

# The Role of Experience Sampling and Graphical Displays on One's Investment Risk Appetite

Christine Kaufmann

Lehrstuhl für Bankbetriebslehre, Universität Mannheim, 68131 Mannheim, Germany,  
kaufmann@bank.bwl.uni-mannheim.de

Martin Weber

Lehrstuhl für Bankbetriebslehre, Universität Mannheim, 68131 Germany; and Centre for Economic Policy Research,  
London EC1V 3PZ, United Kingdom, weber@bank.bwl.uni-mannheim.de

Emily Haisley

Barclays PLC, London E14 5HP, United Kingdom, emily.haisley@barclays.com

Financial professionals have a great deal of discretion concerning how to relay information about the risk of financial products to their clients. This paper introduces a new risk tool to communicate the risk of investment products, and it examines how different risk-presentation modes influence risk-taking behavior and investors' recall ability of the risk-return profile of financial products. We analyze four different ways of communicating risk: (i) numerical descriptions, (ii) experience sampling, (iii) graphical displays, and (iv) a combination of these formats in the "risk tool." Participants receive information about a risky and a risk-free fund and make an allocation between the two in an experimental investment portfolio. We find that risky allocations are elevated in both the risk tool and experience sampling conditions. Greater risky allocations in the risk tool condition are associated with decreased risk perception, increased confidence in the risky fund, and a lower estimation of the probability of a loss. In addition to these favorable perceptions of the risky fund, participants in the risk tool condition are more accurate on recall questions regarding the expected return and the probability of a loss. We find no evidence of greater dissatisfaction with returns in these conditions, and we observe a willingness to take on similar levels of risk in subsequent allocations.

*Key words:* risk taking; asset allocation; risk perception; experience-description gap; presentation format

*History:* Received July 15, 2010; accepted June 11, 2012, by Teck Ho, behavioral economics. Published online in *Articles in Advance* December 10, 2012.

## 1. Introduction

One of the most important financial decisions is how much risk to bear in one's investment portfolio. The behavioral finance literature shows that people find it extremely difficult to build portfolios that match their preferences and can be easily influenced by irrelevant features of the decision-making environment. Regulatory agencies often focus on how the complexity of these decisions can leave people unprepared for the risk they take on, but underparticipation in the stock market is a risk as well. According to standard models of portfolio choice or lifetime consumption, households should invest at least a small fraction of their wealth into the stock market as soon as they start saving (e.g., Samuelson 1969, Merton 1969, Arrow 1971). In the United States, however, only 56% of the population directly participate in the stock market, and this figure is only 36% in the Netherlands, 23% in Great Britain and

Northern Ireland, and 6% in Germany (DAI 2011).<sup>1</sup> There are several findings in the literature explaining the nonparticipation, among them education, wealth, and participation costs due to the decision complexity (e.g., Haliassos and Michaelides 2003, van Rooij et al. 2011). Aside from nonparticipation, those households who participate often only invest a small fraction of their wealth (e.g., Ameriks and Zeldes 2004, Gomes and Michaelides 2005, Campbell 2006).

To assist with these important decisions, financial professionals should provide clients with tools that better explain risk-return profiles of investment opportunities. Such tools should result in stable decisions and increase the subjective understanding of the potential decision consequences associated with the risk-return profile of the chosen portfolio. In this

<sup>1</sup> The participation rate increases a little when mutual funds are included; participation rates are, however, still low.

paper, we introduce a new “risk tool” to communicate the risk-return profile of (risky) assets in investment decisions. Our tool is based on important insights in decision analysis that decisions from description tend to differ from decisions from experience. We show that the tool is feasible and leads to more risk seeking, accompanied by a higher recall ability and subjective comprehension of the underlying risk-return profile and a stronger commitment to the decision made. We conducted five experiments and consistently found that participants increase their allocation to the risky fund (opposed to a risk-free alternative) by 5 to 15 percentage points when risk is presented with the help of the risk tool compared with an ordinary description.

The manner in which people acquire knowledge about risk of investment products may affect how palatable they find it and may influence the risk they are willing to accept. The decision-making literature distinguishes between two fundamentally distinct ways in which people learn about risk: *description* versus *experience* (e.g., Hertwig et al. 2004). Decisions from *description* are based on explicitly stated probabilities associated with outcomes. Decisions from *experience* are based on sampling possible outcomes, meaning that the underlying probabilities must be judged or inferred based on the observed evidence. In an investment context, risk can be *described* in summary form, e.g., historical returns in factsheets. Alternatively, knowledge about risk can be acquired through *experience*, through feedback about the outcomes of previous decisions or observing outcomes in the market. The literature documents situations in which these two decision modes lead to different decisions. Decision making from experience can additionally reduce or reverse decision-making biases such as overweighting of rare events as described by prospect theory (Barron and Erev 2003). There are also other ways of communicating risk, aside from experience sampling, that have an influence on risk taking. Previous research suggests that the use of graphical presentation formats, e.g., displaying distributions, may also increase risk taking (e.g., Weber et al. 2005, Benarzi and Thaler 1999, Beshears et al. 2011). These findings raise the issue of what is the best way to present information about the risk of investment products. As empirical researchers, it may seem intuitive to us that risk should be described in summary statistical form. However, this is not obvious from this literature.

In this paper, two ways of acquiring knowledge about probabilities are combined in the risk tool with the intention to communicate the risk-return profile of investment possibilities in the financial decision-making context. We ran a series of experiments where participants could allocate a specific amount between a risky and a risk-free fund and

were randomly assigned to different presentation formats. The risk tool incorporates both experience sampling and a graphical display of the full historical distribution of the MSCI USA Index. A simulation forces participants to interactively sample possible outcomes for a five-year investment in a stock fund—the “risky fund.” Each sampled outcome is used to build up the distribution, and then the entire distribution is displayed. Finally, participants make an allocation between the risky fund and the risk-free fund. We contrast this simulation with a numerical *description* of the expected value and variance of the risky fund. Furthermore, we break down the simulation into its constituent parts with a pure experience sampling and a pure distribution condition to determine their relative contributions. In two of the five experiments, we vary the investment horizon (1 and 10 years instead of 5) and the underlying distribution (MSCI USA versus an index of stocks, bonds, and commodities) as a robustness check. The four different risk-presentation modes (risk tool, description, distribution, experience sampling) are tested in an incentive compatible experimental investment portfolio, conducted online with participants drawn from a German university and the general population in the United States (participants of the elab of Yale University as well as participants from the amazon mechanical turk subject pool).

We find that the risk tool increases the propensity to take financial risks in that participants invest a higher fraction of their endowment into the risky fund. This effect appears to be driven more by experience sampling than by the displays of historical distributions. We find no evidence of greater dissatisfaction with returns in that condition and observe a willingness to take on similar levels of risk in subsequent allocations. To further evaluate the effect, we document three potential psychological mechanisms that vary with risk-presentation format. We find that the higher risk taking in the risk tool is accompanied by a reduced *overestimation* of the small probability of a loss, a lower risk perception, and higher confidence about investing in the risky fund.

The main contribution of this paper is to present a new method of communicating risk to investors. Goldstein et al. (2008) have already shown that such tools may help to elicit consumers’ preferences. Their tool, namely, the distribution builder, uses distributions to aid decision making in the context of retirement portfolio selection. The distribution builder elicits parameters like loss aversion and relative risk preferences by enabling consumers to construct the outcome distribution that they would like, to determine their income in retirement within cost constraints. We add to that literature in two dimensions. First, we analyze the effect of a risk simulation

on risk taking, where distributions are experienced and sampled (not constructed) as a consequence of an asset allocation decision. Second, we focus on a different research question. Whereas Goldstein et al. (2008) introduce a tool to elicit investors' preferences and analyze the parameters' reliability and validity, this paper analyzes investors' behavior by comparing how risk taking differs between different modes of risk presentation.

Communicating risk with the help of experience sampling and graphical displays in the risk tool condition leads to greater risk taking in the context of investing, which is desirable under certain circumstances, e.g., if investors stay the course and do not base their decision on unrealistic expectations of the gain potential. Another potential benefit of the risk tool is that it leads participants to be less reactive when they receive a return that falls below expectations. Instead of accepting lower risk in a subsequent allocation decision, akin to pulling out of the market after a downturn, participants in the risk tool condition are more likely to "stay the course" and make a consistent subsequent allocation decision. Furthermore, the risk tool enhances recall abilities and subjective understanding of the risk-return features of the stock fund along several dimensions: the expected return, the perceived probability of a loss, and how informed they feel.

Our study has important implications for policy making. The question of how risk-presentation format influences investing is important because financial professionals have a great deal of discretion concerning how to relay this information to their clients. At worst they do not assess risk preferences at all or ask irrelevant questions about risk seeking in other domains, such as "Are you a bungee jumper?"<sup>2</sup> Often, they assess willingness to take financial risks using psychometric scales. In the European Union, advisors are legally obliged to assess customers' risk preferences and issue "appropriate guidance on and warnings of the risks associated with investments" during the advisory process.<sup>3</sup> Similarly, the Securities and Exchange Commission in the United States instructs banks to inform their clients about past performance of investment products and their special risks. Nevertheless, there is little instruction about how risk information should be presented. Therefore,

this research is needed to elucidate the implications of risk-presentation format on willingness to accept and understand risk.

The remainder of this paper proceeds as follows: Section 2 provides a literature review and formulates our hypotheses. Section 3 describes the experimental paradigm and the results of an initial test of the risk tool against a description condition. Section 4 presents a second experiment that breaks down the constitutional parts of the risk tool by testing four different presentation formats: (i) numerical description, (ii) experience sampling, (iii) graphical displays of distributions, and (iv) the combination of these with the risk tool. Section 5 explores the recall abilities and underlying psychological factors that affect the allocation decision and augments the analysis on whether participants accept a similar level of risk in a subsequent allocation decision. Section 6 describes results of two experiments conducted to increase generalizability and perform further robustness checks by varying the time horizon and the return distribution. Section 7 provides a general discussion of our findings.

## 2. Literature Review and Hypotheses

### 2.1. Risk Presentation and Risk Taking

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

Given identical underlying probability distributions, decisions based on description and experience can be substantially different, particularly for decisions that involve rare events. Hertwig et al. (2004) demonstrated that decisions based on numerical descriptions of outcomes and their associated

<sup>2</sup> This was an item in a risk tolerance assessment of an European bank, which we will keep anonymous. Hanoch et al. (2006) showed in their study on domain specificity in risk taking that those individuals with high levels of risk taking in one domain (e.g., bungee jumpers) are sometimes very risk averse in other domains (e.g., financial decisions).

<sup>3</sup> See Article 19 of the Markets in Financial Instruments Directive (MiFID) of the European Union (European Parliament and European Council 2004).

probabilities differ significantly from decisions based on experience, in which probabilities are learned through pushing buttons to sample possible outcomes. Decisions based on numerical descriptions are consistent with the overweighting of small probabilities, described by the probability weighting function of prospect theory (Kahneman and Tversky 1979). Numerous studies find that experience sampling choices are consistent with a reduced overweight or even an underweight placed on rare effects, despite little consensus about the underlying mechanisms behind the effect (Barron and Erev 2003, Weber et al. 2004, Hau et al. 2008, Hadar and Fox 2009; see Rakow and Newell 2010 for review). Fox and Hadar (2006) and Hadar and Fox (2009) challenge whether the apparent reduced overweighting of rare events is truly a change in the psychological weight assigned to rare probability events. They argue that the effect can be accounted for by sampling error, an information asymmetry between the two conditions, which leads people to underestimate the probability associated with rare events in the experience condition. The empirical evidence is equivocal on this point. In favor of a sampling error explanation, the prospect theory weighting function applied to the *sampled* rather than *objective* probability can account for observed choices (Fox and Hadar 2006). However, Abdellaoui et al. (2011) elicit the prospect theory weighting function for both experienced and described probabilities and find an overweighting of small probabilities in the weighting function for experience-based decisions, but to a lesser extent than for description-based decision (in the gain domain only). We remain open to the possibility that the experience-description gap may be more than an artifact of sampling error and that experience sampling may affect judgments about possible outcomes. The literature is clear on the point that experience sampling leads to greater risk taking among experimental lotteries that have a small probability of a loss. The decision we analyze—to invest in an equity fund over a multiyear time horizon—fits the risk profile of a small probability of a loss. For example, over a five-year time horizon, the probability of a loss is less than 20%.<sup>4</sup> In this context, experience sampling, which is implemented in the risk tool condition, is expected to increase risky allocations.

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

the distribution of returns graphically. Many who initially declined the gamble subsequently accepted it after seeing the return distribution. Using a different graphical presentation format, Beshears et al. (2011) also found that distributions can increase risk taking. The graphs they used showed the historical percentage returns of equity funds over a 30-year time horizon, ordered by lowest return to highest return. These displays increased allocation to equities by 11%–12%. These results lead us to hypothesize greater risk taking in the risk tool condition. *Thus, we hypothesized that riskier allocations would be made in the risk tool condition compared with the description condition* (Hypothesis 1).

A criterion for assessing the merits of a decision aid is postoutcome evaluation. We wanted to ensure that increased risk taking was not associated with dissatisfaction with outcomes or second guessing about the validity of one's original allocation decision after receiving an unfavorable return (a tendency documented by research on the outcome bias; see Baron and Hershey 1988). Several studies in the literature have documented a robust experience-description gap when feedback is included (for an overview, see Hertwig and Erev 2009), which means that increased risk taking was persistent over several decision rounds. To assess whether participants experienced decision regret that lead them to reevaluate their original risk exposure after receiving their return in the risk tool condition compared with other conditions, participants reported satisfaction with the return and were asked to make a subsequent allocation decision. *We hypothesized that greater risk taking in the risk tool condition would persist in subsequent allocation decisions after participants got feedback about their decision outcome, even if the outcome was poor* (Hypothesis 2).

## 2.2. Drivers of Risk Taking

It is imperative that a decision aid that results in an increase in risk taking should not be used unless the understanding of potential decision consequences and features of the decision context are similar or even greater. Lejarraga (2010) demonstrated that experience sampling can increase recall ability, as measured by frequency judgments of potential outcomes. In Lejarraga's description condition, participants viewed the probability of rain in four cities. In the experience condition, participants were allowed to sample whether there was sun or rain on a given day in each of the four cities. Following a delay period, participants estimated the number of days it would rain in a 10-day period in each of the cities. Frequency estimates were more accurate in the experience than in the description condition. Fox and Hadar (2006) asked participants to estimate the probabilities

<sup>4</sup> Based on the historical returns of the distribution we use, the MSCI USA (1973–2008), the probability of a five-year return less than the capital invested is 16%.

associated with outcomes following experience sampling and found a high degree of accuracy. Ungemach et al. (2009) also documented a high level of accuracy associated with experience sampling. *Based on these findings, we expected the risk tool to increase recall ability and probability judgments regarding the expected return of the risky fund* (Hypothesis 3A).

Benartzi and Thaler (1999) proposed that the increased risk seeking they observed after displaying return distributions could be explained by the tendency to overestimate the probability of a loss prior to viewing the return distribution. They recommend that investors be presented with aggregated distributions that reflect the range of possible outcomes of their investment decisions because people seem unable to comprehend the characteristics of this distribution from descriptions of probabilities. Other researchers in the investment decision-making area have also stressed the important role of the perceived probability of a loss (see Klos et al. 2005). However, as far as we know, the perceived probability of a loss has never been explicitly assessed in the context of investment decisions. We expected that experience sampling would reduce the perceived probability of a loss given the robust finding that for prospects with a small probability of a loss, experience sampling leads to choices consistent with a reduced overweighting of this probability. *We hypothesize that using the risk tool instead of other presentation formats results in more accurate estimates of the probability of a loss* (Hypothesis 3B).

There are additional factors documented in the literature that either do or *should* influence risk taking. Their influence in combination with different risk-presentation modes is not quite obvious. According to classical portfolio theory (Markowitz 1952) the decision about how much risk to accept in an investment portfolio is a trade-off between an investment's expected return and variance, determined by the individuals' risk attitudes—and should not differ depending on the manner in which the risk is presented. Recent behavioral studies imply that individuals' risk-taking behavior can be better explained by *subjective* measures such as risk perception and perceived return (see Sarin and Weber 1993, Jia et al. 1999, Nosić and Weber 2010). The behavioral model of risk taking suggests  $Risk\ Taking = f(Perceived\ Return; Risk\ Attitude; Perceived\ Risk)$ .

These subjective beliefs can vary depending on the domain and situational features of the decision-making environment (e.g., Weber and Milliman 1997, Weber et al. 2002, Nosić and Weber 2010), and subjective perceptions will be influenced by the manner in which risk is communicated. We assessed perceived risk because it predicts risky choice, despite its weak relationship to the more objective measures such as

standard deviation (Keller et al. 1986, Klos et al. 2005). Perceived return may also vary with features of the decision-making environment. Appetite for risk was measured, though this is generally conceived of as a more stable aspect of individuals' personality.

We also assessed confidence in the risky fund, because an aim of the risk tool is to provide information in a way people can feel confident and committed to their decision. Furthermore, the provision of richer information in the risk tool condition might result in information overload. Measuring subjective confidence provides an additional indication about whether participants feel overburdened or whether they believe in the decision they make. Though there is a vast literature on *overconfidence* and investment behavior (e.g., for a review, see Glaser and Weber 2010), little research has examined the role of subjective feelings of confidence.

We assess these subjective measures in Experiment III and analyze their role in the relationship between presentation mode and risk taking. *We hypothesize that the risk tool will increase decision confidence and lower participants' risk perception of the risky fund* (Hypothesis 3C).

### 3. Experiment I: Risk Taking— Risk Tool vs. Description

**Experimental Task.** Participants were asked to allocate an endowment of €1,000 between two funds. Fund A was a risk-free fund, and Fund B was a risky fund whose payoff was based on the historical returns of the MSCI USA (which was not made explicit to participants).<sup>5</sup> Participants first received information about the five-year return of the risk-free fund, then about the return distribution of the risky fund. The manner in which this information was presented varied between conditions in a between-subject design (described further in the "Stimuli" section).

Next participants made an *initial allocation*, which allowed them to view the diversified risk-return profile of this initial allocation over a five-year time horizon. They could adjust their allocation via a scroll bar and observe how the risk-return profile of the portfolio as a whole changed as many times as they wanted before deciding on their *final allocation*. The final allocation was assessed in an incentive compatible manner. Participants were informed that at the end of the

<sup>5</sup> We calculated the average return based on the historical returns of the MSCI USA from 1973 to 2008, namely, 8.95%. We assumed normally distributed returns to calculate final wealth. Note that because of the underlying continuous-time framework, the final value of the portfolio's risky fraction follows a lognormal distribution. For the risk-free return, we assumed an interest rate of 3.35%, which was based on the actual five-year interest rate.

experiment a “financial market simulation” would be run to determine the five-year return on their *final allocation* decision. It was explained that this simulation randomly generated a return based on the underlying distribution of the allocation decision that they chose and that they had the chance to win Amazon.com gift cards for their simulated return.<sup>6</sup>

Participants were asked to provide their risk attitude, financial literacy (adapted from van Rooij et al. 2011), stock ownership, and demographics (see Appendix A for exact wording of measures). Next, the financial market simulation was run. Participants reported satisfaction with their outcome and were asked how they would hypothetically allocate their endowment between the risk-free and the risky fund if they could make the same investment decision again. See Appendix B for an overview of the experimental flow.

**Stimuli.** Experiment I was conducted to test Hypotheses 1 and 2 and included a description condition and the risk tool condition. In the description condition, participants were given the expected return as a percentage and as the expected amount of final wealth for each of the funds. The variance of the risky fund was explained in terms of frequencies (“in 70 out of 100 cases your final wealth will be between  $X$  and  $Y$ , in 95 out of 100 cases between  $U$  and  $Z$ ”; see Appendix C). They entered an initial allocation and saw the corresponding return and variance of the portfolio numerically. Next, they could adjust the allocation and see the corresponding effects on the return and variance until they decided on a final allocation.

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

and Fund B and went through the simulation again, which now reflected the underlying distribution of their chosen diversified portfolio. They were able to adjust this allocation and repeat the simulation until they decided on a final allocation.

**Data and Participants.** Experiment I was run at the University of Mannheim with 133 undergraduates (82). The mean age was 22 with a range from 18 to 50 years. Approximately 30% of the students reported owning stocks. It took participants on average 19 minutes to complete the experiment online. Participants allocated €1,000, and we randomly selected 10 students to receive an Amazon.com gift card for the amount of the financial market simulation divided by 100 (which resulted in payments between €10 and €18).

**Results and Discussion.** We find that the manner in which people acquire knowledge about risk does affect their allocation decision. In line with Hypothesis 1, the final allocation was significantly higher in the risk tool condition: participants allocated on average 60.4% (with a standard deviation of 26.3) to the risky fund in the description condition compared with 74.15% (with a standard deviation of 23.60) in the risk tool condition, and this difference is significant ( $t_{131} = 3.11$ ,  $p < 0.01$ ). The increased risky allocation remains significant when we include control variables using ordinary least squares (OLS) regression analysis<sup>7</sup> (Table 1, column (I)).<sup>8</sup> Consistent with previous literature (Hong et al. 2005, Nosić and Weber 2010, van Rooij et al. 2011) self-reported risk attitude is a highly significant predictor of risk taking. Also age significantly predicts risk taking. The control variables financial literacy, gender, and stock ownership were insignificant. Education and income were not collected from the student population because education is relatively constant in the sample and it is difficult to meaningfully assess income in a student sample. See Appendix A for an explanation of the variables used in this and all other analyses. There was no significant difference in the initial allocation between conditions.

In addition to the allocation behavior, we asked whether the manner in which people acquire information about risk influences their satisfaction with their outcomes (Hypothesis 2). Those in the risk tool condition might only be temporarily convinced to accept greater risk and later come to regret their decision,

<sup>7</sup> All regression results also hold using Tobit regression analysis censored by €0 and €1,000 for Experiments I and V and \$0 and \$100 for Experiments II–IV.

<sup>8</sup> Fox and Hadar (2006) invoke that results might be explained by sampling error or recency effects. After controlling for these variables, we continue to find a significant difference between the risk tool and description.

<sup>6</sup> Consistent with the existing procedures of the subject pool, we used gift cards instead of real money, which can be sent via email and precluded the need for subjects to provide a name and mailing address.

**Table 1** Final Allocation to the Risky Fund

	Experiment I	Experiment II		Experiment III	
	Description vs. risk simulation (I)	Description vs. risk simulation (II)	Experience and distribution vs. description (III)	Description vs. risk simulation (IV)	Experience and distribution vs. description (V)
<i>Risk simulation</i>	132.72*** (38.42)	13.83*** (5.24)		12.273*** (3.60)	
<i>Experience</i>			7.50 (5.13)		9.74*** (3.79)
<i>Distribution</i>			7.78 (5.21)		4.94 (3.86)
<i>Risk attitude</i>	137.69*** (22.63)	10.09*** (2.91)	8.70*** (2.42)	10.25*** (1.99)	7.38*** (1.76)
<i>Financial literacy</i>	7.19 (7.99)	1.20 (1.22)	1.02 (1.05)	−1.10 (0.86)	−0.50 (0.67)
<i>Stock ownership</i>	−48.85 (44.72)	11.98** (5.61)	5.30 (5.02)	1.34 (4.13)	0.86 (3.80)
<i>Age</i>	16.04** (6.23)	0.06 (0.23)	−0.37* (0.20)	0.005 (1.15)	0.09 (0.14)
<i>Gender</i>	31.70 (40.92)	3.70 (5.85)	−0.03 (4.74)	1.01 (4.18)	6.68* (3.55)
<i>College</i>		7.81 (5.49)	−4.22 (4.51)	8.64** (3.79)	2.95 (3.39)
<i>Income</i>		−0.15 (0.10)	0.05 (0.07)	−0.22 (0.17)	−0.37 (0.52)
<i>Constant</i>	−189.03 (156.06)	2.89 (13.45)	27.12** (11.78)	27.60*** (8.99)	31.83*** (7.62)
Observations	133	89	145	192	268
R-squared	0.33	0.32	0.17	0.21	0.13

Notes. This table reports OLS regression analysis of final allocations to the risky fund. See Appendix A for an overview of control variables.

\*Significance at the 10% level; \*\*significance at the 5% level; \*\*\*significance at the 1% level (income expressed in 10 thousands; standard errors in parentheses).

especially if they receive a loss or a return that does not meet their expectations. After receiving the outcome of their decisions from the financial market simulation, participants reported satisfaction with their return (4.25 in the description condition versus 4.10 in the risk tool condition on a 7-point scale; difference not significant). We find no evidence that people in the risk tool condition regretted their relatively high allocations to the risky fund. Even for people whose return fell below the expected value of their allocation decision, satisfaction was not reduced for those in the risk tool condition (3.03 in the description condition versus 3.28 in the risk tool condition on a 7-point scale). Another indicator of how people evaluate their allocation, decision after receiving their return is their subsequent (hypothetical) allocation decision. Across conditions, there are high correlations between the final allocation and subsequent allocation ( $r = 0.52$ ). In a subsequent allocation, participants in the description condition allocated 68.9% to the risky fund, whereas subjects in the risk tool condition allocated 77.6% to it, and the difference is

significant ( $t_{131} = 1.96, p = 0.05$ ), consistent with the patterns of results for the final allocation.

The increased risk taking in the risk tool raises the question of whether it is the presence of one or both of its features (experience sampling and the distribution function) that results in riskier allocations. This is explored in Experiment II by adding a pure experience sampling and a pure distribution condition (in contrast to the risk tool where both communication methods are incorporated). To increase generalizability of our results, we use a different subject sample in Experiment II, namely, participants from the general U.S. population.

#### 4. Experiment II: Risk Taking and Risk Tool Components—Experience Sampling vs. Distribution Function

**Experimental Task.** The experimental task was only changed slightly in comparison to the setup in Experiment I. Participants also had to allocate an endowment between a risky and a risk-free fund over

a five-year time horizon. Instead of investing €1,000, participants allocated an amount of \$100. We furthermore collected additional control variables like income and education. For an overview of the differences between experiments, see Appendix D.

**Stimuli.** Experiment II attempts to deconstruct the risk tool condition by examining two additional conditions, again in a between-subject design: a pure experience sampling condition and a pure distribution condition. In the experience condition, participants first drew returns from the distribution of the two funds separately, similar to the sampling procedure in Hertwig et al. (2004). Participants had to sample at least three times from the risk-free fund (which was always an outcome of \$118) and at least eight times from the risky fund<sup>9</sup> and then enter an initial allocation. Next, they sampled from the diversified portfolio of their initial allocation and were able to adjust their allocation and continue to sample until they decided on a final allocation (see Appendix C).

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

**Data and Participants.** Experiment II recruited 190 participants (66 male) from the general population using the subject pool of the Yale School of Management. The mean age was 34 with a range from 18 to 70 years. Participants were predominantly Caucasian, with a median income of \$40,000 (ranging from \$0 to \$199,000). Fifty percent were college educated and approximately 45% owned stocks. Participants again completed the experiment online and were offered a \$5 Amazon.com gift certificate for their participation plus a 1 in 20 chance to earn additional performance-based money dependent on the outcome of their final allocation decision. Participants allocated an endowment of \$100, and earnings ranged from \$96 to \$144.

**Results and Discussion.** We replicate the results from Experiment I in a nonstudent population in a different country and a different investment amount. Participants allocated on average 54.4% (with a standard deviation of 26.0) to the risky fund in the description condition compared with 66.53% (with a standard deviation of 25.50) in the risk tool condition, and this difference is significant on the 5% level performing a *t*-test and significant on the 1% level

performing an OLS regression including control variables (Table 1, column (II)). The results from Experiment I concerning the subsequent allocation were also replicated (in line with Hypothesis 2): participants allocated on average 53.77% to the risky fund in a subsequent allocation were in the description condition compared with 67.4% in the risk tool condition, and this difference is significant ( $t_{87} = 2.27$ ,  $p < 0.01$ ). There is no evidence that participants regret their decision in a subsequent allocation in the risk tool.

The intention of Experiment II was to decompose the information presentation effects of the risk into its single components. Participants allocated on average 59.52% to the risky fund in the distribution condition and 61.0% to the risky fund in the experience condition. Though elevated neither condition was significantly higher than the description condition. An OLS regression in Table 1 also finds that neither of the two conditions is significant when control variables are included in the model (Table 1, column (III)).

We find that participants increased their subsequent allocation in the experience condition to invest 64.06% in the risky fund and reduced their allocation in the distribution condition to 53.06%. These results indicate that it is more experience sampling than the distribution function making participants stay the course when risk is communicated via the risk tool. Overall, risk taking in the subsequent allocation decision is highest in the risk tool condition, followed by experience sampling.

The results of Experiment II suggest that it is the combination of factors, experience sampling and adding a distribution function, leading to higher risk taking, whereas the commitment to the decision seems to be driven by experience sampling. We further investigate these two components with an increased sample size in Experiment III. Until now, we have found that the risk tool increases investors' willingness to take on risk, which does not decrease in a follow-up decision. An increase in risk taking can be desirable so long it is a more accurate reflection of investors' preferences and not driven by unrealistic expectations. We hence sought to better understand subjective comprehension of the risk and associated psychological drivers in the risk tool.

## 5. Experiment III: Potential Psychological Drivers and Further Analysis of Ex Post Decision Evaluation of Risk Taking

**Experimental Task.** Aside from the assessment of additional survey questions, the experimental task

<sup>9</sup> On average, participants drew 14.48 times. The number of draws did not influence final allocations significantly.

was held constant to the setup in Experiment II. Participants also had to allocate an endowment of \$100 between a risky and a risk-free fund over a five-year time horizon (see Appendix D).

To explore potential explanations for the increased risk taking in the risk tool condition, we analyze whether the manner in which people acquire information affects their recall abilities and their subjective comprehension.<sup>10</sup> Three recall questions had objectively correct responses and required participants to estimate aspects of the underlying risk-return profile of the risky fund: expected return, probability of a loss (downside), and the probability of a high gain (upside). We additionally assessed how informed they felt regarding the risky and risk-free fund (see Appendix A for the exact wording).

The behavioral model of risk taking posits that risk taking is a function of risk attitude, perceived return, and perceived risk. We assessed these three variables in our questionnaire. Participants reported, using a 7-point scale, how risky they perceived the risky fund to be. In addition to the factors of the behavioral model, we assessed confidence about investing into the risky fund.

**Stimuli.** The stimuli were not changed in comparison to the setup in Experiment II. Participants were randomly assigned to one of the four conditions (description, risk tool, distribution, and experience).

**Data and Participants.** We increased the sample size to 362 (162 male) using the subject distribution list of the Yale School of Management. Demographics were similar to those in Experiment II. Participants again completed the experiment online in exchange for a 50% chance to earn a \$5 Amazon.com gift certificate and a 1 in 40 chance to earn additional performance-based pay based on the outcome of their final allocation decision.

**Results and Discussion.** *Patterns of Asset Allocation.* We replicated the increased risk taking in the risk tool condition (mean allocation to the risky fund: 70.59) compared with the description condition (mean allocation to the risky fund: 57.71  $t_{(190)} = 3.38$ ,  $p < 0.01$ ; see also OLS regression analysis Table 1, column (IV)). Results of Experiment II suggested that risky allocations are elevated in the experience and distribution conditions compared with the description condition but are not significantly different (see again Table 1, column (III)). In Experiment III, participants allocated on average 62.46% to the risky fund in the distribution condition and 66.65% in the experience condition. With the increased sample size in

Experiment III, the difference between experience and description (which is omitted in the OLS regression) is significant (see Table 1, column (V)). Experience sampling<sup>11</sup> does, however, not explain the entire effect. The difference between the description and risk tool conditions is greater than the difference between the description and experience conditions.

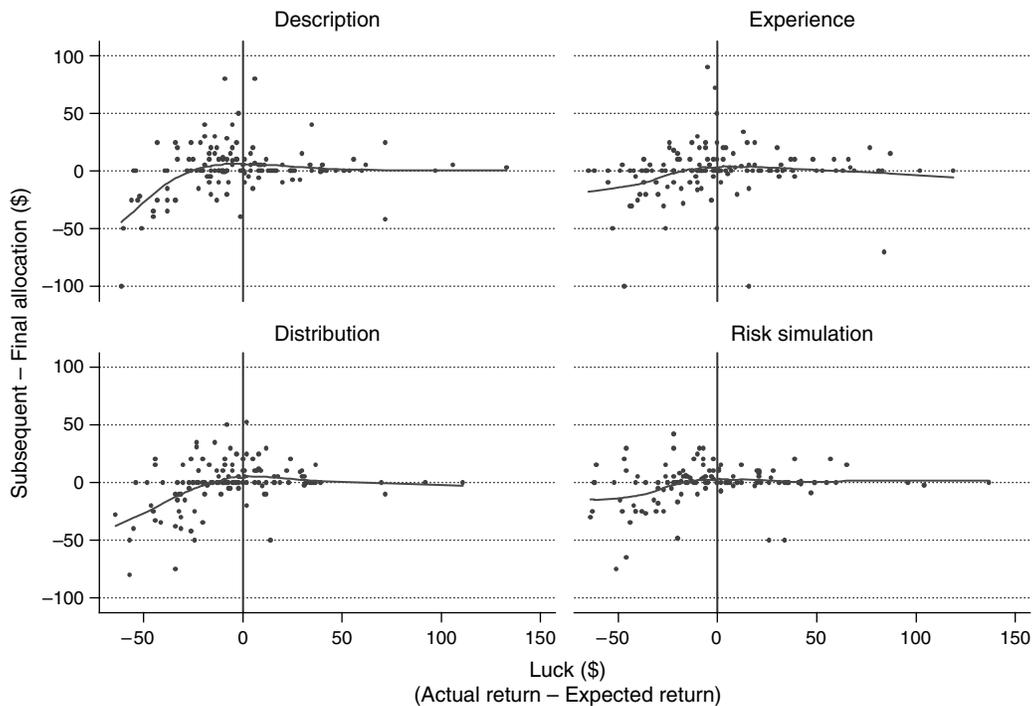
We have shown in Experiments II and III that participants do not regret their increased risk taking in the risk tool condition (Hypothesis 2). Nevertheless, we only analyzed the absolute subsequent allocation, not the relative differences to the risk level allocated in the final allocation decision. In other words, we now analyze the difference between the final and the subsequent allocation to the risky fund to gain a better understanding of the subjects' reactivity to returns between conditions. Figure 1 plots the subsequent minus the first allocation against the variable, "luck," which reflects whether subjects earned more or less than their expected return in their final outcome. For example, if a participant invested the total \$100 endowment in the risky fund and received an outcome of 160 in the financial market simulation, the variable luck is calculated as  $160 - 153$  (the expected return) = 7. We combine the data from Experiments II and III, in which participants allocated a \$100 endowment.<sup>12</sup>

Changes in risk taking depend on the outcome of the market simulation and on the manner risk was presented to participants (the condition). Across conditions, participants are strongly reactive to losses but not gains. They reduce their allocation to the risky fund in reaction to a return less than the expected value of their allocation (i.e., luck < 0). This tendency appears less pronounced in the risk tool and experience conditions compared with the description and distribution conditions (see Figure 1). To assess this pattern more formally, we focus on the subsample of participants where the expected value falls short of the realized return (i.e., luck < 0) and regress the difference between subsequent and final allocation on the interaction terms of the dummy variables for the condition and luck. A higher coefficient suggests that participants reduce their risky allocation in a hypothetical subsequent allocation as a result of a more negative difference between expected and realized return. We find evidence for a lower reactivity to losses in the risk tool condition. Participants are significantly less reactive in the risk tool condition compared with the distribution condition ( $F_{(1,314)} = 6.59$ ,

<sup>10</sup> We asked participants about their recall abilities and their subjective assessments. We are aware that these measures might differ from actual (objective) comprehension, which we did not assess.

<sup>11</sup> The difference between the risky allocation in the risk tool condition is higher compared with the allocation in the experience sampling condition, but it is not significant.

<sup>12</sup> Results also hold if we picture the figures separately for each of the experiments.

**Figure 1** Subsequent Allocation as a Function of Investment Success (Luck)

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

$p = 0.01$ ). Furthermore, participants are less reactive in the experience condition compared with distribution ( $F_{(1,314)} = 4.26$ ,  $p = 0.04$ ). The reactivity in the risk tool condition and the experience condition is also lower compared with the description condition; however, this effect is not significant.

*Recall Ability and Subjective Comprehension.* Hypothesis 3A predicted greater recall and comprehension of the expected return in the risk tool condition. We assessed participants' perception of the expected return of the risky fund after five years. Note that in all conditions except the experience condition, participants were explicitly given the number and only had to recall it correctly. The correct answer was \$153 and participants chose among five intervals. The highest percentage of right answers was in the risk tool condition (57%), though this is not significantly higher than any of the other conditions. In the experience condition, where the exact expected return was not stated, correct responses (47%) were similar to the description condition (46%; see row 2 of Table 2). To understand the direction and magnitude of incorrect answers, we created a new variable to reflect overestimation by assigning the value  $-1$  to the \$100–\$140 interval (the interval that underestimated the return),  $0$  to \$141–\$180 (the correct interval),  $1$  to \$181–\$220,  $2$  to \$220–\$260, and  $3$  to  $>$ \$260. Using ordered probit analysis with control variables, there is significantly less overestimation of the return in

the risk tool condition compared with the description condition ( $z = 2.28$ ,  $p = 0.02$ ). Using the midpoint of each interval to estimate the magnitude of overestimation in each condition, the expected return in the risk tool condition is overestimated by \$13 in the risk tool condition and \$24 in the description condition (see row 3 of Table 2).

Participants estimated the probability of receiving a loss, i.e., that the five-year return of a \$100 allocation to the risky fund would fall below \$100 (correct answer 16%). They also estimated the probability of a high gain exceeding \$150 (correct answer 54%). Note that the correct responses to these questions were not explicitly stated; participants had to have a sense of the risk-return distribution to give a correct answer.

Estimations about the probability of a loss were significantly more accurate in the risk tool condition compared with the description condition (see row 4 of Table 2), in line with Hypothesis 3B.<sup>13</sup> Results also hold in an OLS regression analysis with control variables ( $\beta = -15.37$ ,  $t = 4.97$ ,  $p < 0.01$ ). In the experience condition, participants were also significantly more accurate about the probability of a loss compared with the description condition ( $\beta = -6.77$ ,  $t = 3.13$ ,  $p = 0.03$ ), suggesting that experience sampling, not the presentation of the distribution function, drives

<sup>13</sup> One observation was dropped because it exceeded 100 (180).

**Table 2** Judgments of the Risk-Return Profile of the Risky Fund

Condition	Description	Risk tool	Distribution	Experience
<i>N</i>	99	93	81	88
Correct return interval (%)	46	57	54	47
Overestimation of the return (\$)	24	<b>13</b>	27	26
Overestimation of the probability of a loss	21	<b>5</b>	23	15
Upside potential (underestimation)	15	21	19	12
Feeling informed	4.60	<b>4.99</b>	4.37	4.39
Risk perception	4.92	<b>4.34</b>	4.94	4.65
Confidence	4.25	<b>4.89</b>	4.12	4.74
Allocation to the risky fund in %	57.71	<b>70.59</b>	62.46	66.65

*Notes.* This table reports the mean deviation from correct answers to recall questions about the risk-return profile of the risky fund assessed in Experiment III. See Appendix A for the exact wording of the questions. The correct return interval reflects how many participants answered that question correctly. The overestimation of return is estimated from the return intervals by averaging the midpoint of the intervals. The overestimation of the probability of a loss is measured in percentage points; e.g., 21 means that participants on average estimated that they received a loss in 37 out of 100 cases and therefore overestimated the correct answer of 16 by 21 percentage points. The upside potential (underestimation of the high gain, meaning an outcome > 150) is also measured in percentage points; e.g., 15 means that participants on average estimated that they received a high gain in 34 out of 100 cases and therefore underestimated the correct answer of 49 by 15 percentage points. The table additionally reports the mean of feeling informed, the risk perception, and the confidence associated with investing into the risky fund on a 7-point scale. Mean allocations to the risky fund are reported to compare judgments to the allocation decision. Numbers in the risk tool condition are in bold in case they are significantly different from the description condition.

the effects in the risk tool condition. This is consistent with the experience-description gap literature, which documents very high calibration between judged and sampled probabilities.

The more accurate estimation of the probability of a loss might, however, also be driven by a framing effect through the way the risk is described in the description condition. Note that participants were told “in 70 out of 100 cases your final wealth will be between \$100 and \$208,” and participants might think that they will probably get a loss in the remaining 30 out of 100 cases. Indeed, 25% of our participants in the description condition estimate that a loss will occur in 30% of the cases. If we exclude participants who stated a probability between “28 and 32,” participants in the risk tool condition are still significantly more accurate in the risk tool condition compared with the description decision. Nevertheless, we will address this by varying the information provided in the description condition in Experiment IV.

Though participants are willing to accept more risk in the risk tool condition, they do not have unrealistically optimistic expectations. They are most

accurate about the perceived return and do not overestimate the probability of a gain to a higher degree than in all other conditions. Instead, they underestimate the upside return potential, but the estimation does not significantly differ from those in other conditions (see row 5 of Table 2). Participants in the risk tool condition may, however, give more accurate estimations, but they do not feel more informed because the risk tool might have been perceived as overly complicated. We asked participants how informed they feel about the risky and the risk-free fund on a 7-point scale. Participants felt significantly more informed in the risk tool condition compared with all other conditions ( $t_{(359)} = 2.84, p < 0.01$ ; see row 6 of Table 2).

There are alternative explanations why participants might have a higher recall ability in the risk tool condition compared with the description condition. First, participants saw the whole distribution in the risk tool condition. Participants, however, also saw the whole distribution in the distribution condition, and we do not find higher accuracy in that condition. Second, the risk tool is more involved. It might be that participants in the risk tool condition simply spend more time with the decision, which hence increases the probability of recall. To address this result, we take a closer look at the time subjects spent in each of the conditions. The median time in the risk tool condition was 11.73 minutes; the median time in the description condition was 9.20 minutes. If we limit the analyses to participants spending between 9 and 12 minutes (25 participants in each of the two conditions) the differences in risk taking and in the estimation of the probability of a loss are still highly significant.

*Risk Perception and Confidence.* The behavioral model of risk taking predicts risk taking as a factor of return perception, risk attitude, and risk perceptions. As described in the previous section, estimates of the expected return were lower in the risk tool condition, making it an unlikely candidate as psychological driver of increased risk taking. Attitude toward risk, always a significant control variable, behaves like a stable personality trait and does not vary based on risk-presentation format. Consistent with Hypothesis 3C, risk perception is significantly lower in the risk tool condition ( $M = 4.34$ ) compared with the description condition ( $M = 4.93$ ;  $t_{(190)} = 3.10, p < 0.01$ ; see row 7 of Table 2). The perceived probability of a loss can be considered an indicator of risk perception. Across conditions, both the subjective report of risk perception and the judged probability of a loss closely track risky allocations: higher (lower) allocations are associated with lower (higher) overestimation of the probability of a loss and a lower (higher) risk perception (see rows 4, 7, and 9 of Table 2).

In line with Hypothesis 3C, confidence is significantly higher in the risk tool condition ( $M = 4.89$ ) compared with confidence in the description condition ( $M = 4.25$ ;  $t_{(190)} = 3.32$ ,  $p < 0.01$ ; see row 8 of Table 2). This coupled with the finding that participants in the risk tool condition feel more informed about their decision is a positive indicator that the risk tool leads to positive subjective feelings regarding the allocation decision. Across conditions, confidence also closely tracks risky allocations (see rows 8 and 9 of Table 2).<sup>14</sup>

Overall, results of Experiments I–III suggest that the risk tool increases investors' risk taking accompanied by more realistic risk-return expectations, stronger decision commitment, and increased confidence. Nevertheless, we have used similar decision contexts and only varied the investment amount and the population between experiments. The observed effects may hence be limited to a certain time horizon or risk-return profile, which we test in two additional experiments.

## 6. Generalizability and Robustness Checks: Experiments IV and V

Experiment IV is conducted as a classical robustness check with one variation, namely, a shorter time horizon. In Experiment V we examined a long-term time horizon of 10 years and dialed up the risk exposure of the risky fund to see whether results still hold under more extreme variations.

### 6.1. Experiment IV

**Experimental Task.** In Experiment IV, we use a short-term investment horizon of one year in addition to the five-year horizon also used in Experiments I–III. Participants had to allocate an endowment of \$100 between a risky and a risk-free fund and were randomly assigned to one of two conditions (see Stimuli) and one of the two time horizons (see Appendix D for differences between experiments).

**Stimuli.** With the intention to increase the generalizability of our main effect, we use the two basic conditions—description and risk tool. To rule out a possible confound, we slightly enhanced the presentation format in the description condition. As in Experiments I–III, we told participants that the final wealth will be between  $x$  and  $z$  in 70 out of 100 cases. However, we added the following sentences: “This means that in 15 out of 100 cases it will be below  $X$  and in 15 out of 100 cases above  $Z$ .” This was done to avoid a

potential misinterpretation, which could make people think that in 30 out of 100 cases the final wealth will be below  $X$ .

**Data and Participants.** Experiment IV was run with 212 participants (104 male) using Amazon's Mechanical Turk (Mturk). Mturk is an online platform in which “requesters” can list tasks along with a specified compensation and are able to set up a certain time frame in which the task should be completed as well as certain requirements the subjects should fulfill (e.g., only subjects out of the United States). Subjects called “workers” in Mturk are offered the possibility to perform these different tasks and elect them based on a brief description. In our Mturk sample, we restricted the subject pool to U.S. citizens. The mean age was 36 with a range from 20 to 68 years. Participants had a median income of \$39,000 (range from \$0 to \$200,000). Fifty-one percent were college educated and approximately 31% owned stocks. Participants again completed the experiment online in exchange for a reward of \$1.30 for successful completion and a 20% chance to earn additional performance-based pay (similar to the other experiments).

**Results and Discussion.** We replicate the results from Experiments I–III (Hypothesis 1) with the Amazon Mechanical Turk subject pool: over a five-year time horizon participants allocated on average 61.30% (with a standard deviation of 32.5) to the risky fund in the description condition compared with 74.05% (with a standard deviation of 28.70) in the risk tool condition, and this difference is significant ( $t_{98} = 2.08$ ,  $p = 0.04$ ). In addition, we show a similar result for a short-term horizon: over a one-year time horizon, participants allocated on average 56.52% (with a standard deviation of 28.5) to the risky fund in the description condition compared with 68.10% (with a standard deviation of 27.2) in the risk tool condition, and this difference is significant ( $t_{109} = 2.19$ ,  $p = 0.03$ ). In line with previous literature, a longer time horizon generally leads to a riskier investment within conditions (Klos et al. 2005, Siebenmorgen and Weber 2004).

The effects concerning the accuracy about the probability of a loss hold if we are more precise in our description to avoid an accidental framing effect. Participants in the risk tool condition were still significantly more accurate compared with the description condition over a five-year time horizon. In the description conditions, participants on average estimated a probability of a loss in 29.7 of the cases and therefore overestimated the probability by 13.7; in the risk tool condition, participants on average estimated a probability of a loss with almost perfect accuracy in 15.4 of the cases, and the difference is significant ( $t_{98} = 3.81$ ,  $p < 0.01$ ).

<sup>14</sup> Mediation analysis for these measures indicates that risky allocations in the tool conditions are mediated by decreased risk perception, increased confidence in the risky fund, and a lower estimation of the probability of a loss. Results are available on request.

## 6.2. Experiment V

**Experimental Task.** The objective of the final experiment was twofold: to ensure that our results are generalizable to a long-term time horizon and to variations in the risk exposure of the risky fund. We conducted a brief experiment with a small student sample using a 10-year time horizon and a €1,000 investment amount. We varied the risk-return profile of the risky fund by doubling its sharpe ratio. Instead of the MSCI USA, we used a World Portfolio index consisting of stocks, bonds, and commodities introduced by Jacobs et al. (2010). The higher diversification of this fund allows us to gain a dominant risk-return profile compared with the MSCI USA, resulting in a higher expected return (10.7% p.a.) and a lower standard deviation (11.4% p.a.). The aim of using another fund was to test whether the differences in risk taking (between the risk tool and description conditions) were specific to the risk-return profile of the MSCI USA used in all other experiments.

**Stimuli.** We use the two basic conditions in Experiment V. Aside from the 70 and 95 quantiles, we added a 20% (in 20 out of 100 cases your final wealth will be between  $x$  and  $z$ ) and a 30% quantile in the description condition to see whether the increased risk taking in the risk tool condition is driven by the fact that the risk tool is more involved because it shows the whole distribution.

**Data and Participants.** Experiment V was run at the University of Mannheim with 39 students (23 male). The mean age was 24, with a range from 18 to 43 years. Approximately 36% of the students reported owning stocks. Participants allocated €1,000, and we randomly selected five students to receive an Amazon.com gift card for the amount of the financial market simulation divided by 100.

**Results and Discussion.** Results of Experiment V show that the allocation pattern also holds in a different decision context—for a longer time horizon, and a different risky fund. Over a 10-year time horizon participants allocated on average 58.19% (with a standard deviation of 20.7) to the risky fund in the description condition compared with 73.60% (with a standard deviation of 25.5) in the risk tool condition, and this difference is significant ( $t_{37} = 2.00$ ,  $p = 0.05$ ).

## 7. General Discussion

The results of the current paper suggest that a risk-presentation format that incorporates experience sampling and distributions of returns may help investors by increasing decision commitment, confidence, and recall ability as well as reducing known biases as the

overestimation of the loss probability. These factors result in an increased willingness to accept risk in one's portfolio. Across five experiments, when the presentation format both includes experience sampling and displays the distribution of returns, risky allocations are higher compared with a descriptive stating of the expected return and standard deviation. The finding is robust and holds for participants from two different countries (Germany and the United States), different subject pools (students as well as the general population using the Yale elab population and the Mturk sample); different time horizons (1, 5, and 10 years); different investment amounts (\$100 and €1,000); and two different risky funds (the MSCI USA versus the World Portfolio; see Appendix D for a summary of results across experiments). Results suggest that experience sampling is the more powerful driver of the riskier allocations compared with displays of return distributions. However, experience sampling does not entirely explain the increased risk taking in the risk tool condition because risk taking in the distribution condition was consistently (though non-significantly) elevated compared with the description condition. Thus, presentation of the distribution function may have some additional effect.

We do not wish to imply that research should generally aim to bolster people's willingness to take on greater investment risks. An increase in risk taking is, however, desirable under certain circumstances. There is evidence in the literature that people historically took on less risk than they optimally should (e.g., Samuelson 1969, Merton 1971, Arrow 1971, Ameriks and Zeldes 2004). Campbell (2006, p. 1564) stated in his article on household finance, "Participation is far from universal, however, even among quite wealthy households." This effect is induced by several factors, among them information costs (e.g., Haliassos and Michaelides 2003). Evidence for that argument is that participation increases with financial literacy (e.g., van Rooij et al. 2011). Stock market participation and the degree of risk taking play an important role for wealth creation, accumulation, and retirement planning (e.g., Poterba 2000, Gomes and Michaelides 2005). Higher risk taking is hence desirable as long as participants understand the risk well enough to make decisions more in line with their preferences. It is essential to understand how the information provided influences the propensity to accept risk. We examine financial risk taking in an experimental paradigm that models a common investment decision: allocating the investment amount between the risk-free return and a diversified equity fund. We have found the effect for a regional but diversified stock fund and a fund diversified over asset classes.

An increase in risk taking might be negative, for example, when people increase their risk taking

because of unrealistic expectations of the upside potential or because they misinterpret the features of the decision context. We examined whether there are negative repercussions to accepting more risk in the risk tool condition. Increased risk taking in the risk tool condition does not compromise participants' recall ability or subjective comprehension. Participants in the risk tool condition were most accurate about the expected return and the probability of a loss, and they felt significantly more informed and also quite confident about their decision. We do not observe any evidence of greater decision regret or unrealistic expectations about the risky fund. Participants in the risk tool condition are no less satisfied with the return they receive, and they maintain the same or greater risk level when they are asked how they would allocate their money if they could make a subsequent allocation decision. In conditions that included experience sampling, subsequent allocation decisions tend to be less reactive to variance in returns. Experience sampling seems to prepare participants for the possibility of a loss, resulting in a decreased tendency to react to losses by taking on less risk in a subsequent decision. If we extrapolate from the current findings, we would predict that experience sampling could assist people in sticking to a long-term investment plan in the face of market volatility.

This research contributes to the objective of helping people understand the risk that they face in their investment decisions. Instead of simply using psychometric scales to assess willingness to accept risk, financial providers could provide tools to further clients' understanding of the implications of portfolios with different risk profiles and ensure suitability. While doing our research on this project, we were given the chance to introduce the risk tool in one of Germany's largest newspapers, and we provided them access to the tool on a website.

During a one month period, several hundred participants visited our website and had the possibility to give feedback. This feedback was predominantly positive. Participants stated that they finally were able to understand the concept of volatility and get a feeling of the risk-return profile they want to picture in their own portfolio. Critical questions were mainly about an enhancement with regard to different underlying distributions or the possibility to display a monthly payment instead of a one-time investment. The risk tool differs from our experimental setup in the way that participants can choose the investment horizon and the investment amount. The risk tool can be tested on our homepage: <http://www.behavioral-finance.de/risktool>.

Given the experimental results and the feedback from real investors, we think that the use of experience sampling and the distribution function in financial simulations may be a fruitful strategy for banks to improve the quality of the information they provide about their investment products. With the help of a risk tool, it is possible to ensure that clients are informed, committed to, and confident about the amount of risk they are prepared to take.

### Acknowledgments

The authors thank two anonymous reviewers; an associate editor; participants at the 2010 Boulder Summer Conference on Consumer Financial Decision Making, the 2009 Subjective Probability, Utility and Decision Making Conference in Italy, and the Campus for Finance 2011; and participants in seminars at the University of Mannheim, Yale School of Management, and Columbia Business School. The authors also thank Ido Erev, Markus Glaser, Dan Goldstein, Thomas Langer, Christoph Merkle, Sebastian Müller, Alexandra Niessen-Ruenzi, Jan-Christoph Rülke, Daniel Smith, Sascha Steffen, and Noah Stoffman for many valuable comments on this work. Special thanks go to Philipp Schaber and Dominic Hiller for programming the risk tool.

## Appendix A. Overview of Variables and Measures

### Allocation variables

<i>Initial</i>	The first number participants typed in for the allocation to the risky fund after viewing information about the two funds separately.
<i>Final</i>	The allocation to the risky fund chosen after being informed about the diversified portfolio return and standard deviation of the initial allocation.
<i>Subsequent</i>	The hypothetical allocation made after seeing the results of the market simulation that determined their payoff.

### Control variables

<i>Risk attitude</i>	Self-reported: Please estimate your willingness to take financial risk (1 = not willing to accept any risk; 5 = willing to accept substantial risk to potentially earn a greater return).
<i>Financial literacy</i>	The score is the sum of the 11 financial literacy questions (highest score, 11; lowest score, 0) adapted from van Rooij et al. (2011).
<i>Age</i>	Age of the participant.

## Appendix A. (Continued)

### Control variables

<i>Gender</i>	Equals 1 if the gender of the participant is male, 0 otherwise.
<i>Stock ownership</i>	Equals 1 if subjects own stocks or stock funds, 0 otherwise.
<i>Income</i>	Self-reported income of participants in 1,000s of dollars/euros.
<i>College</i>	Equals 1 if the participant has a college degree, 0 otherwise.

### Subjective variables

<i>Risk perception</i>	How risky do you perceive Fund B (the risky fund) to be? (1 = not risky at all, 7 = very risky)
<i>Confidence</i>	How confident do you feel about investing in the risky fund? (1 = completely unconfident, 7 = completely confident)

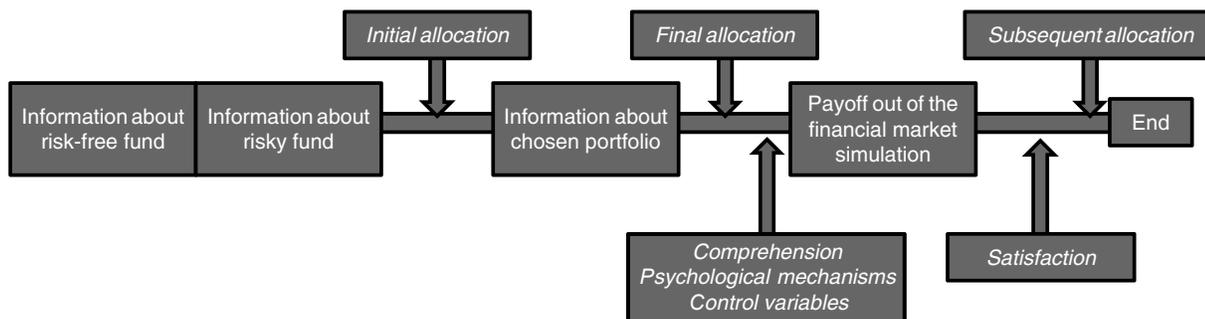
### Recall and subjective comprehension variables

<i>Perceived return</i>	If we put \$100 in the riskier fund, what is the expected return of the \$100 after five years? (Give your best estimate.) Coded to reflect under- and overestimation: -1 = \$100–\$140, 0 = \$141–\$180 (correct interval), 1 = \$181–\$220, 2 = \$221–\$260, 3 > \$260
<i>Perceived probability of a loss</i>	If we put \$100 in the riskier fund, in how many out of 100 cases will the return fall below \$100 after five years? In _____ out of 100 cases.
<i>Upside potential</i>	If we put \$100 in the riskier fund, in how many out of 100 cases will the return fall be above \$150 after five years? In _____ out of 100 cases.
<i>Informed</i>	How informed do you feel about the funds? (1 = completely uninformed, 7 = completely informed)

### Postreturn decision evaluation

<i>Satisfaction</i>	Question asked after participants were shown their simulated return after five years: How satisfied are you with your return? (1 = completely unsatisfied, 7 = completely satisfied)
<i>Luck</i>	A variable measuring the outcome of the market simulation minus the expected return of the final allocation.

## Appendix B. Overview of Experimental Setup



## Appendix C. Overview of Experimental Conditions

### Description Condition

1. Participants read descriptions of the risk-free and risky fund:

You will choose how much to invest in a risk-free asset and how much to invest in a riskier asset.

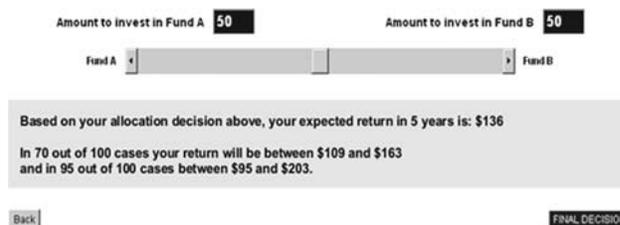
Fund A is a risk-free asset. It has a guaranteed annual return of 3.35% for sure. If you invest the full \$100 in Fund A, you will have a return of \$118 in five years, net of fees.

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

You can change the amounts you allocate to Fund A and Fund B by moving the scroll bar below and seeing how the expected return and the standard deviation of your total

investment amount changes. When you have decided, click *final decision* below.

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

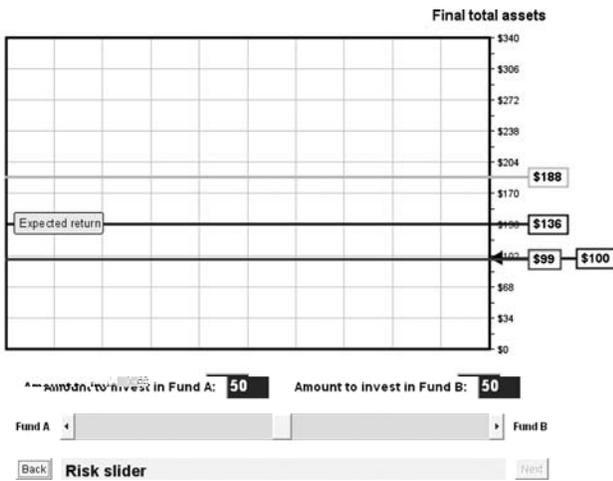


### Risk Tool Condition

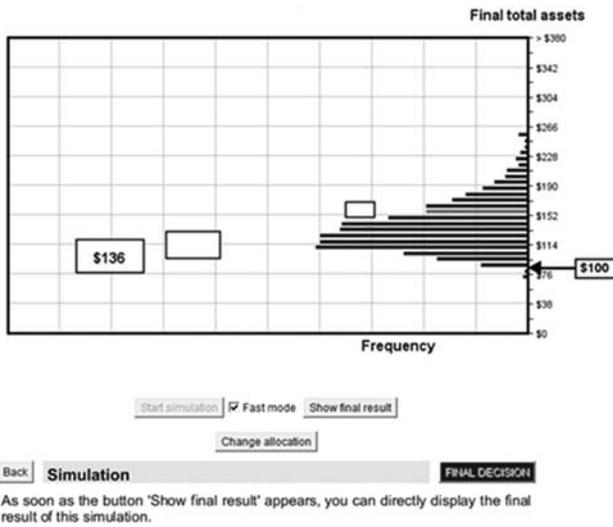
1. An experience sampling simulation draws the return of the risk-free fund, resulting in a flat line.

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

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



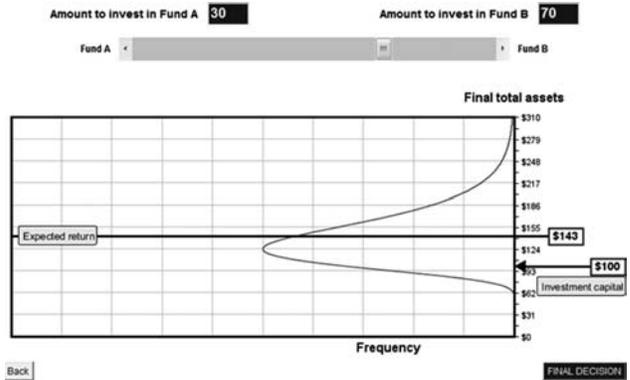
4. Experience sampling is used to build up the distribution of the risky fund based on the initial allocation. Participants can change their allocation and watch the simulation again as often as wanted until they decide on a final allocation.



**Distribution Condition**

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

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



**Experience Condition**

1. Participants draw possible returns for the risk-free fund (at least three draws).

2. Participants draw possible returns for the risky fund (at least eight draws).

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



**Appendix D. Overview of Experimental Methods**

	Experiment I	Experiment II	Experiment III	Experiment IV	Experiment V
Allocations to the risky fund					
Description	60.4	54.4	57.7	61.3	58.2
Risk tool	74.2	66.5	70.6	74.1	73.6
Distribution		59.5	62.46		
Experience		61.0	66.65		
Context					
Time horizon	5 years	5 years	5 years	1 and 5 years	10 years
Investment amount	€1,000	\$100	\$100	\$100	€1,000
Measures					
Risk attitude	X	X	X	X	X
Financial literacy	X	X	X	X	X

Appendix D. (Continued)

	Experiment I	Experiment II	Experiment III	Experiment IV	Experiment V
Measures					
Risk perception			X		
Confidence			X		
Probability of a loss			X	X	
Expected value			X		
Informed			X		
Data					
Population	German students	U.S. population (Yale)	U.S. population (Yale)	U.S. population (Mturk)	German students
N	133	190	362	212	39
Mean age	22	34	35	36	24

References

- Abdellaoui M, L'Haridon O, Paraschiv C (2011) Experienced vs. described uncertainty: Do we need two prospect theory specifications? *Management Sci.* 47(10):1879–1895.
- Ameriks J, Zeldes S (2004) How do household portfolio shares vary with age? Working paper, Columbia Business School, Columbia University, New York.
- Andersen S, Nielsen KM (2011) Participation constraints in the stock market: Evidence from unexpected inheritance due to sudden death. *Rev. Financial Stud.* 24(5):1667–1697.
- Arrow KJ (1971) *Essays in the Theory of Risk-Bearing* (North-Holland Publishing Company, Amsterdam-London).
- Baron J, Hershey JC (1988) Outcome bias in decision evaluation. *J. Personality Soc. Psych.* 54(4):569–579.
- Barron G, Erev I (2003) Small feedback-based decisions and their limited correspondence to description-based decisions. *J. Behavioral Decision Making* 16(3):215–233.
- Benartzi S, Thaler R (1999) Risk aversion or myopia? Choices in repeated gambles and retirement investments. *Management Sci.* 45(3):364–381.
- Beshears J, Choi J, Laibson D, Madrian M (2011) Can psychological aggregation manipulations affect portfolio risk-taking? Evidence from a framed field experiment. NBER Working Paper 16868, National Bureau of Economic Research, Cambridge, MA.
- Campbell JY (2006) Household finance. *J. Finance* 61(4):1553–1604.
- DAI (2011) DAI Factbook 2011, [http://www.dai.de/internet/dai/dai-2-0.nsf/dai\\_statistiken.htm](http://www.dai.de/internet/dai/dai-2-0.nsf/dai_statistiken.htm).
- European Parliament and European Council (2004) Markets in financial instruments directive. Directive 2004/39/EC.
- Fox CR, Hadar L (2006) Decisions from experience = sampling error + prospect theory: Reconsidering Hertwig et al. (2004). *Judgment Decision Making* 1(2):159–161.
- Glaser M, Weber M (2010) Overconfidence. Baker HK, Nofsinger J, eds. *Behavioral Finance: Investors, Corporations, and Markets* (John Wiley & Sons., Hoboken, NJ), 241–258.
- Goldstein DG, Johnson EJ, Sharpe WF (2008) Choosing outcomes versus choosing products: Consumer-focused retirement investment advice. *J. Consumer Res.* 35(3):440–456.
- Gomes FJ, Michaelides A (2005) Optimal life-cycle asset allocation: Understanding the empirical evidence. *J. Finance* 60(2):869–904.
- Hadar L, Fox CR (2009) Information asymmetry in decision from description versus decision from experience. *Judgment Decision Making* 4(4):317–325.
- Haliassos M, Michaelides A (2003) Portfolio choice and liquidity constraints. *Internat. Econom. Rev.* 44(1):143–177.
- Hanoch Y, Johnson JG, Wilke A (2006) Domain specificity in experimental measures and participant recruitment. *Psych. Sci.* 17(4):300–304.
- Hau R, Pleskac TJ, Kiefer J, Hertwig R (2008) The description-experience gap in risky choice: The role of sample size and experienced probabilities. *J. Behavioral Decision Making* 21(5):493–518.
- Hertwig R, Erev I (2009) The description–experience gap in risky choice. *Trends Cognitive Sci.* 13(12):517–523.
- Hertwig R, Barron G, Weber EU, Erev I (2004) Decisions from experience and the effect of rare events in risky choice. *Psych. Sci.* 15(8):534–539.
- Hong H, Kubik JD, Stein JC (2005) Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. *J. Finance* 60(6):2801–2824.
- Jacobs H, Müller S, Weber M (2010) How should private investors diversify? An empirical evaluation of alternative asset allocation policies to construct a “world market portfolio.” Working paper, University of Mannheim, Mannheim, Germany.
- Jia J, Dyer JS, Butler JC (1999) Measures of perceived risk. *Management Sci.* 45(4):519–532.
- Kahneman D, Tversky A (1979) Prospect theory: An analysis of decision under risk. *Econometrica* 47(2):263–292.
- Keller CR, Sarin RK, Weber M (1986) Empirical investigation of some properties of the perceived riskiness of gambles. *Organ. Behav. Human Decision Processes* 38(1):114–130.
- Klos A, Weber EU, Weber M (2005) Investment decisions and time horizon: Risk perception and risk behavior in repeated gambles. *Management Sci.* 51(12):1777–1790.
- Lejarraga T (2010) When experience is better than description: Time delays and complexity. *J. Behavioral Decision Making* 23(1):100–116.
- Markowitz H (1952) Portfolio selection. *J. Finance* 7(1):77–91.
- Merton RC (1969) Lifetime portfolio selection under uncertainty: The continuous-time case. *Rev. Econom. Statist.* 51(3):247–257.
- Merton RC (1971) Optimum consumption and portfolio rules in a continuous-time model. *J. Econom. Theory* 3(4):373–413.
- Nosić A, Weber M (2010) How risky do I invest: The role of risk attitudes, risk perceptions and overconfidence. *Decision Anal.* 7(3):282–301.
- Poterba JM (2000) Stock market wealth and consumption. *J. Econom. Perspect.* 14(2):99–118.
- Rakow T, Newell BR (2010) Degrees of uncertainty: An overview and framework for future research on experience-based choice. *J. Behavioral Decision Making* 23:1–14.
- Samuelson PA (1969) Lifetime portfolio selection by dynamic stochastic programming. *Rev. Econom. Statist.* 51(3):239–246.
- Sarin R, Weber M (1993) Risk-value models. *Eur. J. Oper. Res.* 70(2):135–149.

- Siebenmorgen N, Weber M (2004) The influence of different investment horizons on risk behavior. *J. Behavioral Finance* 5(2):75–90.
- Ungemach C, Chater N, Stewart N (2009) Are probabilities overweighted or underweighted when rare outcomes are experienced (rarely)? *Psych. Sci.* 20(4):473–479.
- van Rooij M, Lusardi A, Alessi R (2011) Financial literacy and stock market participation. *J. Financial Econom.* (2):449–472.
- Weber EU, Milliman R (1997) Perceived risk attitudes: Relating risk perception to risky choice. *Management Sci.* 43(2):123–144.
- Weber EU, Blais A-R, Betz NE (2002) A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *J. Behavioral Decision Making* 15(4):263–290.
- Weber EU, Siebenmorgen N, Weber M (2005) Communicating asset risk: How name recognition and the format of historic volatility information affect risk perception and investment decision. *Risk Anal.* 25(3):597–609.
- Weber EU, Shafir S, Blais AR (2004) Predicting risk sensitivity in humans and lower animals: Risk as variance or coefficient of variation. *Psych. Rev.* 111(2):430–445.