Do Risk Simulations Lead to Persistently Better Investment Decisions?

Meike A. S. Bradbury[1], Thorsten Hens[1,2] and Stefan Zeisberger[3,*]

[1] *Department of Banking and Finance, University of Zurich, Switzerland*

[2] *Department of Finance, Norwegian School of Economics, Bergen, Norway*

[3] *College of Business, Stony Brook University, USA*

**Corresponding author, stefan.zeisberger@stonybrook.edu*

This version: July 12, 2016

Abstract

Risk simulations based on experience sampling were found to significantly improve initial investment decisions. We analyze the advantages and limitations of risk simulations in a setting in which investors can adjust their investment strategy before the end of the investment horizon. Our experimental results underscore the positive effects of risk simulations on investors' understanding of the risk-return trade-off. Furthermore, we find that investors who are informed via description require multiple investment periods until they show stable average risk-taking behavior and similar allocations to the risky asset as investors informed via risk simulations. We do not find any effects of initial simulation-based learning on investors' trading volume or trading behavior with regard to previous investment outcomes.

JEL Classification: D81; G11

Keywords: Behavioral finance, simulated experience, experience sampling, investment decision, risk communication, financial advice, Fintech

Acknowledgements

We are thankful to Helga Fehr-Duda, Eric Johnson, Chrsitine Kaufmann, David Laibson, Miles Kimball, Pascal St-Amour, Martin Weber and participants at the following conferences and seminars: Behavioural Finance Working Group Conference in London 2016, Consumer Financial Protection Bureau (CFPB) research conference in Washington DC in 2015, Behavioral Decision Research in Management (BDRM) Conference in London 2014 and University of Innsbruck Finance Seminar 2014 for their valuable comments and suggestions. We also thank Marius Wolfensberger for his programming support and Behavioural Finance Solutions GmbH for financial support. This research was gratefully supported by the Swiss National Science Foundation (100018-149934). Old title: "How Risk Simulations Improve Long-Term Investment Decisions"

1. Introduction

Behavioral finance has demonstrated that investors often make sub-optimal decisions. This can be very costly with respect to their overall wealth (Gomes and Michaelides 2005; Campbell 2006; Calvet et al. 2007). Kaufmann et al. (2013) were the first to propose risk simulations based on experience sampling (Hertwig et al. 2004) to improve the investment decisions of individuals (see also Ehm et al. 2014). Risk simulations enable investors to experience final return distributions by random sampling of possible returns. These studies demonstrate that investors can significantly improve their decision-making ability due to a better understanding of the underlying return distribution.[1] As a consequence, investors are willing to accept higher financial risks without regretting these riskier decisions afterwards. Bradbury et al. (2015) show the robustness of the positive effects of risk simulations for a more complex investment decision context, i.e. for structured products.

Importantly, these studies focus on the point of time at which the investor makes his initial investment decision. As a consequence, any possible investor reactions after experiencing actual intermediate investment outcomes are ignored. This is a crucial lack in the current literature since findings in behavioral finance provide evidence that investors follow their emotional instincts during their investment journey and question their decisions along the way (Shefrin and Statman 1994; Odean 1999; Barber and Odean 2001; Cohn et al. 2015). For example, the literature on myopic loss aversion (Benartzi and Thaler 1995) shows that with frequent feedback and short periods of commitment, myopia significantly reduces investors'

[1] Many alternative studies also propose methods to improve saving and investment decision behavior, including, for example, pre-commitment (Thaler and Benartzi 2004), elaborating on the value of future rewards (Weber et al. 2007) or presenting investors with their future selves (Hershfield et al. 2011). These methods have the aim to "nudge" investors to invest better for one-off decisions but they do not support investors' understanding of the underlying decision problem, in particular the risk return trade-off.

willingness to take risks and reduces their overall wealth levels (e.g. Gneezy and Potters 1997; Thaler et al. 1997).

Given this gap in the literature, this paper analyzes the persistence of the positive effects of risk simulations based on experience sampling, taking into account possible reactions by investors to intermediate actual outcomes when they experience them. We use a long-term experiment to simulate a multi-year investment horizon. It is of particular interest how actual investment feedback interacts with the initial benefits of risk simulations. Important research questions are:

- Do risk simulations lead to persistently higher investments in risky assets?
- Do they affect investors' reactions to previous outcomes?
- And do they lower trading volume?

Against this background, we have, in addition, developed a new and enhanced means of communicating investment risk in which investors are not only shown final investment outcomes but also wealth paths over time. The underlying idea of this "wealth path simulation" is to make investors aware that intermediate losses can occur but are usually offset over longer time horizons.

In contrast to the vast majority of experiments which use a classical short-term design, even when analyzing long-term decision situations, we apply a more realistic long-term experimental approach over weeks, which is an important element in providing our research question external validity. Beshears et al. (2015) and Zeisberger et al. (2014) demonstrate that time considerations can play a crucial role in experiments. If the positive effects of risk simulations would vanish in our set up, this would likely also be the case in reality with even longer time horizons.

Our study provides valuable insights into risk communication and investment advice by exploring their advantages and limitations, in particular with regard to the persistence of investment decisions. This is a field of strong ongoing academic, practitioner and regulator interest of high importance for all financial institutions and individual advisors, and is further fueled by the digitalization trend of investment services (e.g. robo-advisors).

Our findings can be summarized as follows: We confirm previous results on the positive effects of risk simulations on the initial investment decision. We observe that investors who receive return information in a descriptive manner allocate lower levels of risk initially. They tend to increase their risk-taking gradually after receiving feedback on actual investment success, but only catching up with the risk levels taken by investors who were informed via experience-based learning after some time. In other words, we find evidence that risk simulations work as a "substitute" for actual investment experience. Comparing different forms of risk simulations, we find that presenting investors with final outcomes is sufficient to increase initial risk-taking. The "wealth path simulation" does not increase risk-taking above a simulation of final outcomes but seems to further improve investors understanding of investment trade-offs. We do not find that risk simulations change investors' reactions to previous outcomes. They also do not lower investors' trading volume and hence not transaction costs.

2. Experimental Design

2.1 General Setup

We programmed a proprietary online experiment, which we designed exclusively for this study. In our experiment, participants had to make 14 consecutive investment decisions, one per calendar day. To facilitate participation, our subjects received an e-mail reminder every day, and we did not request participants to make decisions on weekends (but they could do so if they wanted).[2] To ease access to the software and to facilitate the smooth functioning of the experiment, we made sure that our software not only worked on desktop computers but also on mobile devices, such as smartphones or tablet computers (e.g., iPad), guaranteeing the same layout on all devices.

2.2 Experimental Task

The experiment followed a general design and was split into three treatments (see Figure 1).

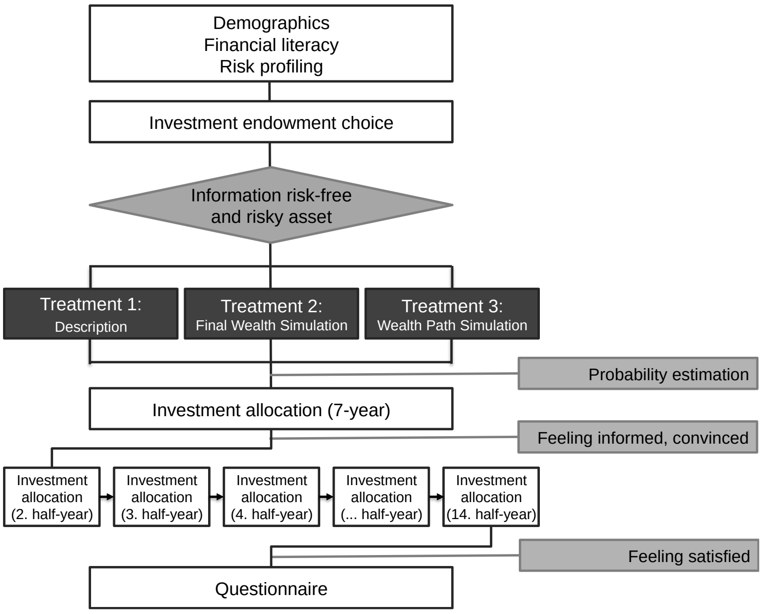


Figure 1. General experimental setup

This figure illustrates the overall sequence of the between-subject experimental design.

On the first day, which took participants on average 16 minutes to complete, participants had to answer some demographic questions, a financial literacy quiz (adapted from Lusardi and Mitchell 2011) and typical risk profiling questions (for an overview and the exact wording see Appendix A). Following the questionnaire, participants were asked to choose an

[2] In addition, we allowed all participants to miss two days in case they forgot to participate or did not have Internet access. The days missed were added to the overall length of the experiment as every participant had to make 14 investment decisions in total.

investment endowment (€5,000, €25,000 or €100,000) that most closely represented their real financial circumstances.

Participants then received information on a risk-free and a risky asset. The *risk-free* asset was introduced as a fixed-term deposit account with a 1.8% rate of return p.a., which corresponds to the average rate of one-year U.S. Treasury Bills for the 10-year period before the experiment (12/31/2002–12/31/2012). To construct the return distribution of the *risky* asset, we calculated empirical half-year returns of the S&P 500 index over 49 years until 12/31/2012 using a one-day rolling time window, which resulted in approximately 12,500 overlapping half-year returns. We hence incorporated six-month autocorrelation structures. We then conducted a bootstrapping technique to construct seven-year returns. We very clearly informed our participants that half-year returns are independent from each other. In one of our robustness checks, we constructed the return distribution using seven-year empirical returns (one-day rolling window resulting in 10,571 returns), hence capturing the autocorrelation structure for the whole seven-year investment horizon (see Section 4).

Following Weber et al. (2005), we did not reveal to the participants that a specific index and time period were used as this has been shown to influence risk perception and investment decisions. For the resulting distribution, the average return amounted to 7.0% p.a., after we included a 0.5% reduction to account for the management fee of a passive index fund. The standard deviation was 16.9% p.a. All information was communicated to the participants in plain language to guarantee their full understanding (see Appendices B-D for instructions).

Participants then had to allocate their chosen investment amount between the two assets for the seven-year period (see Section 2.3 for details). They were able to adjust the allocation to see how the risk-return profile cohered with the chosen allocation between risk-free and risky assets before choosing their final allocation. After making the investment decision, participants had to state how well informed they felt about the two assets and how convinced they were that they had chosen the appropriate allocation for themselves.

At the end of the first day, participants were informed that over the following 14 working days their seven-year investment horizon would be simulated in half-year steps. Hence, one day represented half a year in the experiment. Every day, participants were asked to make an investment decision, which related to the following half year (next day). Participants were also informed that if they changed their allocation, they would incur costs. The costs amounted to 1% of the asset value shifted between the risk-free and the risky asset.

On all following days in the experiment, participants were informed about the past performance of their investment strategy (see Appendix B for a screen shot) before being asked if they want to adjust their asset allocation for the next half year. Participants did not have to change their allocation, and as in reality, the default was to leave the asset allocation constant, but it was also easy to change the allocation.

2.3 Treatment design

The manner in which the risk-free and risky assets were presented to participants varied between three treatments in a between-subject design. Participants were randomly assigned to one of the three treatments. Appendices B to D provide illustrations of risk presentations in the treatments.

Description Treatment (DESCRIP)

In the treatment "Description" (DESCRIP) we informed participants in a descriptive and graphical manner about the relevant underlying return distribution of their investment (see Appendix B). We provided participants with the expected yearly return and the expected absolute amount after seven years. In the case of the risky asset, participants were also given the asset's yearly standard deviation. The expected yearly return, the expected absolute amount after seven years and the yearly standard deviation were provided in all three treatments in the same way. As most investors find standard deviations difficult to comprehend (Das et al. 2011) and because our empirical return distribution is not perfectly normal, we additionally provided a graphical illustration of the risky asset's return distribution using a detailed bar chart.

Final Wealth Simulation Treatment (FINAL)

The procedure in this treatment "Final Wealth Simulation" (FINAL) is based on the "risk tool" as proposed by Kaufmann et al. (2013). Participants manually sampled 15 random returns from the return distribution of the risky asset by clicking with the computer mouse. These returns were displayed on the screen consecutively. After the 15 draws, participants were free to continue with further manual draws if they wanted, or they could view a further 35 random draws that were presented automatically. No matter how many manual draws participants chose to make, a total of 50 random draws were plotted to ensure that the simulation did not result in major sampling errors (Bradbury et al. 2015). After this, the final distribution was displayed graphically on the *y*-axis (see Appendix C).

Wealth Path Simulation Treatment (PATH)

Both the DESCRIP and FINAL treatments focus on the wealth distribution at the *end* of the investment horizon. Making investors aware of the fact that final outcomes are reached by different paths might better prepare them to cope with short-term volatility, so that they keep to their initially chosen investment strategy and become less reactive when experiencing intermediate losses. However, given insights from the literature on myopic loss aversion (showing that final distributions should be presented to increase risk-taking) it might also have adverse effects. Against this background, we not only focused on the comparison between DESCRIP and FINAL, but also included a new means of investment risk communication in a third treatment. This treatment additionally visualized the wealth paths toward achieving the final outcomes. More precisely, the “Wealth Path Simulation” (PATH) treatment adds to the FINAL treatment by not only plotting final outcomes but also every half-year outcome during the investment horizon, i.e., the wealth path to the final outcome. To further enhance the investor’s understanding, the software animates each random seven-year path by building it up time-wise in half-year steps from the day of the decision to the end of the investment horizon. All paths were displayed after each other with increasing speed. In addition, the highest and lowest interim wealth value and largest half-year loss were indicated for every path (see Appendix D).

2.4 participants and Monetary incentives

We recruited a total of 894 participants with the survey institute “Research Now” in Germany, which enabled us to use a broad and relatively representative sample of German citizens aged 18–65 years (Levitt and List 2007). We excluded apprentices, school children and unemployed persons from taking part in the experiment to focus in potential real-world investors. Furthermore, we specified the gender distribution, two thirds being men as this more accurately represents the actual gender distribution of financial decision makers (see, e.g., Barber and Odean 2001). Overall, 895 participants took part in the three treatments and robustness checks (551 in main treatments).[3] The mean age of participants was 40 years (s.d.=12) and 58.8% of the participants had completed secondary school at the minimum. A

[3] We excluded 37 participants (an additional 20 from the robustness checks) from the analysis because they rushed through the instructions and hence did not read them with the necessary diligence. The exclusion rule is: If a participant hurried through the instruction quicker than one fifth of the median amount of time all participants took to read the instructions on two or more instruction screens, he or she was excluded from the analysis. The amount of time spent on the screens explaining the risky asset and the initial asset allocation choice varied by treatment.

relatively large fraction (52.5%) reported currently owning stocks or equity funds. Appendix F provides details.

We incentivized participants with real monetary rewards. There was a fixed reward component and an incentive-compatible variable component. For the fixed component, each participant received €2.50 for the first day, €0.15 for every following day, and an additional €1.00 for finishing the experiment. Hence, participants who finished the experiment were sure of receiving €5.60. For the additional, incentive-compatible component, each participant received a monetary endowment of €100.00 at the beginning of the experiment, which corresponded to their chosen experimental investment capital. At the end of the whole study, 20 participants were randomly selected from those who finished and received the final outcome they had achieved over the seven-year investment horizon, based on the initial €100.00 endowment. We did not pay all participants since paying a fraction of participants with higher amounts was shown to have no significant effects on experimental outcomes and stated risk preferences, sometimes higher amounts increase the incentive effect, even for unknown winning probabilities (March et al. 2015). This "between-subjects random incentive system" has been frequently used (Dohmen et al. 2010; Haigh and List, 2005; Cohn et al. 2015; Kirchler et al. 2016). The average amount received was €132.40 with a substantial range from €87.80 to €278.90. All payment details were clearly communicated to all participants at the beginning of the study.

3. Results

3.1 The effect of information presentation on initial investment decision and understanding of the risk–return tradeoff

In this first section we include all n=551 participants who initially took part in the study Using only the 384 participants who finalized the study leads to qualitatively very similar results. We find that the way in which risk is communicated has a considerable influence on the initial allocations to the risky asset. We find a higher average allocation to the risky asset in the two simulation treatments compared to DESCRIP: FINAL 51.6%, PATH 49.8%, and DESCRIP 43.8%. Both differences to DESCRIP are significant (one-tailed *t*-test, FINAL vs. DESCRIP: p=.001, PATH vs. DESCRIP: p=.006). We find no significant difference between FINAL and PATH ($p=.225$). Risk simulations hence lead to increased risk-taking.

Increased risk-taking does not necessarily mean a better decision. We thus further asked participants how well informed they felt about the decision problem, and how confident they were of having made the right investment decision based on the information provided. Both questions were measured on a six-point Likert scale (1 = not at all, 6 = very) and were asked directly after participants' first investment decision. Based on previous findings, we expect to find higher values for feeling informed in the FINAL treatment (Kaufmann et al. 2013; Bradbury et al. 2015). The outcome for the PATH treatment, however, might not be as straightforward. This treatment could have been perceived as more complex and participants might have concentrated too much on the investment paths, distracting them from the interpretation of the risk–return distribution *at maturity*.

We find evidence that investors feel significantly better informed if risk is communicated via FINAL compared to a descriptive communication of financial risks, as anticipated (see Table 1). The same holds true for the communication via PATH. However, we do not find a significant difference in feeling confident between treatments. These findings are generally in line with those of Kaufmann et al. (2013) and Bradbury et al. (2015).

Table 1. Differences in allocation to the risky asset and participants' feeling informed and confident

This table shows mean allocations to the risky asset for all three treatments. It also reports mean responses for feeling informed and confident, measured on six-point Likert scales. To compare allocation decisions one-tailed *p*-values of *t*-tests are reported, for feeling informed and feeling confident Mann-Whitney-*U*-tests are used. *P*-values in bold indicate significance at the 5% level.

Treatment	**Description**	**Final Wealth Simulation**	**Wealth Path Simulation**
Allocation to risky asset	43.8%	51.6%	49.8%
p-values vs. DESCRIP		***p=.001***	***p=.006***
p-value FINAL vs. PATH			*p=.450*
Feeling informed	3.45	3.72	3.89
p-values vs. DESCRIP		***p=.022***	***p=.000***
p-value FINAL vs. PATH			*p=.310*
Feeling confident	3.96	3.98	4.09
p-values vs. DESCRIP		*p=.909*	*p=.324*
p-value FINAL vs. PATH			*p=.399*
N	189	179	183

These measures for improved investment decision making might be subjective as they are based on self-reported answers. Hence, we also analyze an objective evaluation of individuals' understanding of possible financial consequences via specific probability judgments. Participants had to estimate the probability of three possible events for the risky asset after seven years: a) achieving less than the initially invested amount (true probability = 17.2%), b) achieving less than the amount one would have realized by investing in the risk-free asset (true probability = 25.2%), and c) achieving more than twice as much as initially invested (true probability = 25.4%). These estimates provide an objective measure of how well investors understand the risk–return profile of the risky asset.

Generally, we find that participants on average overestimate the probability of a loss,[4] and they underestimate the probabilities of the upside potential over all treatments. Comparing

[4] This is in line with Benartzi and Thaler (1999) and Weber et al. (2005), who also found their subjects to substantially overestimate the probability of a loss in a repeated play of simple gambles or more difficult distributions, which is comparable to an asset allocation decision context with a long-term investment horizon.

the three probability estimates between treatments, we find the estimates in the FINAL and PATH treatments tend to be slightly better compared to DESCRIP (see Table 2). For FINAL two out of three estimates are closer to the true values, for PATH it is three out of three. The standard deviations of participants' estimates are smaller in the FINAL and PATH treatments compared to DESCRIP in most cases with the *p*-value between 0.001 and 0.055. Interestingly, PATH leads to similarly good results as FINAL (*p*-values are even lower), although wealth paths have the potential to distract investors with some irrelevant information with respect to the probability estimation. Estimates for the loss likelihood in PATH were significantly better (one-tailed *t*-test, $p=.027$) compared to FINAL, the other differences are not significant.

Overall, these results are very interesting as the positive effects of risk simulations appear even though there are sampling errors in the active sampling phase. Hence, even with these sampling errors in the active sampling, estimates tend to be better compared to a description with an easy to read bar chart. We hypothesize that learning though risk simulations is more engaging, leading to better results.

Table 2. True and estimated probabilities of the risky asset's return distribution

This table shows true values for return probabilities, the difference of participants' average estimate to the true values, and average absolute deviations of estimates from true values as well as standard deviations for all participants for three probability events. To calculate the *p*-values of the one-tailed *t*-tests, we use absolute deviations from estimated to true values to avoid opposite signs canceling each other out. *P*-values in bold indicate significance. See Appendix G for the precise phrasing of the estimation prompts.

	P(r<0%)	P(r<r_f)	P(r>100%)
True value	**17.2**	**25.2**	**25.4**
Description vs. Final Wealth Simulation			
Average deviation of participants' estimate from true value			
DESCRIP	+14.2	+10.3	-2.8
FINAL	+13.0	+12.2	-1.4
Average absolute deviation of estimates to true value			
DESCRIP	21.6	22.3	21.7
FINAL	18.4	19.4	17.3
t-test	***p=.052***	***p=.055***	***p=.004***
Standard deviation of estimates			
DESCRIP	20.8	18.8	17.2
FINAL	17.1	15.8	13.9
Description vs. Wealth Path Simulation			
Average deviation of participants' estimate from true value			
DESCRIP	+14.2	+10.3	-2.8
PATH	+10.6	+10.0	-0.9
Average absolute deviation of estimates			
DESCRIP	21.6	22.3	21.7
PATH	15.0	18.2	17.2
t-test	***p=.001***	***p=.013***	***p=.003***
Standard deviation of estimates			
DESCRIP	20.8	18.8	17.2
PATH	16.1	15.5	13.3

Although many differences are statistically significant, our effect sizes are smaller compared to previous studies (Kaufmann et al. 2013; Bradbury et al. 2015). However, previous research in this area did not include a graphical illustration in the form of an easy-to-read bar chart in the description condition as we did, except for the robustness check on "information asymmetry" in Bradbury et al. (2015). We conclude that an appropriate presentation, such as in the form of a detailed and easy-to-read bar chart, improves investors' risk perception, but not to the extent that a risk simulation does. Generally, we find evidence that risk simulations increase investors' risk-taking and improves understanding of risk–return tradeoffs. This is true not only for simulating final returns but also for the case in which investors are presented with wealth paths (which incorporate some irrelevant information).

3.2 The impact of risk simulations on the persistency of investment decisions

With a better alignment of perceived risk with actual risk, participants chose higher allocations to the risky asset in the FINAL and PATH treatments for their *initial* investment decision. We now turn to analyzing the investment behavior over the whole investment horizon, which means we focus on the n=384 participants who fully completed the study.

Controlling for attrition bias

To ensure that our results are not driven by an attrition bias (early dropouts), we conducted a series of tests. First, we do not find any significant differences in dropout rates (participants who did not finish the experiment over the 14 trading days) between all three treatments: DESCRIP = 27%, FINAL = 33%, PATH = 31%. Additionally, we compared the average half-year return of the dropout participants with those who completed the experiment. We do not find any significant difference between the average returns achieved (two-tailed t-test, p=.751), average returns until dropout amount to 2.03% in the case of the dropout participants and 2.12% for those who completed all 14 investment decisions (two-sided t-test p=0.68). Furthermore, the dropout behavior does not seem to be driven by negative events. Also, the last return that was experienced for the risky asset before a participant dropped out does not differ significantly from the overall average return realized, nor does it differ from the average return of those who remained in the experiment until the end. Overall, we conclude that participant dropouts do not seem to be linked in any systematic way to specific events or treatments.

Risk-taking

Our results show that allocations in subsequent periods, i.e. after the initial allocation, remain significantly higher in the FINAL and PATH treatments up to a certain point in time (see Figure 2 for a graphical illustration). Participants in DESCRIP take seven periods (3.5 years) of feedback to reach a peak in their allocation to the risky asset, very close to the point in time at which the average allocation to the risky asset becomes similar between the three treatments. As a result, participants in DESCRIP show a significant increase in their allocation to the risky asset from the beginning of the investment horizon to t=3.5 years by approximately 7 percentage points (paired t-test, p=.000), whereas participants' investment risk in the FINAL and PATH treatments remain relatively stable on average over the first 3.5 years. This provides evidence that participants initially presented with descriptive statements need to learn how much risk they are willing to take, whereas participants presented with a form of risk communication that incorporates simulated experience start off with higher allocations and keep to them. A simulation seems to prepare investors to cope with the risk of their investment. From a wealth accumulation perspective, higher allocations to the risky fund from an early stage are beneficiary for investors.

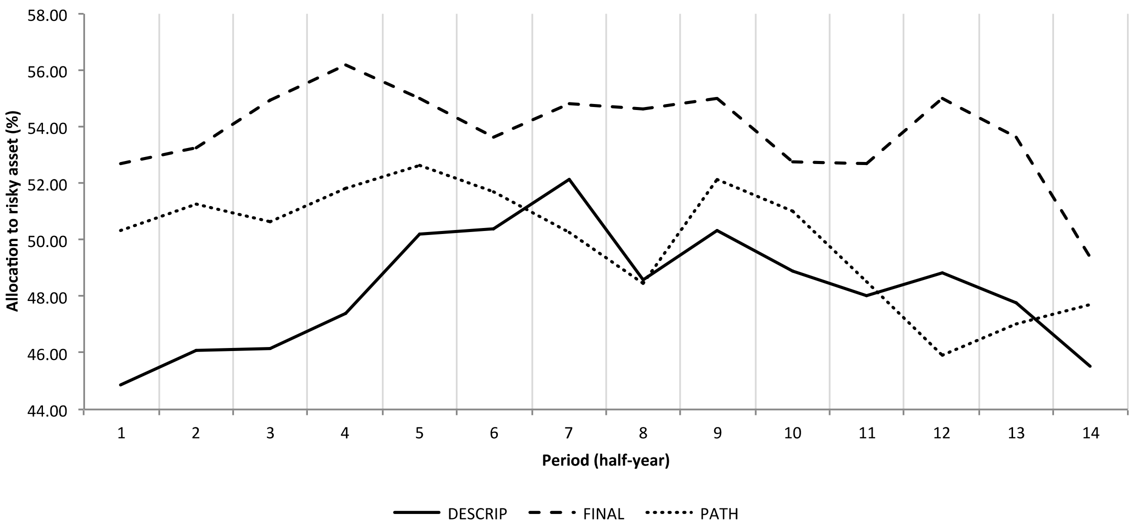


Figure 2. Mean allocation to the risky asset
This figure shows the mean allocations to the risky asset over the full investment horizon for each treatment.

What also becomes evident from Figure 2 is that risk-taking is consistently highest in the FINAL treatment. It seems that presenting investors with final outcomes only vs. presenting them with wealth paths leads to higher allocations to the risky asset, however, we do not want to oversell this finding since the difference in allocation is only significant in a few periods. Furthermore, allocations to the risky asset remain relatively stable in the FINAL and PATH treatments when comparing participants' initial investment decisions to all following decisions. This is different for treatment DESCRIP, where we find significant differences between the first allocation and allocations for periods 5 to 13.

Table 3 shows differences in the risk-taking behavior between treatments in more detail. We observe that in the FINAL treatment, allocations remain significantly higher in the first five periods and again toward the end of the investment period compared to DESCRIP. Similarly, but to a lesser extent, we observe risk-taking in the PATH treatment to be higher over the first four periods compared to DESCRIP, after which no further differences are observed. We conclude that risk simulations lead to higher risk-taking, but we do not find risk-taking to be consistently higher for the entire investment period.

Table 3. Differences in allocation to the risky asset

This table shows mean allocations to the risky asset between treatments. To compare allocation decisions, *t*-test results and one-tailed *p*-values are reported. *P*-values in bold indicate significance.

Period	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
DESCRIP	44.9	46.1	46.2	47.4	50.2	50.4	52.1	48.6	50.3	48.9	48.0	48.8	47.8	45.4
FINAL	52.7	53.3	54.9	56.2	55.0	53.7	54.8	54.6	55.0	52.7	52.7	55.0	53.6	49.4
PATH	50.3	51.3	50.7	51.8	52.7	51.7	50.3	48.5	52.1	51.0	48.5	45.9	47.0	47.7
Description (DESCRIP) vs. Final Wealth Simulation (FINAL)														
p =	***.004***	***.008***	***.003***	***.003***	***.070***	*.153*	*.211*	***.037***	***.088***	*.131*	***.092***	***.040***	***.056***	*.148*
Description (DESCRIP) vs. Wealth Path Simulation (PATH)														
p =	***.027***	***.035***	***.069***	***.071***	*.222*	*.332*	*.287*	*.486*	*.297*	*.264*	*.252*	*.206*	*.416*	*.268*

For a better understanding of how much investors have learned about their risk appetite we also measure *individual* absolute deviations from the initial allocation. After half the investment horizon (t=7 periods), we find some indication that allocation adaptations might be smaller in the simulation treatments. Mean absolute adaptations are 16.7% in treatment DESCRIP vs. 15.3% in treatment FINAL (p=0.22 one-sided t-test) and vs. 15.1% in treatment PATH (p=0.10). We receive slightly stronger differences if we focus on the first rounds, i.e. for t=5 and t=6, i.e. after investors have received feedback for 4 or 5 times.

Regarding the second half of the investment horizon we find strong similarities between all treatments. Generally, risk-taking decreases towards the end of the investment horizon. There are different possible explanations for this. One is that participants potentially aim to lock in gains (see, for example, Benzoni et al. 2007; Cocco et al. 2005; Gourinchas and Parker 2002). Similarly, a shortened investment horizon might cause investors to be more risk averse, to some extent consistent with myopic loss aversion (Benartzi and Thaler 1999). As participants gain wealth over time, this kind of behavior is also consistent with increasing relative risk aversion (IRRA), which holds for example with mean-variance preferences. This decrease in risk-taking is interesting as it is consistent with investor behavior in real financial markets, but it is in contrast to nearly all short-term laboratory experimental results.[5]

Satisfaction

Does higher risk-taking in the simulation treatments lower investor satisfaction due to a higher variance in returns and hence possibly higher losses? Our answer is no. Despite differences in risk-taking, we do not find differences in participants' satisfaction with their choice of investment strategy. We measured satisfaction after the end of the experiment by asking participants how satisfied they were with their choice of strategy, i.e. their allocation between the risk-free and the risky asset, using a six-point Likert scale (1 = not at all, 6 = very). The results were: DESCRIP 4.43 vs. FINAL 4.29 (*p=0.454*), and DESCRIP 4.43 vs.

[5] At most, a reduction is limited to the last period, as in Langer and Weber (2008) in the form of a "final-round effect".

PATH 4.41 (*p*=*.950*). Hence, we do not find evidence that investors show regret concerning increased risk-taking behavior in hindsight when previously presented with a simulation.

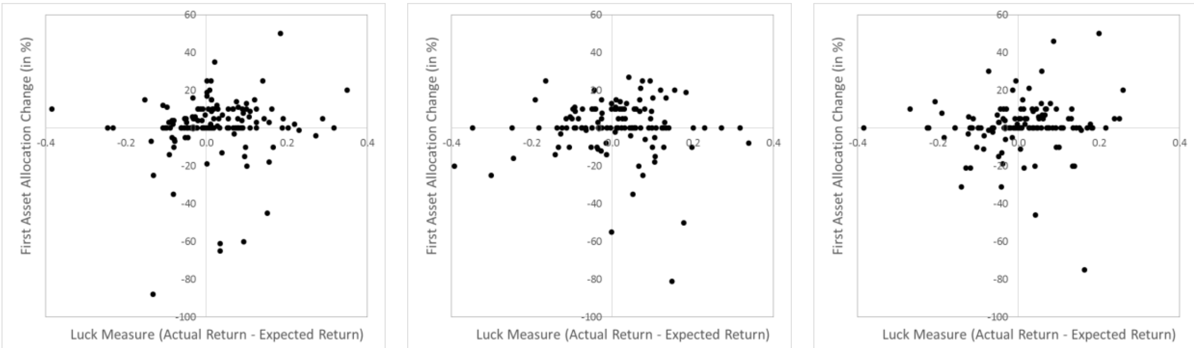
Trading activity

We analyze whether simulated experience affects trading activity. One hypothesis is that risk simulations, in particular like in our PATH treatment, might prepare investors to trade less. Regarding the overall trading volume (and thus transaction costs) we indeed find the lowest average and median volumes for PATH (median: 90% total turnover in relation to initial endowment). Somewhat surprisingly, this is followed by DESCRIP (95%). The highest turnover is observed for FINAL (109%). However, none of the differences are statistically significant (PATH vs. FINAL: one-tailed *t*-test *p*=.514).

Reactivity to previous outcomes

It could be that the fact that we did not find any differences in trading volume between using and not using risk simulations is due to the fact that positive effects vanish relatively quickly, but are present shortly after the learning of the investment problem. Hence, in a further analysis, we compared only the first allocation change in each treatment, i.e. the change from the initial allocation. Also, if risk simulations have an effect on how investors reaction to previous gains and losses then this effect is likely to be highest for the first possible allocation change. However, we do not find significant differences between the three treatments here either. The average absolute change (in %) in allocation: DESCRIP: 8.8, FINAL: 9.2; PATH: 7.8. The difference between PATH and DESCRIP is not statistically significant (one-sided t-test *p*-value: 0.182). This finding also holds true if we split the analysis and analyze reactions to gains and losses separately.

For more insights, Figure 4 shows how investors react to the gain or loss (relative to the expected return which depends on their asset allocation) in the three treatments. We find that in each treatment, a majority of participants slightly increases risk-taking after the first period. There are some differences with respect to how many participants leave their allocation unchanged after the first period: DESRIP: 30.7%, FINAL: 34.2%, and highest in PATH with 39.7%.



DESCRIP FINAL PATH

Figure 4. Asset Allocation Changes in First Period

This figure depicts the asset allocation changes in the first period for all participants in each of the three treatments separately in relation to a luck measure, i.e. actual return – expected return, similar to the analysis in Kaufman et al. (2013). Positive numbers for asset allocation changes indicate increases from the initial allocation in the risky asset after the first period.

Overall, we conclude that simulated experience hardly seems to affect trading volume (and transaction costs) or reactions to previous gains and losses in our setting. This is an interesting insight as Kaufmann et al.'s (2013) analysis on investor's reactions to outcomes seems to suggest that investors who use a risk simulation show a less extreme reaction to losses. Our results indicate that these effects might not be present to the same extent in a real-world setting with higher time lag. This finding might give some evidence that risk simulation influence risk perception (i.e. probability estimates of the return distribution) but not risk preferences such, at least with regard to reactions to previous gains and losses.

4. Robustness of Results

4.1 Control variables

Our results remain stable when controlling for self-reported financial risk attitude, financial literacy, experience, being invested in real life and further demographic variables (see Appendix A for detailed information on the control variables) in a Tobit regression analysis (see Table 4). We find self-reported financial risk attitude to be a strong predictor for the allocation to the risky asset, confirming the findings of a broad spectrum of literature in the financial decision-making context (see, e.g., Schooley and Worden 1996; Nosić and Weber 2010; Dohmen et al. 2011; Halko et al. 2012; Ehm et al. 2014). We also find financial literacy, measured by a quiz, to be a relatively reliable indicator of risk-taking behavior, which supports evidence from existing literature that there is a link between financial literacy or sophistication and financial decision making (Campbell 2006; Agarwal et al. 2015). On the other hand, experience, being invested, having a university degree, age, gender, and income have hardly any predictive power in relation to participants' actual risk-taking.[6]

We also ran Tobit regressions for each treatment separately to see whether risk attitude and financial literacy have varying strengths in predictive power depending on the way in which risk is communicated (see Appendix H). We find self-reported financial risk attitude and financial literacy to have strong predictive power in the DESCRIP treatment for the allocations to the risky asset over all periods. This effect is weaker for the FINAL treatment and even more so for the PATH treatment, in which predictive power for risk attitude can be observed in the first few asset allocation choices only. This is an interesting result since it suggests that—given the superiority of simulation-based risk communication—classically used bank risk questionnaires might not be an appropriate way to assess investors' risk preferences. At least in our study, once investors have gained some (simulated) experience, answers to these questions have lower predictive power for the actual investment strategy.

[6] Conducting the analysis for the first period with all 551 subjects leads to qualitatively the same results.

Table 4. Tobit regression: Allocation to the risky asset

This table reports Tobit regression coefficient estimates with the allocation to the risky asset as the dependent variable. The DESCRIP treatment is compared to the FINAL treatment (upper part of the table) and the PATH treatment (lower part of the table). Six-point Likert scale responses are treated as ordinal independent variables (risk attitude and income). Standard errors are in brackets. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Dependent variable: Allocation to the risky asset/DESCRIP vs. FINAL

Investment period	1	4	7	10	14
Treatment dummy	9.19***	10.50***	3.68	4.95	4.73
	(2.79)	(3.02)	(3.44)	(3.55)	(3.97)
Financial risk attitude	6.50***	5.95***	5.56***	4.02**	7.01
	(1.36)	(1.47)	(1.67)	(1.73)	(3.97)
Financial literacy	2.90***	2.72**	1.80	2.78**	1.52
	(1.10)	(1.18)	(1.35)	(1.39)	(1.55)
Experience	-1.16	2.56	-2.38	-2.37	-4.93
	(3.51)	(3.80)	(4.31)	(4.46)	(4.98)
Invested	3.29	4.07	4.32	3.99	-.31
	(3.43)	(3.72)	(4.23)	(4.37)	(4.89)
University	-.04	-.26	1.11	.30	-2.76
	(2.94)	(3.19)	(3.62)	(3.75)	(4.18)
Age	.01	.06	.13	.20	.26
	(.13)	(.14)	(.16)	(.16)	(.18)
Male	-.50	3.74	3.00	6.41	6.95
	(3.25)	(3.52)	(4.00)	(4.13)	(4.61)
Income	-1.31	-1.75*	-.37	-.79	-.18
	(.97)	(1.04)	(1.19)	(1.23)	(1.37)
Constant	15.84**	15.57*	21.31**	14.24	8.15
	(7.44)	(8.04)	(9.14)	(9.43)	(10.58)
Observations			**258**		
LR X^2 (9)	55.93	59.63	28.68	27.76	28.32

Dependent variable: Allocation to the risky asset/DESCRIP vs. PATH

Investment period	1	4	7	10	14
Treatment dummy	6.20**	5.01*	-1.96	2.43	1.73
	(2.80)	(3.01)	(3.41)	(3.66)	(3.76)
Financial risk attitude	5.17***	5.12***	5.75***	4.25**	4.98***
	(1.39)	(1.49)	(1.96)	(1.82)	(1.86)
Financial literacy	2.83**	2.35*	3.19**	2.40	.68
	(1.16)	(1.24)	(1.41)	(1.51)	(1.55)
Experience	-1.27	2.11	-6.40	-2.02	-6.51
	(3.74)	(4.01)	(4.55)	(4.88)	(5.01)
Invested	1.32	1.94	1.63	2.46	7.27
	(3.48)	(3.73)	(4.23)	(4.54)	(4.66)
University	1.17	3.53	-.74	2.18	5.37
	(2.91)	(3.13)	(3.54)	(3.80)	(3.91)
Age	-.01	.11	.18	.20	.31*
	(.13)	(.13)	(.15)	(.16)	(.17)
Male	.20	3.18	2.34	3.87	2.92
	(3.29)	(3.53)	(4.00)	(4.29)	(4.42)
Income	-1.59	-1.37	.25	-.17	1.78
	.98	(1.05)	(1.19)	(1.27)	(1.32)
Constant	21.76***	17.06**	15.10	15.27	5.99
	(7.78)	(8.34)	(9.45)	(10.15)	(10.42)
Observations			**264**		
LR X^2 (9)	35.80	39.70	26.65	20.01	28.68

4.2 Characteristics of return distribution

To ensure that our general conclusions are not based on the specific return distribution of the risky asset, we repeated our experiment in the PATH treatment using a different return distribution. To construct the underlying return distribution we took the actual empirical return distribution of the S&P 500 without smoothing it via a bootstrapping approach (see Figure 5 for a comparison of the baseline and the control return distributions). We thus capture seven-year autocorrelation structures. Both distributions have the same expected yearly return and yearly standard deviation.

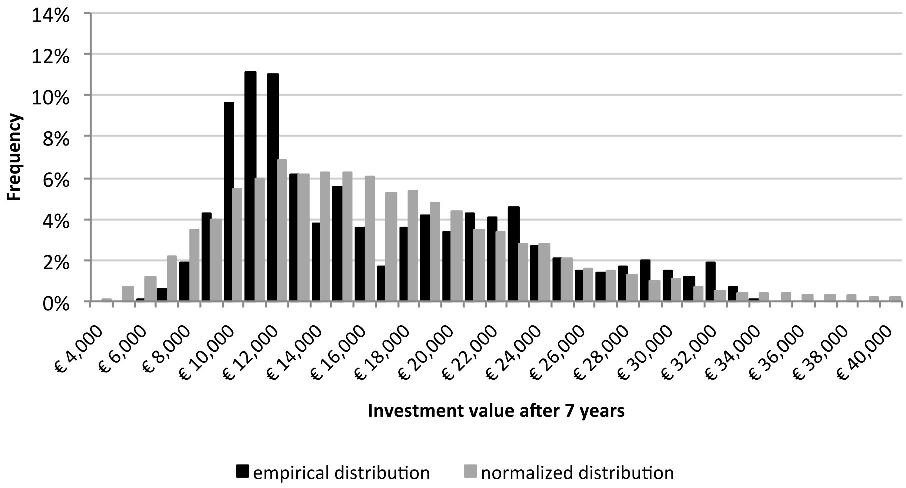


Figure 5. Comparison of the empirical and normalized return distributions

This figure compares the two different return distributions. The black bars represent the empirical distribution of the S&P 500 index since inception. The grey bars represent the return distribution of the S&P 500 index smoothed through a bootstrapping technique to resemble more closely a log-normal distribution.

We recruited another 174 participants with the same underlying socio-demographic characteristics, of whom a total of 117 completed all the investment decisions. We find our baselines results to be robust, i.e. no systematic difference in the risk-taking behavior to our baseline results. For the first investment decision, participants on average allocate 51.7% (s.d.=23.9%) to the risky asset compared to 49.8% in the PATH treatment for the baseline return distribution, which is not significantly different from each other (two-tailed *t*-test, *p*=0.44). We also find the same trading patterns as in our baseline study. In particular, participants in the new PATH treatment learned how much risk to take through the simulation and did not show significant changes in allocations over time on average. These results provide evidence that our findings are robust with regard to the return distribution. Regarding trading behavior, we can reconfirm our previous finding and find similar trading volumes for average and median levels. The median total trading turnover is 101% of the initial investment amount, and does not differ from the original PATH treatment (two-tailed *t*-test *p*=0.80).

4.3 Transaction costs

Another possible concern is transaction costs. It could be that these costs prevented our participants from changing their risky allocations. In a further robustness check with another 170 subjects (of whom 126 completed the whole study), we ran an additional experiment in the PATH treatment with the original return distribution, but we refrained from imposing transaction costs, i.e. shifting between both assets was free of charge. In the instructions, we therefore left out any information about costs. We find that the initial allocation to the risky asset (which could not have been affected by transaction costs) equals 51.1% (s.d.=23.1%) in the new PATH treatment, and it is not significantly different from the baseline treatment of 49.8% (two-tailed *t*-test, *p*=.60). Total trading turnover over all periods in relation to the initial endowment equals 74% (median value), which is not significantly different from the original PATH treatment (new PATH vs. original PATH: two-tailed *t*-test *p*=.90). Hence, we do not find that transaction costs significantly reduced allocation shifts.

5. Conclusions

Risk simulations based on experience sampling were shown to have positive effects for one-off investment decisions (Kaufmann et al. 2013; Bradbury et al. 2015). When possible outcomes are presented via a risk simulation, people improve their investment decisions due to a better understanding of the risk-return relationship, i.e. they have more accurate views of the return distribution. What is less clear is whether risk simulations have a lasting positive effect on investor behavior or whether the effects are only short-term and are superimposed by actual investment experience. These questions are an important extension of the existing literature and have strong practical implications.

This study aims to provide answers to these questions. We offer a number of interesting insights on the advantages and limitations of risk simulations. First, we can confirm our previous findings that risk simulations are superior to more descriptive ways of communicating risk. Secondly, the previously mentioned positive effects of risk simulations are to some degree persistent, even when investors receive feedback about their actual investment success over their investment journey. Investors who are initially informed in a descriptive manner (as opposed to a risk simulation) require actual investment experience to decide how much risk they are willing to take and to reach risk levels similar to investors who were informed via a form of risk simulation. Only after receiving this actual feedback, does their average risk appetite become similar to that of investors who gained simulated experience prior to actually investing. Hence, simulated experience seems to serve as a form of substitution for actual experience, and it can thus prevent costly investment mistakes, at least at the beginning of the investment horizon. At the same time, we do not find that risk simulations lead to persistently increased risk-taking behavior over the entire investment horizon. After having received feedback, investment behavior becomes independent of the way investors learned about the investment problem.

While we find that risk simulations support investors in accepting a higher level of risk at an earlier stage of their investment journey, we do not find that risk simulations reduce trading frequency or that it changes the behavior to losses. Hence, reactions to previous actual gains and losses do not systematically differ between different forms of the initial risk communication. This also holds if the risk simulation is comprised of wealth paths, i.e.

presenting investors with the ups and downs over the investment journey in form of a price chart instead of only final outcomes. To some extent this seems to contrast with the results of Kaufmann et al. (2015) who find a less pronounced reaction to losses when investors were informed by a risk simulation. We believe that our long-term experimental design represents a more realistic setting compared to classical short-term lab experiments. Hence, our results seem to indicate some limitations on the benefits of risk simulations in business practice. In a real-world setting, the time difference between the initial decision and subsequent possible changes in asset allocations are likely to be larger than in our experiment, casting some doubts that a one-time risk simulation persistently solves problems with short-term over reactions to previous outcomes. It might be helpful to use risk simulations on a more permanent basis, not just for the initial investment decision.

We further find that showing investors easy-to-read return histograms as a descriptive form of risk communication seems to partially close the experience description gap. The relatively strong differences in risk-taking and understanding the investment problem in earlier studies (Kaufmann et al. 2013; Bradbury et al. 2015) arising between descriptive and experiential risk communication seem partially explained by the fact that a purely verbal presentation of risk is non-intuitive and difficult to comprehend for investors. It is interesting that well-explained return histograms are already a good way to improve risk communication. However, importantly, we still find significant differences in risk-taking and risk perception.

A remaining question is how easy it is for investors to change their initially chosen investment strategy. In our study investors were asked periodically if they wished to change their allocation. This is similar to reality where investors receive periodic performance reports on the status of their investment (with increasing frequency due to the digitalization trend in banking). However, in many cases, depending on the advisory setting, the investors will have to take action themselves in order to make adaptations to their asset allocations—

except for an automatic rebalancing which is frequently applied by some online investment platforms.

Our results also have implications for business practice, in particular for financial advice, e.g. in the case of so-called robo-advisors. These are fully automated, purely algorithmically driven tools that offer diversified portfolio allocations based on a client's investment goal and willingness to take risk. There is no interaction with a financial advisor in person. In this case, it becomes even more essential to communicate financial risk in a way that ensures a reliable understanding of the consequences faced in market downturns. Our long-term online experiment and our wealth path simulation give insights on how to design optimal risk profilers and learning tools that could be useful for financial institutions. Our findings are also relevant to human advisors who are supported by interactive computer-based risk-profiling methods.

References

Agarwal, S., Pan, J. and Qian, W. (2015). Age of decision: Pension savings withdrawal and consumption and debt response. *Working Paper* http://ssrn.com/abstract=2487658

Barber, B. M. and Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics* **116**, 261–292.

Benartzi, S. and Thaler, R.H. (1995). Myopic loss aversion and the equity premium puzzle. *Quarterly Journal of Economics* **110**, 73–92.

Benartzi, S. and Thaler, R.H. (1999). Risk aversion or myopia? Choices in repeated gambles and retirement investments. *Management Science* **45**, 364–381.

Benzoni, L., Collin-Dufresne, P. and Goldstein, R. S. (2007). Portfolio choice over the life-cycle when the stock and labor markets are cointegrated. *The Journal of Finance* **62**, 2123–2167.

Beshears, J., Choi, J., Laibson, D. and Madrian, B. (2015). Does aggregated returns disclosure increase portfolio risk-taking? *Working Paper* http://faculty.som.yale.edu/jameschoi/aggregation.pdf

Bradbury, M. A. S., Hens, T. and Zeisberger, S. (2015). Improving Investment Decisions with Simulated Experience. *Review of Finance* **19**, 1019–1052.

Calvet, L. E., Campbell, Y. Y. and Sodini, P. (2007). Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy* **115**, 707–747.

Campbell, J. Y. (2006). Household finance. *The Journal of Finance* **61**, 1553–1604.

Cohn, A., Engelmann, J., Fehr, E. and Maréchal, M. (2015). Evidence for countercyclical risk aversion: An experiment with financial professionals. *American Economic Review* **105**, 860–885.

Cocco, J., Gomes, F. J. and Pascal Maenhout, J. (2005). Consumption and portfolio choice over the life-cycle. *Review of Financial Studies* **18**, 491-533.

Das, S., Markowitz, H., Scheid, J. and Statman, M. (2011). Portfolios for investors who want to reach their goals while staying on the mean-variance efficient frontier. *The Journal of Wealth Management* **14**, 25–31.

Destatis (2013). Statistical Year Book: Germany and International 2013. Technical Report.

Dohmen, T., Falk, A., Huffman, D. and Sunde U. (2010): “Are Risk Aversion and Impatience Related to Cognitive Ability?,” American Economic Review, 100, 1238–60

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. and Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association* **9**, 522–550.

Ehm, C., Kaufmann, C. and Weber, M. (2014). Volatility inadaptability: Investors care about risk, but cannot cope with volatility. *Review of Finance* **18**, 1387–1423.

Gourinchas, P.-O. and Parker, J. (2002). Consumption over the life cycle. *Econometrica* **70**, 47–91.

Gneezy, U. and Potters, J. (1997). An experiment on risk-taking and evaluation periods. *Quarterly Journal of Economics* **112**, 631–645.

Haigh, M., and List J. (2005). Do Professional Traders Exhibit Myopic Loss Aversion? An Experimental Analysis. *The Journal of Finance* 60, 523–534.

Halko, M-L., Kaustia, M. and Alanko, E. (2012). The gender effect in risky asset holdings. *Journal of Economic Behavior and Organization* **83**, 66–81.

Hershfield, H. E., Goldstein, D. G., Sharpe, W. F., Fox, J., Yeykelis, L., Carstensen, L. L. and Bailenson, J. N. (2011). Increasing saving behavior through age-progressed renderings of the future self. *Journal of Marketing Research* **48**, 23–37.

Hertwig, R., Barron, G., Weber, E. U. and Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science* **15**, 534–539.

Kaufmann, C., Weber, M. and Haisley, E. (2013). The role of simulated experience and graphical displays on one's investment risk appetite and comprehension. *Management Science* **59**, 323–340.

Kirchler, M, Lindner, F., and Weitzel, U. (2016). Rankings and Risk-Taking in the Finance Industry, Working Paper, http://ssrn.com/abstract=2760637.

Klos, A., Weber, E. U. and Weber, M. (2005). Investment decisions and time horizon: Risk perception and risk behavior in repeated gambles. *Management Science* **51**, 1777–1790.

Langer, T. and Weber, M. (2008). Does commitment or feedback influence myopic loss aversion? An experimental analysis. *Journal of Economic Behavior & Organization* **67**, 810–819.

Levitt, S. D. and List, J. A. (2007). What do laboratory experiments measuring social preferences reveal about the real world? *Journal of Economic Perspectives* **21**, 153–174.

Lusardi, A. and Mitchell, O. S. (2011). Financial literacy around the world: An overview. *Journal of Pension Economics and Finance* **10**, 497–508.

March, C., Ziegelmeyer, A., Greiner, B., Cyranek, R. (2015). Monetary Incentives in Large-Scale Experiments: A Case Study of Risk Aversion, Working Paper.

Nosić, A. and Weber, M. (2010). How risky do I invest: The role of risk attitudes, risk perceptions and overconfidence. *Decision Analysis* **7**, 282–301.

Odean, T. (1999). Do investors trade too much? *American Economic Review* **89**, 1279– 1298.

Schooley, D. K. and Worden, D. D. (1996). Risk aversion measure: Comparing attitudes and asset allocation. *Financial Services Review* **5**, 87–99.

Shefrin, H. and Statman, M. (1994). Behavioral capital asset pricing theory. *Journal of Financial and Quantitative Analysis* **29**, 323–349.

Thaler, R. H. and Benartzi, S. (2004). Save more tomorrow: Using behavioral economics to increase employee saving. *Journal of Political Economy* **112**, 164–187.

Thaler, R., Tversky, A., Kahneman, D. and Schwarz, A. (1997). The effect of myopia and loss aversion on risk-taking: An experimental test. *Quarterly Journal of Economics* **112**, 647–661.

Weber, E. U., Johnson, E. J., Milch, K. F., Chang, H., Brodscholl, J. C. and Goldstein, D. G. (2007). Asymmetric discounting in intertemporal choice: A Query Theory account. *Psychological Science* **18**, 516–523.

Weber, E. U., Siebenmorgen, N. and Weber, M. (2005). Communicating asset risk: How name recognition and the format of historic volatility information affect risk perception and investment decision. *Risk Analysis* **25**, 597–609.

Zeisberger, S., Langer, T. and Weber, M. (2014). Do changes in reporting frequency really influence investors' risk-taking behavior? Myopic loss aversion revisited. *Working Paper*. http://ssrn.com/abstract=1786360.

Zion, U., Erev, I., Haruvy, E. and Shavit, T. (2010). Adaptive behavior leads to under-diversification. *Journal of Economic Psychology* **31**, 985–995.

Appendix A: Demographics, Financial Literacy and Risk Profiling Questionnaire

Variable	Response options/description
Financial risk attitude	How would you classify your willingness to take financial risks? Strongly avoid risks ○ ○ ○ ○ ○ ○ ○ willing to take risks
Financial literacy*	Sum of six financial literacy questions (highest score = 6, lowest score = 0)
Experience	Self-reported investment experience with risky assets (such as stocks, derivatives, alternative investments, etc.) above 3 years equals 1, otherwise 0
Invested	Self-reported portion of current financial wealth invested in stocks or stock funds greater than 0% equals 1, otherwise 0
University	University degree equals 1, otherwise 0
Age	Age of the participant
Male	If gender male, then equals 1, otherwise 0
Income	Self-reported income based on predefined bandwidths (1 = < €20,000, 2 = €20,000–30,000, 3 = €30,000–40,000, 4 = €40,000–50,000, 5 = €50.000–60.000, 6 = €60.000–70.000, 7 = > €70.000)
* Questions:	Suppose you had €1,000 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? Imagine that the interest rate on your savings account was 2% per year and inflation was 3% per year. After 1 year, how much would you be able to buy with the money in this account? Buying a single company's stock usually provides a safer return than a stock mutual fund. True or false? With which asset class would you have achieved the highest return over the last 50 years? Which asset class shows the highest value fluctuation over the past 50 years? Imagine that you are invested in an asset that achieves a 10% return per year, how many years would it take to double your investment?

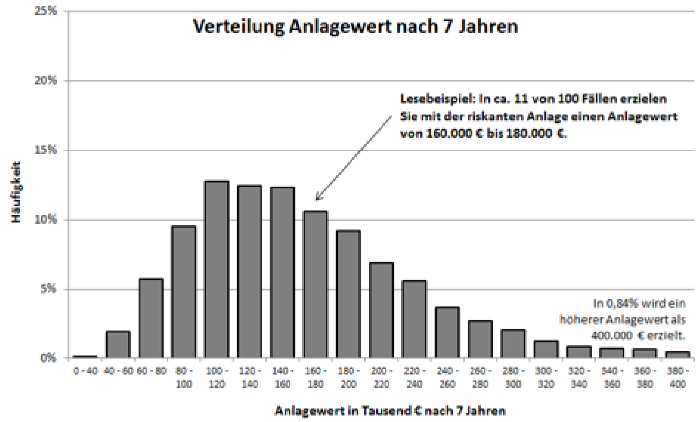
Appendix B: Screen Shot of Description (DESCRIP) Treatment

Riskante Anlage

Bei der riskanten Anlage handelt es sich um einen Aktienindex. Dieser bildet die Wertentwicklung von Aktien ab. Die **erwartete Rendite beträgt 7,0% pro Jahr**, d.h. **im Durchschnitt** können Sie eine Rendite von 7,0% erwarten. Die tatsächlich erzielte Rendite ist jedoch **nicht sicher**, sie kann deutlich höher aber auch deutlich tiefer ausfallen. Die jährliche **Standardabweichung**, d.h. die als „normal" betrachtete Abweichung von diesen 7,0%, beträgt **16,9%**.

Falls Sie Ihren zuvor gewählten Investitionsbetrag von 100.000 € ausschließlich in die riskante Anlage investieren, können Sie nach 7 Jahren einen Anlagewert von 164.100 € erwarten. Wie erwähnt ist dieser Wert jedoch nicht sicher, er könnte deutlich höher aber auch deutlich tiefer ausfallen.

Folgende Grafik zeigt Ihnen die Verteilung Ihres Anlagewertes am Ende der 7 Jahre, wenn Sie ausschließlich in die riskante Anlage investieren. Beispielsweise würden Sie in ca. 11 von 100 Fällen einen Anlageendwert zwischen 160.000 € und 180.000 € erzielen.



Beispielsweise ist es wahrscheinlich (**in 50 von 100 Fällen**), dass nach 7 Jahren daraus:

Zwischen **113.000 €** und **201.100 €** werden.

Mit hoher Wahrscheinlichkeit (**in 90 von 100 Fällen**) werden daraus:

Zwischen **72.200 €** und **296.500 €**.

Mit sehr hoher Wahrscheinlichkeit (**in 98 von 100 Fällen**) werden daraus:

Zwischen **52.000 €** und **394.200 €**.

Figure C.1 Description (DESCRIP) treatment

English translation:

[Title:] Risky asset

[Text:] The risky asset is a stock index. It represents the growth of stocks. The expected return is 7% per year, which means you can expect a return of 7% on average per year. However, the actual return is unknown; it can turn out considerably higher but also considerably lower. The yearly standard deviation, i.e., the deviation from the 7% considered normal, is 16.9%.

If you invest the full investment amount of €100,000 previously chosen in the risky asset, you could expect a final amount of €164,100 after 7 years. However, as mentioned, this amount is not certain; it could turn out considerably higher but also considerably lower.

The following chart shows you the distribution of your initial wealth after 7 years if you had invested the full investment amount in the risky asset. For example, you would achieve a final wealth of between €160,000 and €180,000 in approximately 11 out of 100 cases.

[Chart:] Wealth distribution after 7 years

Reading example: In approximately 11 out of 100 cases you can achieve a final wealth of between €160,000 and €180,000 with the risky asset.

In 0.89% of cases, a final wealth greater than €400,000 is achieved.

[x-axis:] **Final wealth in thousand € after 7 years**

[y-axis:] Frequency

[Text:] It is likely, for example, that (**in 50 out of 100 cases**) after 7 years it will be:

between **€113,000** and **€201,000**.

It is very likely that (in 90 out of 100 cases) it will be:

between **€72,200** and **€296,500**.

It is highly likely that (in 98 out of 100 cases) it will be:

between **€52,000** and **€394,200**.

Appendix C: Screen Shot of Final Wealth Simulation (FINAL) Treatment

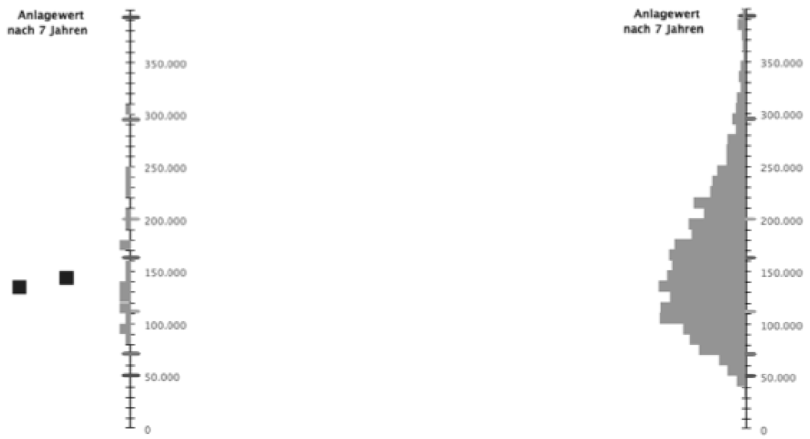


Figure C.2 Final Wealth Simulation (FINAL) treatment

English translation of pop-up on screen (not shown in Figure C.2):

[Title:] Risky asset

[Text:] See *description of the risky asset for the description treatment (DESCRIP)*

You will be presented with possible, final values, for the case that you invest the full initial amount over 7 years in the risky asset. The final values are drawn randomly from the distribution described above. Click “draw” to view a further value. You need to draw at least 15 times. Afterwards, further values are drawn and automatically displayed one after another. In total, 50 random values will be displayed.

Appendix D: Screen Shot of Wealth Path Simulation (PATH) Treatment

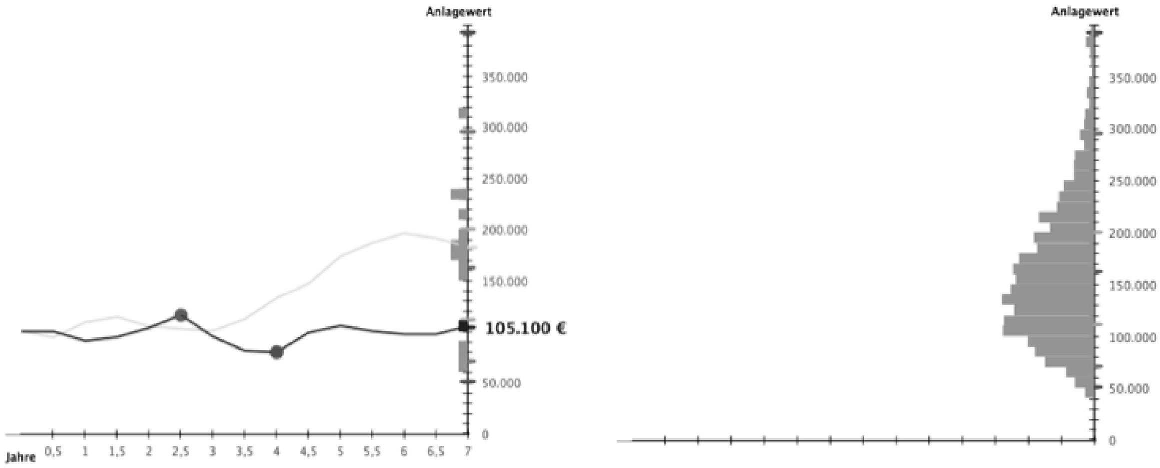


Figure C.3 Wealth Path Simulation (PATH) treatment

The left screen shot illustrates the build-up of the return distribution, as it was experienced by participants, and the right screen shot shows the final distribution.

English translation of pop-up on screen (not shown in Figure C.3):

[Title:] Risky asset

[Text:] *Same as for the Final Wealth Simulation (FINAL) treatment*

Appendix E: Screen Performance Overview

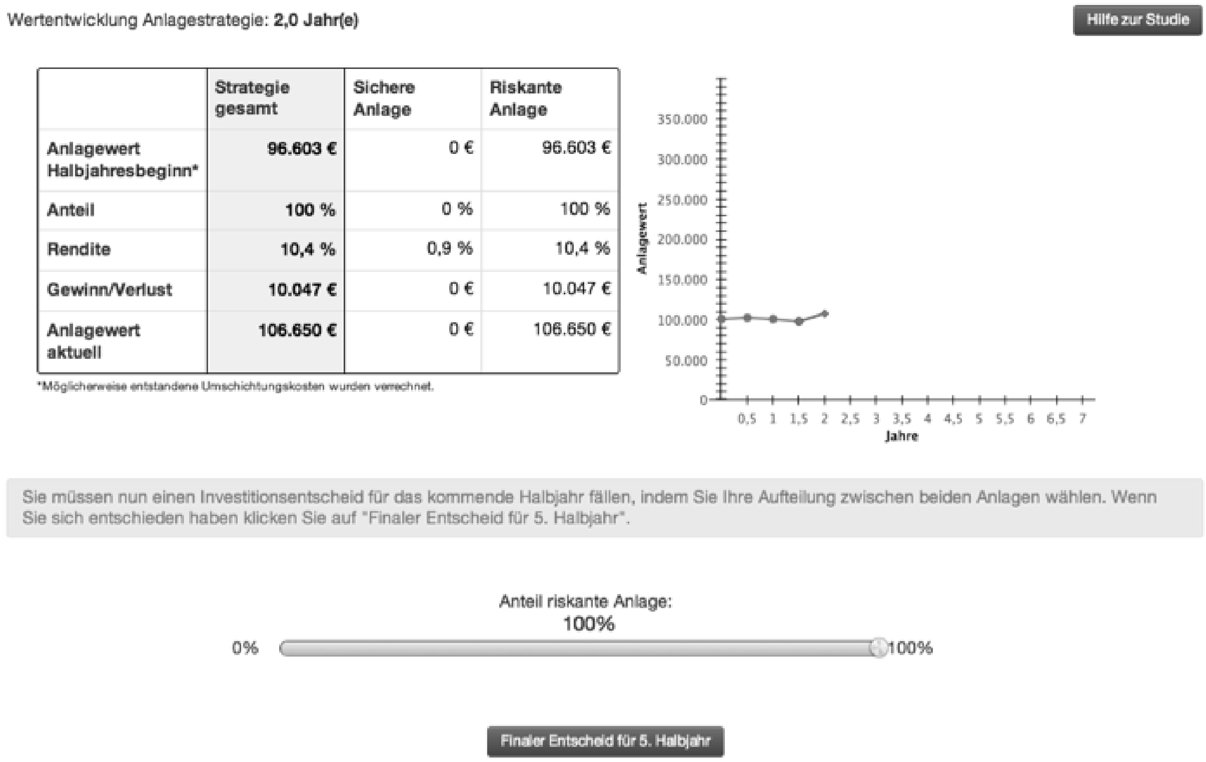


Figure C.4 Performance overview of portfolio strategy

English translation:

[Title:] Performance portfolio strategy

[Table:] First row: Overall strategy/risk-free asset/risky asset

First column: Investment value at beginning of half year/allocation/return/gain–loss/current investment value

[Slider:] Allocation to risky asset

Appendix F: Summary Statistics

Table 1. Overview of socio-economic characteristics of the participants

This table shows summary statistics of socio-economic variables, the education level, and income distribution of participants within each treatment. Income ranges were derived based on the average gross income of German households (€3,871 per month in 2011 (Destatis 2013), extending the range by two classes above the average).

Treatment	**Description**	**Final Wealth Simulation**	**Wealth Path Simulation**
Age (average)	40	40	40
Min	18	18	18
Max	66	65	66
Gender (male)	65%	65%	73%
Stock/equity fund owners	54%	51%	52%
Education			
Still in school	1%	1%	1%
Secondary modern school	9%	9%	8%
Junior high school	31%	31%	34%
Secondary school	25%	22%	15%
University	34%	36%	42%
PhD	1%	2%	1%
N/A	1%	1%	0%
Income			
< €20,000	24%	23%	20%
€20,000–30,000	20%	16%	15%
€30,000–40,000	14%	15%	18%
€40,000–50,000	29%	30%	31%
€50,000–60,000	11%	9%	10%
€60,000–70,000	3%	7%	5%
> €70,000	0%	0%	0%
N	189	179	183

Appendix G: Probability Estimations

Consider an investment in the aforementioned risky asset. Please estimate in how many out of 100 cases your investment amount will …

- come out below your initial investment amount after 7 years.
- come out below the amount you would have achieved by investing in the risk-free asset (*€113.300*) after 7 years.
- come out above *€200.000* after 7 years.

Appendix H: Allocation to the Risky Asset and Predictability per Treatment

This table reports Tobit regression coefficient estimates with the allocation to the risky asset as the dependent variable. Six-point Likert scale responses are treated as ordinal independent variables (risk attitude and income). Standard errors are in brackets. Controls at the bottom of the table account for experience, being invested, having an University degree, age, male and income. They are indicated to be included in the regression analysis by yes but are hardly ever significant. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Dependent variable: Allocation to the risky asset/Description (DESCRIP)

Investment period	1	4	7	10	14
Financial risk	6.93***	4.95**	9.26***	6.76***	9.37***
attitude	(2.00)	(2.05)	(2.31)	(2.41)	(2.67)
Financial literacy	2.93**	2.83*	3.36**	3.61**	2.38
	(1.45)	(1.48)	(1.67)	(1.74)	(1.93)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	17.91	16.80	8.93	13.37	-17.68
	(10.9)	(11.14)	(12.55)	(13.10)	(14.56)
Observations			**138**		
LR X^2 (8)	31.43	34.38	25.69	20.86	25.89

Dependent variable: Allocation to the risky asset/Final Wealth Simulation (FINAL)

Investment period	1	4	7	10	14
Financial risk	5.59***	6.15***	2.14 (2.40)	1.30	5.18*
attitude	(1.87)	(2.13)		(2.50)	(2.78)
Financial literacy	3.00*	3.29*	-.50	1.18	1.94
	(1.72)	(1.97)	(2.22)	(2.29)	(2.52)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	25.59**	28.53**	34.73***	19.22	34.51**
	(9.84)	(11.25)	(12.68)	(13.11)	(14.52)
Observations			**120**		
LR X^2 (8)	20.86	23.71	11.93	12.07	14.64

Dependent variable: Allocation to the risky asset/Wealth Path Simulation (PATH)

Investment period	1	4	7	10	14
Financial risk	3.32*	5.00**	2.15	70 (2.71)	.61
attitude	(1.91)	(2.15)	(2.48)		(2.54)
Financial literacy	2.10	1.00	2.32	-.08	-2.20
	(1.90)	(2.15)	(2.46)	(2.69)	(2.53)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	33.02***	26.18**	18.90	24.88	33.75**
	(10.78)	(12.17)	(13.98)	(15.32)	(14.34)
Observations			**126**		
LR X^2 (8)	7.21	11.44	8.15	8.98	13.87