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# Communicating Asset Risk: How Name Recognition and the Format of Historic Volatility Information Affect Risk Perception and Investment Decisions

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An experiment examined how the type and presentation format of information about investment options affected investors' expectations about asset risk, returns, and volatility and how these expectations related to asset choice. Respondents were provided with the names of 16 domestic and foreign investment options, with 10-year historical return information for these options, or with both. Historical returns were presented either as a bar graph of returns per year or as a continuous density distribution. Provision of asset names allowed for the investigation of the mechanisms underlying the home bias in investment choice and other asset familiarity effects. Respondents provided their expectations of future returns, volatility, and expected risk, and indicated the options they would choose to invest in. Expected returns closely resembled historical expected values. Risk and volatility perceptions both varied significantly as a function of the type and format of information, but in different ways. Expected returns and perceived risk, not predicted volatility, predicted portfolio decisions.

**KEY WORDS:** Behavioral finance; home bias; portfolio decisions; risk perception; volatility forecasts

## 1. INTRODUCTION

Investment portfolio decisions are supposed to be a function of expected return, 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.

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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). This raises the question of how investors might arrive at their expectation about the return and riskiness of assets, given the types of information typically 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, i.e., that they use historical returns to estimate future returns and their likely volatility or risk. If so, 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. If so, knowing the name of the investment becomes crucial, as it indicates the type, market, and other special characteristics of the asset. Our research approach is in line with other studies in behavioral finance. We take a normative theory as a benchmark and assess to what degree intuitive behavior deviates from that benchmark. We return to this point in the discussion section.

Questions about the perception and proper communication of asset returns and asset risks are no longer of simply academic interest, but are occupying the minds of consumer protection and regulatory agencies. In Germany, banks and investment houses have recently been legally mandated to inform clients about the risk of any asset they intend to buy (WpHG No. 31(2)). In particular, banks are required to inform investors about the past performance of the asset as well as special (e.g., industry-specific) risks. The Securities and Exchange Commission in the United States has been contemplating similar regulations. Thus there is practical motivation to find out how the type of information and its presentation format influence 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 (e.g., Fig. 1) or whether such information is presented as a continuous probability density function, using appropriate distributional assumptions (e.g., Fig. 2). Each presentation format highlights different aspects of the same past-return information (with the time-series representation showing possible trends in returns and the distributional representation putting greater focus on both average and maximum and minimum possible returns) and the two formats are not entirely equivalent. However, it is hard to argue that one format is more "appropriate," more "honest," or more "accurate" than the other in terms of informing investors about asset risk and returns. Choice between presentation formats, instead, may need to be informed by empirical results about the way common investors react to different types of information and different presentation formats.

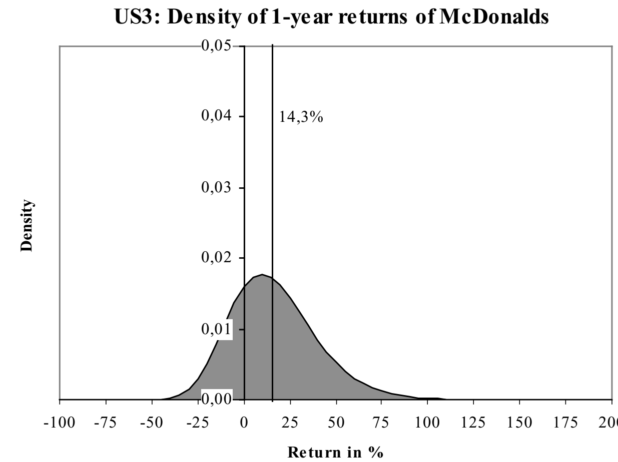


**Fig. 2.** Ten-year investment returns of an investment option in condition D+, presented as a continuous probability density function.

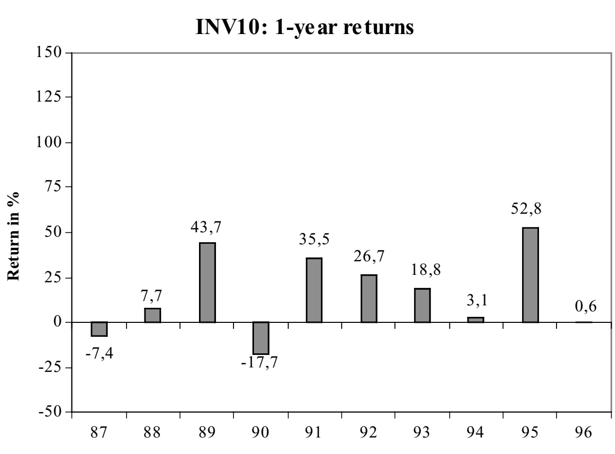


**Fig. 1.** Ten-year investment returns of an investment option in condition R−, presented in a historical time series.

In this article we therefore study the influence of past-return information and knowledge of the asset name on people's perceptions of investment options and on their asset allocation. Raghubir and Das (1999) suggest that theoretical and empirical investigations of financial investment decisions ought to examine perception of existing information, retrieval of information from memory, and integration of multiple sources of information. Our experimental manipulations allow us to separate the effect of *perceptual* biases resulting from the format in which statistical information about historical returns was provided from the effect of *memory* biases resulting from knowledge of asset names and types, as well as the interactions between these two types of effects. In a between-subject design, some investors received information about the historical performance of 16 investment alternatives, some investors were provided with the names and thus identity of these investment alternatives, and some investors received both types of information. For each type of information, we looked for normatively expected influences on asset evaluations, but also for normatively less defensible avenues of influence for which, nevertheless, some empirical evidence exists.

More specifically, for historical return information, we examined how the format in which it is provided translated into investor perceptions of future asset return, asset volatility, and asset risk. Ibrekk and Morgan (1987) looked at the effect of nine different presentation formats on people's evaluation of expected value and judgments of the probability of certain events, but did not include time-series bar graphs like those typically used for investment returns in their set of presentation formats and did not evaluate the effect of presentation format on predictions of volatility or risk. Unser (1999) found differences in judgments of the riskiness of hypothetical investment alternatives when participants were given historical return information either in tables or time-series histograms, but did not compare those to continuous probability density functions often used by financial institutions, and did not examine expected returns or expected volatility judgments.

Traditional risk-return models in finance assume that asset allocation is guided by predicted return and volatility as a measure of risk and that, therefore, predicted volatility and perceived risk should be closely related. While information format may influence the expectation of volatility and risk through its focus on different aspects of the historical return information, these effects should be similar for both risk and volatility predictions. Empirical studies of perceived risk, on the other hand, have found marked differences between the two constructs and find that choice is often poorly predicted by volatility indices but better predicted by subjective judgments of risk (Keller *et al.*, 1986; E.U. Weber, 1988, 1999; Sarin & M. Weber, 1993; Brachinger & M. Weber, 1997; Jia *et al.*, 1999; Baz *et al.*, 1999). One of the reasons that perceived risk predicts choice better than outcome volatility is that perceptions of riskiness incorporate affective reactions to outcome uncertainty, which also drive choice (Highhouse & Yüce, 1996; Holtgrave & E. U. Weber, 1993; Loewenstein *et al.*, 2001; E.U. Weber & Milliman, 1997).

Building on, but extending, previous research, we predicted that our information manipulation conditions would affect investor judgments of assets' expected return, volatility, and risk, but that the effect of both historical return presentation format and of provision of asset names would interact with the judgment task. Since the two formats in which historical return information is typically seen by investors differ mostly in their depiction of the range of possible outcomes and probably do not elicit vastly different affective reactions about the investment option, we predicted that historical returns format would affect expected volatility, but probably not expected returns or expected risk. For the provision of asset name information, on the other hand, which can be expected to result in a difference in emotional reactions to the assets, as discussed in the next paragraphs, we predicted to see strong effects on perceived risk, but weaker or no effects on expected volatility. As a result, we predicted that risk judgments and expected volatility judgments would not be highly correlated, and that risk judgments would predict asset choice better than volatility judgments.

For the provision of asset name information, we examined whether the identification of asset type (e.g., German government bond, U.S. stock index fund) influences asset evaluation. In addition to possibly normative changes in return, volatility, and risk expectations through the incorporation of knowledge about asset type or industry-specific opportunities or risks, we also looked for two irrational biases in asset evaluation and choice. The first one, the home bias, has been well documented for investment decisions (e.g., Cooper & Kaplanis, 1994) and refers to the fact that investors hold far too little of their financial portfolios in foreign investments, despite large potential gains from international diversification. Behavioral explanations for the effect hinge on the fact that the greater familiarity with domestic investments breeds greater liking (Huberman, 2001) or greater perceived competence (Kilka & M. Weber, 2000), and that these positive feelings translate into more likely investment selection. There is little work so far on the nature of the processes that map positive feelings of familiarity or competence into greater choice. French and Poterba (1991) conjectured that investors may be more optimistic about their home markets, and Shiller *et al.* (1996) found that Japanese and American investors were more optimistic about their domestic market based on forecasts of stock market indices. Risk-return models of asset choice would predict that feelings of familiarity, competence, or optimism give rise to a home-biased prediction of return or risk (or both), which, in turn, results in home-biased choice. Consistent with this hypothesis, Kilka and M. Weber (2000) found that German and American students underestimated the dispersion of the returns of domestic stocks relative to foreign stocks. Because risk judgments (due to their greater ambiguity) are more strongly influenced by emotional factors than judgments of probability or expected volatility (which are more objectively defined), we expected to find a stronger home bias for risk judgments than for volatility judgments in our study. For the same reason, we also expected a smaller home bias effect on judgments of expected returns.

The second irrational bias potentially used in asset choice as the result of providing investors with asset names is use of the recognition heuristic (Goldstein & Gigerenzer, 2002). Experimental demonstrations of the use of this heuristic, which refers to the rule of choosing the member of a pair that the decisionmaker recognizes whenever only one member elicits recognition, have not looked at investment decisions (i.e., preference tasks), but have been restricted to inference tasks (e.g., binary judgments of relative magnitudes such as the size of foreign cities). Borges *et al.* (1999) report results potentially consistent with the use of the recognition heuristic for investment decisions. They found that a portfolio of 10 stocks recognized by at least 90% of German investors performed substantively better over a six-month period in 1996 (a bull market) than a portfolio of 10 stocks not recognized by investors. This held for stocks recognized by both laypeople and by investment experts, though those results did not replicate for American laypeople or investment experts. A replication of the study in a bear market found that the recognition heuristic resulted in worse returns than random stock selection (Boyd, 2001). While there are many explanations for these results, it is possible that greater name recognition boosted demand for the stock, resulting in greater price increases in a bull market. Our study examined the possibility of a recognition bias in financial asset evaluation, analyzing whether more recognizable asset names were evaluated as providing greater returns, lower volatility, and/or lower risk.[4]

The remainder of the article is organized as follows. Section 2 describes an experiment, conducted in Germany and the United States, designed to answer the questions outlined above. Section 3 describes the nature of our analyses to assess the effects of historical return and asset name information on expected return and volatility forecasts and risk perception. Section 4 presents the results of those analyses, as well as the relationship between the three types of asset judgments and asset choice. Section 5 summarizes the insights and implications of our study.

[4] These comparisons were post hoc. We thank both of our reviewers for this suggestion.

## 2. EXPERIMENT

Our research participants were business students from the United States (Ohio State University, $n = 120$) and Germany (Universität Mannheim, $n = 120$) who were asked to respond to a series of judgment and decision tasks related to financial investing, in return for a payment of \$10 in the United States or 15 DM in Germany. Average response time was about an hour. The response rate was 58% in Germany ($n = 70$) and 64% in the United States ($n = 77$).[5] 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 investing this money for one year. Individual, large index cards provided information about each of 16 investment alternatives (listed in Table I), which differed in country of origin (Germany or the United States) and in type of investment (bonds, stocks, index funds, index funds purchased on credit, and a portfolio of stock index funds and bonds). We used respondents and investment options from the two countries to extend the generalizability of observed results, since regulatory agencies in both Germany and the United States have been considering questions that might be informed by our results. It also allowed us to investigate possible home biases in respondents' asset evaluations in a way that did not confound nationality of assets and nationality of respondents. We did not expect to find any country main effects in responses, based on previous empirical investigations of risk perception and its consequences for risky choice in the two countries (Keller *et al.*, 1986; E. U. Weber & Hsee, 1998).

For greater generalizability, we used two different sets of individual stocks from each country (indicated as conditions A1 vs. A2 in Table I). Some stocks had greater name recognition, while others were less well known. Those were assigned between-subjects. Crossed with this manipulation, five between-subject information conditions differed in the combination of information about each investment. For the different conditions, each card showed:

Condition N: Only the name of the investment, exactly as shown in Table I.

[5] Since potential research participants were registered students in classes at each university, we had some demographic information about them (gender, age, major). For at least those variables, there were no significant differences between those who chose to respond to our request for participation and those who did not.

**Table I.** Sixteen Investment Options Used in Our Study

| Investment No. | Condition A1 | Condition A2 |
|---|---|---|
| 1 | German government bonds (TTM[a] 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 | |

[a]Time to maturity.

Condition R−: The annual % returns[6] of each investment for the years 1987–1997[7] as a bar chart, *without* the name of the investment, as shown in Fig. 1.

Condition R+: The annual % returns of each investment for the years 1987–1997 as a bar chart as in R−, *and* the name of the investment.

Condition D−: A continuous distribution[8] of annual % returns, estimated from the annual return data for the years 1987–1997, *without* the name of the investment.

Condition D+: A continuous distribution of annual % returns as in D−, *and* the name of the investment, as shown in Fig. 2.

Participants in the last four conditions received a short paragraph of instructions on how to interpret the graphs of annual % returns they were provided with.

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 by sorting the information cards representing the 16 investment options into three piles, representing "low," "intermediate," and "high" risk, respectively, and then further subdividing the cards in each of these three categories into more fine-graded classes according to their riskiness, resulting in a rating of perceived riskiness on a scale from 1 (no risk) to 9 (highest risk). Finally, respondents created an investment portfolio by selecting up to five assets and indicated the desired relative percentage of those assets for their portfolio. To test for possible order effects, we counterbalanced the order in which the German and American investment options were presented.[9] 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."[10]

6 For the German questionnaires we used historical data calculated in Deutschmarks; for the U.S. questionnaires the data were calculated in U.S. dollars.

7 The study was conducted in 1998.

8 For the German questionnaires, we assumed the returns to be normal. For the American questionnaires, we assumed the returns to be log-normal.

9 An ANOVA showed that the order in which American and German investment assets were presented did not affect any of the respondents' judgments ($F(1,2,287) = 0.32$, n.s.). Thus order was not considered in any subsequent analyses. In this and subsequent analyses, we assume a 0.05 level of significance unless otherwise stated.

10 Respondents' own assessment of risk attitude as showing "little," "moderate," or "great" tolerance for risk (with most respondents choosing the "moderate" option) was associated with differences in risk perception. Investors who characterized themselves as having greater tolerance for risk tended to report lower levels of perceived risk, consistent with the result that apparent differences in risk attitude are often the result of differences in risk perception, rather than attitude toward risk as it is perceived (E.U. Weber & Milliman, 1997; E.U. Weber, 2001). None of the other variables were associated with any of the response measures and thus will not be mentioned any further below.

## 3. MODELING AND PREDICTING ASSET EVALUATION

### 3.1. Expected Returns

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

We estimated investor *i*'s prediction of asset *j*'s expected return from the investor's stated median projected one-year return for asset $j$ ($Y_{ij}^{0.5}$) and the stated 10th and 90th percentile of possible returns ($Y_{ij}^{0.1}$ and $Y_{ij}^{0.9}$):

$$\text{Return(pred)}_{ij} = \text{mean}_{ij} = 0.3 \cdot Y_{ij}{}^{0.1} + 0.4 \cdot Y_{ij}{}^{0.5} + 0.3 \cdot Y_{ij}{}^{0.9}. \qquad (1)$$

To compare investors' expectations of asset returns to the expected value based on historical returns, we also used the following logarithmic measure:[11]

$$\text{Mean(bias)}_{ij} = \ln\left(\frac{\text{mean}_{ij}}{\text{Mean(hist)}_j}\right) \qquad (2)$$

and calculated an average mean bias[12] for each investor, $i$,

$$\overline{\text{Mean}}\text{(bias)}_i = \frac{1}{16}\sum_{j=1}^{16} \text{Mean(bias)}_{ij}. \qquad (3)$$

To compute historical return and historic volatility of assets, we assumed log-normal stock prices. We then used the historical data for the years 1987–1997 to estimate the parameters $\mu$ and $\sigma$ of the log-normal distribution and used them to compute the volatility and mean of the asset returns for a one-year horizon ($t = 1$):[13]

$$\text{Vol(hist)}_j = \sqrt{e^{2\cdot\mu\cdot t} \cdot (e^{\sigma^2\cdot t} - 1)} \quad \text{and}$$
$$\text{Return(hist)}_j = e^{\mu\cdot t}. \qquad (4)$$

### 3.2. Expected Volatility

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

$$\text{Vol(pred)}_{ij} = \sqrt{\begin{aligned}&\left(0.3 \cdot \left(Y_{ij}{}^{0.1}/100\right)^2 + 0.4 \cdot \left(Y_{ij}{}^{0.5}/100\right)^2\right.\\ &\left.+ 0.3 \cdot \left(Y_{ij}{}^{0.9}/100\right)^2\right) - (\text{mean}_{ij})^2\end{aligned}} \qquad (5)$$

with $\text{mean}_{ij}$ as defined in Equation (1).

### 3.3. Predicting Expected Returns, Expected Volatility, and Perceived Risk

Regression analyses were used to assess the following effects on respondents' estimates of the expected return, volatility, and risk, respectively, of the 16 assets: (1) historical returns (mean and volatility, respectively), (2) graphic presentation format of the asset's historical returns, (3) knowledge of the name of the asset, (4) the interaction of presentation format and knowledge of asset name, (5) asset-specific expectations as a function of asset type (bond, stock, portfolio, purchased on credit, domestic or foreign investment, stock with familiar vs. unfamiliar name), and (6) the nationality of respondents.

Our repeated-measures design (with each respondent assessing all 16 investment options) and the nested relationship of predictor variables violates the independence assumptions of traditional regression

11 We use this logarithmic measure to make sure that overestimations and underestimations are weighted equally. An alternative linear measure like $\text{Mean(bias)}_{ij} = \frac{\text{mean}_{ij}}{\text{Mean(hist)}_i} - 1$ resulted in qualitatively similar results.

12 The term "bias" in this context is used simply as 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.

13 See Hull (1993, ch. 10.2).

methods (Osborne, 2000). We therefore employed hierarchical linear modeling (HLM) instead (Bryk & Raudenbush, 1992). In an HLM analysis, the relationship between the dependent measure of interest and one or more predictors is initially evaluated for the units at the lowest level of the nested design (in our case, each respondent's judgment for each of the 16 investment options). Regression coefficients are estimated separately for each unit as a function of predictor variables at the next level of the design, resulting in a vector (rather than a point estimate) for each regression coefficient. Those vectors of coefficients are then, themselves, predicted by a regression equation that relates the coefficients to variables at the higher level. The advantage of this procedure is that it results in an error term that takes into account the lack of independence between observations at the lowest level. Iterative maximum-likelihood rather than ordinary-least-squares estimation is used to estimate the coefficients in the model.

The software package used for the analyses was HLM 5 by Raudenbush *et al.* (2000). Level-1 analyses regressed the predictions of respondents $i$ for assets $j$ on the corresponding historical variable and on dummy variables that coded for asset characteristics. For the dependent measure of predicted asset volatility, for example, the Level-1 regression equation looked as follows:

$$\begin{aligned}\mathrm{Vol(pred)}_{ijk} = {} & \mathrm{const}_k + \beta_k \mathrm{Vol(hist)}_j \\ & + \alpha 1_k \mathrm{d(bond)}_j + \alpha 2_k \mathrm{d(stock)}_j \\ & + \alpha 3_k \mathrm{d(portfolio)}_j + \alpha 4_k \mathrm{d(credit)}_j \\ & + \alpha 5_k \mathrm{d(homebias)}_j \\ & + \alpha 6_k \mathrm{d(familiarity)}_j + \varepsilon_{ijk}. \end{aligned} \tag{6}$$

The same equation was used to predict the dependent measure perceived risk. The regression equation that predicted expected asset return was identical to Equation (6) except for the fact that it substituted *historical return* as a predictor for *historical volatility*. Dependent measures and Level-1 intercept and regression coefficients are subscripted by $k$, where $k$ denotes different groups (respondents from the United States vs. Germany, and respondents who were in different information conditions).

In Level-2 analyses, the vectors of regression coefficients from the Level-1 analysis become the dependent measures that are being predicted from Level-2 variables. For our Level-2 analyses, we used nationality of the respondents as a predictor variable for all regression coefficients of the Level-1 analyses to test for country differences on any of these variables. We also added four contrasts as predictors of the Level-1 regression coefficient for historical return (when predicting expected return) or historical volatility (when predicting expected volatility or perceived risk). Contrasts C1 to C3 applied to only the last four information presentation conditions and coded for presentation of historical returns in either the D or the R format (C1), for the additional identification of the asset by name or not (C2), and for the interaction between the two (C3). Contrast 4 applied only to information conditions N, R+, and R− and coded whether assets were described by name alone or by name and historical returns. Level-2 analyses thus had the form,

$$\alpha 1_k = \gamma_0 + \gamma_n \mathrm{d(nationality)} + \varepsilon_k,$$

for the intercept, $\mathrm{const}_{k,}$, and for regression coefficients $\alpha 1_k$ to $\alpha 6$, and

$$\begin{aligned}\beta_k = {} & \gamma_0 + \gamma_n \mathrm{d(nationality)} + \gamma_1 \mathrm{C1} + \gamma_2 \mathrm{C2} \\ & + \gamma_3 \mathrm{C3} + \gamma_4 \mathrm{C4} + \varepsilon_k. \end{aligned} \tag{7}$$

Hierarchical linear modeling provides accurate levels of significance for the nested and repeated-measures effects that are being tested. One drawback of HLM is the fact that the approach has no equivalent for the $R^2$ measure in OLS regression, which provides an index of the variance in the dependent measure accounted for by the predictor variables in the model. In the results section below, we report the significance levels of the appropriate HLM analyses. For relative comparison purposes only, we also report the value of $R^2$ from the corresponding single-level OLS regression analyses of the same predictor variables.

## 4. RESULTS

### 4.1. Expected Returns

Expectations about asset returns closely resembled historical expected values, i.e., mean biases as defined in Equation (3) were small in all information presentation conditions (N: 0.014, R+: 0.006, D+: −0.008, R−: −0.0.15, D−: −0.015). Historical returns were an extremely strong predictor of expected returns ($t(139) = 15.1$, $p < 0.0001$), with a slope that was not significantly different from one and an intercept not significantly different from zero.[14] The provision of asset names was the only manipulation that

[14] $R^2$ of the regression equation including all predictors was 0.16.

affected expected returns, with significantly greater return expectations as a function of historical returns when the assets' names were provided (C2: $t(2{,}279) = 3.96$, $p < 0.001$). There was no significant effect of the historical information format (C1) and contrasts C3 and C4 were also not significant. Knowledge of the asset names introduced only one asset-specific effect, namely, the underestimation of the return of bonds relative to their historical returns ($t(142) = -4.17$, $p < 0.001$). Familiarity of stock names did not influence expected returns ($t(138) = -0.88$, n.s.), and there was no home bias ($t(138) = -0.62$, n.s.). Finally, there was an effect of nationality of respondents on the slope relating historical returns to expected returns ($t(2{,}279) = -5.47$, $p < 0.0001$) in the direction that German respondents were less optimistic about expected returns than American respondents by having a significantly lower slope relating past returns to expected returns ($\beta_{\text{German}} = 0.94$ vs. $\beta_{\text{US}} = 1.15$).

### 4.2. Expected Volatility

Historical volatility was a strong predictor of expected volatility ($t(139) = 14.7$, $p < 0.0001$), with a slope that was significantly lower than one and an intercept significantly greater than zero ($t(139) = 13.02$, $p < 0.0001$).[15] With historical volatility being an imperfect predictor of future volatility, respondents were appropriately regressing their predictions of future volatility toward the mean. The slope relating historical to predicted volatility differed significantly as a function of nationality. Consistent with the results on expected return, Germans were again more pessimistic than American respondents, predicting greater future asset volatility as a function of historical volatility ($\beta_{\text{German}} = 0.60$ vs. $\beta_{\text{US}} = 0.54$, $t(2{,}279) = 1.98$, $p < 0.05$). The format in which historical volatility information was provided strongly affected volatility forecasts (C1: $t(2{,}279) = -5.99$, $p < 0.0001$), with respondents in the D− conditions predicting greater volatility based on historical volatility ($\beta_{\text{D}} = 0.77$) than respondents in the R− conditions ($\beta_{\text{R}} = 0.42$). Provision of assets names did not affect predicted volatility as a main effect (C2: $t(2{,}279) = -1.61$, $p > 0.10$), but interacted with historical return information format (C3: $t(2{,}279) = 2.22$, $p < 0.05$). Predicted volatility was greater for assets identified by name when historical information was provided as a density distribution, but smaller when historical information was provided as a bar graph, suggesting that the provision of the asset name amplified the tendency to see greater or less volatility induced by the historical information presentation format.

Knowledge of the asset names introduced several asset-specific effects. Respondents underestimated the volatility of bonds relative to their historical returns ($t(138) = -8.98$, $p < 0.0001$), and overestimated the volatility of portfolios ($t(138) = 2.48$, $p < 0.05$). They underestimated the volatility of stocks relative to their historical returns ($t(138) = -4.73$, $p < .0001$), an effect that was more pronounced for German than for American respondents ($t(138) = 3.45$, $p < 0.0005$). There was marginally significant evidence of a home bias ($t(138) = -1.69$, $p < 0.10$), which was stronger for German respondents than for American respondents ($t(2{,}279) = -1.97$, $p < 0.05$). Familiarity with stock names did not influence expected volatility ($t(138) = 0.20$, n.s.).

### 4.3. Risk Perception

Historical volatility was also a strong predictor of perceived riskiness ($t(139) = 26.3$, $p < 0.0001$).[16] The regression intercept of 0.77 and slope coefficient $\beta$ of 12.30 predicted that the investment asset with the lowest historical volatility of 5.41% would be classified as having almost no risk (PR = 1.43). The investment option with the highest historical volatility of 54.98% was predicted to be classified as close to the maximum risk (PR = 7.43). Both intercept and the slope relating historical to predicted volatility differed significantly as a function of nationality. The risk judgments of German investors were less sensitive to historical volatility, in the sense of having a smaller regression coefficient for historical volatility ($\beta_{\text{German}} = 11.20$ vs. $\beta_{\text{US}} = 13.42$, $t(138) = -2.88$, $p < 0.005$), though a larger intercept ($\text{const}_{\text{German}} = 0.93$ vs. $\text{const}_{\text{US}} = 0.54$, $t(2{,}279) = 3.91$, $p < 0.001$). Perceived risk did not differ significantly as a function of information condition (C1: $t(2{,}279) = -0.18$, n.s.), but differed significantly as a function of providing asset names. The slope relating risk judgments to historical volatility was significantly lower when the asset name was provided in addition to return information (C2: $t(2{,}279) = -2.86$, $p < 0.005$) and when only the asset name was known (C4: $t(2{,}279) = -2.22$, $p < 0.05$). Both of these effects resulted in reduced perceptions of risk for most assets when their names were known.

Knowledge of the asset names introduced some asset-specific effects. Respondents judged assets

[15] $R^2$ of the regression equation including all predictors was 0.41.

[16] $R^2$ of the regression equation including all predictors was 0.54.

known to be bonds to have lower risk ($t(138) = -1.99$, $p < 0.05$), an effect that was significantly stronger for German than for American respondents ($t(2{,}279) = -4.40$, $p < 0.0001$). Their stereotypes of the relative risks of portfolios of multiple assets went contrary to conventional financial wisdom, with assets known to be portfolios being judged as more risky ($t(138) = 2.37$, $p < 0.02$). There was evidence of a home bias in judgments of asset riskiness ($t(138) = -4.73$, $p < 0.0001$), with a stronger home bias for German than for American respondents ($t(2{,}279) = -2.07$, $p < 0.05$). Finally, more familiar stocks were judged to have lower risk than less familiar stocks ($t(138) = -2.23$, $p < 0.03$).

### 4.4. Judgments of Competence

We also analyzed investors' judgments of the competence they felt in making their asset return predictions. Competence judgments were the only response measure that showed a systematic gender effect, with female respondents reporting feeling less competent ($F(1{,}327) = 5.39$, $p < 0.05$). Judgments of competence were not affected by the format in which historical information was provided (C1), nor by the provision of a name in addition to historical return information (C2), or their interaction (C3). When asset name information was the only type of information respondents received, judged competence for making these judgments was significantly lower (C4: $F(1, 327) = 4.75$, $p < 0.05$). Consistent with the results of Kilka and M. Weber (2000), there was evidence of a connection between perceived competence and home bias, in that respondents felt greater competence when evaluating assets from their home country than foreign assets ($F(1{,}327) = 15.22$, $p < 0.0001$). Asset name familiarity also affected perceived competence, with respondents feeling more competent when evaluating stocks with more familiar names than with less familiar names ($F(1{,}327) = 11.47$, $p < 0.001$).

### 4.5. Summary

Investors' expectations of asset returns were closely related to historical expected values and were not affected by the format in which historical return information was provided. Not unreasonably, the slope relating historical expected value to expected return was somewhat smaller than one when the asset name was not known, reflecting greater uncertainty and thus a more regressive judgment. However, the average slope coefficient did not differ significantly from one, suggesting that the use of expected values as a measure of return in behavioral risk-return models seems quite justified.

As predicted, judgments of the riskiness of assets were only moderately related to expected asset volatility ($r(146) = 0.53$, $p < 0.001$). Both asset evaluations were influenced by historical asset volatility, but the format in which historical returns were provided and knowledge of asset names and thus about asset types influenced volatility forecasts and risk perceptions in different ways. Providing historical return information in the form of a smoothed probability density function rather than as a time series of annual returns in the form of a bar graph led to greater estimates of future volatility, but no significant increase in perceived riskiness. Knowledge of the asset name, on the other hand, reduced judgments of asset riskiness but had no significant main effect on estimates of future volatility.

Consistent with the risk-as-feelings hypothesis by Hsee and Weber (1997) and Loewenstein *et al.* (2001), perceptions of asset risk were more strongly influenced by manipulations known to influence respondents' emotional reactions, whereas judgments of future asset volatility were more strongly influenced by variables known to influence respondents' cognitive reactions. The probability density distribution format of historical returns made extreme asset returns far more salient than the time-series bar graphs, a cognitive (perceptual salience) manipulation that resulted in greater estimates of future asset volatility. The provision of asset names, on the other hand, allowed respondents to experience the positive emotion of feeling in control, which gave rise to both a home bias and a familiarity or "recognition" bias. Support for the assumption that asset name information resulted in such increased feelings of control comes from the fact that respondents reported feeling more competent to predict asset returns for domestic assets and for more familiar assets. Those feelings of control or increased competence, however, mostly affected judgments of asset riskiness, which showed strong evidence of home bias and asset name familiarity, and affected expectations of asset return or asset volatility only in a much reduced fashion (and mostly for German respondents). These results are summarized in Table II.

Knowledge of asset names also resulted in some asset-type effects. Knowing that an asset was a bond resulted in lower judgments of expected return, expected volatility, and risk than seeing historical return information for this asset alone. Respondents did not appreciate the potentially risk-reducing effect of

**Table II.** Summary of Effects Observed for the Study's Five Dependent Measures

| Dependent Measure | Format of Historical Return | Provision of Asset Name | Home Bias | Familiarity |
|---|---|---|---|---|
| Expected return | | * | | |
| Expected volatility | * | | | |
| Perceived riskiness | | * | * | * |
| Competence | | * | * | * |
| Asset choice | | * | * | * |

diversification and, instead, provided greater judgments of expected volatility and risk when provided with the information that the asset was a portfolio of either domestic or international stocks and bonds.

### 4.6. Explaining Asset Choices

Investors were required to allocate their investment stake to a minimum of one and a maximum of five investment options. On average, investors distributed their investment among 3.9 options, allocating between 2% and 100% of their stake to a chosen option, with a mean of about 25%. To examine the effect of investors' expectations about asset return, volatility, and risk on their asset allocation decisions, we compared the ability of different variants of a risk-return model to predict asset choices. Across investors, we examined whether beliefs about the risks and returns of the 16 available investment options predicted the percentages of investment each investor allocated. Belief about return was operationalized as the investor's expectation of asset return as defined in Equation (1). Belief about risk was operationalized in two ways, either as the investor's expectation of asset volatility as defined in Equation (5) or as the investor's perceived risk judgment.

Comparing the fit of the first two risk-return models in Table III, which differed in their operationalization of belief about asset risk, we find that the model that used investors' forecast of future asset volatility did not predict observed asset allocation decisions nearly as well as the model that used investors' judgments of perceived asset risk. While neither model accounts for a large percentage of the variance in asset choice,[17] the model using perceived risk rather

**Table III.** Fit of Risk-Value Models Predicting Percentage of Asset Allocation

| Predictors | Regression Coefficient | $p$-Value | $R^2$ of Regression |
|---|---|---|---|
| Intercept | −0.48 | n.s. | 0.006 |
| Return (predicted) | 6.84 | 0.001 | |
| Volatility (predicted) | −4.96 | 0.004 | |
| Intercept | 3.13 | n.s. | 0.03 |
| Return (predicted) | 6.46 | 0.001 | |
| Risk (predicted) | −0.85 | 0.0001 | |
| Intercept | 2.00 | 0.03 | 0.05 |
| Home bias | 2.73 | 0.02 | |
| Name familiarity | 3.83 | 0.001 | |
| Intercept | −14.42 | 0.0001 | 0.12 |
| Return (predicted) | 17.08 | 0.0001 | |
| Volatility (predicted) | −7.33 | 0.01 | |
| Home bias | 2.35 | 0.03 | |
| Name familiarity | 2.21 | 0.05 | |
| Intercept | −2.05 | ns | 0.15 |
| Return (predicted) | 11.39 | 0.0001 | |
| Risk (predicted) | −1.14 | 0.0002 | |
| Home bias | 2.30 | 0.03 | |
| Name familiarity | 1.45 | n.s. | |

than expected volatility as a predictor accounts for five times as much variance, confirming 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).

This result is confirmed and visually illustrated by comparing the residuals of the models discussed above (which predicted expected return, volatility, and risk, respectively, from historical return information and their presentation format and from asset name information) for assets in two categories: residuals of assets that *were* chosen by the investor versus residuals of assets that were *not* chosen. Fig. 3, which depicts the median value of the residuals of those regressions separately for chosen and nonchosen assets, shows that chosen assets had larger predicted returns than nonchosen assets (top panel), reflecting sensible allocation. The middle panel of Fig. 3, on the other hand, suggests that expected asset volatility is *not* a good predictor of asset choice, since the residuals indicate that the expected volatility of chosen assets was, in fact, *higher* than the expected volatility of nonchosen assets, which would suggest a dubious asset-selection rule. Instead, as shown in the bottom panel of Fig. 3, investors' perceptions of asset risk were a good predictor of asset selection. The residuals

17 Investors are known not to make their allocation decisions based on risk-value models (or even simpler, more descriptive versions), but to use simpler heuristics instead as, for example, naive diversification (Benartzi & Thaler, 1998; Siebenmorgen & M. Weber, 2000).

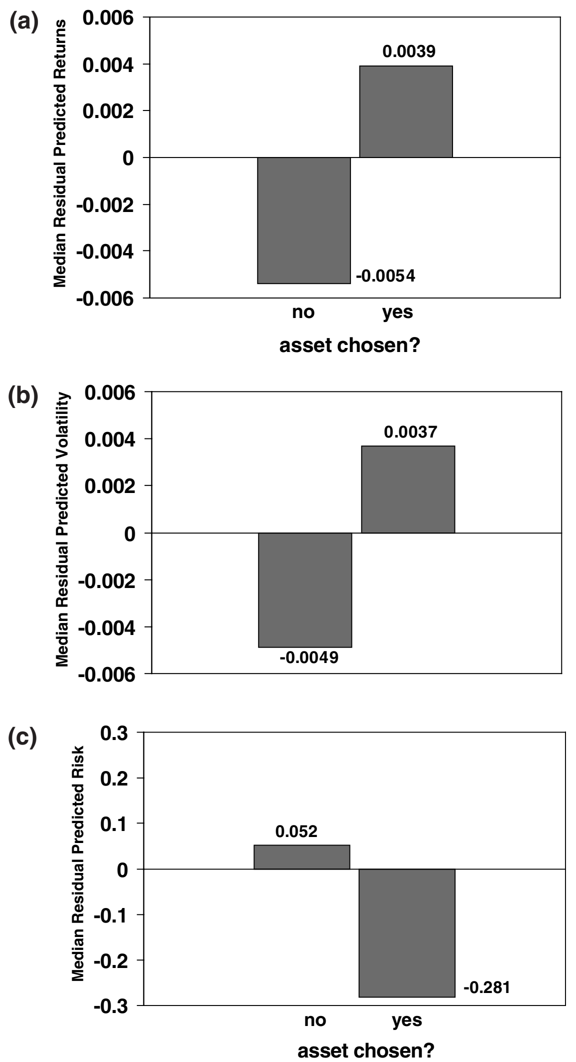


**Fig. 3.** Median residuals of regression models predicting (a) expected return, (b) expected volatility, and (c) risk as a function of historical returns, asset names, and information format, separately for assets that *were* chosen by investors and assets that were *not* chosen by investors.

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 nonchosen assets.

As discussed in the introduction, investors may make asset allocation decisions using criteria other than asset risks and returns. We examined whether the respondents in our study showed any evidence of either home bias or of the recognition heuristic in their asset allocations. The third-row panel of Table III shows that this was indeed the case. Investors allocated more funds to domestic versus foreign assets ($t(2{,}285) = 2.57$, $p < 0.02$) and to stocks that had greater name recognition ($t(2285) = 3.57$, $p < 0.001$). In combination, those two predictors alone accounted for a larger proportion of the asset allocation variance than either of the two risk-return models.

Evidence of a home bias and a name familiarity effect for asset allocation provides a possible explanation for the better fit of risk-return models that use subjective perceptions of asset risk than models that use expectations of asset volatility. As discussed above, investors' perception of asset risk showed a home bias effect (with domestic assets judged to be less risky) and were also influenced by asset name familiarity (with more familiar assets judged to be less risky), suggesting that subjective risk judgments may (partly or completely) mediate the effect of asset nationality and familiarity on allocation decisions. The two regression analyses reported in the fourth- and fifth-row panel of Table III provide a test for this mediation hypothesis. Since expected volatility showed only weak evidence of a home bias and no evidence of a familiarity effect, we predicted that the two dummy variables coding for a domestic asset and an asset with a more familiar name would continue to be significant predictors of asset allocation when added to the risk-return model using expected volatility as an operationalization of risk. Consistent with our prediction, both home bias and name familiarity continued to predict asset allocation when expected asset return and volatility were in the regression equation. The proportion of variance accounted for increased from 0.006 to 0.12 as the result of including these predictors. In contrast, when the domestic asset and familiar asset predictors were added to the regression equation containing expected asset return and predicted asset risk, asset name familiarity no longer predicted asset allocation ($t(2{,}283) = 1.31$, $p > 0.20$), though the home bias predictor did ($t(2{,}283) = 2.22$, $p < 0.03$). The fact that an asset was domestic rather than foreign influenced asset allocation above and beyond the effect that it already had on investors' perceptions of asset risk. The effect of asset name familiarity on allocation decisions, on the other hand, was completely mediated by the effect of that variable on perceived asset riskiness.

## 5. CONCLUSIONS AND IMPLICATIONS

### 5.1. Determinants of Asset Choices

Before going into the discussion of our results, it is useful to review our research approach (or the research approach of behavioral finance in general).

Financial theory as taught in basically all business schools worldwide gives some clear normative predictions of how subjects should behave in experiments like ours (and, of course, in real-life situations similar to those addressed by a study). A key concept of finance is the concept of efficient markets, i.e., the assumption that all available information is correctly incorporated into the price of an asset (e.g., Fama, 1970). As a result, investors' knowledge or opinions about an asset should not matter, since nobody can outperform the market. Knowing more about Dell than about other companies is no normative reason to buy Dell (unless it is insider information). Knowing more about U.S. stocks than about German stocks is no normative reason to buy U.S. stocks. Whether peoples' intuitive judgments and observed behavior agree or disagree with this clear normative benchmark was the topic of our study.

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 utilized information about historical volatility and historical mean returns of assets. On the negative side, asset allocation was also influenced by nonnormative factors, in particular a strong home bias and asset name familiarity. Respondents reported a greater feeling of competence when evaluating domestic and familiar assets, which translated into a lower estimate of asset risk. In the case of asset name familiarity, its effect of perceived riskiness completely accounted for its effect on asset selection. In the case of home bias there was an additional effect on asset allocation, i.e., domestic assets were more likely selected above and beyond the home bias effect already included in investors' judgments of risk.

### 5.2. 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 both cognitive and affective biases. Our study shows that, in the financial asset domain, people's risk perceptions—among other things—show evidence of a home bias and underestimate diversification effects.

The results of our study suggest that legal mandates about the proper communication of asset risks need to consider more than just the *format* of historical return information. While nominally equivalent presentation formats of historical asset returns had significant effects on expected asset volatility, they had a smaller and nonsignificant effect on judgments of asset risk, which in turn were better predictors of asset allocation than expected volatility. Other factors, such as the familiarity of asset names, on the other hand, had strong effects on investors' perceptions of risk (making it lower) and of return (making it higher), thus providing a mechanism for the hypothesis implicit in Borges *et al.* (1999) that asset name recognition can lead to greater choice. While asset selection based on familiarity or asset name recognition may feel good to investors, it is definitely not a recipe for successful investing (Boyd, 2001). Consumer protection efforts may want to consider ways to alert investors to the potential pitfalls of such investment rules.

#### *5.2.1. Nationality of Respondents*

As expected, we found little evidence of national differences in asset evaluation or asset choice. While there were small differences in the strengths of relationships in various parts of our model relating information type and information format to different types of asset evaluation and to asset allocation decisions, the overall pattern of results was remarkably similar for American and German respondents. Both were influenced by rational and irrational factors in their asset evaluations and choices, including strong evidence of a home bias, which, of course, referred to preferential evaluation of choice of different assets by German and by American investors, eliminating stock- or asset-specific explanations for such preferential treatment.

#### *5.2.2. Future Studies*

None of our models of asset allocation accounted for a large proportion of the variance. It is possible 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.

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