards. The allocation can be chosen from the range of 0% to 100%; however, 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 one could be tempted to allow borrowing. As subjects already face a complex decision, the task is kept simple by omitting such a borrowing possibility. Furthermore, investors are often advised against buying risky assets on loan, which could affect the results: even subjects who would have understood the design might have been reluctant to take a loan. While these problems are circumvented by omitting a borrowing possibility, the results do not lose generality (this issue is considered in more detail in section 3).

To give subjects a sense of the volatility of their allocation, we also presented the expected return and some quantiles of the return distribution of their allocation. Two lines that enclose 70% of all possible outcomes and two lines that enclose 95% of all possible outcomes are added to the graphical interface (see Figure 2(c)).[2] Analogous to the presentation of the risky asset, the portfolio resulting from the initial allocation is simulated. If the historical returns were normally distributed, the first two lines would indicate the expected outcome using the risk tool. Afterwards, subjects can change their

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

allocation and try as many different allocations as they want. When they believe they have enough information, they are asked to provide their final allocation. This final allocation is analyzed in the remainder of the paper. As an incentive to state their real preferences, participants are told that 500 participants will win an amazon.com gift card, the amount of which depends on the chosen final allocation to the risky asset. Participants are informed that a "financial market simulation" will be run at the end of the experiment to determine the return on 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. After the final allocation, subjects are asked how risky they perceive their allocation to be on a seven-point scale.

Elicitation of explanatory variables with survey questions

Subsequently, participants are asked for some personal characteristics. They first answer a set of advanced financial literacy questions (van Rooij et al. (2011)) and then provide their gender, age, education, and income. They are also asked whether they are financial professionals and whether they invest in the stock market. Then, they provide their self-reported risk attitude on a seven-point scale. While a variety of alternative measures exists, such as lotteries or questions on risk taking in other domains, most alternatives have been found to be inferior to the simple scale. Risk attitude is domain-specific (E. Weber et al. (2002); Vlaev et al. (2009); Nosic 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 financial risk on a Likert scale (e.g. Dorn and Huberman, 2005, 2010).

2.2 Participant Characteristics and Descriptive Statistics

Participants were recruited from the German population via articles in various German newspapers (national papers such as Tagesspiegel or Börse Online as well as regional newspapers), reports on various German radio stations (e.g. Deutschlandfunk), and a behavioral finance e-mail newsletter. The articles were published following a press release that included a link to our on-line-experiment, explained a new EU regulation on mutual funds, and described fund risk. Participants were offered a summary of their results and a classification of their chosen portfolio in terms of the seven risk categories used by the EU key investor information document. So as not to influence the results, journalists were explicitly asked not to describe the experiment in more detail. Newspaper articles and radio reports were screened for information that exceeded the information given in the press release but no further information was found. The recruitment process resulted in a large and random sample, and overall, 1,958 participants completed the study.

The average participant exceeds the average German in knowledge and financial expertise. The median income range is €30,000 - €50,000, which fits the German average of €33,700 (see Table 2(a)). Around 52% are college-educated at the graduate level and Ph.D. level, which is clearly above the German average of nearly 14% (see Table 2(b)).

The average of the stated risk attitude is also higher than the German average (for risk attitude and the remaining characteristics, see Table 2(c)). Participants on average have high financial knowledge and over 80% own stocks (German average: 25%). Participants are significantly younger than the average German, a high number are male, and financial professionals seem to be overrepresented. While these characteristics indicate that the sample is not representative of the German population, the results do not lose generality, as all relevant variables indicate that participants have above-average experience with financial decision making. If a selection bias is present, it will lead to subjects' decisions appearing to be better or more rational. Nevertheless, we split the sample to control for such effects.

Insert Table 2 here.

Participants' responses appear to be intuitively consistent and coherent. The subjects' choice of investment amount and investment horizon are intuitive, and investment amounts are almost equally distributed across participants (see Table 3(a)). The investment amount chosen increases with age, male gender, financial knowledge, and a preference for saving (regressions not reported). Across all conditions almost 50% of participants choose a time horizon of five years for their investment (see Table 3(b)). The chosen time horizon increases with education, employment in the financial industry, risk attitude, 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 section.

Insert Table 3 here.

Across all conditions, participants on average allocate 59.8% to the risky asset. The distribution of *allocation* seems to be wide spread and does not look unusual (see Figure 3). Participants show a preference for rounding to the nearest 10, as 25% of the participants use multiples of 10% for their allocation. Similar effects have been shown in the literature (e.g. Huberman and Jiang, 2004). As mentioned previously, lending is not allowed so as not to confuse participants. Owing to this restriction, 12.4% of participants allocate 100% to the risky asset; whenever a participant preferred an allocation above 100%, he should choose exactly 100%.

Insert Figure 3 here.

Table 5 gives a descriptive overview of *allocation* for different risky assets and self-selected time horizons. *Allocation* increases with the time horizon (cf. Klos et al., 2005; Siebenmorgen and Weber, 2004). Participants on average invest 59% in de-levered asset, compared to 57% in the basic asset and 55% in the levered asset.

Insert Table 5 here.

Participants on average report a risk attitude of 4.23 on a seven-point scale (1= not willing to accept any risk; 7=willing to accept substantial risk). This score is slightly above the midpoint of the scale, which indicates that the average investor is prone to take some financial risks.

3 Results

3.1 The Relationship between Risk and Risk Taking

Our experimental set up offers different possibilities for measuring risk taking. We use two measures: the percentage allocation to the risky asset and the chosen volatility of the investor?s portfolio consisting of the risky and the risk-free asset. For participants in one condition these two measures do not differ, as the chosen percentage allocation also determines the chosen volatility. The measures do differ, however, for participants in dissimilar conditions if they choose the same allocation. Since the volatility of the risky assets in our experimental design differs between conditions, a person choosing 30% in one condition ends up with a volatility different from that of a person in another condition also choosing to invest 30% into the risky asset.

The first measure we use to analyze the relationship between risk taking and risk attitude is the allocation to the risky asset. The mean allocation is monotonically increasing with risk attitude (see Figure 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 ($t_{468} = 15.99, p = 0.00$). Of 21 pairwise differences, 19 differences are statistically significant ($p = 0.00$).[3]

The correlation between *allocation* and *risk attitude* is equal to 0.455 and is highly significant (p<0.01), also implying a strong relationship between these two variables. At first glance, these univariate results support the notion that an investor's risk attitude is strongly related to the percentage he chooses to invest in the risky asset.

Insert Figure 4 here.

Results stay significant in an OLS regression with *allocation* to the risky asset as the dependent variable: risk attitude significantly predicts risk taking (see Table 4), and 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 (E. Weber and Milliman, 1997; Sitkin and Pablo, 1992; Nosic 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* or in *investment amount* leads to higher risk taking, which also shows that participants do something sensible: with 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%.[4]

[3]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 reflects the small number of participants with a risk attitude of 1.

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

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; Nosic 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. Our results are similar, albeit weaker, if we use the chosen volatility instead of the percentage allocation to analyze risk taking across participants. The correlation between *chosen volatility* and *risk attitude* is equal to 0.332 and is significant ($p < 0.01$).

Insert Table 4 here.

Overall, the findings enable us to answer our first research question. Investors in fact do a sensible thing; they invest a higher fraction into the risky asset when they are less risk-averse and when they perceive the risk to be lower. However, although we have analyzed the absolute level of risk taking and its relationship to risk attitude, we do not know how risk taking varies if we change the volatility of the risky asset. To investigate this question we look not at absolute risk taking, but at the differences in risk taking between conditions.

3.2 Influence of Differences in the Risk-Return Profile Given on Risk Taking

A variation in the risk-return profile between conditions should result in different, condition-specific allocations, leading in turn to similar chosen volatilities for the average final portfolio (independent of the condition). In other words, 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, we observe only minor changes in allocation between conditions (see Table 5), 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 as well as for different time horizons.

Insert Table 5 here.

The small adjustments between conditions may nevertheless lead to similar portfolios in terms of risk and return. Figure 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.[5] The risky assets provided differ in the risk-return profile, but are approximately[6] located on the same capital market line. A possibility, then, is to end up with a similar risk-return profile (that is, on the same point in the graph) between conditions varying the allocation, thus combining the risky asset with a certain fraction of the risk-free asset. The graph

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

[6]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 Appendix A) However, changes are only marginal and the constructed portfolios differ from each other by much more than the difference with regard to the interest rates could explain.

shows that the mean allocation in the de-levered condition of 56.3% results in an annual expected return of 5.2% and a volatility of 6.4%. If the same investor were in the basic (levered) condition, he could achieve the same profile by investing 40% (30%) in the risky asset. However, the graph shows a different picture: the mean allocations (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 allocation to the risky asset between conditions are far from 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 pairwise t-tests as well as for the Bonferroni post-hoc pairwise 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 percentage allocations suggest the existence of a severe volatiltiy inadaptability.

Insert Figure 5 here.

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 6(a)) reveals no evidence that similar mean allocations in the de-levered, the basic, and the levered market portfolio can be explained by extreme values or an abnormal distribution in one ore more of the conditions. Figure 6(b) shows the distributions of volatilities[7] that correspond to the chosen percentage allocations, and again reflects participants' volatility inadaptability: a variation of the riskiness of the risky asset between subjects results in significantly different chosen volatilities as participants only slightly adapt their percentage allocation.

Insert Figure 6 here.

Figure 6(b) shows that the distribution of selected volatilities becomes broader if the provided risky asset is riskier. In general, a broader distribution is sensible, as participants get a broader range of possible volatilites that can be chosen in the levered condition compared to the de-levered condition. For this reason, more participants should be investing 100% in the risky asset in the de-levered condition (where the risky asset faces a lower volatility) than in the basic condition, as well as more in the basic condition than in the levered condition. However, 11% of participants invest 100% in the risky asset in the de-levered condition, compared to 9% in the basic and 11% in the levered condition. With respect to the chosen volatility the volatility inadaptability 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

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

allocation to the risky asset over the potential range independently of changes in the risk-return profile of the provided risky asset.

Further evidence for the strength of the volatility inadaptability bias emerges from a comparison of the cumulative distribution of the observed percentage allocations with a hypothetical distribution that would be consistent across our conditions. 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 condition if participants wanted to obtain the same final allocation on the capital market line. For example, a participant investing 60% in 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 7(a).

Insert Figure 7 here.

The left part of Figure 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 7(a) shows what the distribution of the chosen allocations in our experiment *actually looks like.* People do not change their percentage allocation to the risky asset if the asset becomes 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 no measurable differences in distributions between conditions.

The results hold in a multivariate OLS regression analysis with *allocation* as well as *chosen volatility* as a dependent variable. Table 6(1) shows that no significant change occurs in percentage allocations induced by providing different risky assets. A precise measure of the volatility inadaptability may be obtained from a regression with chosen volatility as a dependent variable. If participants were to adapt if risky assets between conditions face a different volatility, 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 6(2)) significantly predict the chosen volatility.

Again, explanatory variables for allocation are risk attitude, investment horizon, and risk perception. Risk attitude is an exogenous variable and is said to be a stable personality trait. It significantly predicts allocation as well as chosen volatility (see Table 6). 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 find no significant differences: participants on average reported a risk perception of 4.5 in the de-levered condition, of 4.6 in the basic condition, and of 4.5 in the levered condition. This result is in line with volatility inadaptability - a risky asset is perceived as risky independently of changes in volatility.

We additionally asked participants about the portfolio risk perception of their chosen allocation instead of the risky asset itself, and 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 -for example 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 basic condition, and 2.82 in the levered condition. The difference is significant for the pairwise 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 pairwise comparison test shows a significant difference between the levered and the de-levered condition, or, in simple terms, portfolio risk perception depends on the percentage allocated to the risky asset and not on the objective riskiness/volatility.

Insert Table 6 here.

So far, our results provide strong evidence that 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 independently of the volatility of the risky asset?" instead of "what risk level (how much volatility) do I wish to take?".

3.3 Robustness Checks

In this section, to increase the generalizability of results, we present several robustness checks varying the type of regression analysis, analyzing different sub-groups and varying the experimental design to increase the generalizability of the results.

General robustness checks. We checked all our regressions for multicollinearity using variance inflation factors, and the maximum variance inflation factor of any of the explanatory variables is 1.31, indicating that multicollinearity is not a problem. As allocation is limited to the interval from 0 to 1, we used a Tobit regression model to confirm the results of our OLS regressions. Results do not qualitatively differ in the Tobit model. The dependent variable allocation is additionally not normally distributed (owing to the number of participants who invest 100% in the risky asset). Tobit and OLS regressions excluding these observations are run (but not reported here owing to space constraints); the results do not differ qualitatively from the results described in any meaningful way.

Choice of time horizon and investment amount - an endogeneity problem? The free choice of investment horizon and investment amount should not lead to endogeneity, as both are chosen before participants have any information on the assets and before they make their allocation decisions. 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 no endogeneity problem is present.

The influence of risk attitude and risk perception. To check whether the results are driven by the experimental design (which does not allow short selling), we investigate whether participants who state a low risk attitude (and who are therefore less likely to desire a higher volatility than possible) show the same allocation pattern. Figure 7(b) shows the CDFs for participants with a risk attitude between 1 and 4. The maximum volatility that can be chosen ranges from 11.4% in the de-levered condition to 29% in the levered condition. Among 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 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. As 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). These results can be replicated in a sub-sample regression (Table 6(3), the same sub-sample we used in Figure 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; rather, the results of the multivariate analysis indicate that other variables influence the allocation decision.

Risk perception could be influenced by risk attitude. An investor caring less about risk could also perceive risk differently. This possibility is modeled by including interaction terms between risk perception and risk attitude in the regressions described above. Results do not change qualitatively; all interaction terms are insignificant, but coefficients for risk attitude differ significantly from each other. A small part of the coefficient is now apparently captured by the interaction term.

To control for the possibility that risk attitude might be endogenous, we estimated models without risk attitude. The remaining coefficients remain similar in size and significance. This result indicates that no endogeneity problem exists from the measured risk attitude.

Strengths of the volatility inadaptability - the influence of financial literacy. We find abundant evidence in the literature that a higher degree of financial literacy improves financial decision making (Campbell, 2006; Calvet et al., 2007). Therefore, we explore the interaction of financial knowledge and volatiltiy inadaptability.

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 difference is not surprising, since financial literacy is significantly positively correlated with risk attitude ($\rho = 0.30, p < 0.00$). Table 7 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 pairwise comparison test shows a significant difference between the levered and the de-levered condition as well as between the de-levered and basic condition at 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 an annual volatility of 7.4%, whereas the 58% invested in the basic and the levered condition result in annual volatility of 11.8% and 17.1% respectively. In the low financial literacy group, a Bonferroni post-hoc pairwise comparison test shows no differences between conditions at all.

Insert Table 7 here.

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 Table 8 (2)) and not significant in the low financial literacy group (Table 8 (1)). However, an OLS regression model with chosen volatility as a dependent variable shows that the changes in allocation are still far from resulting in similar portfolios in terms of volatility. The volatility inadaptability bias still persists in both financial literacy groups (compare Table 8 (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).

Insert Table 8 here.

An additional effect we observe in the regressions is that the influence of investment horizon is significant only 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, 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, whereas only standard deviation has a significant influence in the low financial literacy group.

Strengths of the volatility inadaptability - provision of a dominating risky asset. To test the strength of the volatility inadaptability, an additional condition with a dominating asset is included. This inclusion enables us to test whether participants adjust their allocation if differences in risk-return profiles become more obvious. We 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% in the risky asset in the basic condition and 62% in the dominating condition. This difference is significant ($t_{642} = 2.14, p = 0.03$).[8]

Insert Table 9 here.

[8] Results are similar if we compare allocations to the levered or the de-levered asset with those to the dominating asset.

Results of an OLS regression model with allocation as a dependent variable show that the significant adjustment for the full sample is driven by the high financial literacy group (see Table 9(2)), whereas no differences in allocations between the basic and the dominating condition can be found in the low financial literacy group (see Table 9(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 in 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, whereas participants with low financial literacy do not seem to do so on the same scale.

Strengths of volatility inadaptability - framing of risky assets with asset names. 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, whereas 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. E. Weber et al., 2005), participants take on higher risk if asset names are provided (see Table 10): 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 the 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, whereas a subjective variation in the sense of information (asset names) does (cf. Siebenmorgen and Weber, 2004). One reason might be that the inclusion of asset names increases investors' feeling of familiarity with their investment. While the absolute level of risk taking increases for both named assets, 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). This finding also holds if we analyze our two sub-samples. When asset names are included, participants with low financial literacy increase their risk taking by four percentage points on average for the DAX (61% instead of 57%) and the World Portfolio (again 61% instead of 57%), but there are still no differences between the two assets. Participants with high financial literacy increase their risk taking by three 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 allows investors to judge differences in volatility between the risky assets. They instead seem to generally increase risk taking, which is likely to be induced by a lower risk perception.

Insert table 10 here.

4 Discussion

We have analyzed two research questions that are highly relevant for private investors and that have important policy implications. The good news is that investors behave more rationally than they are often said to. They base their decision on risk attitude and risk perception.

Nevertheless, we also find strong volatility inadaptability when it comes to differences between risky assets: on average, participants do not change their *allocation* when the risk-return profile of the asset changes. These findings do not seem to be explained by a lack of experimental validity, as our sample size is by far larger than samples in comparable experiments and our participants are assigned randomly to different risky assets. Characteristics across conditions hardly differ. Our results also differ from naïve diversification. Only 11% of the participants choose a fifty-fifty allocation consistent with this naïve diversification, while Benartzi and Thaler (2001) report numbers between 21% and 34%. Reasons for this considerable difference may be the result of the different experimental designs: whereas 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. Additionally, whereas Benartzi and Thaler (2001) use fixed graphical displays, we simulate the assets in much more detail.

Our conclusion is that investors seem to have two mental accounts -one for their risk-free investment, another for their risky investment- with a fixed percentage allocation to each of the two accounts in mind and the overall portfolio volatility disregarded. An adjustment seems to be non-existent for participants with low financial literacy, whereas people with a higher financial literacy adjust slightly when differences between risk-return profiles of given assets become more obvious, but their adjustment is still insufficient.

An explanation for the inability to adapt to volatility might be that investors use decision heuristics induced by the advisory process in banks. Generally, advisers elicit risk preferences by asking customers to state them on a scale, such as a scale ranging from 1 = "not willing to accept any risk" to 5 = "willing to accept a substantial risk in order to have the chance to receive higher returns." This information is then used to recommend investment products. Some banks use model portfolios with different risky shares for different risk attitudes, but these differing percentage rates are not directly related to the portfolio volatility. In this case, customers are taught that the riskiness of their portfolio is determined by the percentage they invest in risky assets, while the portfolio volatility is *not* taken into account in this step. Model portfolios serve as default options and they reduce complexity, as it is less complicated to decide how much to invest risk-free than to think about an overall portfolio volatility. Future research could analyze different default options.

One way to mitigate volatility inadaptability might be to further educate investors by a different information supply or by showing them probability functions of different risky assets to make them aware of the meaning of different volatilities. Another alternative might be to patronize people more. Building on the way the KIID regulation works, a 1-7 scale could be provided that is based on some volatility intervals that in most cases are unknown to the investor. An investor choosing high risk (implying high expected return) would be presented with a 100% investment in a fund similar to the MSCI world. The investor might not know (or want to know) that the average yearly volatility for the last five years has been between 15% and 25% and may be unconcerned about how this distribution would make him feel.

So far, we have assumed that the observed volatility inadaptability is not rational. But what if investors have a different risk concept in mind? For private investors, risk could be measured not by risk indicators but as everything that is not invested safely. Investors could, for example, think about the amount they need for certain after the investment period and then allocate this amount to the risk-free asset. Although participants probably will not lose all the money they invest in risky assets, they have only ambiguous statistics to rely on (Taleb et al., 2009). Even if an asset has only a low historical risk, extreme outcomes could occur. This idea is supported by the fact that participants perceive the same percentage *allocation* across different assets as similarly risky, even if the objective risk in terms of volatility differs significantly. Participants were asked for the minimum amount they need to control for this possibility. This amount significantly predicts asset allocation decisions (not reported in the results section). When a small minimum amount is needed, participants make large risky investments and still achieve their minimum. A medium amount leads to a small allocation to the risky asset, but they still achieve the minimum amount. If a large minimum amount is needed investors gamble, as this is the only way to achieve their minimum amount.

All of the above indicates that a two-step approach may be needed to fit investors' portfolio to their preferences. Firstly, the amount needed to be reserved as safe could be determined. Secondly, investors could be advised on allocating their risky asset money while taking the safe asset money into account. Investors may be more attentive to thinking about the "risky account" and choose from differences between risky options once they are sure that the amount they need to keep safe has been set aside.

Apart from their theoretical relevance, our findings have important policy implications, as they contribute to the current debate on the communication of investment risks and the measurement of investors' risk attitude. Volatility inadaptability makes the choice of the risky asset used for the elicitation of risk preferences crucial. A riskier asset will lead to a lower measured risk aversion. We know from the literature that volatility is a concept private investors do not understand well, and quantitative analysts also seem to fail to handle calculations correctly (Taleb et al., 2009). Even the use of a risk simulation -which does not state the volatility but lets investors experience it- does not lead to major attention to 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), state 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 historical volatility. To choose from these seven categories, investors would first have to find their personal category. Our findings show that the elicitation of such a personal 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 to avoid conscious and unconscious manipulations resulting from the choice of different reference assets. Future research needs to investigate whether the indicator itself can help to better incorporate and understand information about the volatility of an asset.

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A Construction of Assets

Two categories of assets have been constructed. The first three assets ("main assets" in Table 1) are in the focus of the analysis, and the second three assets ("robustness check assets" in Table 1) are only used for robustness checks.

The main assets all approximately lie on the same line in a μ-σ-diagram such that they can be transformed into one another by combining them with the risk-free asset. All the main assets are based on a combination between historical monthly DAX returns (from 1973 to 2009) and risk-free returns. The return of the risk-free asset used has to be either a fixed rate or based on historical risk-free returns that fluctuate over time. Historical interest rate fluctuations may not be independent from historical DAX returns; for example, both risk-free returns and stock returns were very high after the reunification of Western and Eastern Germany. Additionally, historical returns are more realistic, since investors could actually have faced these returns. We used the historical Frankfurt Interbank Offered Rates (FIBOR) as the risk-free asset as this is a natural choice for the German market. For all the main assets, participants are not told about these two "ingredients"; they are simply told that they face a diversified fund. The use of DAX returns for the main assets allows us to compare these assets with one of the robustness check assets. The *basic asset* is identical to the DAX; the percentage of the risk-free asset is zero.

The second asset's return and risk are reduced by replacing some of the DAX's share with this risk-free asset, with the resulting asset referred to as the *"de-levered asset"*. The third asset's return and risk are increased by lending at the respective risk-free rate and increasing the DAX's share above 100% (*"levered asset"*). For every month, a new return is computed by combining the historical FIBOR with the historical DAX return. For the levering and de-levering process, the new DAX share has to be chosen from 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 assets do not matter as long as they are sufficiently different from those of the *basic asset*. The standard deviation of one of the robustness check assets has been chosen as the target value for the *de-levered asset*. This allows for a comparison of the de-levered asset and the respective robustness check asset. Analogously, the return of the same robustness check asset has been chosen as the target value for the *levered asset*.

Three assets are used for robustness checks. The first of these assets dominates the three *main assets* as it has a lower risk and/or a higher return. This asset is referred to as the *"dominating asset"*; its returns are based on historical returns of "the world portfolio" described by Jacobs et al. (2010). The dominating asset's risk and return are used as target values for the *de-levered asset* and the *levered asset*. Participants with this asset are again told that they face a diversified fund. The second robustness check condition shares the return distribution of the *dominating asset* but participants receive additional information on the asset; they are told that they face a world index invested in common stock (60%), bonds (25%), and commodities (15%). It can be inferred from this information that this asset is broadly diversified. Consequently, this asset is named *"World portfolio (named)"*. The third robustness check asset shares the return distribution with the *basic asset*. Additionally, participants with the *"DAX (named)"* are told that they face the DAX and that the DAX is a pure stock index that contains the 30 largest German companies according to market capitalization.

Table 1: Return and standard deviation of the risky assets

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

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.

Table 2: Descriptive Statistics

(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	1958	

(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	1958	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				

Table 2(a) shows the number of participants in a certain income range. The German average is taken from Destatis (2006). Table 2(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 2(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).

Table 3: Self-selected decision context

(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

Table 3(a) reports the number of participants who choose a certain investment amount and table 3(b) reports the number of participants who choose a certain investment horizon.

Table 4: Allocation to the risky asset

	(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	1958
Adjusted R^2	0.265

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.

Table 5: Percentage allocations to the risky assets

	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

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 6 for regressions controlling for other influences.

Table 6: Chosen allocation and volatility

	(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 provided)	-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 participation	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

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.

Table 7: Percentage allocations to the risky assets

	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

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 8 for regressions controlling for other influences.

Table 8: Chosen allocation and volatility for different financial literacy groups

	(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 provided)	-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

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.

Table 9: Chosen allocation for basic and dominating asset

	(1) alloc. low FL	(2) alloc. high FL	(3) alloc. low FL named	(4) alloc high FL named
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 provided)	-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

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.

Table 10: Allocations to the basic and the dominating asset (non-named and named)

	Basic		**Dominating**		**Dax (named)**		**Dominating (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

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 9 for regressions controlling for other influences.

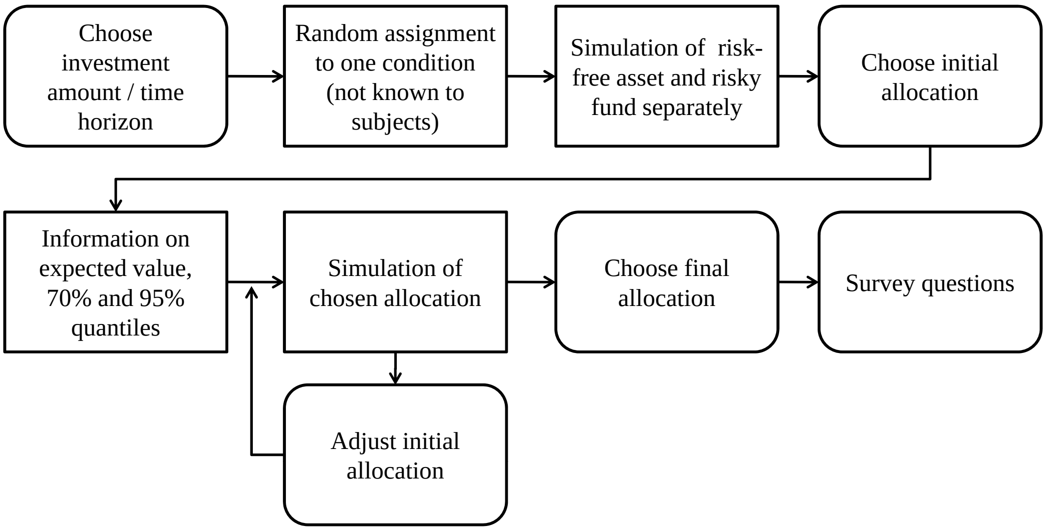
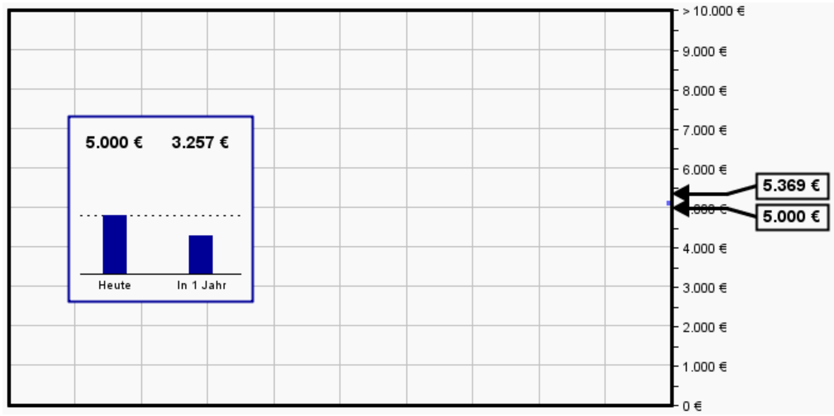
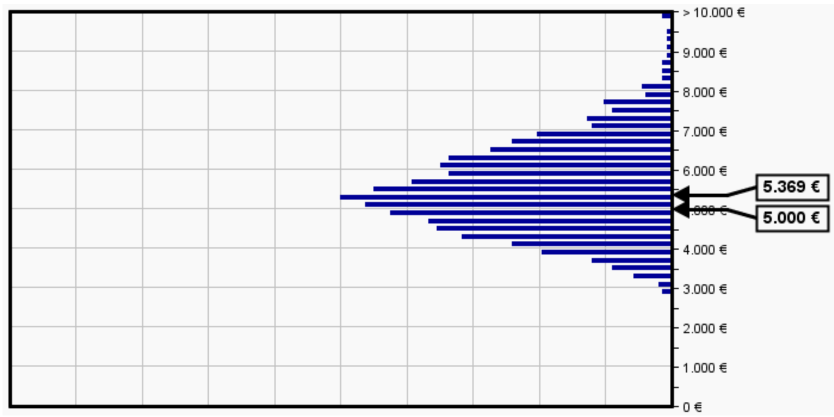


Figure 1: Information given and decisions taken

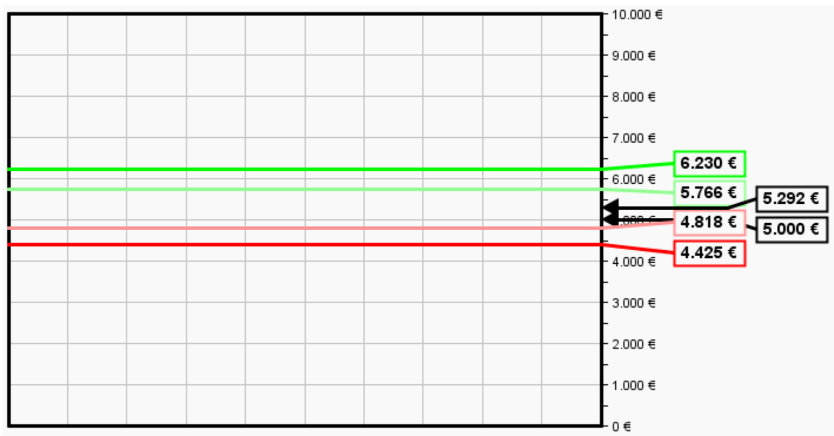
This figure gives a graphical overview of the experimental design. Decisions which participants have to take are in round boxes, the information they are provided with is in square-cut boxes.



(a) Simulation



(b) Complete distribution after simulation



(c) Lines indicating 70% and 95% intervals

Figure 2: The risk simulation tool

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

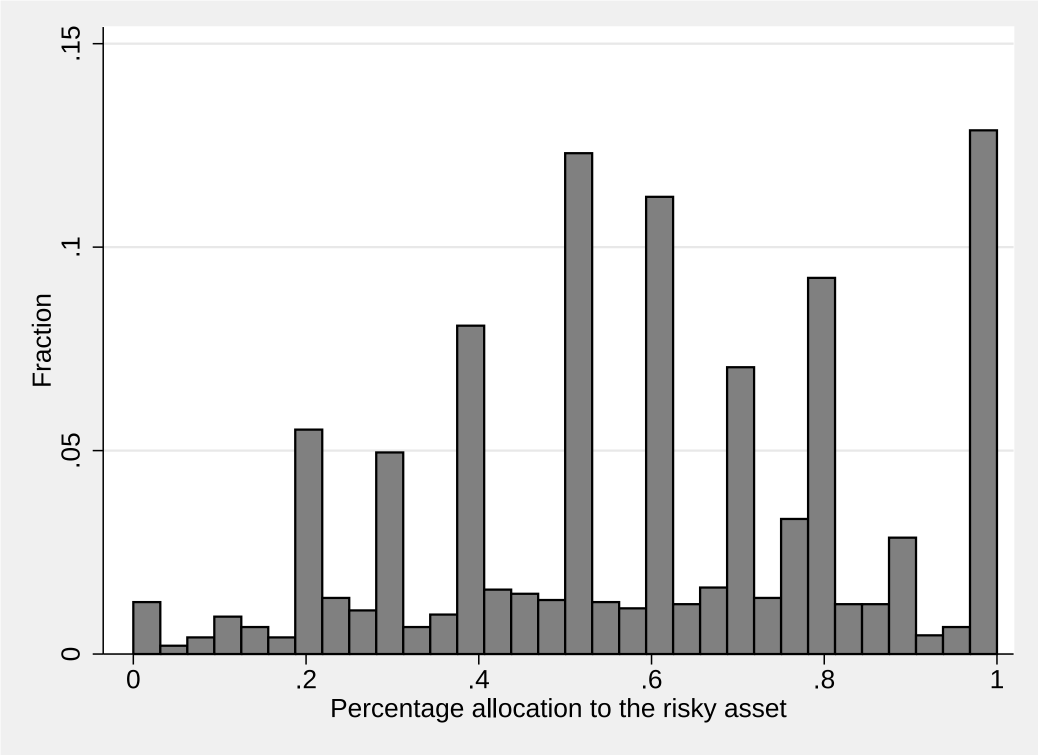


Figure 3: Histogram of percentage *allocations* to the risky asset

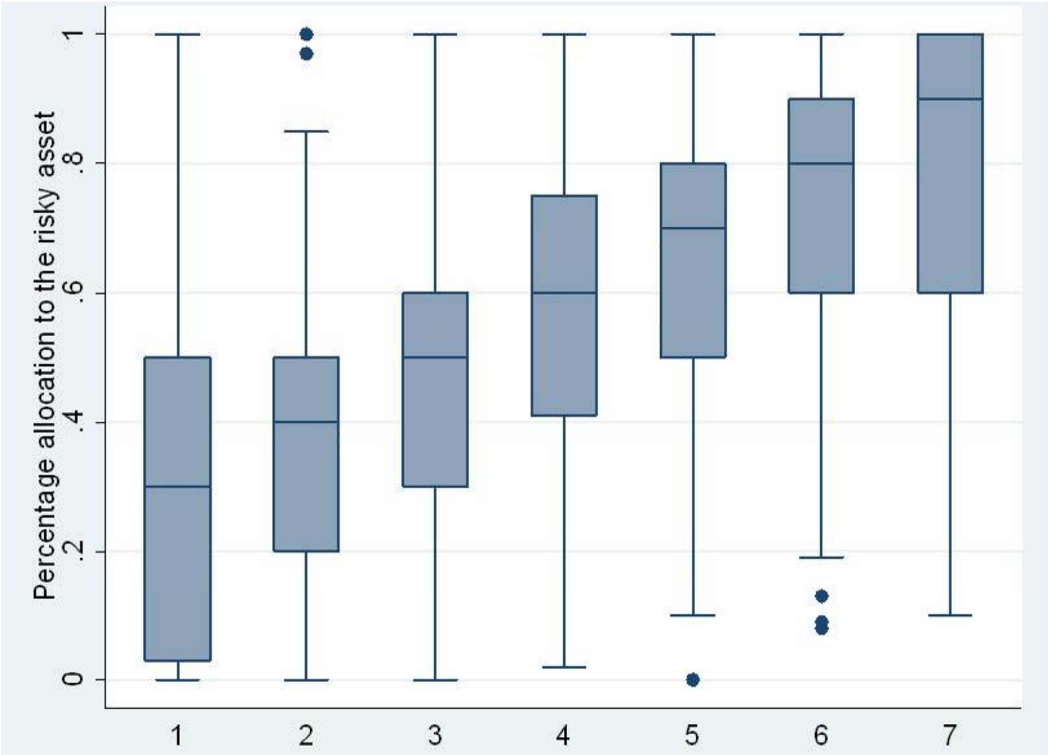


Figure 4: Allocation to the risky asset for different values of *risk attitude* (with 1 being least risky); the bottom and top of the box are the 25th and 75th percentile, the band in the box reflects the median; the ends of the whiskers represent the lowest datum still within the 1.5 interquartile range of the lower quartile, and the highest datum still within 1.5 interquartile range of the upper quartile.

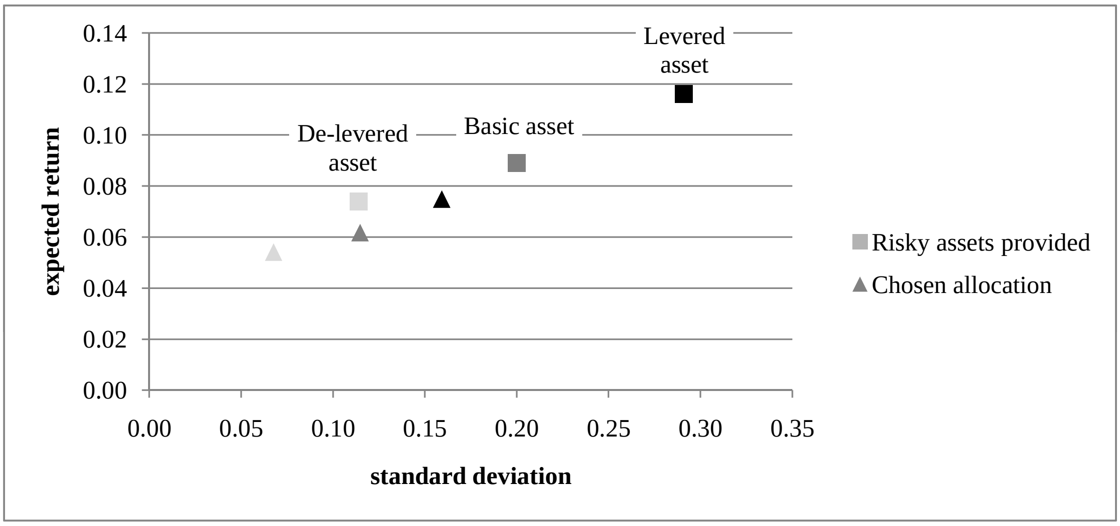
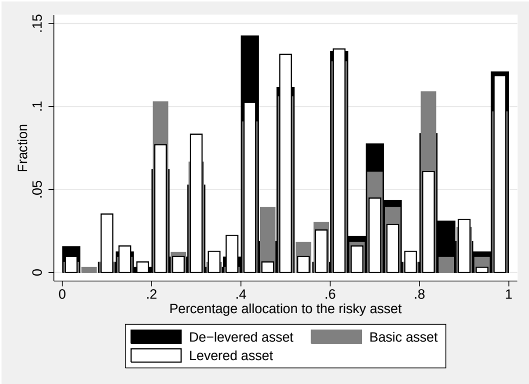
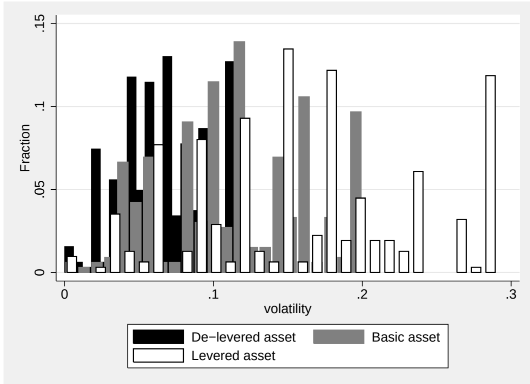


Figure 5: $\mu - \sigma$ diagram of risky assets provided and chosen allocations
Figure 5 displays the annual expected return and the annual standard deviation of the he risky assets provided in the main conditions, exemplarily for the five year time horizon. The respective triangles reflect the average 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%.



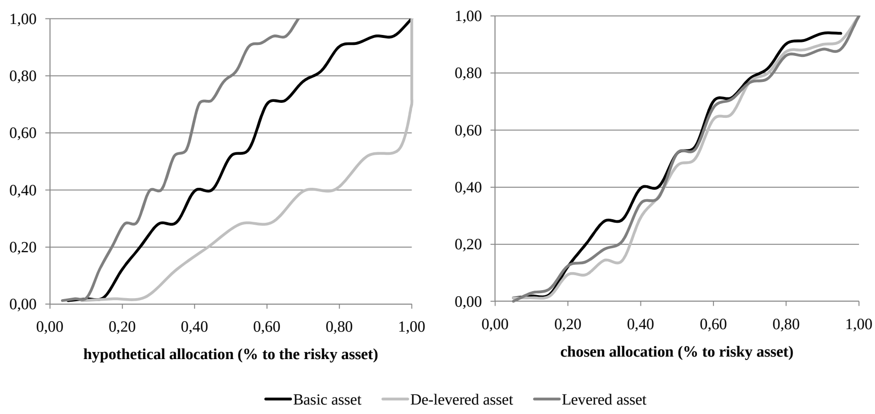
(a) Percentage allocations



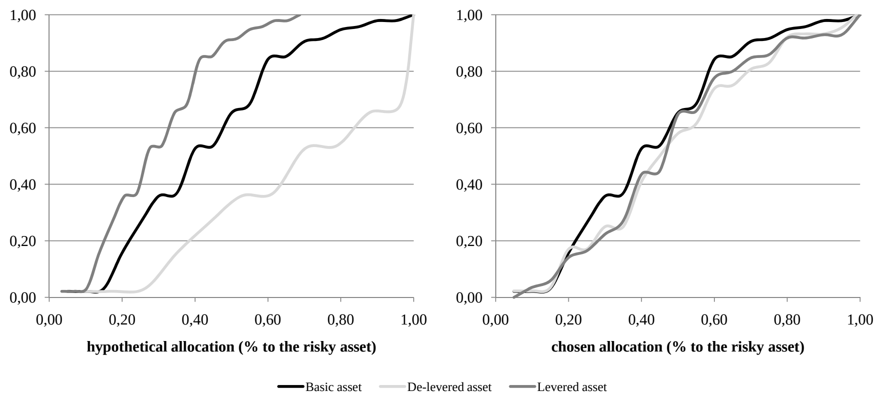
(b) Resulting volatilities

Figure 6: Distributions of chosen portfolios across conditions

Figure 6(a) displays the distribution of allocation to the risky asset in % of participants over conditions. Figure 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) Full sample



(b) Risk attitude 1-4 only

Figure 7: Cumulative distribution functions of percentage allocations to the market portfolios

The left part of figure 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 7(a) shows the empirical allocation - what participants really have chosen - for all three conditions. Figure 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).