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Communicating Asset Risk*

How the format of historic volatility information affects risk perception and investment decisions

Risk Perception; Volatility Forecasts; Portfolio decisions; Behavioral Finance

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* This research was supported by Sonderforschungsbereich 504 and the Graduiertenkolleg 'Allokation auf Finanz- und Gütermärkten' at the University of Mannheim and by NSF grant SES-0096015. We thank Angelika Eymann and all members of the 'Behavioral Finance Group' in Mannheim for useful comments.

Abstract

Questions about the perception and proper communication of risk are of increasing theoretical and practical interest. An experiment examined how the type and presentation format of information about investment options affected the expectations held by investors about asset risk, returns, and volatility. Some respondents were provided with the names of investment options in addition to historical (1987-97) volatility data, and some were not. Historical volatility was presented either as a bar graph of returns per year or as a continuous density distribution of returns over the 10-year period. Risk and volatility perceptions both varied significantly as a function of type and format of information, but in different ways. Biases in risk perception, but not in volatility forecasts, affected portfolio decisions.

1. Introduction

Investment portfolio decisions are supposed to be a function of expected returns, variance and the covariance structure of the returns of all available investment alternatives. Markowitz (1952) showed how to optimally select assets for a portfolio, using these variables. The Capital Asset Pricing Model (CAPM) by Sharpe (1964), Lintner (1965), and Mossin (1966) employed these variables in an equilibrium theory that allowed for asset pricing as well.

Informational constraints or bounded rationality may prevent ordinary investors from considering correlations or covariances when making portfolio allocations. However, at the very least, they should think about the expected return and likely variance of assets returns, or about other, more appropriate, measures of risk (Sarin & M. Weber, 1993; E.U. Weber, 1999)[1]. This raises the question of how such investors might arrive at some expectation about the return and riskiness of assets, given the types of information usually available to them (e.g., provided by investment brokers, the internet, newspapers, or other news services). One possibility is that people use the past performance of investment options to predict future performance, that is, that they use historical returns to estimate future returns and their likely volatility or risk. In this context, the format in which historical returns are presented might influence estimates of future performance. Another possibility is that people use information such as macroeconomic indices, expected trends, or company-specific facts to arrive at expectations about the risks and returns of investment options. In this case, knowledge of the name of the investment becomes important, as the name indicates the type, market and other special characteristics of the asset.

In this paper, we study the influence of these two types of information on people's perceptions of investment options and their asset allocation. We also examine how perception and allocation decisions were affected by the format in which information about historical performance is provided. In a between-subject design, we provided potential investors with information about the historical performance of sixteen investment alternatives, using two different presentation formats. In addition to (or instead of) the historical return data, some investors were also provided with the names or identity of these investment alternatives. We measured investors' expectations of future returns as well as their volatility forecasts (i.e., the standard deviation of predicted returns) for the sixteen investment alternatives. In addition to volatility forecasts, we also assessed investors' perception of the riskiness of the investment options. Finally, we elicited their portfolio decisions. These data allow us to examine the relationship between objective, historical volatility and either expected volatility or perceived riskiness of assets. They also allow us to test which of these two expectations is a better predictor of portfolio choices in a risk—return framework.

Researchers from several disciplines have been discussing different measures of risk and their ability to predict decisions under uncertainty in a risk—return framework (Keller, Sarin & M. Weber, 1986; E.U. Weber, 1988, 1999; Sarin & M. Weber, 1993; Brachinger & M. Weber, 1997; Jia, Dyer, & Butler, 1999; Baz, et al., 1999). Whereas the utility of separating risk perception and perceived-risk attitude in risk—return models of risky choice is well established (Highhouse & Yuce, 1996; E.U. Weber & Milliman, 1997), less is known about the effect that the type and format of investment information have on people's perception of the options' riskiness[2]. In theory, format should not have any influence on investors' risk behavior[3]. But Unser (1999) found differences in judgments of the riskiness of hypothetical investment alternatives when participants were given past performance information in either charts of the historical asset prices or histograms of the historical returns. Using a wide range of content domains, Ibrekk and Morgan (1987), on the other hand, found few systematic differences between the probability estimates of participants who had received information about stochastic variables in nine different presentation formats, including pie charts, histograms, boxplots, probability densities, and cumulative probabilities plots.

Questions about the perception and proper communication of risk are also of increasing practical relevance. In Germany, for example, banks and investment houses have recently been legally mandated to inform their clients about the risk of assets they intend to buy (WpHG No. 31(2)). In particular, they are required to inform investors about the past performance of assets, as well as special (e.g., industry-specific) risks. The SEC in the U.S. has been contemplating similar regulations. In this context, there is motivation to find out how type of information and presentation format influences investors' perceptions of future risk and return, and how these perceptions influence portfolio decisions. Financial institutions differ, for example, on whether past returns are shown as discrete values, in historical sequence by year, in a bar graph, or whether such information is presented as a continuous probability density function, using appropriate distributional assumptions. Each presentation format highlights different aspects of the same past-return information (and the two formats are, in that sense, not entirely equivalent), but it is hard to argue that one format is more “appropriate” or more “honest” or “accurate” than the other in terms of informing investors about risk and returns. Choice between presentation formats needs, therefore, to be informed about empirical results about the way common investors react to different presentation formats of (essentially) equivalent information.

Our paper is organized as follows. Section 2 describes an experiment designed to answer these questions, conducted in Germany and the United States. Section 3 proposes a model of volatility forecasts and risk perceptions. Section 4 presents the results of our study regarding the perception of expected returns, expected risk, and expected volatility, as well as their effects on portfolio choice. Section 5 summarizes the insights and implications of our study.

2. Experiment

120 business students from the United States (Ohio State University) and Germany (Universität Mannheim) were asked to fill out a questionnaire that provided them with a series of judgment and decision tasks, in return for a payment of $10 in the U.S. and 15 DM in Germany. The response rate was 58% in Germany and 64% in the U.S. The data of three respondents (one German and two Americans) were removed from the study, because their responses were incomplete.

Participants were asked to imagine that they had inherited $30,000 (in Germany: 50,000 DM) from a distant relative and were committed to invest this money for one year. A deck containing sixteen cards provided information about sixteen investment alternatives (listed in Appendix A) which differed in country of origin (Germany or U.S.) and in type (bonds, stocks, index funds, etc.). The identity of the individual stocks was varied between-subjects. Crossed with this manipulation, five between-subject information conditions had information cards that provided the following information about each investment (see Appendix B for examples):

1. Condition **N :** Only the name of the investment, as shown in Appendix A.
2. Condition **R-** : The annual % returns[4] of each investment for the years 1987-97[5] as a bar chart, *without* the name of the investment.
3. Condition **R+** : The annual % returns of each investment for the years 1987-97 as a bar chart as in **R-,** *and* the name of the investment.
4. Condition **D-** : A continuous distribution[6] of annual % returns, estimated from the annual return data for the years 1987-97, *without* the name of the investment.
5. Condition **D+** : A continuous distribution of annual % returns as in **D-,** *and* the name of the investment.

Participants who were provided with the names of the available investments (conditions N, R+, D+) also got an information sheet that provided a description of the different types of assets.

Participants first made three predictions about the value that a 100 DM/$100 investment in each investment alternative would have after one year: a prediction of the median value, of a lower bound (10%-percentile) and of an upper bound (90%-percentile). They also rated (on a scale from 0 to 6) how competent they felt in making these predictions. Participants then rated the risk of each investment (on a scale from 1 (no risk) to 9 (highest risk)) by sorting the information cards representing the 16 investment options into three piles of low, intermediate, and high risk, and then further subdividing the cards in each of these three categories according to their riskiness. Finally, respondents created an investment portfolio by selecting up to five investments and indicated the relative percentage of each for their portfolio. To control for order effects, we counterbalanced the order in which the German and American investment options were presented. The questionnaire closed by asking respondents about their income bracket, prior investment experience, and knowledge about finance. They also rated their risk attitude as showing either "little", "moderate" or "great tolerance for risk".

3. Modeling Volatility Forecasts and Perceived Risk

The general structure of the regression models is shown in Figure 1 and Figure 2. They assume that investors' volatility forecasts and perception of the riskiness of an asset derive from information about the asset's historical volatility. To test the hypothesis that the format in which historical volatility information is provided influences investors' volatility forecasts and risk perception, we allowed the regression coefficient for historical volatility to differ for the two information format conditions **R** and **D**. Appropriate dummy variables also tested for an effect of having knowledge of the names of the assets and for an effect of the type of asset. Finally, one variant of the models also included investor-specific variables to control for our repeated-measures design.

[Insert Figure 1 here.]

Volatility Forecasts

Using investor i's stated median projected one-year return for each asset j ($Y^{0.5}_{ij}$), and the stated 10th and 90th percentile of possible returns ($Y^{0.1}_{ij}$ and $Y^{0.9}_{ij}$), we calculated an estimate of respondents' volatility forecasts (the projected standard deviation of one-year returns) by using the three-point approximation of Pearson and Tukey (see Keefer and Bodily (1983)):

$$\mathrm{Vol(point)}_{ij} = \sqrt{\left(0.3\cdot\left(Y^{0.1}_{ij}/100\right)^2 + 0.4\cdot\left(Y^{0.5}_{ij}/100\right)^2 + 0.3\cdot\left(Y^{0.9}_{ij}/100\right)^2\right) - \left(\mathrm{mean}_{ij}\right)^2} \qquad (1)$$

with $\mathrm{mean}_{ij} = 0.3\cdot Y^{0.1}_{ij}/100 + 0.4\cdot Y^{0.5}_{ij}/100 + 0.3\cdot Y^{0.9}_{ij}/100\,.$ (2)

Historical volatility of asset *j* was computed as follows. Assuming lognormal stock prices and using the historical data of the years 1987-97, we estimated the parameters μ and σ of the lognormal distribution and used them to compute the volatility and mean of the historical asset returns for a one-year horizon (t=1)[7]:

$$\mathrm{Vol(hist)}_j = \sqrt{e^{2\cdot\mu\cdot t}\cdot\left(e^{\sigma^2\cdot t}-1\right)} \qquad \text{with} \qquad \mathrm{Mean(hist)}_j = e^{\mu\cdot t}. \tag{3}$$

Model V1 regresses investors' volatility forecasts on each asset's historical volatility, allowing for an information-format specific effect, and on dummy variables for different types of assets:

$$\mathrm{Vol(point)}_{ij} = \mathrm{const.} + \mathrm{Vol(hist)}_j \cdot \left(\beta + d(R)_i \cdot \beta(R) + d(D)_i \cdot \beta(D)\right) + \sum_{k\in K}\alpha(k)\cdot d(k)_{ij} + \varepsilon_{ij} \tag{4}$$

Parameters β, $\beta(R)$ and $\beta(D)$ describe the influence of historical volatility Vol(hist) on investors' volatility forecasts. $d(R)_i$ and $d(D)_i$ are dummy variables that indicate the format in which historical volatility information had been provided (as a continuous **D**istribution or as a bar graph of annual **R**eturns):

$$d(R)_i = \begin{cases} 0 \\ 1 \end{cases} \text{if information condition} = \begin{matrix} \text{N, D- or D+} \\ \text{R- or R+} \end{matrix} \tag{5}$$

$$d(D)_i = \begin{cases} 0 \\ 1 \end{cases} \text{if information condition} = \begin{matrix} \text{N, R- or R+} \\ \text{D- or D+} \end{matrix} \tag{6}$$

Dummy variables $d(k)_{ij}$ characterize asset-specific characteristics, as shown in Appendix C. The $\alpha(k)$ are asset type specific regression coefficients, and the ε_{ij} are the residuals.

Model V2 regresses volatility forecasts on historical volatility, again allowing for information-format effects, but also includes an investor-specific parameter, δ_i, to control for the fact that the volatility forecasts in our repeated-measures design are not independent:

$$\mathrm{Vol(point)}_{ij} = \mathrm{Vol(hist)}_j \cdot \left(\beta + d(R)_i \cdot \beta(R) + d(D)_i \cdot \beta(D)\right) + \delta_i + \varepsilon_{ij} \tag{7}$$

To see whether knowledge of the name or type of investment asset—in addition to historical volatility information—affects investors' volatility forecasts, we analyzed whether the investor-specific parameters, δ_i, differed for participants who were provided with the names (and thus the types) of the assets and those that were not. Residuals ε_{ij} were analyzed for asset-type specific effects.

[Insert Figure 2 here.]

Risk Perception

The models of investors' judgments of the riskiness of each investment, shown in Figure 2, were modeled in essentially the same way as volatility forecasts, with the following differences. We used the logarithm of the historical volatilities as predictors, as those provided a better fit. Because of this, the parameters β(R) and β(D) of Model R1 are now additive constants:

$$\mathrm{RP}_{ij} = \mathrm{const.} + \ln(100 \cdot \mathrm{Vol(hist)}_j) \cdot \beta + d(R)_i \cdot \beta(R) + d(D)_i \cdot \beta(D) + \sum_{k \in K} \alpha(k) \cdot d(k)_{ij} + \varepsilon_{ij} \quad (8)$$

Model R2 again uses a two-step analysis, with the first step controlling for the repeated-measures design by adding an investor-specific personal parameter, δ_i, to the regression:

$$\mathrm{RP}_{ij} = \ln\left(100 \cdot \mathrm{Vol(hist)}_j\right) \cdot \beta + \delta_i + \varepsilon_{ij} \quad (9)$$

The second step analyzes these personal parameters for any effects of the format and type of information about the assets. In contrast to model V2, we tested for the format-specific effect of information here by comparing the investor-specific parameters, since we did not use the proportional parameters β(R) and β(D) in this logarithmic model. Finally, we again analyzed the residuals for asset-type specific effects.

4. Results

Order Effects

The order in which American and German assets were presented did not affect any of the respondents' judgments in either country.

Perception of Expected Returns

In classical risk-value models, expected return is typically modeled as the expected value of returns, based on past performance of the asset. Our data allowed us to test this assumption. In particular, we investigated whether investors' expectations of return were equal to the expected value of historical returns and whether they were influenced (a) by the format in which information about historical returns was provided and (b) by having information about the name and type of available assets, above and beyond their historical returns.

Investors' expectations of asset returns (per dollar or DM invested) were estimated as $\text{mean}_{ij} = 0.3 \cdot Y_{ij}^{0.1} / 100 + 0.4 \cdot Y_{ij}^{0.5} / 100 + 0.3 \cdot Y_{ij}^{0.9} / 100$. To compare investors' expectations of asset returns to the expected value based on historical returns, we used the following logarithmic measure[8]:

$$\text{Mean(bias)}_{ij} = \ln\left(\frac{\text{mean}_{ij}}{\text{Mean(hist)}_j} \right) \tag{10}$$

and calculated an average mean bias for each investor, *i*:

$$\overline{\text{Mean}}\text{(bias)}_i = \frac{1}{16} \sum_{j=1}^{16} \text{Mean(bias)}_{ij} \tag{11}$$

The term "bias" in this context is used simply used a label for systematic deviations of future expected returns from past historic returns. No other connotation (e.g, of "irrationality") is intended, as it may well be rational under certain circumstances for (individual) expectations about the future to differ from historic levels. As shown in Table 1, expectations about asset returns closely resembled historical expected values, i.e., biases were close to zero. Kruskal-Wallis tests for the German (p=0.416) and the U.S. data (p=0.266) showed that there was no significant information-format effect on investors' mean bias in the perception of the expected returns. Knowledge of the asset names introduced only a few asset-specific effects, i.e., mean biases that were different from 0 at the .05 level of significance. In particular, the returns of stocks of lesser-known companies were underestimated relative to historical returns (German data: Henninger Bräu, -11.1%; Krom Schröder, -11.6%; Bethlehem Steel, -9.8%; US data: Henninger Bräu, -19.1%; Krom Schröder, -4.8%) and those of better-known or more frequently discussed companies were overestimated (German data: Bayer, +7.53%; US data: Boeing, +5.33%). In both data sets, average returns of stock index funds were overestimated by 2%-4% and returns of German bonds were underestimated by 2%-3%.

[Insert Table 1 here.]

Volatility Forecasts

Model V1—German Data. As shown in Appendix D, model V1 predicted the volatility forecasts of German investors quite well, accounting for 53.6% of the total variance. Volatility forecasts had a non-zero (5%) intercept and a regression coefficient for historical volatility of less than one. Given that historical volatility is undoubtedly an imperfect predictor of future volatility, investors seem to have appropriately regressed their predictions towards the mean, as shown in Figure 3. The format in which historical volatility information had been provided strongly affected investors' volatility forecasts, with respondents in the **D-**conditions (with a density distribution of 1 year return data) forecasting additional volatility compared to the grand mean ($\beta(D)=0.20$, $p=0.000$) and respondents in the **R-**conditions (with a bar graph of annual return data plotted for each year in order) forecasting less volatility ($\beta(R)= -0.15$, $p=0.000$). There were several asset-specific effects. The volatility forecasts of foreign bonds was lower than those of other assets (after controlling for their historical volatility) (α(US-bonds)=-0.07, $p=0.000$), probably due to an underestimate of exchange rate risk, which is the main part of the risk of foreign bonds. Consistent with this interpretation, the dummy variable for U.S. bonds was significantly lower than that for German bonds. There was some evidence of a home bias (Kilka & M. Weber, 1997). While the volatility forecasts of foreign index funds were not different from those of other assets, the volatility of the domestic stock index fund was estimated to be lower (α(GER-stocks)=-0.05, $p=0.001$). Finally, forecasts of the volatility of investments on credit were lower than those of other assets (α(investment on credit)=-0.10, $p=0.000$).

[Insert Figure 3 here.]

Model V1—U.S. Data. Model V1 accounted for 27.4% of the total variance of the volatility forecasts of the American investors. Volatility forecasts again had a non-zero (12%) intercept and a regression coefficient for historical volatility of less than one ($\beta=0.44$, $p=0.000$), showing even stronger evidence of regression towards the mean. Just as in the German data, investors in the **D-**conditions tended to forecast greater volatility than investors who had seen the same historical return information in the **R**-condition format ($\beta(D)=0.16$, $p=0.003$; ($\beta(R)=-0.11$, $p=0.046$). Volatility of both German and U.S. bonds was estimated as lower than that of other assets, after controlling for historical volatility.

Model V2—German Data. Similar to the results for Model V1, presenting historical asset volatility as a density distribution resulted in significantly higher volatility forecasts than presentation of the same historical returns in an annual return bar chart. The β coefficient was less than one ($\beta=0.459$, $p=0.000$) and $\beta(D)$ was significantly greater than zero ($\beta(D)=0.297$, $p=0.000$), while $\beta(R)$ was not. To examine the effect of knowing the names of the assets on volatility forecasts, we compared the δ_i of investors who were provided with the names of the assets (conditions D+, R+ and N) with those of investors who were not (conditions D- and R-). For the former group (n=43), δ_i averaged 0.03; for the latter group (n=26), the average δ_i was 0.07, a difference that was nearly significant on a 5%-level ($p=0.054$) by a Mann-Whitney test. Knowing the name of the assets decreased investors' estimates of future volatility. Analysis of the residuals ε_{ij} for asset-specific effects confirmed the results of model V1. Forecasts of the volatility of bonds (and especially foreign bonds) was judged to be lower than that of other assets (α(US-bonds)=-0.04, $p=0.000$). There was again evidence of a home bias, with U.S. stock indices receiving significantly greater volatility forecasts (α(US-stocks)=0.054; $p=0.000$). Forecasts of the volatility of investments on credit were also again lower (α(investment on credit)=-0.061, $p=0.000$).

Model V2—U.S. Data. Just as for the German data, presenting historical asset volatility as a density distribution resulted in higher volatility forecasts than presentation of the same historical returns in an annual return bar graph. β was less than one ($\beta=0.40$, $p=0.000$) and $\beta(D)$ was greater than zero ($\beta(D)=0.20$, $p=0.002$), while $\beta(R)$ was not. Comparing the personal constants for investors who were or were not provided with the names of the investments, we again found a slightly smaller average δ_i for the first group (0.10) than for the second group (0.11), though the difference was not significant ($p=0.276$). Examination of the asset-specific effects showed that estimates of the volatility of both German and U.S. bonds were lower than that of other assets (α(GER-bonds)=-0.027, $p=0.024$ and α(US-bonds)=-0.035, $p=0.003$).

Visual Summary. To illustrate the information condition effects on volatility forecasts described in this section, we standardized investors' volatility forecasts in the same way we standardized their return expectations, i.e., by dividing forecasts by historical levels[9]:

$$\mathrm{Vol(bias)}_{ij} = \ln\left(\frac{\mathrm{Vol(point)}_{ij}}{\mathrm{Vol(hist)}_{j}}\right), \tag{12}$$

and calculating an average volatility bias $\mathrm{Vol(bias)}_{ij}$ for each investor:

$$\overline{\mathrm{Vol}}\mathrm{(bias)}_{i} = \frac{1}{16}\sum_{j=1}^{16}\mathrm{Vol(bias)}_{ij}\ . \tag{13}$$

Figure 4 plots average volatility bias as a function of information condition for German and American respondents. The left panel shows that German investors tended to provide future volatility estimates that were significantly lower than historical volatility. Volatility forecasts differed as a function of the information condition. The median volatility bias for respondents who were just provided with the name and type-description of the sixteen assets (condition N) was -.65, i.e., investors provided volatility forecasts that were smaller than historic volatility. The median bias was -.34 for participants who received only the bar graph of historical returns over the past ten years, without knowing the name or type of the underlying assets (condition R-). The median bias (i.e., underestimation) was even larger (-.71) when these two types of information were combined (condition R+). Participants who were provided with only historic volatility information as a density distribution (condition D-), on the other hand, gave volatility forecasts that were larger than historic volatility, i.e., had a median bias of +.09. Knowing also the name and type of the assets (condition D+) again resulted in lower volatility forecasts, for a median bias of -.24. In general, volatility forecasts were greater when historic volatility information came in the form of a density function, which focuses attention on extreme outcomes which are visually more prominent in this presentation format. That is, investors in the D-condition may have paid too much attention to possible extreme values, while ignoring their low probability of occurrence. A Kruskal-Wallis test rejected the null-hypothesis that the forecast biases under the five information-conditions were equal ($p=0.006$). In a Mann-Whitney U test, differences between pairs of conditions were significant for N/D- ($p=0.006$), R-/D- ($p=0.008$), R+/D- ($p=0.001$) and R+/D+ ($p=0.049$).

[Insert Figure 4 here.]

The right panel of Figure 4 shows the average volatility forecast biases of American investors, which differed from those of German investors in absolute, but not relative, terms. American investors tended to overestimate volatility forecasts across all 16 investment assets, perhaps because the historical volatility in the United States from 1987 to 1997 was lower than volatility in Germany. When comparing forecast bias in the five information conditions, we find similar results as for the German data. Again the R conditions lead to a lower perception of volatility than the D conditions. R+ and N again lead to the most negative bias (medians of -.19 and -.15) and condition D- to the most positive bias (median of +.22). A Kruskal-Wallis test of differences between conditions was again significant (p=0.013). A Mann-Whitney U-test showed that differences between pairs of conditions were significant for R-/R+ (p=0.050), R-/D- (p=0.009), R+/D- (p=0.000) and R+/D+ (p=0.044).

Risk Perception

<u>Model R1—German Data.</u> Model R1 accounted for 68.8% of the variance in the judgments of perceived riskiness of investment assets by German respondents. As shown in Appendix E, most of the predictor variables were significant[10]. Estimated model parameters were reasonable, with a constant of -3.15 and a β of 2.67, for example, predicting that an investment with a historical volatility of 4.73% would be classified as having "no risk" (PR=1). The maximum risk category ("highest risk", PR=9) would be reached with a historical volatility of 94.67%. The historical volatilities calculated in Deutschmark in our study range from 5.73% to 55.24%, which correspond to risk ratings of PR=1.51 and PR=7.56. Just as for the volatility forecasts, there was a significant tendency to rate asset risks higher in the D-conditions that provided investors with estimated density functions of historic returns (β(D)=0.332, p=0.007). Different from the volatility forecasts, there was a weaker but significant tendency to also rate assets higher in risk in the R-conditions, where historical returns of the years 1987 to 1997 were provided as a bar graph (β(R)=0.287, p=0.025), relative to the N-condition. Examination of the asset-specific effects confirmed our hypothesis that exchange rate risk were underestimated, as the risk of American bonds was rated significantly lower than that of other assets (α(US-bonds)=-1.192, p=0.000), again controlling for historical volatility. There also was evidence of a home bias in risk perceptions. The risk of German stocks was judged to be significantly lower than that of other assets (α(GER-stocks)=-0.891, p=0.000), while the risk of U.S. stocks was not

significantly different. Just as for the volatility forecasts, there was a tendency to underestimate diversification effects, by judging the risks of mixed portfolios to be higher than that of other assets ((α(portfolios)=0.454 p=0.001).

Model R1—U.S. Data. Model R1 accounted for 52.3% of the variance of the risk judgments of American respondents. Model parameters (a constant of -2.88 and a β of 2.80) were such that the lowest historical volatility calculated in U.S. dollar of 5.41% corresponded to a perceived risk of PR=1.84 and the highest volatility of 54.98% to PR=8.34. Perceived risk did not differ significantly as a function of information condition. The risk of U.S. bonds was judged to be lower than that of other assets (α(US-bonds)=-0.568, p=0.009), while the risk of German bonds was not significantly different, probably because of the extraordinary low historical volatility of the German bonds calculated in U.S. dollar. While not significant, there was a trend in the direction of a home bias for stocks. The risk of mixed portfolios was again significantly larger than average (α(portfolios)=0.639, p=0.000).

Model R2—German Data. Model R2, designed to control for the repeated-measures design of our study, yielded essentially the same results as model R1. Figure 5 provides the mean of investors' personal parameters, δ_i, in the five information conditions. Participants who knew the names of the assets (conditions N, R+ and D+) perceived less risk (i.e., had more negative δ_i's) than participants who only had statistical information about the historical returns (conditions R- and D-) (Mann-Whitney U test: p=0.026). Especially the group that had *only* the name of the assets (condition N) perceived asset risks to be low. Furthermore, risk perceptions were higher for participants who were provided only with the estimated density functions (condition D-) than for participants who were provided only with the historical returns bar graph (conditions R-). Analysis of the residuals ε_{ij} (in conditions N, R+ and D+) for asset-specific effects showed the same effects as model R1: risk perception was lower for U.S. bonds (α(US-bonds)=-0.832, p=0.000) and German stocks (α(GER-stocks)=-0.524, p=0.000), and higher for portfolios (α(portfolios)=0.457, p=0.000).

Model R2—U.S. Data. The results of model R2 again confirmed those of model R1. Knowing assets names resulted in lower perceptions of risk, just as in the German data. While an omnibus Kruskal-Wallis test of differences between information conditions was not significant (p=0.396), investors in conditions that informed them of asset names had marginally more negative personal constants δ_i than investors in the other conditions (Mann-Whitney U test: p=0.068). The asset-specific results described above were also confirmed (α(US-bonds)=-0.482, p=0.014; (α(portfolios)=0.568, p=0.003).

[Insert Figure 5 here.]

Summary of Perceptions of Future Return, Volatility, and Risk

While investors' perception of expected returns were not affected by information conditions, type and format of information clearly influenced their perceptions of future volatility and asset risk. Providing historical return information in the form of an estimated density function rather than as a bar graph of annual returns led to greater estimates of volatility and risk, consistent with the results of Ibrekk and Morgan (1987). Knowledge of the name and type of assets, on the other hand, led to lower estimates of volatility and risk. Differences in the format in which historical volatility information was provided had a larger impact on volatility forecasts than risk perception, whereas knowledge of name and thus type of assets had a larger effect on risk perception.

Our results regarding the effects of information format on volatility forecasts and risk are consistent with Raghubir and Das' (1999, p. 64f) hypothesis that "decision makers may be prone (...) to initial anchoring. Decision makers sample from an information distribution; the points that are most perceptually salient (such as the end-points of the distribution) are the most likely to be selected as initial anchors in the decision process." The density distributions of the D-conditions of our experiment made extreme values far more salient than the bar graphs of the R-conditions, resulting in greater estimates of asset risk and especially volatility.

The home bias hypothesis (Kilka & M. Weber, 1997) predicts that volatility and risk of foreign assets should be judged to be higher than that of domestic assets. This prediction was confirmed only for stocks. For bonds, we found the opposite results for German investors, who provided lower estimates of the risk and volatility of U.S. bonds than German bonds, probably because exchange rate risk (which is the major risk of foreign bonds) was underestimated. We did not find this result in the U.S. data, probably because of the amazingly low historical volatility of German bonds (calculated in U.S. dollar). In both countries, we found clear evidence that investors underestimated the risk-reducing effect of diversification. A dummy variable that tested for such an effect (encoding international portfolios and bond/stock-portfolios) was positive for the regressions of volatility forecasts and significantly positive for those of risk perceptions.

Raghubir and Das (1999, p. 62) demand that models of information processing ought to "include the stages of perception of existing information, retrieval of information from memory, and integration of multiple sources of information." Our experimental manipulations and models described above successfully separated and integrated *perceptual* biases resulting from the format in which statistical information about historical returns (existing information) was provided and *memory* biases that were driven by knowledge of asset names and types (which allowed the use of information from memory).

Information format and prior knowledge about asset types affected volatility forecasts and risk perceptions in similar but not identical ways. The correlation between volatility forecasts and perceived risk was .57 ($p<0.0001$) for the German data and .45 ($p<0.0001$) for the U.S. data, confirming that volatility forecasts and perceived risk are related but not identical constructs.

Explaining Asset Choices

To examine the effect of investors' expectations about asset risk, volatility, and return on their portfolio decisions, we compared the ability of six variants of a risk-return model to predict asset choices. For each investor, we tested investor's belief about the risks and returns of the 16 available assets as a function of their decision to select or *not* to select the assets for their portfolio. Belief about risk was operationalized in one of three ways as: (a) assets' historical volatility, (b) the investor's volatility forecast, or (c) the investor's perceived risk judgment. Belief about return was operationalized in one of two ways as: (a) historical expected return, or (b) the investor's return expectation (see Table 2).

[Insert Table 2 here.]

Comparing the fit of risk—return models that differed in their operationalization of risk, we found that the models that used either historical volatility or investors' forecast of future volatility did not predict observed asset choices nearly as well as the models that used investors' judgments of perceived risk. This result confirms previous demonstrations of the fact that variance-based risk measures as used, for example, in the Markowitz (1952) model, are worse than subjective risk assessments in describing portfolio decisions (E.U. Weber, 1997, 1999; E.U. Weber & Hsee, 1998)[11].

These results are confirmed and visually illustrated by comparing the residuals of models V2 and R2 (that controlled for historical volatility and information format effects) for assets in two groups: residuals of assets that *had* been chosen by the investor *versus* residuals of assets that had *not* been chosen. Figure 6 shows the median residuals of model V2 (i.e., of the regression of investors' volatility forecasts) for both chosen and non-chosen assets. These residual show that volatility forecasts are *not* a good predictor of asset choice in either the German data (left panel) or the U.S. data (right panel). For both groups, the residuals indicate that the judged volatility of chosen assets was, in fact, *higher* than the judged volatility of non-chosen assets, which would suggest a dubious asset-selection rule.

[Insert Figure 6 here.]

The story is different for the relationship between investors' perceptions of asset risk and asset selection. Figure 7 shows the median residuals of model R2 (i.e., of the regression of investors' asset risk judgments) for both chosen and non-chosen assets. These residual show that risk perception *is* related to asset choice in a sensible way, with the risks of chosen assets judged to be lower than the risks of non-chosen assets.

[Insert Figure 7 here.]

Even though there was relatively little bias in investors' perceptions of expected returns, as discussed earlier, perceived expected return still explained asset choices better than historical expected returns, though only significantly so for the German data. Figure 8 illustrates this in its plot of the residuals of the regression of perceived asset returns on historical returns, for both chosen and non-chosen assets. The residuals show that investors had higher return expectations for chosen assets than for non-chosen assets, consistent with the notion that they used their (biased) return expectations in their asset selection.

[Insert Figure 8 here.]

In summary, subjective perceived asset risk and subjective expectations of asset returns provided the best prediction of asset choices within a risk—value framework for investors in both countries. Given that our study identified a number of ways in which both perceptions of returns and perceptions of risk were biased in systematic ways, we can make predictions about biases in asset allocation that should be expected as a consequence. As discussed earlier, returns were expected to be higher for better-known or more frequently discussed stocks than for stocks with less name-recognition, predicting that such stocks should be more frequently selected. This prediction was confirmed in our data and is also found in real financial markets.

Risk perception, on the other hand and as discussed above, was affected by the format in which historical volatility information was provided, with asset risk judged to be greater in the D-conditions. This bias in risk perception also resulted in differences in asset allocation. In general, there were fewer differences in asset allocation between experimental conditions than in risk and volatility expectations, most likely because investors do not apply risk—value models (or even simpler, more descriptive versions) in the appropriate way. Instead, investors have been shown to engage in naive diversification (Benartzi & Thaler, 1998; Siebenmorgen & M. Weber, 2000). The results of our study also show that investors do not fully understand the effect of diversification on risk. It is also likely that investors selected assets using rules that compared relative, rather than absolute, levels of risk and return. If so, then biases in perceived risk and returns would not affect asset allocations in our study that varied type and format of asset information in a between-subject design. Future studies may want to vary the type and format of asset information in a within-subject design.

Our data suggest that asset allocation decisions were driven by risk and return expectations, rather than the other way around. While we found strong effects of type and format of asset information on risk perception and volatility forecasts, information-driven effects on asset selection were much weaker. Secondly, while volatility forecasts and risk perceptions were significantly correlated and risk perceptions and asset choices were significantly correlated, volatility forecasts and asset choices were not. If reports of perceived asset risk were the result of portfolio decisions (rather than the other way around), we should not find either of these two patterns of results.

In their own assessment of risk attitude (as showing “little”, “moderate” or “great” tolerance for risk), most respondents chose the “moderate”-option. Using a Kruskal-Wallis test, we found that differences in self-assessment of risk-attitude predicted differences in risk perception for the American investors. Investors who characterized themselves as having greater tolerance for risk tended to report lower levels of perceived risk (i.e., had lower personal constants δ_i in model R2) (p=0.006), consistent with the result that apparent differences in risk attitude are often the result of differences in risk perception, rather than attitude towards risk as it is perceived (E.U. Weber & Milliman, 1997; E.U. Weber, 2001).

Finally, there was no relationship between the number of finance courses respondents had taken at their university or their actual investment experience and their judgments and asset selections in our experiment.

5. Conclusions and Implications

Determinants of Asset Choices

The results of our study can be summarized as a mixture of "good news" and "bad news." On the positive side, investors' asset allocation decisions clearly utilized information about historical volatility and mean historical returns of assets. However, expectations of future asset returns and especially asset risk were biased in systematic ways as a function of factors that should not have had any effect (e.g., presentation format of historical returns) and failed to be influenced by factors that should have had an effect (e.g., diversification). Our results also show that perceived asset risk is not synonymous with expected volatility and that it is perceived risk, rather than expected volatility, that determines asset selection. A summary of these results is provided in Figure 9.

[Insert Figure 9 here.]

Proper Risk Perception and Risk Communication

Our results confirm the importance of the ongoing discussion about the correct measure of perceived risk mentioned in the introduction. They provide some insights about possible extensions of current models of risk to account for perceptual biases that are driven by attributes other than just the probability distribution of a single dimension (E.U. Weber, 1988, p. 201), e.g., historical returns. Our study shows that, in the financial asset domain, people's risk perceptions—among other things—show evidence of a home bias, underestimate exchange rate risks and underestimate diversification effects.

The results of our study also illustrate that legal mandates about the proper communication of asset risks need to consider not only the *type* of asset information with which financial institutions should provide potential investors, but also the *format* of any such information, e.g., historical returns. Given that nominally equivalent presentation formats lead to different impressions of asset risks, which translate into differences in investment behavior, and given that no gold standard exists to indicate a correct level of perceived risk, policy makers need to realize that decisions about the appropriate content and format of financial risk communication cannot be made in an objective or value-free fashion.

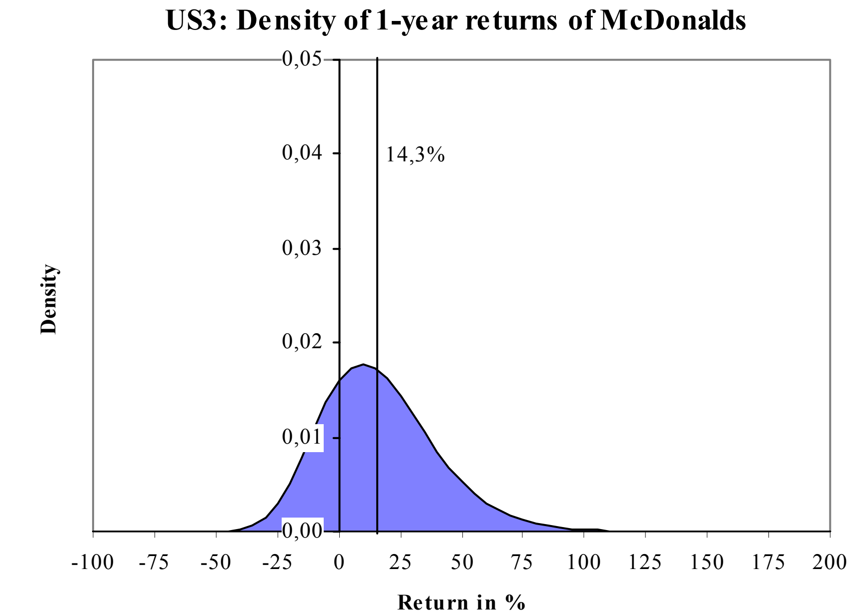
Appendix

A. Available Investments in our Study

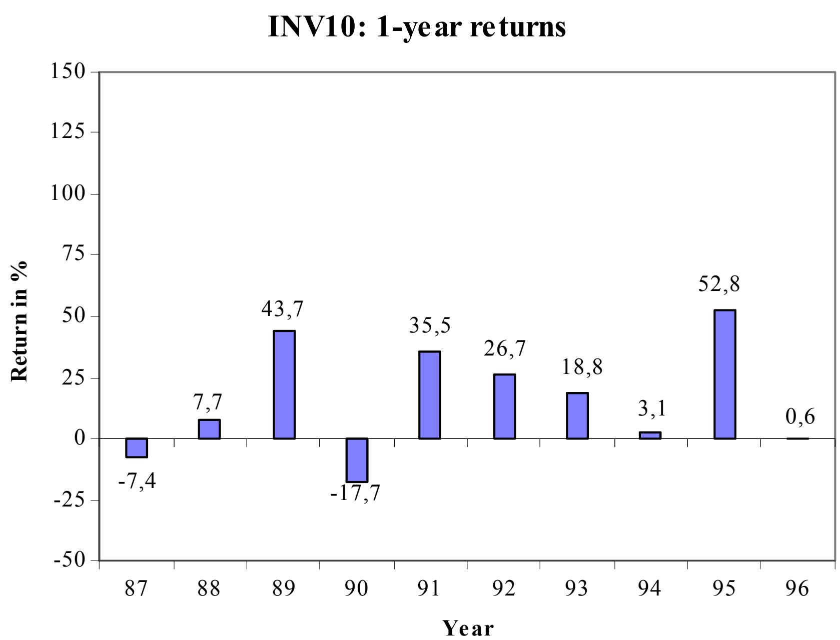
Inv. No.	condition A1	condition A2
1	German Government bonds (TTM[12] 5 years)	
2	German Government bonds (TTM 10 years)	
3	Mannesmann	Bayer
4	Henninger Bräu	Krom Schröder
5	DAX (German Stock Index)	
6	DAX on credit	
7	50/50 portfolio of DAX and German bonds	
8	U.S. Government bonds (TTM 5 years)	
9	U.S. Government bonds (TTM 10 years)	
10	McDonalds	Boeing
11	Halliburton	Bethlehem Steel
12	S&P 500 (U.S. Stock Index)	
13	S&P 500 on credit	
14	50/50 portfolio of S&P 500 and U.S. bonds	
15	50/50 portfolio of S&P 500 and DAX	
16	50/50 portfolio of German and U.S. bonds	

B. Information about Investment Returns

Example for conditions D+



Example for conditions R-



C. Definition of asset-specific dummy variables:

Investment no. / $d(k)_{ij}$	1	2	3 (A1)	3 (A2)	4 (A1)	4 (A2)	5	6	7	8	9	10 (A1)	10 (A2)	11 (A1)	11 (A2)	12	13	14	15	16
GER-bonds	1		0	0	0	0	0	0	½	0	0	0	0	0	0	0	0	0	0	½
US-bonds	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	½	0	½
GER-stocks	0	0	0	0	0	0	1	1	½	0	0	0	0	0	0	0	0	0	½	0
US-stocks	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	½	½	0
Mannesmann	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bayer	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Henninger Bräu	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Krom Schröder	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mc Donalds	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Boeing	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Halliburton	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Bethlehem Steel	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
investment on credit	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
portfolios	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	1

N.B.: The asset-specific dummy variables are only 1 or ½ if the participant j knows the name of the assets (conditions N, R+ and D+) otherwise (conditions R- and D-) the dummy variable is always 0.

D. Results of model V1

German data:

(R^2=53.6%)

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	t	Sig.
1	(Constant)	.0496	.0104	4.769	.000
	beta	.6714	.0458	14.651	.000
	beta (D)	.2000	.0352	5.683	.000
	beta (R)	-.1454	.0363	-4.010	.000
	alpha (GER-bonds)	-.0351	.0154	-2.286	.022
	alpha (US-bonds)	-.0676	.0145	-4.668	.000
	alpha (GER-stocks)	-.0538	.0163	-3.296	.001
	alpha (US-stocks)	.0207	.0165	1.251	.211
	alpha (Mannesmann)	-.1777	.0287	-6.198	.000
	alpha (Bayer)	.0458	.0279	1.642	.101
	alpha (Henninger Bräu)	-.1958	.0291	-6.720	.000
	alpha (Krom Schröder)	-.0068	.0287	-.239	.811
	alpha (McDonalds)	-.0855	.0267	-3.208	.001
	alpha (Boeing)	.0475	.0280	1.698	.090
	alpha (Halliburton)	-.0846	.0267	-3.162	.002
	alpha (Bethlehem Steel)	.0367	.0286	1.286	.199
	alpha (investment on credit)	-.1022	.0208	-4.916	.000
	alpha (portfolios)	.0152	.0123	1.232	.218

a. Dependent Variable: Vol(his)

U.S. data:

(R^2=27.4%)

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	t	Sig.
1	(Constant)	.1161	.0095	12.172	.000
	beta	.4405	.0629	7.004	.000
	beta (D)	.1639	.0543	3.021	.003
	beta (R)	-.1105	.0552	-2.001	.046
	alpha (GER-bonds)	-.0391	.0164	-2.378	.018
	alpha (US-bonds)	-.0474	.0166	-2.857	.004
	alpha (GER-stocks)	-.0075	.0186	-.401	.688
	alpha (US-stocks)	-.0175	.0189	-.926	.355
	alpha (Mannesmann)	-.0232	.0405	-.573	.567
	alpha (Bayer)	.0533	.0274	1.944	.052
	alpha (Henninger Bräu)	-.1250	.0440	-2.844	.005
	alpha (Krom Schröder)	.0068	.0297	.230	.818
	alpha (McDonalds)	.0019	.0395	.048	.962
	alpha (Boeing)	.0516	.0284	1.816	.070
	alpha (Halliburton)	.0383	.0396	.968	.333
	alpha (Bethlehem Steel)	-.0171	.0298	-.576	.565
	alpha (investment on credit)	.0225	.0219	1.025	.305
	alpha (portfolios)	.0194	.0145	1.343	.179

a. Dependent Variable: Vol(his)

E. Results of model R1

German data:

(R^2 = 68.8%)

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	t	Sig.
1	(Constant)	-3.1460	.3179	-9.897	.000
	beta	2.6692	.0938	28.462	.000
	beta (D)	.3315	.1236	2.683	.007
	beta (R)	.2865	.1274	2.248	.025
	alpha (GER-bonds)	-.2361	.1845	-1.280	.201
	alpha (US-bonds)	-1.1924	.1574	-7.576	.000
	alpha (GER-stocks)	-.8910	.1774	-5.021	.000
	alpha (US-stocks)	-.1906	.1753	-1.087	.277
	alpha (Mannesmann)	-1.4971	.3005	-4.982	.000
	alpha (Bayer)	.0693	.3078	.225	.822
	alpha (Henninger Bräu)	-.4338	.3023	-1.435	.152
	alpha (Krom Schröder)	.4731	.3074	1.539	.124
	alpha (McDonalds)	-.1365	.2871	-.475	.635
	alpha (Boeing)	.1206	.3013	.400	.689
	alpha (Halliburton)	.5682	.2950	1.926	.054
	alpha (Bethlehem Steel)	.9796	.3065	3.196	.001
	alpha (investment on credit)	-.0357	.2063	-.173	.863
	alpha (portfolios)	.4536	.1319	3.438	.001

a. Dependent Variable: RP

U.S. data:

(R^2=52.3%)

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	t	Sig.
1	(Constant)	-2.8836	.3384	-8.521	.000
	beta	2.8004	.1020	27.464	.000
	beta (D)	.1462	.1734	.843	.399
	beta (R)	.1167	.1762	.662	.508
	alpha (GER-bonds)	-.0658	.2069	-.318	.750
	alpha (US-bonds)	-.5683	.2171	-2.618	.009
	alpha (GER-stocks)	-.2287	.2338	-.978	.328
	alpha (US-stocks)	-.3195	.2341	-1.365	.173
	alpha (Mannesmann)	-1.5983	.5032	-3.176	.002
	alpha (Bayer)	-.2369	.3440	-.689	.491
	alpha (Henninger Bräu)	-1.8406	.5157	-3.569	.000
	alpha (Krom Schröder)	-.6149	.3597	-1.710	.088
	alpha (McDonalds)	.5315	.4926	1.079	.281
	alpha (Boeing)	-1.5614	.3528	-4.426	.000
	alpha (Halliburton)	.2126	.4952	.429	.668
	alpha (Bethlehem Steel)	-1.0287	.3599	-2.858	.004
	alpha (investment on credit)	-.2538	.2704	-.939	.348
	alpha (portfolios)	.6385	.1817	3.515	.000

a. Dependent Variable: RP

F. Significance of the Results

		Volatility Forecasts				**Risk Perception**			
		German data (one year)		U.S. data (one year)		German data (one year)		U.S. data (one year)	
		V1	V2	V1	V2	R1	R2	R1	R2
	constant>0	✔		✔					
	β<1	✔	✔	✔	✔				
Information-driven results	β(D)> β(R)	✔	✔	✔	✔	✓		✓	
	β(D)>0	✔	✔	✔	✔	✔		✓	
	β(R)<0	✔	✓	✔	✓	✖		✕	
	names lead to underestimation		✓ p=0.054		✓		✔		✓ p=0.068
Asset-specific results	bonds underestimated	✔	✔	✔	✔	✔	✔	✔	✓
	α(foreign bonds)< α(domestic bonds)	✔	✔	✕	✕	✔	✔	✖	✖
	α(foreign stocks)> α(domestic stocks)	✔	✔	✓	✓	✔	✔	✓	✓
	α(investments on credit)<0	✔	✔	✕	✕	✓	✓	✓	✓
	α(portfolios)>0	✓	✓	✓	✓	✔	✔	✔	✔

shadowed fields = evaluation not possible; V1/R1 = Method 1 ("ordinary" regression), V2/R2 = Method 2 (two-step regression considering the participant-specific dependency in the data); ✔ = significant result ($p<0.05$), ✓ = found but not significant, ✕ = not found, ✖= not found and opposite is significant ($p<0.05$)

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Figures and Tables

Figure 1: Modelling Volatility Forecasts

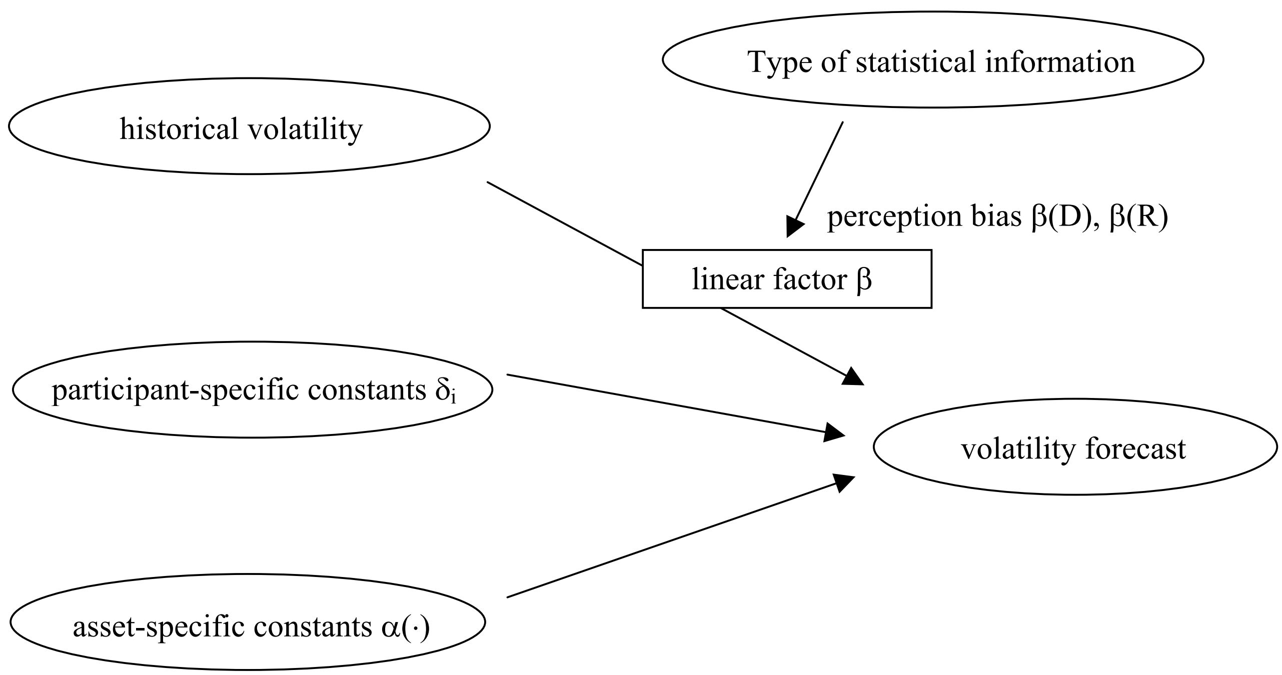


Figure 2: Modelling Risk Perception

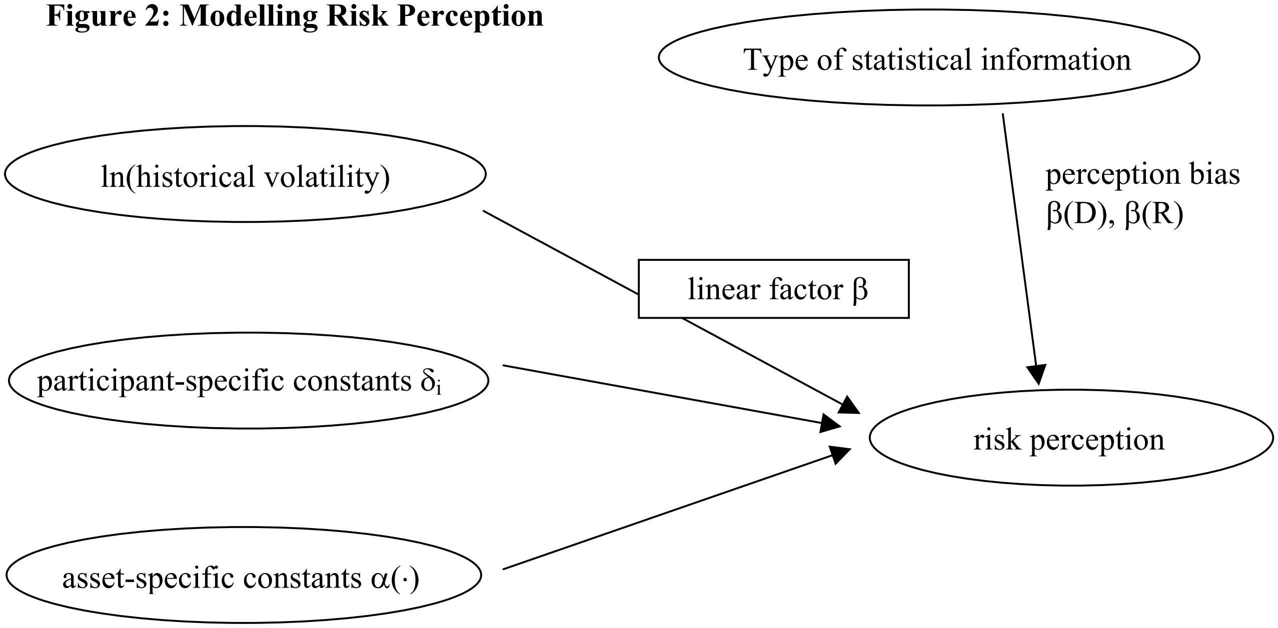


Figure 3: Historical and Perceived Volatilties

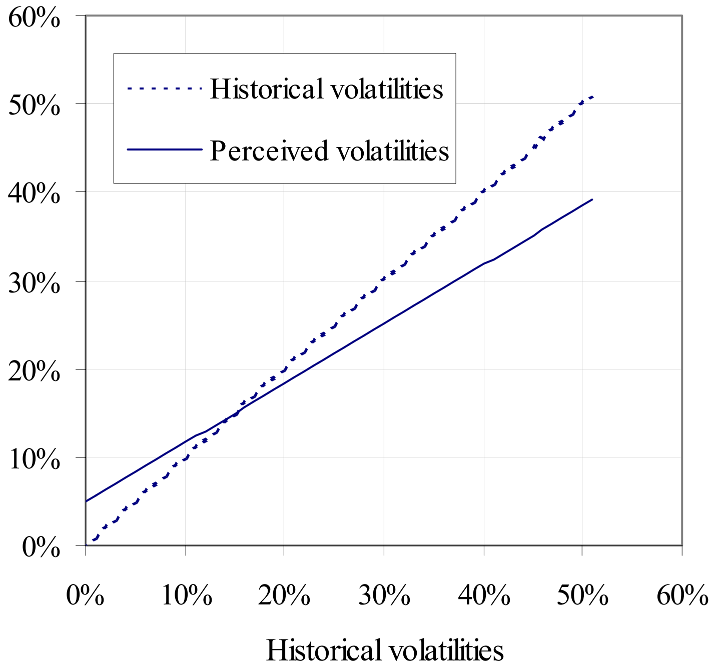


Figure 4: Volatility Forecasts

German participants American participants

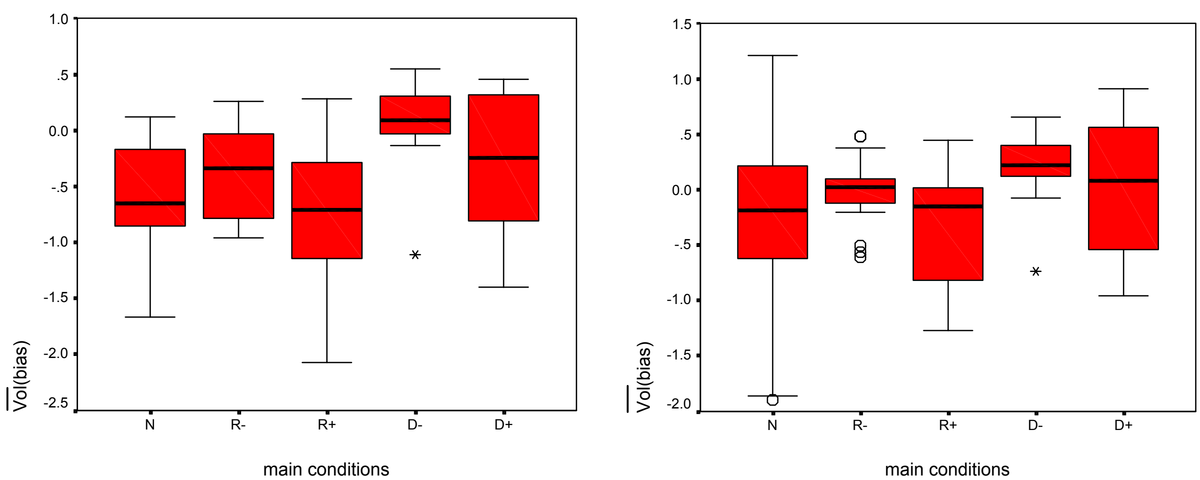


Figure 5: Risk Perception

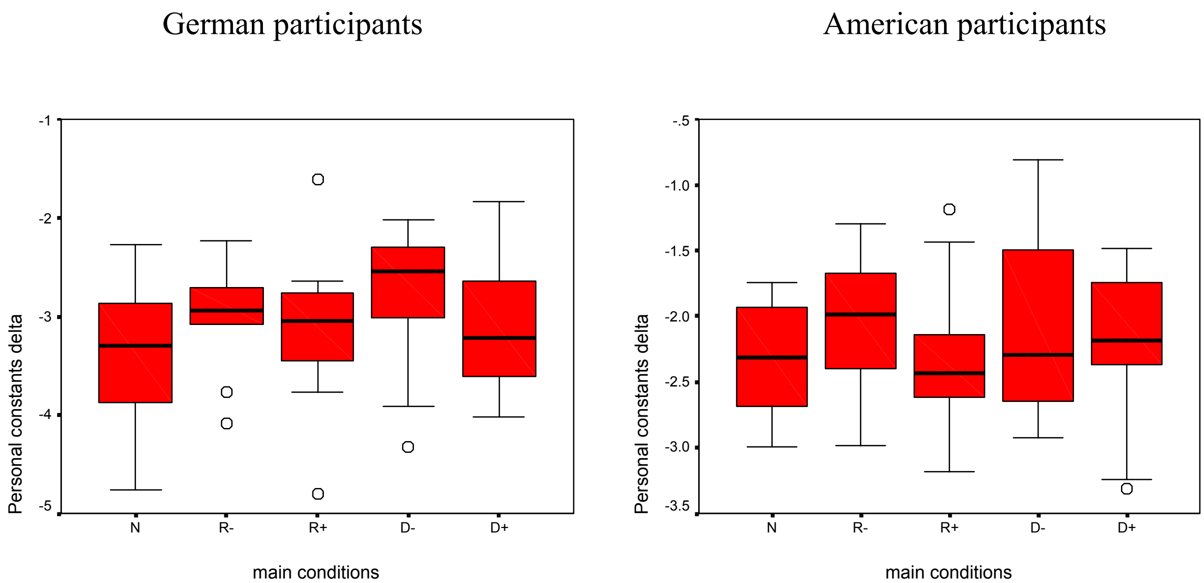
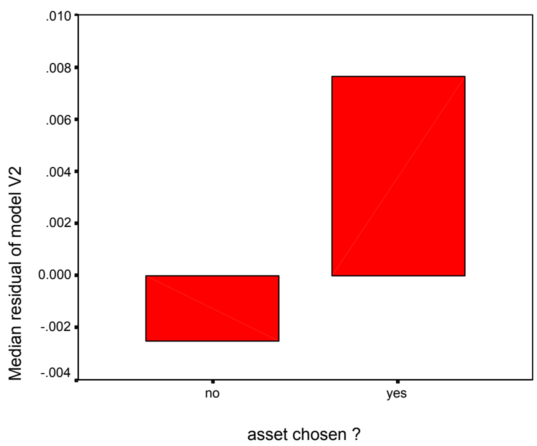
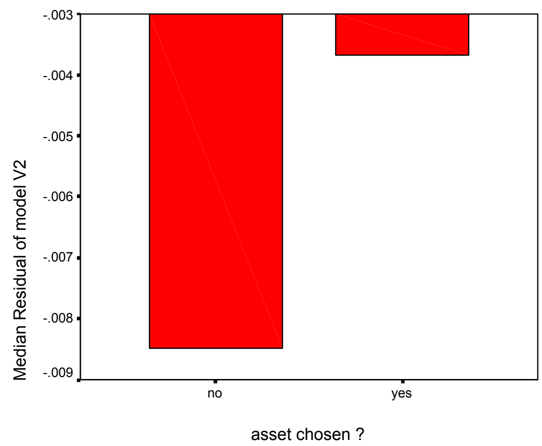


Figure 6: Effects of Biases in Volatility Forecasts on Investment Decisions

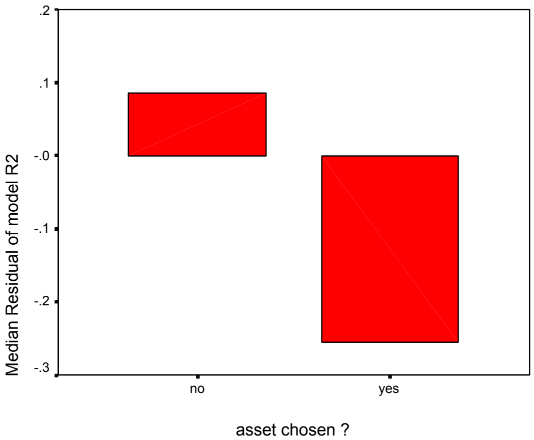


German data (Mann-Whitney U test: p=0.017)

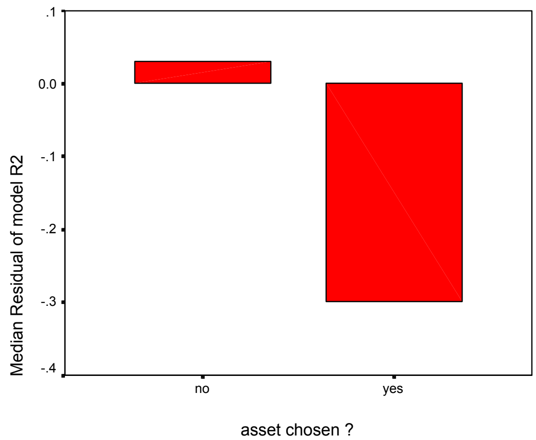


U.S. data (Mann-Whitney U test: p=0.078)

Figure 7: Effects of Biases in Risk Perception on Investment Decisions

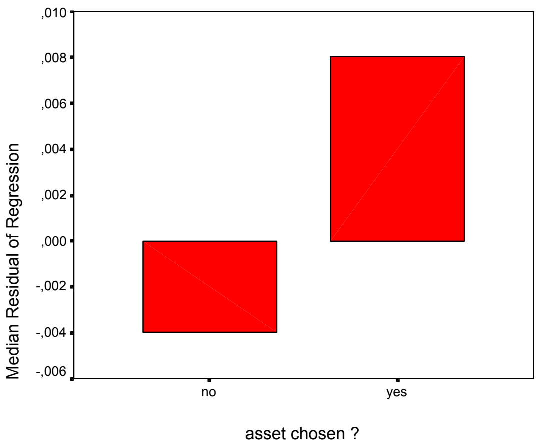


German data (Mann-Whitney U test: p=0.000)

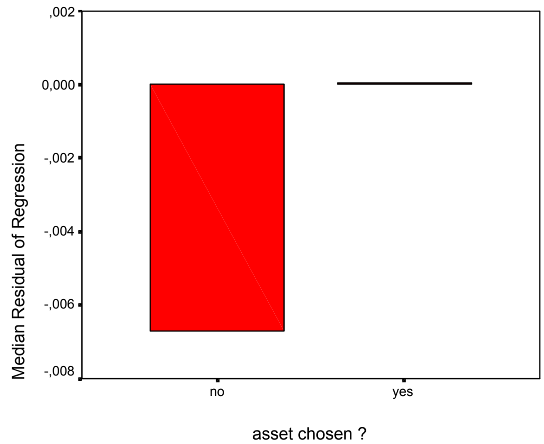


U.S. data (Mann-Whitney U test: p=0.000)

Figure 8: Effects of Biases in Return Perception on Investment Decisions



German data (Mann-Whitney U test: p=0.000)



U.S. data (Mann-Whitney U test: p=0.060)

Figure 9: Dependencies in the Investment Decision Process

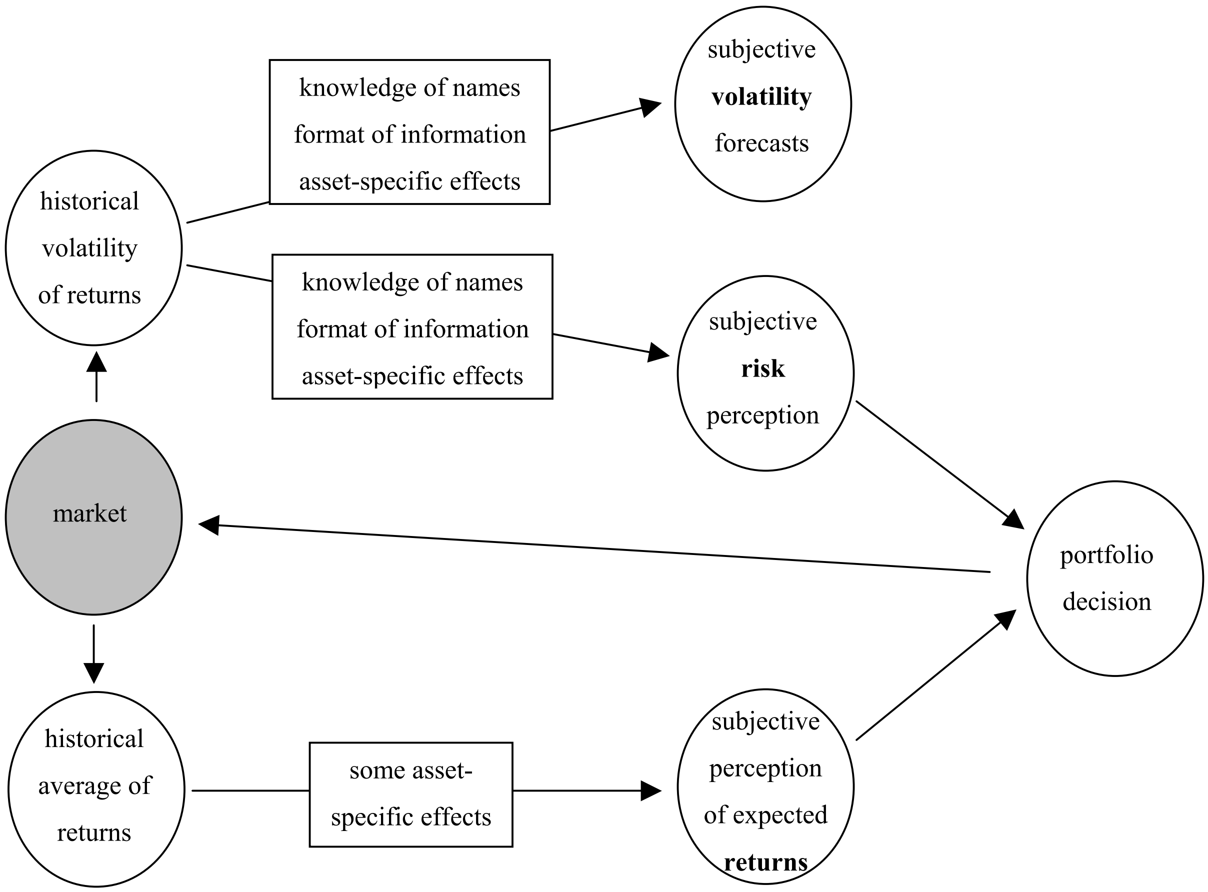


Table 1: Perception of Expected Returns

main conditions	$\text{Average}\left(\overline{\text{Mean}}(\text{bias})_j\right)$	
	German participants	U.S. participants
N	-.012	+.038
R-	-.023	+.016
R+	+.001	+.010
D-	-.023	-.008
D+	-.025	+.008

Table 2: Fit of risk-value models

	(a) historical expected return				(b) investors' return expectations			
	German data		U.S. data		German data		U.S. data	
	Z	p	Z	p	Z	p	Z	p
(a) assets' historical volatility	-2.52	0.012	-5.84	0.000	-4.04	0.000	-4.44	0.000
(b) investors' volatility forecasts	-2.31	0.021	-0.87	0.386	-3.73	0.000	-1.39	0.170
(c) investors' risk judgements	-6.69	0.000	-6.44	0.000	-6.83	0.000	-5.43	0.000

Z- and p-value result from a Mann-Whitney U test, which tests the difference between the exemplary performance measures return-1.0·volatility (first two rows) and return-0.05·risk (last row) depending on the investment decision.

Footnotes

[1] We will not consider any liquidity constraints here.

[2] Bull, Stone & Sieck (1998) examine the influence of different graphical presentations on perceived risk.

[3] In theory the type of information certainly has an impact.

[4] For the German questionnaires we used historical data calculated in Deutschmarks; for the U.S. questionnaires the data was calculated in U.S. dollars.

[5] We compared the 10-year data with 30-year data and did not find major differences.

[6] For the German questionnaires, we assumed the returns to be normal. For the American questionnaires, we assumed the returns to be lognormal.

[7] See Hull (1993), chapter 10.2

[8] We use this logarithmic measure to make sure that overestimations and underestimations are weightened equally. Alternatively we used a linear measure like $\mathrm{Mean(bias)}_{ij} = \frac{\mathrm{mean}_{ij}}{\mathrm{Mean(hist)}_i} - 1$ and we get qualitatively similar results.

[9] Again we find similar results using a linear measure.

[10] We also evaluated model R1 using an ordered probit analysis and got qualitatively similar results.

[11] Psychological literature (Wells, 1992; O. Huber, Wider & O.W. Huber, 1997; Windschitl & Wells, 1998) also describes the tendency that people do not base their decisions under uncertainty on information about probabilities.

[12] Time to maturity