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What Are Investors Willing to Pay to Customize Their Investment Product?

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Even though buy-and-hold (B&H) investment strategies can take the risk tolerance of an investor into account by specifying a suitable stock proportion, the outcome profiles of B&H strategies are restricted to a specific class of return distributions. For investors with particular risk preferences, further customization should thus provide additional value. The objective of this paper is to investigate the strength of preference for such customized distributions and to draw conclusions about the demand for personalized investment products. In two experimental studies, 256 participants could adjust the return distribution of an initially chosen B&H investment by using an interactive software program. Our main finding is that most investors make extensive use of the customization option and many are willing to pay a substantial fee for this additional flexibility. We further find that the willingness to pay for customization is lower if the fee is integrated into the display of the return distribution, making its impact on final returns more obvious. We also observe that investors can be clustered into distinct subgroups via their adjustment patterns, but individually elicited prospect theory parameters are barely able to explain and predict these adjustments. As a robustness check, we also survey real investors at an investors fair to compare their preferences with those of our main pool of student subjects. We find that the willingness to pay for customization is slightly lower for these real investors and the main effect of fee integration is also less pronounced. In summary, we observe a strong willingness to pay for additional flexibility even though the actual benefits of customization vary markedly according to the individual. In many cases the accepted fees are so high that standard B&H strategies stochastically dominate the customized distributions after fee integration.

Key words: behavioral economics; investment behavior; customization; distribution builder; decision support; experimental economics; prospect theory
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1. Introduction

> From a practical point of view... it may well prove easier for the investor to choose directly his optimal payoff function... than it would be for him to communicate his utility function to a portfolio manager.
>
> (Brennan and Solanki 1981, p. 295)

This paper assumes that investors should make investment decisions based on overall return distributions, whereas the actual investment products in the portfolio are largely irrelevant. Following Goldstein et al. (2008), we develop a tool that supports such a process and use it to analyze whether investors wish to customize the return distributions of standard investment products. Although buy-and-hold (B&H) investment strategies that simply mix stocks and bonds can take the investor's general risk tolerance into account by specifying a suitable stock proportion, their outcome profiles remain restricted to a specific class of distributions. For investors with particular risk preferences, further customization should thus provide additional value. As Goldstein et al. (2008) have shown, many investors indeed have a preference for a distribution that cannot be obtained through a simple mix of stocks and bonds.

It should be clear, however, that merely observing substantial customization does not mean that the process produces significant utility gains. It is also possible that investors adjust distributions around a flat utility maximum and raise utility only marginally, even though the distribution adjustments are considerable. In such a situation, the willingness to pay (WTP) for customization would be low, even though the customized distributions differ markedly from what B&H strategies can generate. Our main research objective is to investigate the strength of preference for tailor-made distributions by eliciting the WTP for customization. Given this research focus, we do not ask subjects to build their preferred distributions from scratch, but rather let them adjust the return profile of an initially chosen B&H investment to their personal preferences. Such a sequential setup offers two important advantages:

1. All adjustments of the standard B&H return profiles are conscious decisions.

2. The setup allows us to determine the WTP for customization in a direct manner.

The design of our software tool is inspired by the distribution builder of Goldstein et al. (2008). We follow their general idea of providing investors with graphical information about aggregated return distributions and allowing them to directly manipulate the distribution, subject to some feasibility constraints. However, our software differs from the distribution builder in some important ways. One crucial difference is that we use a more discrete type of return presentation, a 10-state chart. Vrecko et al. (2009) demonstrated that people judge the comprehensibility of the 10-state chart to be the highest among a set of different presentation modes (that also included density functions and cumulative distributions). The 10-state chart, described in more detail in the next section, is simple enough to be easily understood by average investors but sufficiently flexible to allow adjustments for specific risk preference patterns.

The second important difference is the aforementioned two-stage approach, in which the initial distribution is determined through the choice of a B&H mixture. The direct distribution manipulation only occurs in the second, the customization stage. This two-stage approach is crucial for our research question about the value of customization and seems to be a promising approach to distribution building in general. We assert that it should be cognitively less demanding for investors to fine-tune a prespecified (self-selected) initial distribution than to build the complete distribution from scratch. Whether this is indeed true and whether this advantage is not offset by undesirable anchoring effects or other problems is not the subject of our current research, but clearly constitutes an important question for future research in this field.

A final minor distinction lies in the way we implement the feasibility constraint. Goldstein et al. (2008) allow subjects maximum flexibility in creating their preferred distribution and introduce a budget meter (BM) to communicate whether the created distributions are accessible within the given budget or need further adjustments. We slightly modify this approach and instead choose an instant feasibility control (IFC) mechanism in which subjects are restricted to feasible distributions during the complete adjustment process. Each customization step trades off some benefit (increased return in one state of the world) with some adequate disadvantage (decreased return in another state of the world), monitored by the software. Subjects start the customization procedure with a feasible return distribution, their self-selected B&H distribution, and transform it through a sequence of feasible adjustment steps into their most preferred distribution. The implementation of the feasibility control in our software builds on the deployment of fairly priced derivatives. More specifically, prices of state-contingent claims are used to determine the trade-offs between returns in the different states.

Both budget meter and instant feasibility control are associated with distinct advantages and disadvantages. It is surely more cumbersome to make large structural changes to the distribution using the IFC approach. Additionally, the BM must be considered superior and more general than the IFC in that the BM allows investors to mimic the IFC by keeping the budget within a healthy range during all their distribution building. In this respect, the BM offers only additional flexibility to investors who prefer to shape their preferred distribution first and to make the necessary adjustments to fulfill the budget constraint later. This said, the restricted flexibility in the process of designing the distribution, could also be considered an advantage of the IFC approach. It accentuates the fact that investors do not get anything for free in financial markets; that is, if they want to avoid bad outcomes in some states, they have to sacrifice return in other states. The IFC seems to be particularly well suited for our two-stage approach, in which no distribution building from scratch is needed but only fine-tuning of a previously selected B&H distribution. Most importantly, however, we feel that some variety in the deployed approaches has academic value for a research stream that has just started to develop. In the long run, it will help us to understand relevant framing issues and the robustness of the research findings.

In addition to our interest in WTP, we are also curious about the customization behavior itself. Thus, we examine whether there are particular patterns in adjustment behavior and whether investors can be clustered into different "customization types." An obvious follow-up issue is whether this customization behavior could be predicted if we knew investors' risk preferences in sufficient detail. To examine this issue, we have to rely on decision theories that go beyond the specific risk attitudes incorporated in expected utility theory. Prospect theory (Tversky and Kahneman 1992), with its complex pattern of risk preferences driven by loss aversion, utility curvature, and probability weighting (Wakker 2010), seems to be best suited to explain and predict investor interest in such customization. For this reason, we also elicit a complete set of prospect theory (PT) parameters for each participant and analyze whether the actual customization behavior conforms to these parameters at an individual level. This analysis is not only interesting from an academic perspective, it also sheds further light on the general debate about the merits of indirectly determining an investor's "optimal" investment strategy through eliciting his risk preferences and the subsequent derivation of the utility maximizing investment. Our experimental finding that the PT parameters have little predictive power for actual customization behavior further supports the claim that these indirect procedures are problematic and should be used and interpreted with caution.

Our analysis focuses on relatively short investment horizons of one and five years. This is done to avoid an interaction of the phenomena we are interested in with issues that are driven by the distinction between real and nominal returns. Within the larger experiment, we also looked at longer investment horizons of 10 and 30 years. However, for these horizons, we did not elicit the WTP for customization, but only explored the dependence of customization behavior on whether distributional information is presented in real or nominal terms. Because the research questions for the long horizons have a distinct flavor, they are not discussed here; however, they are discussed in a different paper (Vrecko and Langer 2010).

2. Experimental Design

The main study took place in June 2010. It consisted of the base experiment with the investment decisions and the elicitation of the WTP for customization, a subsequent part that elicited PT parameters, and a short final questionnaire. The main experiment is described in detail below. To derive the PT parameters, we applied the method of Zeisberger et al. (2012) and jointly determined all five PT parameters (λ, α, β, δ^+, and δ^-). The parameter λ is the degree of loss aversion, α and β describe the curvature of the PT power value function, and δ^+ and δ^- determine the shape of the probability weighting function (following the functional forms suggested by Tversky and Kahneman 1992). The elicitation method uses maximum likelihood estimation based on stated certainty equivalents for a set of 24 two-outcome lotteries—9 gain, 9 loss, and 6 mixed lotteries (for more details about the procedure, see Zeisberger et al. 2012). In the final questionnaire, we collected personal data including a self-assessment of risk aversion on a 7-point scale (1 = not risk averse at all; 7 = extremely risk averse). The average length of the total experiment was 50 minutes and the distribution-customization part lasted about 25–30 minutes, including the instruction phase. Overall, 202 advanced undergraduate students from the University of Muenster, Germany, participated in the main experiment. The majority of students had chosen finance as their field of specialization. The average age of the participants was 23 years, and 27% of the subjects were female. The experiment was run in 16 separate sessions with a maximum of 20 participants.

The experiment was computer based and, except for a one-page introduction that was read aloud by the experimenter, all instructions were provided on the screen (see Appendix A for the full written instructions). Throughout the experiment, the investment options were presented in the form of 10-state charts. In this presentation format, investment returns are calculated for 10 states of equal probability and sorted from the worst outcome (state 1) to the best outcome (state 10). A bar chart visualizes the returns associated with states 1–10 and also presents the resulting final wealth positions below the x-axis. As the starting endowment, we chose €100 to facilitate incentive-compatible payouts without any rescaling. Distortions in the perception and processing of probabilities are a major issue in evaluating investment alternatives. By holding probabilities constant at 10% throughout all the stages, the 10-state chart is less susceptible to some important perceptual biases than other presentation formats (Vrecko et al. 2009).

Our experimental task of customizing an initially chosen B&H investment to personal preferences used a three-step procedure:

Step 1. Selecting the B&H mix
Step 2. Customizing the return distribution
Step 3. Determining the WTP for customization

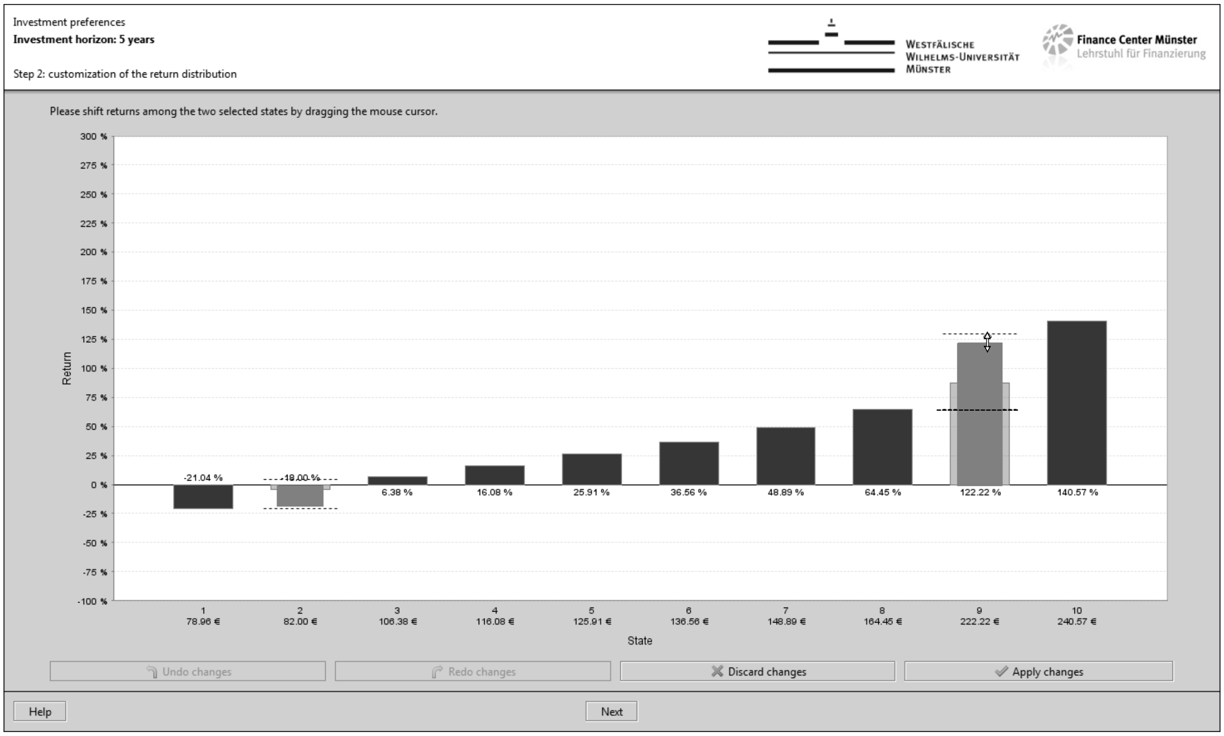
To check for robustness, we repeated Steps 1–3 for an investment horizon of five years after completing the one-year scenario. Subsequently, subjects were also confronted with a 10- and 30-year scenario. Because the experimental design differed for these investment horizons, we will not discuss them in this paper.

Step 1: *Selecting the B&H mix*. The first step allowed subjects to select their preferred stock proportion of a B&H investment strategy (0%–100% stocks) prior to customizing the return distribution to individual preferences. The return distributions of the mix were derived from given distributions for a risky asset and a riskless asset, both were based on standard assumptions. They were parameterized to reflect a market-wide stock index (such as the S&P 500) and a guaranteed interest rate comparable to Treasury bills.[1] Subjects had the opportunity to specify and adjust their preferred stock proportion by clicking on a slider. The corresponding return profiles updated themselves automatically, enabling the evaluation of various alternatives quickly, before making the final selection by clicking an "OK" button.

Step 2: *Customizing the return distribution*. In the second step, subjects were given the opportunity to

[1] See Appendix B for details of the derivation of the state prices and the technical functionality of the software.

Figure 1 Example of Computer Screen During the Customization (Step 2)



Notes. In this example states 2 and 9 have been selected for customization. The original profile remains semitransparent in the background. The dashed horizontal lines indicate the maximal possible improvement/decline for both states.

adjust the previously chosen B&H mix to their personal preferences. To facilitate the use of the software, all adjustments could be made with a mouse through clicking and dragging. First, the user decided on the two specific states among which he wanted to trade off returns and selected them with two mouse clicks. Then, by dragging the mouse cursor, the return in one of the two states could be either increased or decreased. The software automatically calculated the necessary adjustments in the other state. To depict the trade-off in returns, the original profile remained semitransparent once an adjustment was made. To accept the current changes and permanently modify the return distribution, an "apply changes" button had to be clicked. Afterward, customization could continue with a new pair of states. Figure 1 provides a sample screen for the customization step (sample screens for Steps 1 and 3 can be found in Appendix C). In this example, the return in state 9 is increased (to 122.22%) at the expense of state 2.

Because the state prices decrease monotonically in value, any sensible investment strategy must achieve its minimal final wealth in state 1, its highest final wealth in state 10, and generally increase in the state index. To prevent unfavorable adjustments during customization, the software displays two sets of dashed lines to indicate the space for adjustment to the user and it prevents the user from taking other actions.

Step 3: *Determining the WTP for customization*. The third step asked subjects for their WTP to invest in the customized return distribution instead of the previously chosen B&H mix. This reveals the economic significance of the interest in customizing return distributions. Specifically, we asked the following question: What maximum fee (in % of the investment) are you willing to pay to invest in the customized return distribution instead of investing in your previously chosen buy-and-hold mix? The WTP was entered by moving a slider within a range from 0% to 10%. With a final click on the "OK" button, the subjects confirmed the percentage figure they had chosen.

In this third step, a manipulation was introduced that resulted in two distinct treatments: fee integration (FI) and no fee integration (NFI). Subjects were randomly assigned to one of the two treatments. While deciding on their WTP, all subjects saw the selected B&H distribution and the customized return distribution in graphical displays side by side (left-hand side B&H, right-hand side customized). However, for subjects in the FI treatment, the customized returns were displayed after fees; that is, the return distribution in the right-hand graph automatically adjusted to the fee indicated by the current position of the WTP slider. In contrast, subjects in the NFI treatment did not have this visual aid for comparing the distributions after costs (fees). For them, the display in the right-hand graph always presented the customized distribution before costs. This manipulation was introduced to examine whether a high observed WTP does indeed reflect a strong preference for the customized distribution or is merely a further example of the general misperception of cost components in investment products if they are not integrated explicitly into the return distribution (Klos et al. 2010).

Given that this experiment represents a complex task, we paid special attention to comprehensibility and also checked whether the subjects indeed understood the mechanism. The instructions embedded in the experiment software were split into three parts, each explaining only the issues that were relevant to the next decision step. To minimize potential problems, animated tutorials were used to familiarize the subjects with the software design. Short quizzes referring to the main concepts had to be passed, so as to complete all three tutorials. The subjects were also encouraged to ask the experimenter for help if they did not fully understand the instructions or had trouble answering the quiz questions.

2.1. Incentive Compatibility

To ensure incentive compatibility, that is, to incentivize subjects to choose investment distributions carefully and to report their true WTP for customization for both investment horizons, every tenth subject received a variable payment based on the initial endowment of €100, in addition to the fixed payment of €8. For these subjects, an effective fee for investing in the customized distribution was randomly drawn from the admissible interval [0%; 10%] using a straightforward application of the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al. 1964). Depending on the stated WTP and the effective fee, either the B&H distribution or the customized distribution (after effective fees) was used to determine the relevant return by a random draw of the state. Payment details were clearly communicated to the subjects in the written instructions preceding the experiment. The exact functionality of the BDM procedure was thoroughly explained in the third tutorial. If a subject belonged to the group of the 21 "winners," she was also paid for the subsequent part on PT parameter elicitation. The variable payment for the whole experiment ranged from €94.64 to €372.86.

3. Results

We start by reporting the results of Step 1, the selection of the B&H mix. This is not the focus of our study, but it demonstrates that the general investment behavior of our subjects is reasonable and within the typical ranges reported in previous work. In the B&H stage, the subjects invested on average about two-thirds of their initial wealth in stocks (mean of 59% for one year and 64% for five years). The absolute levels of the stock proportion are within the range of previous findings in similar scenarios (e.g., Kaufmann et al. 2013), the slightly higher stock proportion for five years is plausible. The correlation between the stock proportions chosen by the 202 subjects in the one- and five-year scenarios is 0.51.[2] For some of the following analyses of WTP and customization behavior, it will be interesting to explore the relevance of the originally selected B&H stock proportion. Therefore, we define subgroups BH1y_low (BH1y_high) that contain the 95 (100) subjects with a one-year B&H stock proportion below (above) the median value 0.6. Accordingly, the subgroups BH5y_low (BH5y_high) contain the 100 (100) subjects with a five-year B&H stock proportion below (above) the median value 0.62.

Next, we turn to the customization behavior (Step 2) and the willingness to pay for customization (Step 3), the main focus of our research. Overall, there was a strong interest in customization. Only 4 of the 202 subjects did not customize their initially chosen one-year B&H mix (6 subjects did not customize in the five-year scenario). Only one participant abandoned the opportunity to customize altogether (in the one- and five-year scenarios). The mean [median] number of customization steps was 9.9 [7.0] in the one-year scenario and 6.4 [5.0] in the five-year scenario, with slightly higher figures for the subgroups BH1y_high and BH5y_high that had invested more aggressively in stocks.

We will return to the details of customization behavior in §3.2, but we first present the findings regarding our main research question: Is there a substantial willingness to pay for such customization?

3.1. Willingness to Pay for Customization

First, it should be reiterated that extensive customization activity does not necessarily imply that the WTP for customization is high. It might well be the case that adjustments occur around a flat utility optimum and the WTP for such an improvement is low or even zero. This alternative conjecture is not reflected in the data, however. Only 10 of the 202 participants (5.0%) state a WTP of 0% in the one-year scenario,

[2] In line with previous findings (Nosić and Weber 2010, Dohmen et al. 2011), the correlation between the self-rated financial risk aversion (on a 7-point scale) and the chosen bond proportion is somewhat smaller (Spearman rank correlation 0.290 for the one-year scenario and 0.384 for the five-year scenario).

Table 1 **Mean [Median] WTP for Customization in FI and NFI Treatments for Both Investment Horizons**

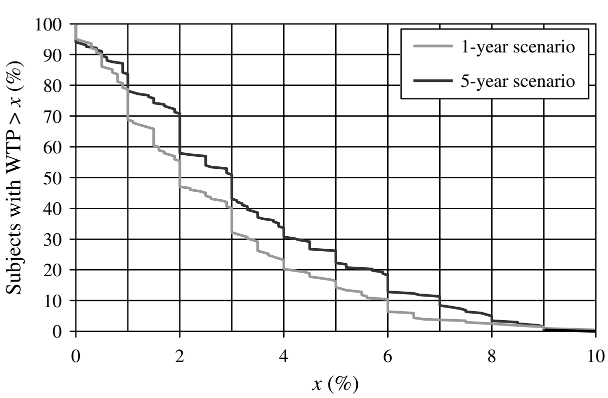
	(1) All subjects $n = 202$	(2) Subjects in FI treatment $n = 101$	(3) Subjects in NFI treatment $n = 101$	(4) Difference between FI and NFI treatments
One-year scenario	2.67% [2.0%]	1.99% [1.5%]	3.34% [3.0%]	1.35% ($p < 0.001$)
Five-year scenario	3.31% [3.0%]	2.69% [2.2%]	3.94% [3.3%]	1.26% ($p < 0.001$)
Diff. between scenarios	0.65% ($p < 0.001$)	0.70% ($p < 0.001$)	0.60% ($p < 0.001$)	

Note. The p-values for differences refer to Wilcoxon rank-sum tests (matched pair for time horizon, unmatched for FI/NFI treatment).

and only 20.8% state a WTP below 1%. The respective proportion of participants with no WTP and a low WTP in the five-year scenario is 5.9% and 15.8%. The mean [median] WTP for the opportunity to invest in the customized return distribution can be found in column (1) of Table 1. It is 2.67% [2.0%] for the one-year investment horizon and 3.31% [3.0%] for the five-year investment horizon. This difference is highly significant ($p < 0.001$) and should have been expected, given the generally higher returns for the longer investment horizon. The full distribution of WTP levels is presented in Figure 2.

So far, we have not distinguished between the two treatments of FI and NFI, the manipulation of whether or not the respective fees are integrated into the display of the return distribution when the WTP is specified. From a prospect theory (Tversky and Kahneman 1992) and hedonic editing (Thaler and Johnson 1990) perspective, the separation of a small loss (the fee paid) from the possible returns should actually make the combination of customized distribution and segregated fee less attractive in the NFI treatment. This would imply a lower WTP in the NFI treatment. On the other hand, it is known that consumers often pay more for a product when small additional costs (peanuts) are separated (Morwitz et al. 1998), and investors often underestimate or even ignore the impact of fee components on final return distributions (Beshears et al. 2011, Klos et al. 2010) in the evaluation of investment products. From this perspective, the FI treatment should be better suited to prevent subjects from accepting fees for minor customization benefits that are so high that they wipe out all the benefits. Overall, we have no clear prediction of whether the WTP for customization will be higher in the FI or the NFI treatment.

Figure 2 **WTP Profiles for the One- and Five-Year Investment Horizons**



Note. The graphs show the percentage of subjects that stated a WTP above any given level between 0% and 10%.

The results of the respective analysis are presented in columns (2) and (3) of Table 1. The mean WTP for customization is much higher in the NFI treatment for both investment horizons. The difference amounts to 1.35% for the one-year scenario and 1.26% for the five-year scenario (for both $p < 0.001$, Wilcoxon rank-sum test). The magnitude of the treatment effect indicates that a substantial part of the high WTP for customization in the NFI treatment obviously stems from investor ignorance or at least misinterpretation of the impact of the fee on the return distribution. On the other hand, the mean WTP for customization remains at a substantial level (1.99%), even in the most conservative condition, namely, the short horizon scenario with fee integration. This supports the proposition that there is indeed a strong preference for distributions that deviate from what a B&H mix can deliver.

Analyzing the dependence of the effect on the original B&H stock proportion, we find higher WTPs for the more aggressive one-year investors (mean WTP 3.12% for the BH1y_high subgroup, 2.22% for the BH1y_low subgroup, $p < 0.01$). For the five-year horizon, the difference is slightly less pronounced (3.64% for BH5y_high, 3.01% for BH5y_low, $p < 0.1$). The treatment effect (WTP for FI versus NFI) is not influenced by the B&H proportions and is observed at levels between 1.2% and 1.4% for each subgroup.

The finding of a strong and robust preference for customized distributions would have major policy implications, for instance, regarding how retirement accounts should be managed. We should thus further validate the effect size and check the data for robustness and reasonability before we draw general policy conclusions.

3.1.1. Plausibility and Robustness Tests. As a first test of the plausibility of the data, we analyze whether the WTP for customization is positively correlated with the actual extent of customization. We define two measures of customization activity: CA_1 is a raw measure and simply counts for each subject and investment horizon the number of adjustment steps performed in the customization process. Note that CA_1 neither takes into account the extent to which the return in a state has been changed in a customization step, nor whether subsequent customization steps have merely cancelled out previous changes. CA_2 is a more refined measure that looks at the overall return adjustment for each of the 10 states. We use the Euclidean norm of the (10-state) adjustment vector for our definition of CA_2. Even though it is not impossible that a high CA_2 level is accompanied by a low WTP for customization—extensive adjustments could lead to only small utility gains—we nevertheless predict the CA_2 levels to be more positively correlated with the WTP for customization than the much noisier indicator CA_1.

The prediction just made is supported by the data. For CA_1, we find a positive correlation with the WTP for both investment horizons. However, the positive correlations are weak (0.161 for the one-year scenario and 0.147 for the five-year scenario). Significance is only given at the 5% level (despite our sample size of $n = 202$). The correlation between CA_2 and WTP is much stronger. For the one-year horizon, we observe a positive correlation of 0.450 ($p < 0.001$), and for the five-year horizon, the correlation is 0.381 ($p < 0.001$). The correlations are even higher (0.551 and 0.505) if we restrict the analysis to the 101 subjects in the FI treatment (0.403 and 0.312 for NFI). This pattern of correlation findings allows us to draw some interesting conclusions. The more the customized distribution differs from the original distribution (high CA_2) the higher the WTP for customization tends to be. This conforms to our expectations and supports the quality and plausibility of the data. A look at CA_1 reveals that we can rule out the explanation that subjects state a high WTP just because they customized a lot (high CA_1) and want to make sure that they receive the distribution in which they invested so much effort. It seems to be less the customization activity itself that drives the preference, but rather the subjects' true preference for a different distribution. This is further supported by the finding of an even higher correlation in the FI treatment, where the comparison of distributions is further facilitated.

We next analyze whether there are subjects who should be eliminated from the analysis, because of decision behavior that is superficial, ill-conceived, or violates basic rationality. Such an analysis will not only shed further light on the reliability of the data, but may also produce more conservative estimates of the WTP for customization. We define three levels of rationality violation. At the first level, we exclude those subjects from the analysis who have not made any changes to the B&H distribution, but nevertheless entered a positive WTP for customization. Such a decision pattern hints at participants who did not take the experiment seriously, did not want to waste any time and effort on the customization procedure, and arbitrarily clicked on the WTP slider thereafter. We refer to such behavior (no adjustments, but positive WTP) as level 1 rationality violation and eliminate these participants from the original subject pool ($n = 202$) to obtain subgroup NRV_1 (no level 1 rationality violation). As can be seen in Table 2, there are only two subjects in the one-year scenario and three subjects in the five-year scenario who display this strong type of rationality violation or lack of interest in the experiment. The mean WTP for customization does not change as a result of these exclusions.[3]

Our second rationality requirement is much stronger. Some subjects may have indicated such a high WTP for customization that the joint effect of customization and maximum acceptable fee would lead to a distribution that is (first order) stochastically dominated by the originally chosen B&H mix. We expect to find such violations of stochastic dominance particularly in the NFI treatment, where the customized distribution after fees is not displayed explicitly. Violations of stochastic dominance can neither be rationalized by expected utility theory with an increasing utility function nor by the cumulative version of prospect theory (Tversky and Kahneman 1992). Note that stochastic dominance is not easy to spot in some return presentation formats, for example, for density functions. However, our 10-state chart presentation facilitates its identification. The customized distribution after subtracting the WTP must yield a lower or the same return in each single state to be stochastically dominated by the B&H mix. According to this property, dominance violations should be particularly obvious for subjects in the FI treatment, as they see the dominating and the dominated distribution side by side. We define the subgroup NRV_2 to contain only those subjects who do not violate stochastic dominance through the specification of their WTP.

As expected, we observe more such rationality violations in the NFI treatment (22 for the one-year horizon and 12 for the five-year horizon), where the dominance relation is less obvious. However, some

[3] We do not exclude subjects overall but only for the investment horizon during which the violation occurred.

Table 2 Mean [Median] WTP for Customization in FI and NFI Treatments for Both Investment Horizons and Different Subgroups

	(1) FI treatment		(2) NFI treatment	
One-year scenario				
All participants	1.99% [1.5%]	$n = 101$	3.34% [3.0%]	$n = 101$
Subgroup NRV_1	2.00% [1.55%]	$n = 100$	3.34% [3.0%]	$n = 100$
Subgroup NRV_2	1.91% [1.5%]	$n = 89$	2.93% [2.6%]	$n = 79$
Subgroup NRV_3	1.83% [1.35%]	$n = 78$	2.82% [2.0%]	$n = 65$
Five-year scenario				
All participants	2.69% [2.2%]	$n = 101$	3.94% [3.3%]	$n = 101$
Subgroup NRV_1	2.69% [2.2%]	$n = 101$	3.84% [3.25%]	$n = 98$
Subgroup NRV_2	2.64% [2.2%]	$n = 97$	3.70% [3.0%]	$n = 89$
Subgroup NRV_3	2.52% [2.0%]	$n = 89$	3.38% [2.9%]	$n = 74$

Notes. NRV_1 contains only those subjects who have not stated a positive WTP for no customization. In NRV_2 the subjects remain who do not violate stochastic dominance in the direct comparison between the chosen B&H mix and customized distribution after fees. NRV_3 contains those subjects who have produced a customized distribution after fees that is not stochastically dominated by any available B&H mix.

violations of this type also occur in the FI treatment (12 for the one-year horizon and 4 for the five-year horizon). Given that low stated WTPs can barely produce any stochastic dominance, and high WTPs tend to be problematic for this criterion, it is not surprising that the mean WTP is lower in the subsample NRV_2 than in the full sample. However, the decrease is moderate. The most conservative scenario, the one-year horizon in the FI treatment, still yields a mean WTP of 1.91%. Further details are in Table 2.

Our final measure of rationality violation has a less behavioral but more normative flavor. It is inspired by the observation that many subjects chose a risky B&H mix in the first step and then used the customization phase to reduce the (downside) risk of their distribution. In combination with a high WTP for the customization, these subjects might have been better off choosing a less risky B&H mix (without any fee) in the first place. Therefore, we analyze whether the customized distribution after fees is stochastically dominated by any available B&H mix, not necessarily the one chosen in the first stage. This type of rationality violation is much less obvious during the experiment and we should therefore not be surprised if many participants behave irrationally in this sense. On the other hand, all the subjects remaining to form the subgroup NRV_3 can be argued to have provided a reasonable combination of customization and WTP. Thus, the mean WTP for this group should be reliable and informative for policy discussions.

As can be seen in Table 2, we had to eliminate 59 of the 202 subjects in the one-year scenario because of a violation of this strongest criterion (23 in the FI treatment and 36 in the NFI treatment). For the five-year horizon, with its generally higher returns, the violation occurs less often (12 times in treatment FI and 27 times in treatment NFI). The most important insight is that the mean WTP remains substantial even for this carefully selected subgroup. The lowest mean WTP (1.83%) is still observed for the one-year FI treatment. The other mean WTPs are between 2.52% and 3.38%. As a general observation, we find the continuing elimination of problematic subjects (NRV_1, NRV_2, NRV_3) to exert a stronger impact on the mean WTP for the NFI treatment. This is consistent with our intuition that the NFI treatment is more susceptible to misperceptions of the impact of fees and produces questionable WTPs more often. Nevertheless, the difference in mean WTP remains significant at the 1% level for all subgroups and investment horizons, except for the five-year case of NRV_3, where the 1% significance level is barely missed. With respect to the original B&H stock proportions, we find a lower number of violations (of all types) for the more aggressive investors in subgroups BH1y_high and BH5y_high. This might come as a surprise, because these investors have been shown to state higher WTPs on average and thus should be more susceptible to dominance violations. In terms of an explanation, we can only speculate that the more aggressive investors might be more attentive toward customizing the return distribution and stating their WTP.

In summary, we can conclude from these additional analyses that our data is plausible and reliable. The finding of a substantial WTP for customization is robust and not driven merely by the superficial or ill-conceived behavior of our experimental subjects. As a final robustness test, we replicated the study with a (smaller) group of real investors at an investors fair. The results of this second experiment are presented in §4.

3.2. Customization Behavior

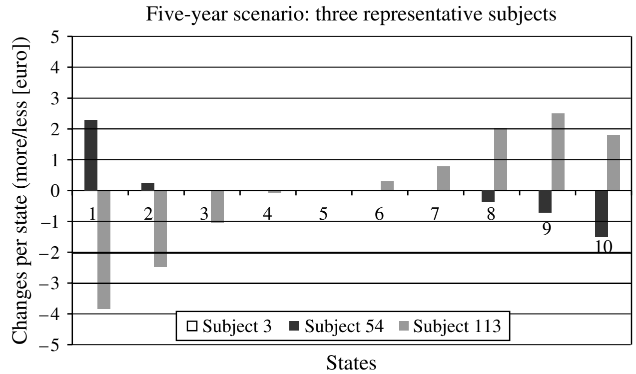
We now take a closer look at the customization behavior in Step 2 of our experiment. First, we examine the data for some effects on the aggregated level. We then account for the heterogeneity in our subjects' preferences, search for recurring customization patterns, and cluster our participants into respective subgroups. It should be noted that we do not have to distinguish between the FI and the NFI treatment in these analyses because the first two steps of the experiment (B&H choice and customization) were exactly identical for both treatments.

There is some evidence in field data that investors have a preference for right skewness (Mitton and Vorkink 2007), and experimental research has confirmed this result. Brünner et al. (2007) and Vrecko et al. (2009) show that subjects act in a skewness-seeking manner in experimental choice tasks. Our data allow us to elaborate on these insights and to analyze whether such a preference for skewness can also be observed in the process of customizing a nonskewed B&H distribution.[4]

When inspecting the data, we encounter a predominant pattern during customization; a large portion of subjects (43.6% for one-year, 45.6% for five-year) increased the return in the worst state (state 1) at the expense of return in the best state (state 10). Taking the initial wealth as the threshold, the lower partial moments of the zero and first order (LPM_0 and LPM_1) are reduced. This behavior fits well with the observation of Unser (2000) that the shortfall probability (LPM_0) is a key component of risk perception. Yet, as the best and not the middle-range states are used predominantly to improve the worst case, the limitation of downside risk is not achieved by increasing skewness. In fact, median skewness even decreases slightly. Despite this predominant pattern, investments in states 1–10 remain almost unchanged before and after customization at the aggregated level. This is because the improvements (by the "worst-case improvers") in states 1 and 2 are offset by a group of subjects who largely disinvest in the worst states in order to boost the returns of the best states to extremely high levels. Consequently, the average portfolio μ and σ remain almost unchanged, although reductions are much more frequently observed than increases (~70% versus 25%). Nonetheless, these "gamblers" do not systematically increase skewness, as they also trade off the outcomes of the extreme states, albeit with the signs reversed. All of the patterns described above can be observed for the one-year time horizon as well as for the five-year time horizon.

3.2.1. Clustering and Customization Types. The data description presented so far suggests that we cannot learn much from the analysis of customization behavior at an aggregated level. There are recurring customization patterns in the population, which differ strongly, are exactly opposite in part, and veiled in the analysis of aggregated data. We thus proceed with some cluster analyses to classify our subjects into different customization types. These analyses are only intended to broadly illustrate the structure of the customization data. Given the complicated dependencies of the adjustments in the different states (from the originally chosen B&H mix and from each other), we refrain from applying sophisticated clustering methods and overinterpreting the findings. Given that customization patterns are more clearly differentiated in the five-year scenario, probably with familiarization and learning effects operating in the background, we only present the results based on the five-year horizon data.[5]

Figure 3 Adjustments Made by the Three Representative Subjects (3, 54, and 113) to Their Previously Chosen Buy-and-Hold Distributions for the Five-Year Scenario



Note. Subject 3 did not perform any adjustments.

We use two typologies based on simple and interpretable clustering methods. In the first approach, three subjects are chosen to represent the customization patterns of the entire group most accurately. To this end, we consider all possible three-subject subsets of the set of 202 participants (these are 1,353,400 subsets). Those three subjects ("representatives") are selected who generate the smallest sum of absolute-value differences (L1 distances) in investment budgets per state, when the other 199 subjects are matched to the best-fitting representative.[6] Subjects 3, 54, and 113 are chosen to be the representatives. In conformity with the above terminology, subject 54 is labeled worst-case improver. Subject 3 opts to stick to the previously chosen B&H investment and is thus named "unchanged." Subject 113 increases overall downside risk so as to generate additional upside potential and is thus termed "risk increaser." A similar adjusted distribution could have been obtained by selecting a higher stock proportion ex ante. Presumably, deeper reflection during the customization phase has promoted the insight that the originally chosen B&H mix was too conservative to match personal preferences. Figure 3 depicts the adjustments made by the three representative subjects. The three subjects each represent 110 (subject 3), 69 (subject 54), and 23 (subject 113) persons.

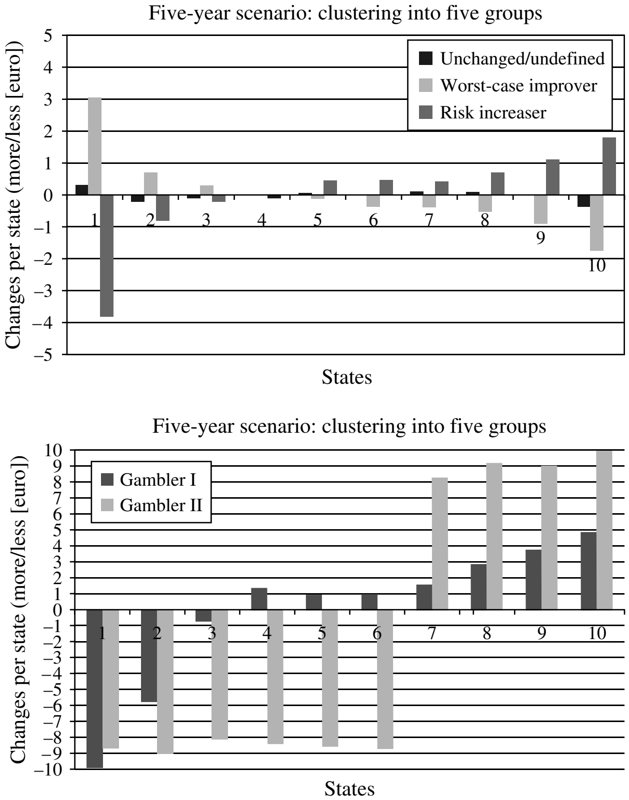
To see whether this classification is robust, we additionally perform a k-means clustering using Euclidian (L2) distances. We ensure the global optimality of the solution by performing 1,000 runs with different

[4] To be exact, the buy-and-hold distributions are mildly positively skewed due to their log-normal return profiles.

[5] The interested reader can find the one-year results in the electronic companion, available at http://www.finanzierungslehrstuhl.de/journals/vrecko-langer/ElectronicSOM.htm.

[6] The concept of "investment budget per state" builds on the technical modeling of our customization tool (see Appendix B for details).

Figure 4 **Adjustment Profiles of the Five Cluster Centers When the *k*-Means Algorithm Is Used to Partition the Five-Year Data Into Five Groups**



Note. The upper panel displays the profiles for the types "unchanged/undefined," worst-case improver, and risk increaser; the lower panel displays the profiles for the two gambler types.

sets of randomly drawn starting values. For this metric, segmentation into five clusters fits the data best. The above three clusters, unchanged (114 subjects), worst-case improver (51 subjects) and "risk increaser" (26 subjects) are complemented by the additional "gambler I" (10) and "gambler II" (1) types. Especially for the *k*-means clustering, the unchanged cluster functions as a collecting point for the various adjustment patterns that do not fit any of the other clusters. We hence rename it unchanged/undefined.[7] As can be seen from Figure 4, the basic characteristics of the different subject types remain intact after changing the clustering algorithm.

From the viewpoint of security-potential/aspiration (SP/A) theory (Lopes 1984, 1987), worst-case improvers and gamblers differ in their dispositional motivation to seek either security or potential. These differences manifest themselves in whether a type pays more attention to the worst or the best outcomes in a distribution. The differences in gambling strategies (gambler I versus gambler II type) can be attributed to differences in aspiration levels.

Interestingly, one can also observe sizable differences in WTP across subject types. Restricting our attention to the NRV_2 subgroup, we observe the unchanged/undefined type to state the lowest WTP: 2.37% for making no, only minor, or unclassified adjustments to the B&H investment. Worst-case improvers (wci) are willing to pay a fee of 3.43% to improve on the worst outcome. Subjects who are willing to allow for more downside risk (risk increaser; ri) are willing to spend 4.12% for increased upside potential. The gambler types lead the pack by stating WTPs of 6.30% and 7.50% (gambler I and gambler II; gI and gII).

To evaluate the significance of the differences in WTP, we estimate a linear regression model and obtain the following predictive equation:

$$WTP_i = 2.90 - 0.96 * feeintegration_i + 0.97 * wci_i + 1.78 * ri_i + 3.88 * gI_i + 4.60 * gII_i.$$

The base case is given by a subject of the unchanged/undefined cluster in the no fee integration treatment. When adjusting standard errors for intragroup correlation, all coefficient estimates turn out to be highly significant ($p < 0.01$).

3.3. Explaining Customization Behavior Through Prospect Theory

If preferences were characterized by constant relative risk aversion in expected utility theory, a B&H investment strategy would always be optimal.[8] The individual coefficient of risk aversion determined the stock proportion and no customization would be expected. In contrast, prospect theory can predict preferences for customized distributions. It is important to note that PT calculations always build on one hidden parameter, the subjects' reference point. Because our experimental software displays the returns as gains and losses from the starting endowment, we assume for our PT calculations that the starting endowment was perceived as the reference point.[9] Our analysis reveals that subjects are far from maximizing their PT utility when they customize their B&H distributions. In fact, the customized distributions generate slightly lower PT utilities on average. In the one-year scenario, the PT utility of the customized distribution is below the utility of the chosen B&H distribution for 52.97% of the subjects, and in the five-year

[7] Only 10 of the 114 subjects in this cluster did not perform any adjustments.

[8] Strictly speaking, a constant mix strategy is optimal, but differences in terminal wealth distributions are negligible here.

[9] The choice of the reference point does not seem to be crucial for the main findings. As a robustness check, we have repeated the calculations for various other reference points and we find similar results.

Table 3 Overview of the Explanatory Power of Prospect Theory Preferences by Cluster

Cluster (Name)	(1) (Unchanged/undefined)	(2) (Worst-case improver)	(3) (Risk increaser)	(4) (Gambler I)	(5) (Gambler II)
No. of subjects in cluster	114	51	26	10	1
% of subjects with higher (or equal) PT value after customization (for endowment as reference point)	41.23	11.76	84.62	90.00	100.00
Median PT parameters by cluster					
α	1.20	1.25	1.08	1.09	0.91
$\delta+$	0.72	0.68	0.84	0.68	0.79
β	0.96	1.00	0.98	0.95	1.56
$\delta-$	0.62	0.59	0.70	0.77	0.47
λ	1.43	1.46	1.31	0.85	0.16

Notes. The figures in column (1) contain the 10 subjects who did not make any adjustments to the chosen buy-and-hold distribution. The parameters α and β determine the curvature of the estimated PT value function; δ^+ and δ^- are the parameters of the probability weighting function. The parameter λ determines the degree of loss aversion. All functional specifications are as in Tversky and Kahneman (1992).

scenario, we observe this surprising effect for 57.92% of the subjects. Some subjects violated stochastic dominance in the process of the PT parameter elicitation. But if we eliminate these subjects from the analysis, the respective figure is even slightly higher: 52.98% (one-year horizon) and 57.53% (five-year horizon).

If we consider the explanatory power of PT preferences by subject type, we gain some further insights (again, the results are presented for the five-year scenario). According to Table 3, worst-case improvers strikingly disagree with their elicited PT preferences in the customization task. One can observe far more agreement for the risk increaser and the two types of gamblers. Our interpretation of these findings is that, for the majority of subjects, lottery-based parameter elicitation represents a gambling task, whereas customization is perceived as an investment task. Consequently, we only find concordance for the small subgroups of risk increaser and gamblers who act in a risk seeking manner during customization and PT parameter elicitation.

Since our approach only provides a joint test of the theory and elicitation method, we should be careful to interpret our findings as a general refutation of prospect theory. It has previously been shown (Zeisberger et al. 2012) that elicited PT parameters are often not very robust and reliable and have to be interpreted with caution. However, we can definitely draw the conclusion from our experimental findings that standard lottery-based PT parameter-elicitation methods do not seem to be particularly well suited for predicting individual behavior in a complex investment context.

4. Replication with Real Investors

Our main experimental study could possibly be criticized because we used a pure student subject pool to examine a phenomenon that is most relevant for nonstudent investors. To counter such criticism and validate the robustness of our general findings, we replicated the experimental study at a large investors fair in Hannover, Germany, in September 2010. We used exactly the same software interface with detailed instructions and quizzes upfront and provided monetary incentives, as in the original experiment.[10] Our robustness check comprised the main experiment with the investment decisions and elicitation of the WTP for customization, but it did not elicit PT parameters due to time constraints. Overall, 54 people participated in the experiment, most of them visitors at the fair but also exhibitors and other staff. The average age of these participants was 42 (students: 23) and 13% of the subjects were female (students: 27%). The experiment was run individually (without specific sessions) with at most six participants in parallel.

The real investors do not differ significantly from the students with respect to the chosen B&H mix. The mean stock proportion of 57% is slightly lower for the one-year horizon (students 59%) and slightly higher (67%) for the five-year horizon (students 64%). The customization activity measured by the mean number of adjustment steps is lower for the real investors (7.0 compared with 9.9 for the one-year horizon; 4.5 compared with 6.4 for the five-year horizon). Because of the much smaller sample size, a separate cluster analysis for the real investor was not feasible. To compare the general customization patterns (proportions of customization types), we assigned each real investor to the best fitting student cluster, selecting the cluster center with minimal Euclidean distance. A higher proportion of real investors (76%, compared with the 56% students) is assigned to cluster 1

[10] As one small difference, we also offered chocolate bars and other food items instead of the fixed fee.

Table 4 Mean [Median] WTP for Customization in FI and NFI Treatments for Both Investment Horizons, Different Subgroups, and Different Types of Participants

	(1) FI treatment	(2) NFI treatment
One-year scenario		
All participants		
Students	1.99% [1.5%] $n = 101$	3.34% [3.0%] $n = 101$
Real investors	1.31% [0.9%] $n = 29$	2.01% [1.9%] $n = 25$
Subgroup NRV_2		
Students	1.91% [1.5%] $n = 89$	2.93% [2.6%] $n = 79$
Real investors	1.27% [0.8%] $n = 23$	1.65% [1.5%] $n = 17$
Five-year scenario		
All participants		
Students	2.69% [2.2%] $n = 101$	3.94% [3.3%] $n = 101$
Real investors	1.98% [1.0%] $n = 29$	2.63% [2.0%] $n = 25$
Subgroup NRV_2		
Students	2.64% [2.2%] $n = 97$	3.70% [3.0%] $n = 89$
Real investors	2.10% [1.0%] $n = 24$	2.53% [2.0%] $n = 19$

(unchanged/undefined). As for the students, worst-case improvers (15% compared with 25%) and risk increasers (6% compared with 13%) are the next two largest clusters. The gambler clusters (4) and (5) contain only one real investor each. The general pattern of customization behavior of the real investors thus does not seem to differ much from what we observed for students.

Our main results with respect to the WTP are summarized in Table 4. There are two main findings: (1) Even though we still observe a substantial WTP for customization, it is consistently lower for real investors than for student subjects. The difference is significant for each combination of treatment, horizon, and subgroup presented in the table at the 5% level with the only exception of the NRV_2 subgroup in the five year FI treatment where the WTP difference between students (2.64%) and real investors (2.10%) is not significant. The lowest mean WTP (still in the one-year/FI treatment) is 1.27%, down from the 1.91% we had observed for students. We can only speculate as to the reasons, and suspect that such an investors fair, with many financial service providers and exhibitors offering (potentially overpriced) products in immediate vicinity, generates a particularly challenging environment for a BDM-mechanism-based elicitation of willingness to pay. From this perspective, the 1.27% should still be considered to be a considerable fee for a service that can actually be provided at (almost) no cost for the financial institution. (2) Real investors seem to be less influenced by the treatment than students. The WTP difference remains positive in all cases and averages about 0.50%. But it is only significant on the 5% level if we consider the one-year horizon and do not further restrict our small sample to the NRV_2 subgroup. If we regress dummies for treatment, investor type, and their interaction on the WTP, we find for both horizons in the NRV_2 subgroup significant coefficients for treatment and investor type ($p < 0.05$) but no significant interaction.

5. Summary and Conclusion

This paper examines whether there is a mismatch between investor preferences and the return distributions that standard buy-and-hold investment strategies can deliver. These B&H strategies are restricted to a specific class of distributions. Further customization could thus provide additional value for investors with specific risk preferences. The research objective was to investigate subjects' strength of preference for such customized distributions and to draw conclusions about their demand for personalized investment products.

Our experimental research builds on the assumption that investors should make investment decisions based on overall return distributions, whereas the actual investment products in the portfolio are largely irrelevant. Following Goldstein et al. (2008) and their distribution builder approach, we present an interactive software tool that employs a two-step procedure for generating return distributions, namely, the choice of an initial B&H mixture followed by the opportunity to customize the initially chosen B&H distribution. This two-step approach is not only interesting from a practical perspective as an alternative to the direct distribution-building introduced by Goldstein et al. (2008), it is also particularly well suited to tackle the research question in which we are interested.

In our two experimental studies with 256 participants (students and real investors), we observe that most participants make extensive use of the customization option and many are willing to pay a substantial fee for this additional flexibility. In many cases, the willingness to pay is so high that violations of dominance are observed. We further find that the willingness to pay for customization is significantly lower if the fee is integrated into the display of the return distribution, making its impact on final returns more obvious. However, even for the subgroup with the most moderate preference for customization, that of real investors with fees integrated into the display and dominance violators eliminated, the average willingness to pay for customization remains at about 1.3% for a one-year investment horizon. This finding suggests a pronounced preference for distributions that cannot be achieved through conventional investment strategies and should inspire some debate about the question of how, for instance, retirement savings accounts are managed. We also observe that investors can be clustered into distinct subgroups in terms of their adjustment patterns. The most distinct investor types are the worst-case improvers and the risk increasers. The highest willingness to pay for customization is observed for the gambler types. We also analyze whether a preference for a specifically customized distribution could be predicted if more detailed risk preferences were known at the individual level. Thus, we contribute to the ongoing debate on how to measure individual risk attitudes to "derive" the most suitable investment strategies for individual subjects. Our finding that individually elicited prospect theory parameters can barely explain the individual customization behavior of our experimental subjects is discouraging for those who intend to apply more sophisticated methods of risk preference elicitation in practice. We have to recognize at the very least that a lottery-based prospect theory parameter elicitation does not seem to be sufficiently reliable to predict individual preferences for overall return distributions. As a robustness check, for our findings, we also surveyed real investors at an investors fair to compare their preferences with those of our main pool of student subjects. We find that the willingness to pay for customization is slightly lower for these real investors and the main effect of fee integration is also less pronounced.

Acknowledgments
The authors are indebted to Maik Dierkes, Sven Nolte, and participants of the Finance Center and econometrics research seminars at the University of Muenster for their helpful suggestions, as well as to Sebastian Dyck for his assistance in running the experiments. The authors also thank the editor and two anonymous referees for their valuable comments and insights that led to a considerable improvement of this paper.

Appendix A. Written Instructions (Translated from the Original German)

Dear experiment participant,

Welcome to our experiment "investment preferences." We would like to thank you in advance for your willingness to participate in this experiment.

Participants of previous experiments have let us know that they perceived economic experiments as very exciting. We hope that you will share this feeling.

As a **basic payment** everybody will receive an allowance to the amount of **8 euros**. This amount is **guaranteed**, i.e., you will earn at least 8 euros for participating in this experiment. Additionally, we will randomly draw **10% of all the experiment participants** and pay them according to their decisions during the experiment. In case you are selected for **payout**, the payoff will **generally** (depending, of course, on your decisions during the experiment) amount to **more than 100 euros**. The drawing of the "winners" will take place during the lecture on Advanced Finance on June, 21, 2010, at approximately 11:30 A.M.

This experiment consists of 4 *parts*:
Experiment part 1: investment preferences, short investment horizons (1 year, 5 years)
Experiment part 2: investment preferences, long investment horizons (10 years, 30 years)
Experiment part 3: lottery decisions
Experiment part 4: questionnaire

Experiment parts 1 and 3 will be executed incentive compatibly, i.e., all of your decisions in parts 1 and 3 can potentially be selected for the payout. A detailed explanation of the exact payout mechanism will follow at the relevant stages during the experiment.

Experiment parts 2 and 4 have no bearing on your remuneration. Unfortunately the subtleties of the underlying problem render this impossible. However, we kindly ask you to take your time with these decisions as well!

At different stages during the experiment we will explain to you the directly following subtask. It is strictly required that you carefully read and comprehend the instructions/tutorials for every subtask. In addition, you have the opportunity to have another look at the current tutorial by clicking on "Help" while working on a subtask. If you still have an open question, please raise your arm and the experimenter will immediately assist you.

Please do not talk to your fellow students during this experiment.

Do you have any questions regarding the experiment at this time?

Experiment part 1: investment preferences, short investment horizons (1 year, 5 years)

Please put yourself into the following scenario: You would like to invest 100 euros. These 100 euros are your only financial investment for the period under consideration (1 year, 5 years). In case you will be selected for variable payout, you invest 100 "real" euros for one of the two investment horizons.

Appendix A. (Continued)

Within the payout of this experiment both

—the investment horizon (1 year, 5 years) and
—the state (state 1, 2, 3, 4, 5, 6, 7, 8, 9 or 10)
relevant for payout are randomly selected by the computer.

Both investment horizons have an equal probability of being drawn. Also, states 1 to 10 all have the same probability of occurrence. More detailed explanations will now follow in Tutorial 1 …

Notes. The original German text and the subsequent animated tutorials containing all the information on the functionality of the software tool (including the test questions) are provided in the electronic companion, available at http://www.finanzierungslehrstuhl.de/journals/vrecko-langer/ElectronicSOM.htm.

Appendix B. Technical Modeling and Calculation of State Prices

A three-stage process is needed to determine the 10 state prices that lie at the heart of the 10-state chart introduced by Vrecko et al. (2009). In a straightforward application of the Black–Scholes model, we assume both the risk-neutral ($\mathbb{Q}$) and the physical measure ($\mathbb{P}$) to be normally distributed with an annual standard deviation of 20% and expected yearly returns of 4% and 8%, respectively:

$$\mathbb{Q}_{1y} \sim N(0.04, 0.20); \quad \mathbb{P}_{1y} \sim N(0.08, 0.20);$$
$$\mathbb{Q}_{5y} \sim N(0.20, 0.45); \quad \mathbb{P}_{5y} \sim N(0.40, 0.45).$$

In the first stage, each state of the 10-state chart is directly mapped to a decile of the physical distribution of the underlying risky asset. This approach has the advantage of being flexible with respect to the specification of the option pricing model. Other models can be adapted directly as long as they specify both risk-neutral and physical distribution. This feature might be of particular relevance to implementation in practice.

For example, state 2 corresponds to the second decile; that is, it extends from the 10% quantile up to the 20% quantile. In the one-year scenario, the corresponding return values are given by $\mathbb{P}_{1y}^{-1}(0.1) = -17.63\%$ and $\mathbb{P}_{1y}^{-1}(0.2) = -8.83\%$. Once these boundaries are set, the amount of probability mass under the risk-neutral distribution that falls within these limits specifies the undiscounted state price. In our example

$$\begin{aligned}\text{state}2_{1y}^{\text{undiscounted}} &= \mathbb{Q}_{1y}(-8.83\%) - \mathbb{Q}_{1y}(-17.63\%)\\ &= 0.26056 - 0.13973 = 0.12083.\end{aligned}$$

Discounting this value by the riskless return of 4% yields the final price of state 2:

$$\text{state}2_{1y}^{\text{discounted}} = 0.12083 * e^{-0.04} = 0.11610.$$

For the investment horizon of five years, the corresponding value can be computed as follows:

$$\begin{aligned}\text{state}2_{5y}^{\text{discounted}} &= [\mathbb{Q}_{5y}(\mathbb{P}_{5y}^{-1}(0.2)) - \mathbb{Q}_{5y}(\mathbb{P}_{5y}^{-1}(0.1))] * e^{-0.20}\\ &= 0.11838.\end{aligned}$$

Table B.1 reports the full set of state prices for both the one- and five-year scenarios. While, the undiscounted state prices add up to one, the discounted state prices add up to $e^{-0.04}$ and $e^{-0.20}$ for the one- and five-year scenario, respectively.

A full investment in the risky asset, that is, a buy-and-hold strategy holding 100% stocks, is equivalent to allocating one-tenth of the budget to every state. To earn the yearly riskless rate of return (4%) safely, the investor needs to allocate his or her budget proportional to the state prices. All other buy-and-hold mixtures can be mapped to investment schemes using the following formula (after the budget has been normalized to 1):

$$Investment_i = Coefficient_i * e^{T*r} + (0.1 - Coefficient_i * e^{T*r}) * BH\%,$$

where i denotes the state, T denotes the investment horizon, r denotes the yearly riskless rate of return, and $BH\%$ denotes the stock proportion of the buy-and-hold mix.

The application of the state price concept to the customization procedure is straightforward. Customizing the buy-and-hold investment translates to shifting a portion of the investment budget from one of the two states selected by the subject to the other state selected. Formally speaking, a customization step increases the investment by the subject into a specific state i ($Investment_i$) while decreasing the investment into the corresponding trade-off state i' ($Investment_{i'}$) by the same amount. The resulting changes in the investment returns follow directly from the associated state prices. For example, shifting €1 from state 6 to state 3 in the five-year scenario will decrease the return of state 6 by $1/0.07006 = 14.2735$ percentage points and increase the return of state 3 by $1/0.10037 = 9.9631$ percentage points.

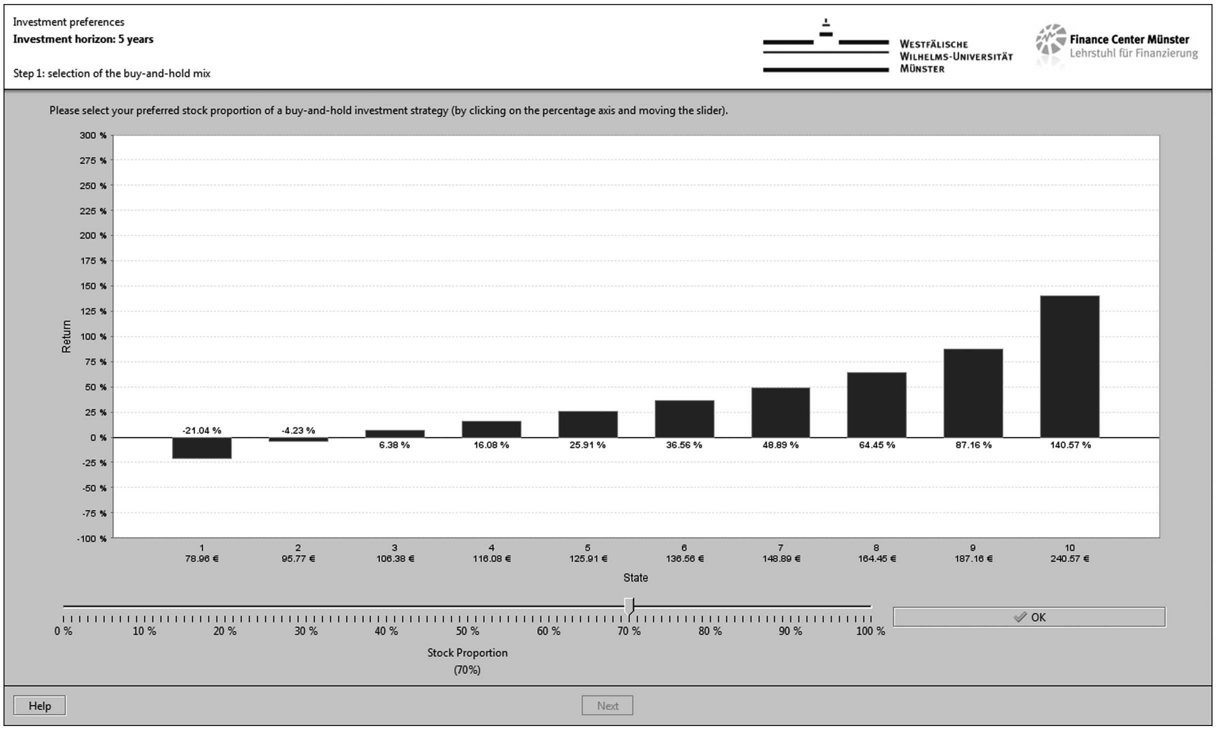
Table B.1 Full Set of State Prices for Both the One- and Five-Year Scenarios

	State									
Investment horizon	1	2	3	4	5	6	7	8	9	10
One Year scenario	0.13425	0.11610	0.10786	0.10176	0.09659	0.09184	0.08718	0.08226	0.07644	0.06652
Five Years scenario	0.16542	0.11838	0.10037	0.08811	0.07842	0.07006	0.06236	0.05477	0.04651	0.03433

Notes. This table quotes the resulting state prices if a Black–Scholes model is used to price the 10 binary options (risk-neutral and physical distribution are both normally distributed and have an annual standard deviation of 20% and expected yearly returns of 4% and 8%, respectively).

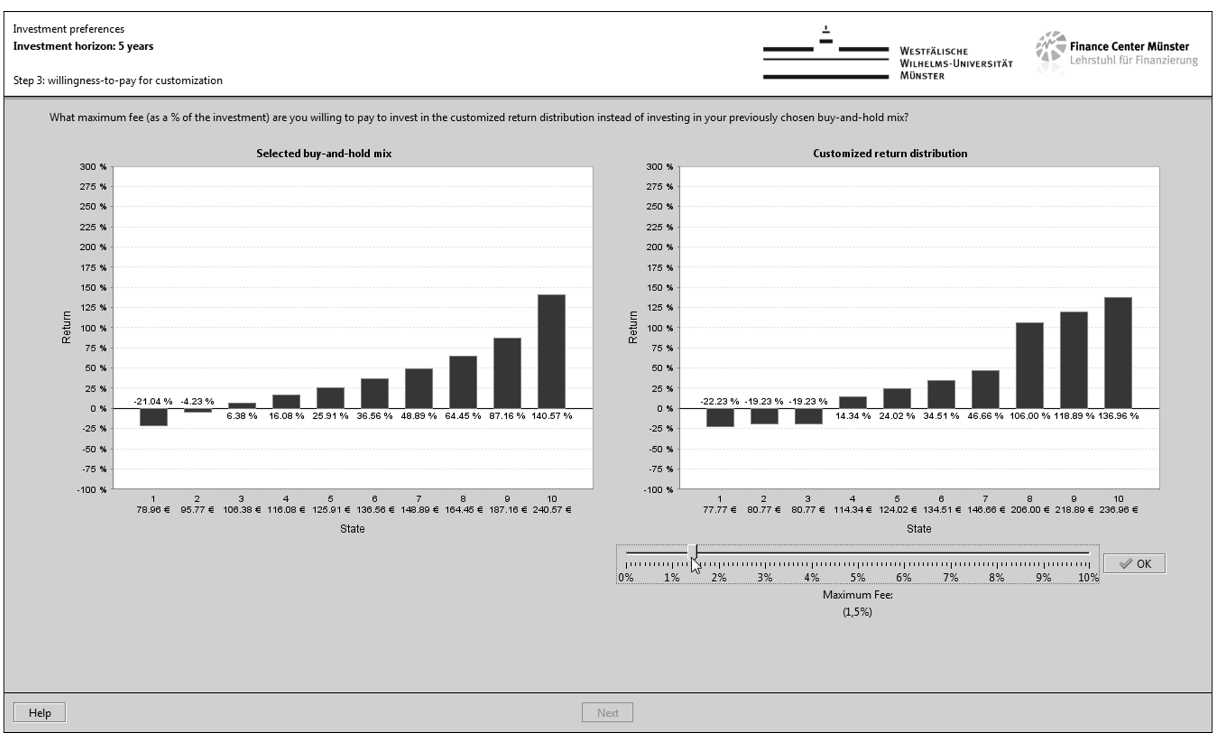
Appendix C. Screenshots from the Experiment

Figure C.1 Exemplary Computer Screen During the Buy-and-Hold Selection (Step 1)



Note. In the example a stock proportion of 70% has been selected.

Figure C.2 Exemplary Computer Screen During the Willingness-to-Pay Step (Step 3) for the Treatment with Fee Integration



Note. The "1.5%" has only been entered for illustrative purposes.

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