“And Lead Us Not Into Temptation”: Presentation Formats and the Choice of Risky Alternatives*

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Abstract

This paper provides a systematic analysis of how framing affects individuals' investment decisions. We conduct experiments in which the way of presenting different alternatives is varied in several dimensions: (i) absolute values versus rates of return, (ii) different confidence intervals for potential gains and losses, and (iii) possible outcomes in either pure numerical form, i.e., tables, or graphical form. The results indicate that the type of presentation has a major impact on individuals' preference for risky investment alternatives. On average, only 28% of the participants make consistent choices. Subjects choose riskier asset allocations when possible outcomes are shown in absolute values and when the loss potential is less obvious. Whether information is presented in tables or in graphical form has no systematic impact on decisions.

JEL Classification: D81, G02

Keywords: Behavioral finance; Decision under risk; Framing effects

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1 Introduction

One important determinant of the decision-making process is the format in which options are framed. Behavioral finance research shows that investors' beliefs and choices are influenced by the format in which information about financial products is conveyed. Previous analyses of financial decision making identify a number of framing effects that impact decisions, among them reference points (Kahneman and Tversky, 1979), the time horizon (Benartzi and Thaler, 1999) and presenting potential terminal values as opposed to rates of return (Diacon and Hasseldine, 2007). Durbach and Stewart (2011) provide a comparison of decisions among risky alternatives when the presentation format is varied. To our knowledge, however, the question of how these framing effects interact in influencing an individual's asset allocation has not yet been addressed.

The issue of how product information should be communicated to retail investors has received a great deal of attention ever since the financial crisis revealed that many retail investors were not aware of the risks inherent in their portfolios. A comprehensive and understandable disclosure of necessary information by product sellers is particularly important since these portfolios held by retail investors often constitute a great share of their old age provision. To address the problem of insufficient or incomprehensible product information, the European Commission developed a proposal for a key information document for investment products.[1] This proposal is based on a number of studies that deal with how different presentation formats influence retail investors' comprehension of investment product information (see e.g. IFF Research and YouGov, 2009). A recent report from Germany discusses appropriate language and design for a standardized product fact sheet (Tiffe et al., 2012). In our analysis, we want to take this a step further by determining exactly how different presentation formats affect individuals' asset allocation.

We draw on results from a number of empirical studies that identify drivers of decision making and conduct a comprehensive experiment in order to quantify the impact of framing effects on the chosen risk level in individuals' portfolios. Here, framing refers to different presentations of identical investment alternatives, i.e., alternatives with the same payoff distribution. The alternatives will be perceived to be the same if one correctly draws inferences from the data presented. We consider settings in which forward-looking contract information is provided, for example, in life insurance contracts. In our analysis, we include various dimensions of framing risky alternatives, such as absolute values versus rates of return, different confidence intervals for potential gains and losses, and graphical versus numerical presentation.

The remainder of the paper proceeds as follows. In Section 2, we discuss the relevant literature and develop hypotheses for our analysis. Section 3 describes the experimental design and gives an overview of the sample. Section 4 contains the results of our empirical analysis. Section 5 provides a discussion of the results and concludes the paper.

[1] See http://ec.europa.eu/commission_2010-2014/barnier/headlines/news/2012/07/20120703_en.htm, retrieved July 30, 2012.

2 Related Literature and Hypotheses

Framing refers to the phenomenon that individuals' decisions depend not only on the objective features of the alternatives, but also on the way information is presented. In their analysis of framing effects, Tversky and Kahneman (1981) laid the groundwork for extensive research in this field. Here, we are concerned with attribute framing in the sense of Levin et al. (1998) which involves changes in item evaluation when the item's attributes are framed differently. We define framing as different presentations of identical alternatives. Our first, rather general hypothesis is based on the idea that in the absence of framing effects, individuals should make the same decisions across settings when the alternatives presented are the same:

H 1 *Preferences for risky investment alternatives should not be influenced by presentation format.*

One dimension of framing is presenting information in absolute or relative terms. Diacon and Hasseldine (2007) find framing effects that are induced by reporting either absolute fund values or rates of return. In an experimental setting, participants were shown the past performance of two funds, first in fund values and then in yield charts. Half the subjects who chose the riskier fund when absolute values were presented switched to the more conservative fund when shown the rates of return. Showing yield charts thus seemed to induce less risky choices. Another study that deals with the impact of framing in absolute and relative terms comes from the field of health economics. Schmitz and Ziebarth (2011) provide evidence stemming from a natural experiment: since 2009, German public health insurers have had to state price differences in absolute values rather than in percentage point payroll tax differences. This resulted in a six-fold increase in an individual's switching probability and a three-fold demand elasticity increase. Thus, this evidence, too, suggests that it is important for consumers whether information is presented in absolute or relative terms. In experiments eliciting purchase decision and evaluation of unit-linked life insurance products, however, Huber et al. (2011) do not find a systematic difference in participants' decisions due to the presentation of prices in different absolute and relative terms. As possible reasons for this contrary result, they propose that a rational present value calculation plays a role in participants' decisions and that the complexity of insurance products reduces the impact of different price presentation formats.

In our analysis, we therefore test the following hypothesis:

H 2 *Decisions should not be influenced by whether absolute values or rates of return are shown to participants.*

There is contradictory evidence as to whether the time horizon of information about rates of return influences individuals' decisions about certain asset allocation. Benartzi and Thaler (1999) compare the decisions of individuals who are either informed of yearly rates of return for debt and equity investments, or of summary information about the 30-year total rates of return. The results indicate that the latter information reduces perceived volatility and highlights the higher expected return. Thus, the time scale of information seems to have an impact on investment choice. Diacon and Hasseldine (2007) also vary the time scale of information provision. In their experiment, some charts shown to participants are based on fund performance over the past 12 months, others on the past 45 months. They conclude that decisions are not influenced by the time scale of information. For the purpose of our analysis, we therefore hypothesize:

H 3 *Investment decisions should not depend on whether total returns or period rates of return are presented.*

Our next hypothesis is concerned with the impact of anchor values on individual decisions. Kahneman and Tversky (1979) highlight the importance of these reference points for decision making. They provide evidence that individuals suffer more from a loss of a certain amount than they benefit from a gain of the same amount, a phenomenon referred to as loss aversion (see also Thaler, 1980). Loss aversion refers to risk aversion in the domain of gains, and to risk seeking behavior in the domain of losses. Abdellaoui et al. (2007) develop a method of measuring loss aversion without having to make parametric assumptions. They find strong evidence in favor of loss aversion as it is defined in the literature. When choosing between investment alternatives, loss aversion might lead to less risky choices if potential losses are emphasized by a presentation format having the zero line as an anchor value. Our next hypothesis reads as follows:

H 4 *Anchor values should not impact investment decisions. In particular, emphasizing the loss potential of different alternatives should not lead to a different choice of risky alternatives.*

As to the question of how framing affects risk-taking, Benartzi and Thaler (1999) find that some people who initially declined multiple plays of a gamble accepted them after being shown the distribution of outcomes. In an experiment, Durbach and Stewart (2011) vary the amount of information about a gamble communicated to participants. In accordance with Benartzi and Thaler (1999), the authors find that individuals' choice of risky alternatives is influenced by the presentation format. Specifically, participants' risk taking decreased when the 95% and 5% quantiles were shown instead of the maximum and minimum of the outcome distribution. We conjecture that this behavior will be evident in our experiment, too, when we compare decisions made following the 95%-5% quantile presentation versus the 75%-25% quantile presentation.

H 5 *When shown the 75%-25% quantiles, participants should have the same preferences for risky investment alternatives as when shown the 95%-5% quantile presentation.*

A further variation of presenting information about stochastic rates of return is to show the full probability distribution function (pdf). This format makes it possible for subjects to observe the probability of extreme rates of return that are not within the 95%-5% quantile range. In addition to providing enhanced information on the tails of the distribution, the pdf format itself might impact the investment decision: Durbach and Stewart (2011) find that showing the probability distribution results in information overload. For our analysis, we propose the following:

H 6 *When presented with the full probability distribution of total rates of returns, participants should not make investment decisions different from those made following the quantile presentation of total rates of return.*

Another aspect of framing is presentation of information in graphic or tableular form. There are a number of studies that find a difference in decisions made after receiving graphically as opposed to tabularly presented information (see, e.g., Remus, 1984; Vessey, 1991, 1994). However, most of these studies analyze decision performance, which can only be measured when there is a benchmark decision against which to evaluate the participants' decisions. To our knowledge, there is as yet no study of the graphs versus tables issue in the field of financial decision making. We seek to fill this gap in our experiment, thus hypothesizing:

H 7 *Individuals make different decisions when information about investment alternatives is presented in graphic form rather than in tables.*

Expected utility maximizers with a concave utility function appreciate gaining a specific amount of money less than they suffer from losing that same amount. Since the slope of the utility function decreases in wealth, the difference between the utility of the expected wealth and the expected utility of wealth is smaller for a lottery in which a small amount of money is at stake than it is for a lottery in which there is potential for large gains and losses. In the absence of framing effects, we would expect the following:

H 8 *When deciding on the investment of small amounts of money, participants tend to prefer riskier investment alternatives than they do for larger amounts of money.*

Our last hypothesis is based on the assumption that when presented with information in a quantile format, individuals are not capable of processing information beyond the graphically conveyed information. We therefore hypothesize:

H 9 *In those pairs of situations in which the underlying return distributions are different but the numerical or graphical representations of quantiles look equal because only a different quantile is chosen, we expect the subjects to decide as if the underlying distributions are the same.*

3 Experiments

3.1 Experiment Design

The experiment began with a quiz designed to discover degree of financial literacy and make sure that the participants understood the main block of the experiment. The participants also were required to answer a questionnaire covering personal characteristics such as age and gender. In the main block, there are a total of 18 situations in which subjects asked to indicate their preferences for four investment alternatives with different risk-return profiles by assigning ranks from 1 (highest preference) to 4 (lowest preference). The ranking determines how the endowed capital will be invested on their behalf. The first preference has the best odds (with a probability of 1/2), followed by the second (with a probability of 1/3), and the third (with a probability of 1/6). This procedure is chosen in order to make sure that the participants rank the investment alternatives carefully in consideration of all the possible ranks. This ranking procedure provides a richer data set on individual decisions than just allowing participants to pick one alternative.

By tying the real payoff for participants to their decisions in the experiment, we prevent biases that may arise in purely hypothetical decision situations (Vlaev, 2012). In 16 of the 18 settings, the virtual initial capital given to participants for investing is 10 Euro. In one setting, the initial capital is 100 Euro (Setting 4). In an additional, purely hypothetical setting, it is 50,000 Euro (Setting 5). At the end of the experiment, one of the 16 settings involving initial capital of 10 Euro resulted in a real payoff to the participants. This payoff depended on the decision made in that setting, thus providing an incentive for a thoughtful desicion.

The main decision block consists of two parts, which differ in how the asset values of the investment alternatives may change. In the first part (Settings 1 to 5), the price evolution corresponds to a binomial model, where the asset value of each alternative may either go up or down by a certain factor in a particular period. Each alternative has a maturity of 10 periods and cannot be liquidated prematurely. In the second part (Settings 6 to 18), the return is drawn from a normal distribution. Each alternative has a maturity of one period.

$<$ Insert Table 1 about here $>$

Table 1 displays the five settings of the first part of the experiment. In Setting 1, the up and down rate of return for each period, as well as the mean, are presented to each participant. In Setting 2, the total (10-period) rate of return is presented (the mean return, the best-case return, and the worst-case return) for the same alternatives as in Setting 1. Setting 3 corresponds to Setting 2, with the exception that terminal values instead of the total rate of return are displayed. Settings 4 and 5 correspond to Setting 3 with respect to the presentation format; however, the capital with which the participants are endowed is altered, as is the chance of participating in this game. The endowed capital is 10 Euro in Setting 3; it is 100 Euro in Setting 4. However, not every participant will be allowed to play this game; instead, due to financial constraints, there is a participation chance of 1 to 900. Setting 5 is a pure thought experiment with an endowed capital of 50,000 Euro that does not result in any real payoffs. Settings 4 and 5 are included to investigate the change in risk appetite as the amount at stake increases.

In the second part of the experiment, each setting consists of four alternatives with normally distributed rates of return. This allows for a more precise determination of quantiles. The settings are based on two parameter sets for the investment alternatives, as shown in Table 2. Note that the parameters are chosen such that no return distribution is dominated by another in terms of mean-variance combinations. In fact, the Sharpe ratio is the same for all three risky investments. The two parameter sets exhibit equal means, but different standard deviations, so that the 95% and 5% quantiles of the first parameter set match the 75% and 25% quantiles of the second set.

< Insert Table 2 about here >

For both parameter sets, participants are shown different presentation formats: tables with the 95%/5% and 75%/25% quantiles of terminal values (Table 3), graphical presentations of the 95%/5% and 75%/25% quantiles for terminal values (Figure 1) and for total rates of return (Figure 2), as well as total rates of return framed as probability density functions (Figure 3). Note that in Settings 11 and 15, investment alternatives A through C look as if they are strictly dominated by alternative D as opposed to Settings 9 and 13, although the parameters are the same.

< Insert Table 3 about here >

< Insert Figure 1 about here >

< Insert Figure 2 about here >

< Insert Figure 3 about here >

Settings 1 to 3, as well as the settings in the second part of the experiment, that are based on identical parameter sets only differ with respect to framing. This is done to elicit whether or not participants are consistent in their preferences as the framing of otherwise identical alternatives is altered. While all participants had full information about the risk-return characteristics of the alternatives, the fact that the alternatives are the same was, of course, not communicated to them.

Table 4 provides an overview of all 18 settings with the dimensions in which the framing is altered.

< Insert Table 4 about here >

3.2 Experiment Sessions and Sample

The experiment was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007). All experiments took place at the Frankfurt Laboratory for Experimental Research (FLEX) at Goethe University Frankfurt. The laboratory invited the individuals registered in its data base to participate in this experiment. A total of 200 participants, most of them students, participated in eight sessions of 25 participants each. Table 5 provides summary statistics about the subjects. With 200 participants and four responses in 18 setting, we have a total of 14,400 observations.

The experiment proceeded as follows. First, the participants read the instructions, which explained the setting and some statistical concepts used in the experiment. Next, they answered a short quiz containing basic financial literacy questions based on van Rooij et al. (2011) as well as questions regarding the statistical concepts explained previously. This allows us to control for degree of comprehension when analyzing the decisions made and thus obtain a less noisy estimate of individuals' risk perception. After all decisions were made in the main part of the experiment, one of the 16 settings involving endowed capital of 10 Euro was played. The setting was randomly chosen by drawing from a deck of cards. A die was rolled to determine which alternative would be relevant for the payout. The performance of the investment was determined as a random draw reflecting the statistical properties of the investment as communicated to the participants. Subsequently, a random draw determined which participant would participate in the game involving endowed capital of 100 Euro. After answering a questionnaire, each participant was paid the amount of money resulting from his or her decisions.

< Insert Table 5 about here >

4 Methodology and Results

4.1 Methodology

To check the consistency of preference order in different settings, we calculate a weighted sigma for the preference order over the four investment alternatives. The probabilities assigned to the different preferences in the experiment are used as weights. With these weights, we calculate the weighted standard deviations for each of the 18 settings and for every participant. The result is a 200 x 18 matrix where σ_1, σ_2, and σ_3 correspond to the standard deviation of the first, second, and third choice, respectively, and $(x_1, x_2, x_3) = \left(\frac{1}{2}, \frac{1}{3}, \frac{1}{6}\right)$:

$$\Sigma = x_1 * \sigma_1 + x_2 * \sigma_2 + x_3 * \sigma_3$$

This measure allows us to compare the risk level that individuals are willing to accept in each setting. However, the risk level depends on the parameter set of the respective situation. Since the standard deviation differs between the two parts of the experiment and between the two parameter sets in the second part, changes in the weighted sigma should be interpreted with caution.

An attractive way of comparing between all situations is to standardize the weighted sigma as follows, where $\sigma_{min,j}$ and $\sigma_{max,j}$ denote the lowest and highest standard deviation, respectively, that are possible in setting j:

$$\sigma_{ij}^{R} = \frac{\sigma_{ij} - \sigma_{min,j}}{\sigma_{max,j} - \sigma_{min,j}}$$

This measure will be referred to as "relative sigma". It ranges between 0 and 1 and allows us to compare the relative riskiness of a subject's choice between all situations.

A third possible measure for the riskiness of a choice is based on the order of the preference ranks. In the second part of the experiment, the least risky choice is always to rank the alternatives (A, B, C, D) as (1, 2, 3, 4), since A is risk- free and the standard deviation increases constantly over B and C to D. It is therefore possible to count how many times a certain preference order needs to be rearranged pairwise until the least risky order (1, 2, 3, 4) is achieved. This number, which will be referred to as the "score", ranges from 0 for the (1, 2, 3, 4) choice to 6 for the (4, 3, 2, 1) choice. The score leads to a ranking of the riskiness of decisions similar to that derived from the relative sigma (see Table 7).

The hypotheses are examined in several ways. One way involves comparing the consistency and average riskiness of investment decisions in the different settings and identifying deviations. The results of this descriptive analysis are described in Section 4.2. They provide an overview of investment behavior and reveal a tendency toward inconsistent decisions for the entire pool of participants. Another method is a formal hypothesis test based on the riskiness of an individual's decision in a particular setting. We employ different measures of the riskiness of a decision and regress them on a number of variables capturing various dimensions of framing. The results of this analysis are described in Section 4.3.1. In a third step, we take a more detailed look at the preference order for each individual and in each of the 18 settings by constructing a data set that makes a pair-wise comparison of all decisions within both parts of the experiment. The resulting matrix has 88 entries for each participant, corresponding to the comparisons made in Tables 8 and 9 at the individual level. This data set enables us to address our central question of what drives changes in individuals' asset allocation when everything but the framing of the decision situation remains equal. The results of this analysis are reported in Section 4.3.2.

4.2 Descriptive Analysis

Table 6 provides an overview of all decisions made in both parts of the experiment. It shows that each investment alternative was assigned each preference by at least some subjects. At this point, it is already clear unanimity between subjects differed in different settings. In Settings 11 and 15, as well as in 14 and 18, the decisions appear very similar. Settings 11 and 15 induced quite risky choices among individuals; decisions made in Settings 14 and 18 are systematically less risky. Since these situations include several variations of the presentation format, we now consider the descriptive statistics through the lens of each hypothesis.

$<$ Insert Table 6 about here $>$

Our first hypothesis is that people make no inconsistent choices across different presentation formats in the sense that the choice of a risky alternative should not be influenced by presentation format. Although Table 6 considers only aggregated preferences for the investment alternatives and not individual choice behavior, it shows that preferences differed between the settings. The percentage of consistent decisions is displayed in Tables 8(a) and 9(a), which allow for a more detailed look at the consistency of individual decisions. In Table 9(a), bold figures indicate consistency of choices within a parameter set. The consistency within a parameter set ranges from 0.17 to 0.66, with a mean of 0.34. More often than not, subjects' choices are thus influenced by how the decision is framed. Our second hypothesis concerns the framing of investment outcomes as either absolute values or rates of return. Table 6 does not provide clear evidence either in favor of or against this hypothesis. Obviously, there was a shift between Settings 1 and 3 toward the riskiest alternative B as the favorite investment (a change from 63 to 106). However, the ranking of A as the risk-free alternative hardly changed. Tables 7 and 8 show that the riskiness of the chosen investments increased in the absolute value setting compared to the rate-of-return setting. The average weighted standard deviation, for instance, increased from 44% to 55%.

$<$ Insert Table 7 about here $>$

$<$ Insert Table 8 about here $>$

To assess whether there is support for our hypothesis concerning the impact of different quantiles, we compare those pairs of settings within a parameter set that differ only with respect to the quantile that is presented to participants. These settings are 7 and 8, 9 and 11, 10 and 12, 13 and 15, and 14 and 16. Table 9(a) shows that for these pairs of settings, the percentage of consistency is not greater than 0.48, so the decisions do appear to have been influenced by presentation format. Panels (b) and (c) show that for each pair of settings, the riskiness of individual choices was systematically higher in the 75% and 25% quantile presentation than in the 95% and 5% quantile presentation except for Settings 9 and 11, and 10 and 12, where the sigma did not change at all.

$<$ Insert Table 9 about here $>$

We further hypothesized that decisions based on the full return distribution will be no different from decisions based on quantile representation. The corresponding settings for this hypothesis are 14 and 18, 16 and 18, 13 and 17, and 15 and 17. Table 9 shows that consistency is relatively low (between 21% and 32%) and that the level of risk accepted by subjects is lower for the full distribution presentation. The difference is smaller for the comparison between the 95%-5% quantiles with the full distribution than for the comparison between the 75%-25% quantiles with the probability density function because of the difference induced by the effect of different quantiles (see Hypothesis 4). Overall, presentation of the full distribution seems to emphasize the downside risk more than other formats.

To see what effect the initial endowment has on investment behavior, in the first part of the experiment we vary the amount of money to be invested. Settings 3, 4, and 5 are identical with respect to presentation format but differ with respect to the capital at stake: Setting 3 is based on 10 Euro, Setting 4 on 100 Euro, and Setting 5 on 50,000 Euro. Tables 7 and 8 show that the risk decreases with increasing stakes. Increasing the capital from 10 Euro to 50,000 Euro, for example, results in a weighted sigma that is about 15% lower on average.

Hypothesis 3, claiming that decisions are not influenced by whether total or period rates of return are shown, can be tested by comparing Settings 1 and 2. Setting 1 framed the investment development as a per-period return, whereas in Setting 2, subjects are presented with the total rate of return in the best and worst cases. Tables 7 and 8 show that although the level of consistency is low (27%), there is no clear tendency toward more or less risky investments. The weighted standard deviation, as well as the relative sigma, increase slightly, whereas the score decreases. However, this framing dimension does not appear to have any systematic effect.

4.3 Regression Analysis

This section reports the results for two sets of regressions. In a first step, we regress different risk measures on variables that identify our hypotheses as well as on personal characteristics (see Section 4.3.1). In a second step, we make a pair-wise comparison of all investment decisions within both parts of the experiment to analyze the drivers of inconsistency and change in proneness to risk (see Section 4.3.2). In both sets of regressions, we include personal characteristics without reporting them in the respective regression tables. This omission is partially due to spatial constraints, but reporting them separately also makes analysis of the impact of personal characteristics easier to comprehend. The results from this analysis are described in Section **??**.

4.3.1 The Riskiness of Choices

To test the impact of various dimensions of framing we define the following set of independent variables that identify settings with respect to these framing dimensions. The variable *absolute* is a dummy that indicates whether the information is presented in terms of absolute values or in terms of rates of return. The variables *q75*, *q95*, and *fulldist* are dummies for the 75%-25% quantile, the 95%-5% quantile, and the full distribution presentation formats, respectively. *logstartcap* is the natural logarithm of the initial capital. Taking the logarithm prevents the coefficient from being too close to 0 due to the large sum of 50,000 Euro in Setting 5. *periodinfo* is a binary variable that takes the value 1 for settings with information about per-period performance instead of total performance. *graphicalinfo* is also a binary variable and indicates whether information is presented in a table (0) or in a graphic format (1). To account for the fact that in some settings investment alternatives can be associated with possible losses, we introduce *n_assets_loss*. This is a cardinal variable that counts the number of alternatives with loss potential. Furthermore, there are some settings in which some investment alternatives seem to dominate other alternatives with respect to their risk-return profile even though this is not actually the case. The variable *dominance* is a binary variable indicating whether or not there is alleged dominance present in the respective situation. *d_pset2* is a binary variable indicating on which parameter set the respective situation is based. Furthermore, we define four different subsets for the second part of the experiment. Within each subset, the parameter set and the quantile range are the same. The first subset consists of settings with the 95%-5% quantiles for the first parameter set (Settings 6, 9, and 13), the second set covers the 95%-5% quantiles for the second parameter set (Settings 7, 10, and 14), the third set contains the 75%-25% quantiles for the first parameter set (Settings 11 and 15), and the fourth set consists of the 75%-25% quantiles for the second parameter set (Settings 8, 12, and 16). The dummies *d_subset1* to *d_subset4* identify these subsets.

The regression equation is:

$$\text{risk\_measure}_{ij} = \alpha_i + \sum_{k=1}^{14} \beta_k^H x_{kij}^H + \sum_{l=1}^{14} \beta_l^P x_{lij}^L + \epsilon_{ij},$$

where $i = 1, \ldots, 200$ denotes the individual, $j = 1, \ldots, 18$ denotes the setting, risk_measure_{ij} is either the score, the sigma, or the relative sigma, $\left(x_{ij}^H\right)$ is the matrix of explaining variables that represent the hypotheses, $\left(x_{ij}^P\right)$ is the matrix of personal characteristics, and β^H and β^P are the vectors of the corresponding coefficients. The regression results are displayed in Tables 10 and 11. For each risk measure, we conducted six regressions, each representing different sets of decisions, which are described in the respective tables. Regression (1) uses the entire data set; regressions (2) to (5) use only part of the data. This was done to check the robustness of results against different types of assets (discrete vs. continuous development) and different parameter sets.

< Insert Table 10 about here >

< Insert Table 11 about here >

The results for the regressions of the score and the relative sigma as dependent variables are not significantly differerent, so for the sake of clarity we omit the regression table for the relative sigma. The coefficient for the variable *absolute* is significant and positive for all risk measures and all six respective regressions, revealing that subjects tend to make riskier choices when absolute values are presented instead of rates of return. This implies that Hypothesis 2 should be rejected. Whether these rates of return are presented as per-period or as total rates of return does not appear to have an impact on decisions, since the coefficient for *periodinfo* is not significantly different from zero. Only in regression (1) in Table 11 is the coefficient negative and significant. Since we have settings with both period and total returns in the first part of the experiment only and the coefficient for *periodinfo* is insignificant in the corresponding regression (5), the coefficient in regression (1) might be picking up some variation for which we did not control. We conclude that Hypothesis 3 cannot be rejected.

Our fourth hypothesis is that the zero line as an anchor value does not influence investment decisions. To test this hypothesis, we introduced the variable *n_assets_loss*. In regressions (1) and (2), the respective coefficient is not significantly different from zero. In regressions (3) and (4), however, we observe a statistically significant impact of the number of investment alternatives with loss potential on the riskiness of the decisions. The sign of the coefficient is positive for regression (3) and negative for regression (4), regardless of which risk measure is used as the dependent variable. Thus, in the parameter set with higher loss potential (parameter set 2, regression (4)), participants exhibit loss aversion, reflected by a substantial reduction of their investment risk. That loss aversion would be induced by explicitly showing the loss potential of the alternatives. For parameter set 1 (regression (3)), the potential losses are far less severe than for parameter set 2. Participants may perceive the risk-return trade-off for this parameter set as more attractive. This higher attractiveness explains an asset choice that is at first sight surprising: participants choose riskier assets even in settings with a higher number of alternatives associated with losses.

The impact of the dummy variable for the 75%-25% quantile (*q75*)is positive and significant in the regressions of the score and the relative sigma. In these regressions, the coefficient of the dummy for settings with the 95%-5% quantile (*q95*) is also positive and significant but smaller. In the regression of sigma, both coefficients are negative and significant, but the 75%-25% dummy is again larger than the 95%-5% dummy. This implies, in contradiction of Hypothesis 5, that choices become more risky on average when 75% and 25% quantiles are shown than when the 95% and 5% quantiles are presented. This is because in the 75%-25% quantile presentation, the downside risk is not as apparent as it is in the 95%-5% quantile presentation.

In regressions (2) and (4), the coefficient for *fulldist*, a dummy for formats with the probability density function, is- with only on exception in the regression of sigma- significant and negative. This indicates that when the full distribution of returns is shown, people prefer less risky alternatives, a finding in contradiction to Hypothesis 6.

Whether investment outcomes are presented in tables or in graphical form does not seem to have an influence on investment decisions, since the coefficient for *graphicalinfo* is not statistically different from zero in any of the regressions. Therefore, Hypothesis 7 cannot be rejected.

Investing larger amounts of money seems to increase risk aversion, as predicted by Hypothesis 8, since the coefficient for *logstartcap* is significantly negative for all three dependent variables. Participants are more likely to gamble with the small amount of 10 Euro rather than with larger amounts. This is not surprising, but it does provide a plausibility check of subjects' responses. Participants do not simply choose the alternatives they picked before, but instead make a new decision based on the information given in that setting.

Hypothesis 9 refers to those pairs of situations in which the quantiles look the same but actually differ because one presentation uses the 95% and 5% quantiles, whereas the other presentation is based on the 75% and 25% quantiles (Settings 6 and 8, 9, and 12, and 13 and 16). To test this hypothesis, we use dummies for the subsets. Settings 6, 9, and 13 constitute subset 1, Settings 7, 10, and 14 constitute subset 2, Settings 11 and 15 constitute subset 3, and Settings 8, 12, and 16 constitute subset 4. If subjects made their choice based solely on the figures or the graphical presentation, i.e., the shape of the rectangles, the score should be the same for subsets 1 and 4. However, the statistically significant parameters for *d_subset1* and *d_subset4* show that the decisions were systematically different in both subsets. Therefore, individuals rely not only on the numbers or graphics, but also incorporate the information about which quantile is being presented. For the score and the relative sigma as dependent variables, the order of the subsets with respect to the associated risk level is $score(3) > score(1) > score(4) > score(2)$, so the risk level of individuals' asset choices is highest in parameter set 1 with the 75% and 25% quantile presentation. Since the absolute sigma does not control for the different assets' sigmas as the relative sigma does, the order of the coefficients is $sigma(4) > sigma(2) > sigma(3) > sigma(1)$. The order within a parameter set is therefore the same ($sigma(4) > sigma(2)$ and $sigma(3) > sigma(1)$), but the order between parameter sets is changed due to the fact that the assets in parameter set 2 are generally associated with higher standard deviations.

In addition to the variables employed to test our hypotheses, we include two other variables in the regression: a dummy for settings with (seemingly) dominating investment alternatives (*dominance*) and a dummy for the second parameter set (*d_pset2*) that controls for the fact that regressions (1) and (2) include both parameter sets. The fact that in Settings 11 and 15 it looks as if some investment alternatives are dominated by others positively influences risk-taking behavior since the coefficient for *dominance* is statistically significant and positive for regression (3) for all dependent variables. To test for the impact of alleged dominance, regression (3) is the most relevant regression because it comprises Settings 11 and 15 and the remaining settings based on parameter set 1 without including settings based on parameter set 2. The coefficient for *d_pset2* is statistically significant and negative for the score and the relative sigma as dependent variable. Subjects thus choose less risky investments in settings with alternatives from parameter set 2, which, by construction, are riskier alternatives than those from parameter set 1. Participants seem to counterbalance this enhanced risk level by choosing less risky alternatives. The significant and positive coefficient for *d_pset2* in the regression of the absolute sigma simply shows that despite the counterbalancing effect, the absolute risk level is still higher in settings based on parameter set 2.

To check whether the low or zero probability of realization in Settings 4 and 5 had an impact on decision making, we ran regressions (1) and (5) again excluding these settings. However, the regression results were not significantly influenced by this modification.

4.3.2 The Drivers of Inconsistency

In a next step, we made a pair-wise comparison of all decisions for every individual to obtain a more detailed look at what drives the numbers in Tables 8 and 9. First, we constructed a binary variable indicating, for each comparison and for each individual, whether or not the decision was consistent. We also computed the change in our three risk measures between the compared settings. To test for the impact of specific framing effects on the inconsistency of decisions, we constructed variables that represent our hypotheses. To test Hypothesis 2, we defined *h2_absolute*, which takes the value - 1 for a change from a setting with absolute values to one with rates of return, 1 for a change in the opposite direction, and 0 if both settings are either based on absolute values or on rates of return. For the analysis with consistency as the dependent variable, it only matters whether the settings being compared differ with respect to this framing dimension, so we used the absolute value of *h2_absolute* for that analysis. The variable *h3_periodreturn* takes the value 1 for the comparison of Setting 1 with each of the Settings 2 to 5. To test whether the number of assets that are shown to be associated with losses impacts decisions, we define *h4_different_n_loss* as the difference in the number of assets with loss potential between the compared settings. To make interpretation of the influence of this variable comparable to that of the other variables, we multiply the difference by - 1; thus, the higher the value of *h4_different_n_loss*, the more similar the settings with respect to this attribute. As the direction of the change does not matter for the analysis of consistency, we take the negative absolute value of *h4_different_n_loss*. For the fifth hypothesis we define *h5_quantiles*, which takes the value - 1 for a change from the 75%-25% to the 95%-5% quantile presentation, the value 1 for a change in the opposite direction, and the value 0 if both settings use the same quantiles. Finally, *h6_fulldist* and *h7_graphicalinfo* are dummies indicating whether the compared settings differ with respect to the presentation of the probability distribution function and presenting information in table form or graphically, respectively. We restricted the following analysis to comparison of equivalent settings indicated by bold figures in Tables 8 and 9. As a result, the variables for Hypotheses 8 and 9 were dropped because they have no variation under that restriction. In an additional regression, we also included interaction terms of the hypothesis variables and the dummy variable for female (variables *h2_female* to *h7_female*) to discover whether male and female participants were similarly susceptible to framing effects (cf. regressions (2), (4), and (6) in Table 12). Interaction terms with other personal characteristics were tested but did not appear to have an influence on the dependent variables. The regression equation is:

$$y_{ij} = \alpha_i + \sum_{k=1}^{12} \beta_k^H x_{kij}^H + \sum_{l=1}^{14} \beta_l^P x_{lij}^L + \epsilon_{ij},$$

where $i = 1, \ldots, 200$ denotes the individual, $j = 1, \ldots, 88$ stands for the 88 comparisons of decisions, y_{ij} is either the binary variable indicating consistency, the difference of the scores or of the sigmas between the compared situations, $\left(x_{ij}^H\right)$ is the matrix of explanatory variables that represent the hypotheses, $\left(x_{ij}^P\right)$ is the matrix of personal characteristics, and β^H and β^P are the vectors of the corresponding coefficients. Table 12 reports the results.

< Insert Table 12 about here >

As in the regression of the risk level, the framing of an investment decision in absolute values or in rates of return also exerts a statistically significant influence on both consistency and change in the riskiness of asset choices. Individuals' are systematically less consistent when this framing dimension is varied; however, the change in the riskiness of asset choices is higher for the change from rates of return to absolute values, i.e., for the second part of the experiment. The negative and significant coefficient of *h3_periodreturn* implies that changing the presentation format of rates of return from per-period to total results in less than average consistent decisions. It does not systematically influence the score or sigma changes, though. When ignoring interaction effects with the gender dummy, *h5_quantiles* has a significant and negative effect on consistency, i.e., participants' choices are influenced by a variation in presented quantiles. Furthermore, and in line with previous findings, a change to the 75%-25% quantile presentation induces more risk taking, as can be seen from the positive and significant coefficients in columns (3) to (6). The negative and significant coefficient for *h6_fulldist* in columns (1) and (2) indicates that, in general, decisions are influenced by whether the information about stochastic payoffs is shown as a probability distribution function or in a different format. The negative coefficients in columns (3) to (6) suggest that in the settings with the probability distribution function, participants choose less risky asset allocations than under the other presentation formats. This supports the findings from our first regression set. When comparing settings with graphic information as opposed to tables, consistency is lower than within both framings. The impact on proneness to risk taking is weak. The negative but small and only partly significant coefficients in columns (3) to (6) suggest that in graphical settings the choices made involve slightly less risk than choices based on information in tables.

The coefficients of the interaction terms of the hypothesis variables with the dummy for female show how differently from men women reacted to various framings. In those instances where we observe a positive coefficient for those interaction terms, women made more consistent decisions, while negative coefficents indicate that women made, on average, less consistent choices than men. The results in Table 12 indicate that women's investment choices were more susceptible to some framing dimensions (for Hypotheses H2, H3, and H7) and less susceptible to others (for Hypotheses H4, H5, and H6). Thus, neither sex is systematically more or less influenced by framing when deciding on investment alternatives. The negative and significant coefficient for the dummy variable *female* indicates that even when controlling for a different degree of susceptibility to framing effects, women still exhibit less consistency in their decisions on average.

4.3.3 The Impact of Personal Characteristics

In all regressions reported in Tables 10 to 12, we included participants' personal characteristics to see how they influenced investment decisions. To compare the impact of those characteristics more easily we report them separately in Table 13.

< Insert Table 13 about here >

The characteristics that seem to have the most pronounced influence on risk-taking are risk attitude toward financial decisions (*risk_finance*) and the gender. The statistically significant and positive coefficients for *risk_finance* in regressions (1) to (3) indicate that, not surprisingly, the more an individual assesses himself or herself as risk seeking in financial decisions, the more risk he or she will take. The positive and significant coefficient in regression (4) means that, on average, individuals with less risk aversion in financial decisions made more consistent choices. The dummy for female participants has a statistically significant and negative impact on risk taking (see regressions (1) to (3)) as well as on consistency (see regression (4)). This is in line with previous studies finding women to have a lower tolerance for risk or to hold less risky portfolios. Croson and Gneezy (2009) provide an overview of both experimental and field studies on this topic. Further evidence based on physiological processes is offered by Sapienza et al. (2009), who find the concentration of salivary testosterone to be negatively correlated with risk aversion. The size of this impact is considerable, especially when compared to all the other personal characteristics listed here. Thus, among individual attributes, sex seems to have the most influence on risk taking and on the consistency of decisions. However, it is possible that the coefficient for the variable *female* also captures the effect of other attributes that we did not include in our analysis. A third variable that has a statistically significant and negative influence on both risk level and consistency is *sem*, the number of semesters completed at university.

4.3.4 Robustness Checks

5 Conclusion

The purpose of this paper is to systematically analyze the impact of framing effects on the preference for risky investment alternatives. To test our hypotheses, we conduct an experiment in which participants rank four investment alternatives in differently framed settings. We find that presentation format has a very strong influence on investment decisions. On average, only 28% of the participants in our experimental study consistently chose the same investment alternatives across different framings. It can be expected that this share of consistent decisions would be even lower for a more representative sample; half the individuals in our sample are students of economics or business administration and therefore familiar with investment decisions.

Beyond this susceptibility to framing in general, we also find that some presentation formats do lead individuals into temptation to invest more riskily. First, when absolute values are shown to individuals, they systematically make riskier investment choices than for the rate of return presentation. Participants seem to accept higher risk in their investments when they see the upside potential that results from the asymmetric shape of the log-normal distribution of terminal values. Second, showing the 75% and 25% quantile instead of the 95% and 5% quantiles also increases the riskiness of participants' preference order. A possible explanation is that some of the downside risk apparent in a wider confidence interval is not revealed in this narrower confidence interval. Third, showing the full probability distribution leads to a further decrease in risk taking, indicating that subjects react to being shown more clearly the full loss potential of riskier investments. Other framings, such as presenting possible payoffs either in a purely numerical format or in graphical form, do not systematically influence investment decisions.

Our results not only contribute to the decision-making literature, but can aid policymakers in the designing of fact sheets for investment and life insurance products, seeing as they document how individuals' product choices are influenced by presentation format. These findings can prevent unintended and unwelcome consequences of the design of product fact sheets for the portfolios of retail investors. In particular, we point out three possible policy implications that can be derived from our results. First, we find that women systematically choose less risky asset allocations than do men. Drawing on standard models of portfolio choice, it is optimal to invest a certain fraction of wealth in stocks, which bear greater risks than other asset classes but, at the same time, generate higher expected rates of return in the long run (see, e.g., Samuelson, 1969; Merton, 1969; Arrow, 1971). From our results, it can be expected that women will be at a comparative disadvantage in their old-age provision due to being less prone to make risky investments. To tackle this problem, financial advisors could explicitly address this bias when advising women in their financial planning.

Second, if the political agenda aims at enhancing stock market participation by both women and men, we recommend presenting payoff prospects in absolute terms in standardized fact sheets. This is especially relevant in the presence of well-functioning state pension systems that serve as a surrogate for low-risk private pension plans and thus increase the budget for risky investments (see Post et al., 2013).

Third, in the presence of less reliable state pension systems, long-term investment guarantees are an important feature of private pension products. These guarantees, however, imply a lower upside potential of benefit payments. To promote annuity products that include such investment guarantees and thereby reduce the risk of poverty among the elderly, our recommendation is to present rates of return on investment product fact sheets.

An interesting extension of our analysis would be to conduct experiments similar to ours and measure physiological processes that are at work while participants make their investment decisions. For example, this could include tracking eye movements to find out what information is actively perceived, as well as monitoring heart rate and blood pressure to identify situations that trigger stress. Research of this type could reveal which formats overtax individuals and therefore lead to suboptimal decisions. Since we do not control for participants' confidence in their decisions, this could be an important extension of our analysis. Furthermore, more elaborate experiments could also make use of electroencephalography (EEG) or functional neuroimaging (fMRI) to link neural responses to investment decisions. This would help us more deeply understand the individual decision process, only the outcome of which is observable in our experimental setting.

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Table 1: Investment Alternatives in the First Part of the Experiment

This table displays Settings 1 to 5. The four assets (A, B, C, D) whose values develop according to a binomial grid have the same "up" and "down" rates of return in each setting. The initial capital is EUR 10 for Settings 1 to 3, EUR 100 in Setting 4, and EUR 50,000 in Setting 5. The "up" and "down" probabilities are 50%.

Period Rates of Return				
Setting 1				
	A	B	C	D
up	4%	30%	8%	15%
mean	4%	7.5%	4%	5%
down	4%	-15%	0%	-5%
Total Rates of Return				
Setting 2				
	A	B	C	D
best case	48%	1279%	116%	305%
mean	48%	106%	48%	63%
worst case	48%	-80%	0%	-40%
Terminal Values for an Initial Investment of EUR 10				
Setting 3				
	A	B	C	D
best case	14.80	137.86	21.59	40.46
mean	14.80	20.61	14.80	16.29
worst case	14.80	1.97	10.00	5.99
Terminal Values for an Initial Investment of EUR 100				
Setting 4				
	A	B	C	D
best case	148.02	1,378.58	215.89	404.56
mean	148.02	206.10	148.02	162.89
worst case	148.02	19.69	100.00	59.87
Terminal Values for an Initial Investment of EUR 50,000				
Setting 5				
	A	B	C	D
best case	74,012.21	689292.46	107,946.25	202,277.89
mean	74,012.21	103,051.58	74,012.21	81,444.73
worst case	74,012.21	9,843.72	50,000.00	29,936.85

Table 2: Investment Alternatives in the Second Part of the Experiment

The parameter sets are used for the second part of the experiment in which subjects had to rank four investment alternatives (A, B, C, D). The returns for each investment follow a normal distribution. The two parameter sets are constructed in such a way that the 95% and 5% quantiles of parameter set 1 corresponds to the 75% and 25% quantiles of parameter set 2.

Parameter Set 1	A	B	C	D
mean	10.00%	20.00%	30.00%	40.00%
standard deviation	0.00%	9.17%	18.34%	27.51%

Parameter Set 2	A	B	C	D
mean	10.00%	20.00%	30.00%	40.00%
standard deviation	0.00%	22.36%	44.72%	67.08%

Table 3: Settings 6 through 8

This table shows the settings 6 to 8 from the experiment where participants had to rank four investment alternatives based on information about possible terminal values of their investment. The columns represent the two parameter sets and the rows represent the quantiles shown to the participants: the upper part contains the settings where the 95%- and 5% quantile as well as the median were shown, whereas the lower part contains the settings where the 75%- and 25% quantile as well as the median were shown. The numbers for Settings 6 and 8 are the same because the parameter sets are determined in such a way that the 95% and 5% quantile of one distribution corresponds to the 75% and 25% quantile of the other distribution.

	Parameter Set 1					**Parameter Set 2**			
	Setting 6					Setting 7			
	A	B	C	D		A	B	C	D
95%	11.05	14.20	18.25	23.45	95%	11.05	17.64	28.17	44.97
50%	11.05	12.21	13.50	14.92	50%	11.05	12.21	13.50	14.92
5%	11.05	10.50	9.98	9.49	5%	11.05	8.46	6.47	4.95
						Setting 8			
	A	B	C	D		A	B	C	D
75%	11.05	12.99	15.28	17.96	75%	11.05	14.20	18.25	23.45
50%	11.05	12.21	13.50	14.92	50%	11.05	21.21	13.50	14.92
25%	11.05	11.48	11.93	12.39	25%	11.05	10.50	9.98	9.49

Table 4: Overview of Settings

This table summarizes all settings included in the experiment. The columns correspond to the dimensions in which the framing is varied.

Setting	**Format**	**Outcome Presentation**	**Endowed Capital**	**Quantile**	**Parameter Set**
1	Table	Period Rates of Return	10		
2	Table	Total Rates of Return	10		
3	Table	Terminal Values	10		
4	Table	Terminal Values	100		
5	Table	Terminal Values	50,000		
6	Table	Terminal Values	10	95%-5%	1
7	Table	Terminal Values	10	95%-5%	2
8	Table	Terminal Values	10	75%-25%	2
9	Graphic	Terminal Values	10	95%-5%	1
10	Graphic	Terminal Values	10	95%-5%	2
11	Graphic	Terminal Values	10	75%-25%	1
12	Graphic	Terminal Values	10	75%-25%	2
13	Graphic	Total Rates of Return	10	95%-5%	1
14	Graphic	Total Rates of Return	10	95%-5%	2
15	Graphic	Total Rates of Return	10	75%-25%	1
16	Graphic	Total Rates of Return	10	75%-25%	2
17	pdf	Total Rates of Return	10		1
18	pdf	Total Rates of Return	10		2

Table 5: Sample - Summary Statistics

This table summarizes the characteristics of the 200 participants in the experiment. The numbers do not always add up to 200 because some subjects did not make a statement. "Tolerance for risk in general" denotes the subject's preference for risk in general, for instance, regarding sports, with 0 being the lowest risk tolerance and 10 the highest.

	n	% of the sample
Gender		
Male	95	47.5%
Female	101	50.5%
Age		
18-22	89	44.5%
23-26	76	38%
27-30	20	10%
>31	11	5.5%
Marital Status		
Single	103	51.5%
In a committed relationship/married	93	46.5%
Education		
High school diploma	155	77.5%
Bachelor's degree	24	12%
Master's degree (or German equivalent)	16	8%
Doctorate	1	0.5%
Field of Study		
Business/Economics	104	52%
Law	18	9%
Medicine	8	4%
Other	70	35%
No. of Semesters Completed		
1-6	135	67.5%
7-10	45	22.5%
>11	13	6.5%
Job Experience (in Months)		
0-12	139	69.5%
13-24	21	10.5%
> 24	36	18%
Tolerance for Risk in General		
0-3	42	21%
4-7	130	65%
8-10	24	12%
Tolerance for Financial Risk		
Very risk-averse	23	11.5%
Somewhat risk-averse	65	32.5%
Risk-neutral	42	21%
Risk-seeking	59	29.5%
Very risk-seeking	8	4%
Ever Inherited Money?		
Yes	36	18%
No	160	80%

Table 6: Decisions

This table summarizes the decisions made throughout the experiment. For every investment alternative A, B, C, and D, the numbers in columns 1 to 4 describe how often subjects assigned the respective preference to that alternative. The lines 1 to 18 stand for the 18 settings. The first part of the experiment consists of Settings 1 to 5 with the same investment alternatives, and the second part consists of Settings 6 to 18 with two different parameter sets. The four numbers assigned to each alternative add up to 200, i.e., the number of participants.

Setting	A				B				C				D			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	21	56	49	74	63	24	37	76	82	46	53	19	34	74	61	31
2	39	46	55	60	67	28	32	73	70	57	45	28	24	69	68	39
3	27	33	65	75	106	20	17	57	34	50	74	42	33	97	44	26
4	43	38	42	77	103	15	32	50	37	50	70	43	17	97	56	30
5	69	42	40	49	59	28	21	92	53	68	52	27	19	62	87	32
6	18	17	26	139	18	20	136	26	22	140	20	18	142	23	18	17
7	35	32	32	101	48	41	88	23	26	104	49	21	91	23	31	55
8	15	25	24	136	22	33	124	21	30	123	34	13	133	19	18	30
9	9	8	19	164	15	30	145	10	59	121	17	3	117	41	19	23
10	30	19	28	123	24	41	115	20	48	104	34	14	98	36	23	43
11	14	9	10	167	10	26	157	7	23	152	21	4	153	13	12	22
12	23	19	18	140	27	43	121	9	61	99	33	7	89	39	28	44
13	15	21	31	133	32	51	107	10	69	94	33	4	84	34	29	53
14	71	36	21	72	50	81	57	12	36	63	89	12	43	20	33	104
15	13	5	10	172	6	17	170	7	18	162	14	6	163	16	6	15
16	21	25	32	122	42	49	101	8	72	82	37	9	65	44	30	61
17	27	24	36	113	51	53	86	10	50	96	41	13	72	27	37	64
18	51	45	35	69	85	58	48	9	29	76	84	11	35	21	33	111

Table 7: Riskiness of Choices

This table displays for each setting the average of the weighted standard deviation (Sigma), the weighted standard deviation as a percentage of the largest possible standard deviation (Rel. Sigma), and the score as a third indicator of the risk level. The score denotes the number of pair-wise changes in the preference order that are necessary to transform a given preference order into the least risky choice. It ranges between 0 and 6.

Setting	Sigma	Rel. Sigma	Score
1	0.44	0.48	3.12
2	0.45	0.49	3.00
3	0.55	0.64	3.80
4	0.53	0.61	3.54
5	0.40	0.43	2.56
6	0.14	0.83	4.87
7	0.29	0.62	3.74
8	0.33	0.79	4.65
9	0.14	0.83	4.94
10	0.31	0.71	4.20
11	0.14	0.86	5.12
12	0.31	0.71	4.26
13	0.13	0.70	4.21
14	0.22	0.41	2.54
15	0.15	0.90	5.33
16	0.29	0.64	3.91
17	0.12	0.61	3.70
18	0.22	0.40	2.47

Table 8: Bilateral Comparison of Decisions in Settings 1 to 5

This table displays (a) the consistency of decisions, (b) the score changes, and (c) the sigma changes for decisions in Settings 1 to 5. The score changes and the sigma changes are derived from Table 7. The percentage consistency is the average of a dummy variable that indicates for each pair of situations whether a subject made a consistent decision, i.e., whether the preference order for the investment alternatives is the same in both settings. A number close to 0 indicates that only a few people made consistent decisions, whereas a number close to 1 indicates a high degree of consistency. The score denotes the number of pair-wise changes in the preference order that are necessary to transform a given preference order into the least risky choice. It ranges between 0 and 6. The score and sigma changes show how the riskiness of participants' choices changed between the situations. Positive values show increasing risk-taking, while negative values represent a decrease in risk-taking. Greay boxes indicate relevant figures for Hypothesis 2, light-greay boxes for Hypothesis 3 and dark-greay boxes for Hypothesis 8.

(a) Consistency

	2	3	4	5
1	**0.27**	**0.23**	0.17	0.16
2		**0.28**	0.17	0.15
3			0.34	0.26
4				0.31

(b) Score Changes

	2	3	4	5
1	**-0.13**	**0.68**	0.42	-0.56
2		**0.80**	0.54	-0.44
3			-0.26	-1.24
4				-0.98

(c) Sigma Changes

	2	3	4	5
1	**0.00**	**0.12**	0.10	-0.05
2		**0.12**	0.10	-0.05
3			-0.02	-0.17
4				-0.15

Table 9: Bilateral Comparison of Decisions in Settings 6 to 18

This table displays (a) the consistency of decisions, (b) the score changes, and (c) the sigma changes for decisions in Settings 6 to 18. The consistency is the average of a dummy variable that indicates for each pair of situations whether a subject made a consistent decision, i.e. whether the preference order for the investment alternatives is the same in both settings. A number close to 0 indicates that only a few people made consistent decisions. The score denotes the number of pair-wise changes in the preference order that are necessary to transform a given preference order into the least risky choice. It ranges between 0 and 6. The score and sigma changes show how the riskiness of participants' choices changed between the situations. Bold figures indicate a comparison within a parameter set. Light-greay boxes indicate relevant figures for Hypothesis 5 and dark-grey boxes for Hypothesis 6.

(a) Consistency of Decisions

	7	8	9	10	11	12	13	14	15	16	17	18
6	0.42	0.48	**0.42**	0.39	**0.51**	0.34	**0.34**	0.20	**0.56**	0.27	**0.30**	0.15
7		**0.41**	0.29	**0.35**	0.36	**0.31**	0.26	**0.25**	0.39	**0.26**	0.25	**0.20**
8			0.38	**0.36**	0.48	**0.35**	0.33	**0.20**	0.51	**0.29**	0.29	**0.17**
9				0.44	**0.48**	0.42	**0.41**	0.17	**0.49**	0.35	**0.28**	0.14
10					0.45	**0.36**	0.37	**0.24**	0.40	**0.35**	0.28	**0.17**
11						0.43	**0.37**	0.20	**0.66**	0.33	**0.31**	0.16
12							0.40	**0.22**	0.43	**0.37**	0.30	**0.18**
13								0.20	**0.39**	0.40	**0.29**	0.20
14									0.21	**0.28**	0.24	**0.32**
15										0.34	**0.32**	0.16
16											0.34	**0.21**
17												0.25

(b) Score Changes

	7	8	9	10	11	12	13	14	15	16	17	18
6	-1.13	-0.22	**0.08**	-0.67	**0.26**	-0.61	**-0.66**	-2.33	**0.47**	-0.96	**-1.17**	-2.40
7		**0.92**	1.21	**0.47**	1.39	**0.53**	0.48	**-1.20**	1.60	**0.17**	-0.04	**-1.27**
8			0.29	**-0.45**	0.47	**-0.39**	-0.44	**-2.12**	0.68	**-0.75**	-0.96	**-2.19**
9				-0.74	**0.18**	-0.68	**-0.73**	-2.41	**0.39**	-1.04	**-1.25**	-2.48
10					0.92	**0.06**	0.01	**-1.67**	1.13	**-0.30**	-0.51	**-1.74**
11						-0.86	**-0.91**	-2.59	**0.21**	-1.22	**-1.43**	-2.66
12							-0.05	**-1.73**	1.07	**-0.36**	-0.57	**-1.80**
13								-1.68	**1.12**	-0.31	**-0.52**	-1.75
14									2.80	**1.37**	1.16	**-0.07**
15										-1.43	**-1.64**	-2.87
16											-0.21	**-1.44**
17												-1.23

(c) Sigma Changes

	7	8	9	10	11	12	13	14	15	16	17	18
6	0.19	0.25	**0.00**	0.23	**0.01**	0.23	**-0.02**	0.12	**0.01**	0.21	**-0.03**	0.11
7		**0.06**	-0.19	**0.03**	-0.19	**0.04**	-0.21	**-0.08**	-0.18	**0.01**	-0.22	**-0.08**
8			-0.25	**-0.03**	-0.25	**-0.02**	-0.27	**-0.14**	-0.24	**-0.05**	-0.28	**-0.14**
9				0.22	**0.00**	0.23	**-0.02**	0.11	**0.01**	0.20	**-0.03**	0.11
10					-0.22	**0.01**	-0.24	**-0.11**	-0.21	**-0.02**	-0.26	**-0.11**
11						0.22	**-0.02**	0.11	**0.01**	0.20	**-0.04**	0.11
12							-0.25	**-0.11**	-0.22	**-0.03**	-0.26	**-0.12**
13								0.13	**0.03**	0.22	**-0.01**	0.13
14									-0.10	**0.09**	-0.15	**0.00**
15										0.19	**-0.04**	0.10
16											-0.24	**-0.09**
17												0.14

Table 10: Regression Results for Score

This table reports results from our ordered probit regression analysis with the score as the dependent variable. *absolute* is a binary variable indicating whether the presentation is in terms of absolute values or rates of return. *q95* and *q75* are binary variables indicating whether the presentation showed the 95% and 5% quantiles or the 75% and 25% quantiles respectively. *fulldist* is a binary variable indicating whether the full probability distribution is shown. *logstartcapital* is the natural logarithm of the initial capital to be invested. *periodinfo* is a binary variable indicating whether the information presented is for developments per period or over the full investment horizon. *graphicalinfo* is a binary variable indicating whether the information is presented in a graphic format instead of a table. *n_assets_loss* is an ordinal variable indicating how many alternatives exhibit loss potential in the respective framing. It ranges from 0 to 3. *dominance* is a binary variable indicating whether there are alternatives that dominate other alternatives with respect to each quantile. *d_pset2* is a dummy variable for the second parameter set. *d_subset1* to *d_subset4* are dummies for the four subsets in Settings 6 to 18.
The regressions are least squares regressions with individual dummies for the following subsets of our data. (1) Including all settings. (2) For the second part of the experiment (Settings 6 to 18). (3) For parameter set 1 from the second part of the experiment. (4) For parameter set 2 from the second part of the experiment. (5) For the first part of the experiment (Settings 1 to 5). (6) For Settings 6 to 18, controlling for the subset.
The coefficients for the individual dummies as well as for the personal characteristics are not reported here. For the latter, please refer to Table 13.

	(1)	(2)	(3)	(4)	(5)	(6)
absolute	0.4706***	0.4709***	0.2355*	0.7405***	0.6587***	0.5050***
	(9.19)	(7.76)	(2.52)	(8.93)	(6.45)	(9.39)
periodinfo	0.0814				0.1241	
	(0.86)				(1.14)	
n_assets_loss	-0.0443	-0.0319	0.2539***	0.0711*		
	(-0.34)	(-0.24)	(4.50)	(2.06)		
q75	1.3537***	0.8773***	1.2929***	0.6282***		
	(9.83)	(3.79)	(10.63)	(9.51)		
q95	0.8930***	0.3973				
	(10.72)	(1.18)				
fulldist	0.4704					
	(1.47)					
graphicalinfo	-0.0906	-0.0916	-0.1979	0.0058		
	(-1.41)	(-1.36)	(-1.64)	(0.07)		
logstartcap	-0.0894***				-0.1200***	
	(-7.79)				(-9.29)	
d_evalset1						0.7203***
						(8.74)
d_evalset2						-0.0714
						(-0.89)
d_evalset3						1.4276***
						(15.10)
d_evalset4						0.4341***
						(5.35)
dominance	0.1605	0.1896				
	(0.83)	(0.97)				
d_pset2	-0.7514***	-0.7687***				
	(-6.81)	(-6.83)				
Observations	3474	2509	1158	1351	965	2509
Pseudo R^2	0.160	0.179	0.205	0.195	0.213	0.174

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Regression Results for Sigma

This table reports results from our regression analysis with the sigma as the dependent variable. *absolute* is a binary variable indicating whether the presentation is in terms of absolute values or rates of return. *q95* and *q75* are binary variables indicating whether the presentation showed the 95% and 5% quantiles or the 75% and 25% quantiles respectively. *fulldist* is a binary variable indicating whether the full probability distribution is shown. *logstartcapital* is the natural logarithm of the initial capital to be invested. *periodinfo* is a binary variable indicating whether the information presented is for developments per period or over the full investment horizon. *graphicalinfo* is a binary variable indicating whether the information is presented in a graphic format instead of a table. *n_assets_loss* is an ordinal variable indicating how many alternatives exhibit loss potential in the respective framing. It ranges from 0 to 3. *dominance* is a binary variable indicating whether there are alternatives that dominate other alternatives with respect to each quantile. *d_pset2* is a dummy variable for the second parameter set. *d_subset1* to *d_subset4* are dummies for the four subsets in Settings 6 to 18.
The regressions are least squares regressions with individual dummies which we conduct for the following subsets of our data. (1) Including all settings. (2) For the second part of the experiment (Settings 6 to 18). (3) For parameter set 1 from the second part of the experiment. (4) For parameter set 2 from the second part of the experiment. (5) For the first part of the experiment (Settings 1 to 5). (6) For Settings 6 to 18, controlling for the subset.
The coefficients for the individual dummies as well as for the personal characteristics are not reported here. For the latter, please refer to Table 13.

	(1)	(2)	(3)	(4)	(5)	(6)
absolute	0.0601***	0.0384***	0.0081**	0.0687***	0.1322***	0.0391***
	(7.99)	(8.16)	(2.70)	(8.49)	(5.89)	(8.85)
periodinfo	-0.0424**				0.0009	
	(-2.82)				(0.04)	
n_assets_loss	0.0392*	0.0392***	0.0097***	0.0069*		
	(1.98)	(3.61)	(4.86)	(1.99)		
q75	-0.3519***	0.0910***	0.0355***	0.0588***		
	(-16.71)	(8.37)	(8.94)	(9.15)		
q95	-0.4430***					
	(-36.21)					
fulldist	-0.3530***	0.0792**				
	(-7.15)	(2.84)				
graphicalinfo	0.0091	-0.0017	-0.0021	0.0061		
	(0.97)	(-0.32)	(-0.53)	(0.75)		
logstartcap	-0.0174***				-0.0214***	
	(-9.70)				(-7.66)	
dominance	0.0085	0.0085				
	(0.30)	(0.54)				
d_pset2	0.1447***	0.1447***				
	(8.44)	(15.37)				
d_evalset1						-0.0730***
						(-10.39)
d_evalset2						0.1109***
						(15.78)
d_evalset3						-0.0523***
						(-7.14)
d_evalset4						0.1627***
						(23.16)
Constant	0.7743**	0.1072	0.0518	0.4390	1.3537	0.2571
	(2.96)	(0.64)	(0.47)	(1.58)	(1.92)	(1.47)
Observations	3474	2509	1158	1351	965	2509
R^2	0.555	0.640	0.403	0.479	0.547	0.603

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Regression Results for Consistency, Score Changes, and Sigma Changes

This table reports results from our regression analysis with consistency (which is a binary variable), score changes, and sigma changes as the dependent variable. For each dependent variable, we conducted two regressions: one with dummies for the hypotheses (regressions (1), (3), and (5)) and one that included interaction variables between the hypothesis variable and the dummy for female (regressions (2), (4), and (6)). The regression of consistency was a logit model, the one for score changes an ordered probit model, and the one for sigma changes a least squares regression. All regressions included individual dummies and are based on a pair-wise comparison of settings from one parameter set (i.e., the bold figures from Tables 8 and 9).
The coefficients for the individual dummies as well as for the personal characteristics are not reported here. For the latter, please refer to Table 13.

	Consistency		Δ Score		Δ Sigma	
	(1)	(2)	(3)	(4)	(5)	(6)
h2_absolute	-0.2729***	-0.4019***	0.3405***	0.3021***	0.0554***	0.0519***
	(-4.39)	(-4.66)	(15.16)	(9.34)	(17.27)	(11.25)
h3_periodreturn	-0.9385***	-1.4082***	-0.0704	-0.0496	0.0188*	0.0189
	(-5.93)	(-6.21)	(-1.17)	(-0.57)	(2.17)	(1.52)
h4_different_n_loss	-0.1604**	-0.0563	0.0697***	0.0208	-0.0116***	-0.0121**
	(-3.07)	(-0.81)	(3.54)	(0.73)	(-4.07)	(-2.97)
h5_quantiles	-0.2829**	-0.1143	0.2620***	0.2086***	0.0513***	0.0384***
	(-2.68)	(-0.80)	(7.55)	(4.16)	(10.27)	(5.35)
h6_fulldist	-1.1602***	-0.9159***	-0.5383***	-0.4058***	-0.0177**	-0.0132
	(-8.65)	(-5.14)	(-11.48)	(-6.00)	(-2.64)	(-1.36)
h7_graphicalinfo	-0.2249***	-0.2572**	-0.0325	-0.0813*	-0.0058	-0.0113*
	(-3.52)	(-2.91)	(-1.26)	(-2.18)	(-1.57)	(-2.12)
h2_female		0.2697*		0.0760		0.0067
		(2.16)		(1.70)		(1.05)
h3_female		0.9671**		-0.0402		-0.0003
		(3.10)		(-0.33)		(-0.02)
h4_female		-0.2463*		0.0936*		0.0011
		(-2.30)		(2.37)		(0.20)
h5_female		-0.3895		0.1042		0.0248*
		(-1.82)		(1.50)		(2.49)
h6_female		-0.5882*		-0.2563**		-0.0088
		(-2.13)		(-2.74)		(-0.66)
h7_female		0.0734		0.0933		0.0106
		(0.57)		(1.81)		(1.43)
female	-1.1998***	-1.3878***	-0.1042	-0.1244	-0.0176	-0.0214
	(-3.55)	(-3.75)	(-0.73)	(-0.84)	(-0.87)	(-1.02)
Constant	-11.3314***	-11.3265***			-0.0722	-0.0703
	(-4.48)	(-4.47)			(-0.49)	(-0.47)
Observations	7293	7293	7527	7527	7527	7527
Pseudo R^2	0.234	0.237	0.056	0.058		
Adj. R^2					0.1567	0.1593

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: The Impact of Individual Characteristics

This table reports the coefficients for the individual characteristics from the previous regressions. Regressions (1) to (3) report the coefficients for individual characteristics from Tables 10 and 11. Regressions (4) to (6) report the coefficients for individual characteristics from Table 12 for the regressions without interaction variables.

	(1) Score	(2) Sigma	(3) Rel.Sigma	(4) Consistency	(5) Δ Score	(6) Δ Sigma
risk_general	-0.1371	-0.0146	-0.0229	-0.1834*	-0.1631***	-0.0170***
	(-1.69)	(-1.79)	(-1.55)	(-2.28)	(-4.75)	(-3.38)
risk_finance	0.4717***	0.0448***	0.0767**	0.7204***	-0.0738	0.0009
	(3.61)	(3.40)	(3.22)	(5.67)	(-1.33)	(0.11)
stake	0.0000	-0.0000	0.0000	-0.0000	0.0000*	0.0000
	(0.15)	(-0.11)	(0.25)	(-1.71)	(2.35)	(1.60)
incomeprospects	-0.3031	-0.0177	-0.0542	-0.3627*	-0.3204***	-0.0416***
	(-1.84)	(-1.06)	(-1.81)	(-2.19)	(-4.63)	(-4.10)
heritage	0.0133	-0.0214	0.0023	1.0664*	0.4457**	0.0218
	(0.04)	(-0.59)	(0.04)	(2.23)	(2.92)	(0.98)
age	-0.0226	0.0004	-0.0069	0.0079	-0.0069	0.0002
	(-0.59)	(0.09)	(-0.99)	(0.16)	(-0.43)	(0.06)
female	-1.3315***	-0.1248***	-0.2215***	-1.1998***	-0.1009	-0.0176
	(-3.94)	(-3.66)	(-3.60)	(-3.55)	(-0.71)	(-0.85)
height	0.0391**	0.0030*	0.0064**	0.0878***	0.0171**	0.0014
	(3.03)	(2.32)	(2.71)	(5.94)	(3.15)	(1.73)
marital	-0.1697	-0.0312	-0.0349	-0.1874	0.0936	0.0258
	(-0.65)	(-1.19)	(-0.74)	(-0.62)	(0.86)	(1.60)
network	-0.0679	-0.0070	-0.0103	-0.5916***	0.2541***	0.0204*
	(-0.52)	(-0.53)	(-0.43)	(-3.31)	(4.59)	(2.51)
degree	-0.3517	-0.0457*	-0.0543	-0.7662***	-0.1268	-0.0304**
	(-1.89)	(-2.43)	(-1.60)	(-3.88)	(-1.63)	(-2.64)
econ	0.6041	0.0517	0.1035	0.5421	0.2946*	0.0638**
	(1.76)	(1.49)	(1.65)	(1.42)	(2.03)	(3.00)
sem	-0.1098***	-0.0111***	-0.0173**	-0.0926**	0.0038	0.0018
	(-3.47)	(-3.48)	(-3.00)	(-2.78)	(0.28)	(0.91)
exper	0.0066*	0.0004	0.0013**	0.0061	0.0023*	0.0002
	(2.36)	(1.54)	(2.63)	(1.68)	(1.98)	(1.20)
Constant	-0.3882	0.2516	0.0378	-11.3314***		-0.0607
	(-0.15)	(0.99)	(0.08)	(-4.48)		(-0.40)
Observations	3474	3474	3474	7293	7527	7527
Pseudo R^2				0.234	0.045	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Terminal Values - Settings 9 to 12

The graphical presentation for settings 9 and 12 are the same because the parameter sets are determined in such a way that the 95% and 5% quantile of one distribution corresponds to the 75% and 25% of the other distribution.

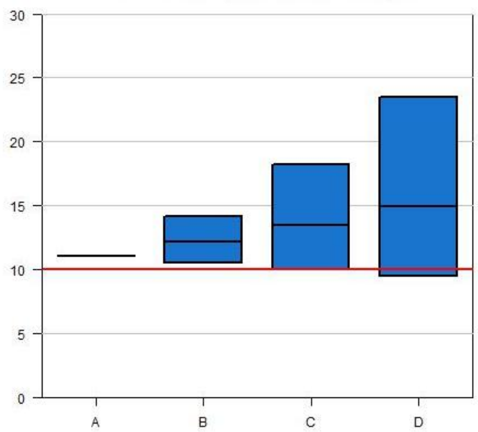
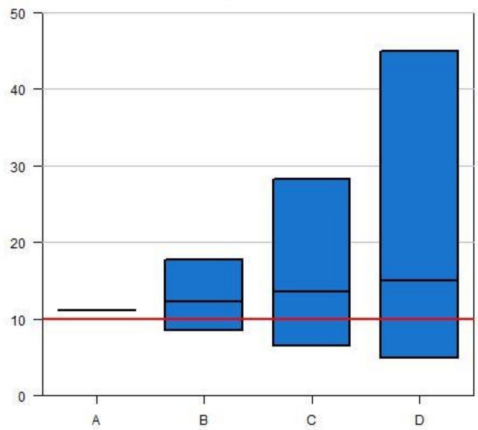
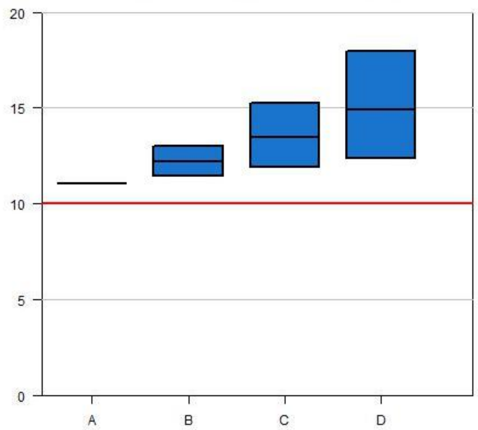
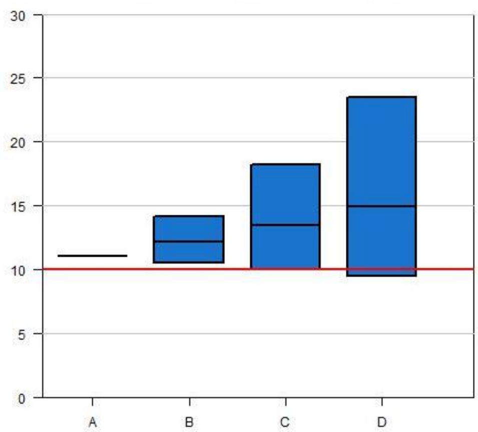
Quantile	**Parameter Set 1**	**Parameter Set 2**
	Setting 9	Setting 10
95%/5%		
	Setting 11	Setting 12
75%/25%		

Figure 2: Total Rates of Return - Settings 13 to 16

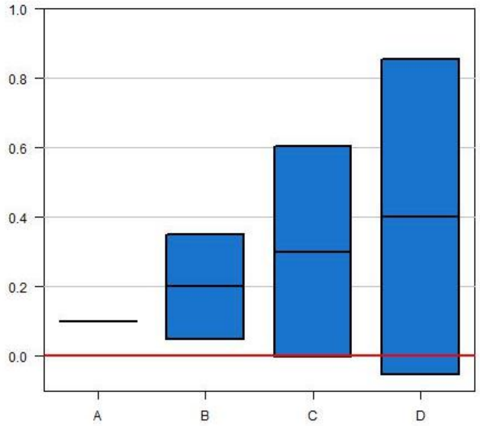
The graphical presentation for settings 13 and 16 are the same because the parameter sets are determined in such a way that the 95% and 5% quantile of one distribution corresponds to the 75% and 25% of the other distribution.

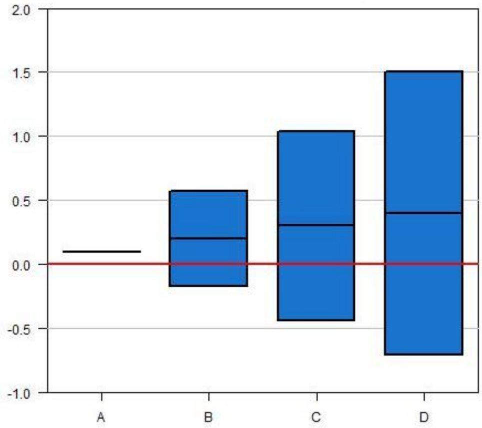
Quantile	**Parameter Set 1**	**Parameter Set 2**

Setting 13

Setting 14

95%/5%

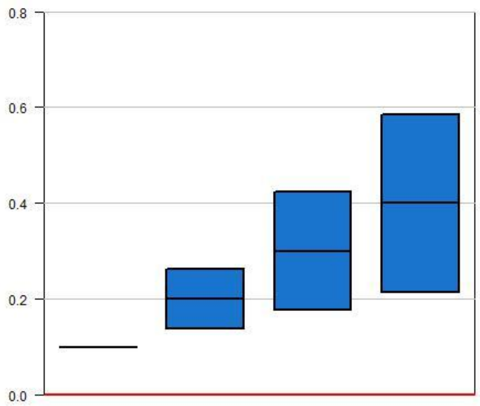




Setting 15

Setting 16

75%/25%



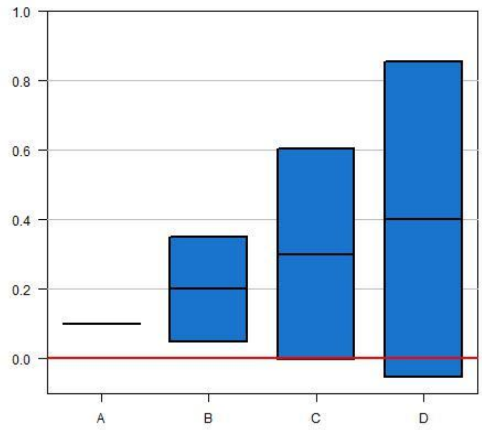


Figure 3: Total Rates of Return - Settings 17 and 18

This figure displays settings 17 and 18. Participants had to rank four investment alternatives based on the probability density function of total rates of return for both parameter sets.

Parameter Set 1	**Parameter Set 2**
Setting 17	Setting 18