Working Paper
Series

FINRISK
National Centre of Competence in Research
Financial Valuation and Risk Management

National Centre of Competence in Research
Financial Valuation and Risk Management

Working Paper No. 402

The Disposition Effect in the Lab

Martin Vlcek   Mei Wang

First version: July 2007
Current version: July 2007

This research has been carried out within the NCCR FINRISK project on
"Behavioural and Evolutionary Finance"

The Disposition Effect in the Lab *

Martin Vlcek and Mei Wang [a]

July 5, 2007

Abstract

We conduct controlled experiments in order to analyze individual trading behavior. Our results suggest that investors measure their gains relative to their initial wealth, and that this reference point together with past stock price changes determine the portfolio choices. Subjects choose a fixed-mix investment strategy in the loss zone and a contrarian strategy in the gain zone. The observed portfolio decisions are in line with the house money effect. We reject the hypotheses that rebalancing, prospect theory with a fixed reference point, or the justification hypothesis explain the disposition effect.

Keywords: Disposition effect, prospect theory, portfolio choice, experimental finance

JEL classification: D01, D14, D81, G11, G12

*We thank Sonia Näf for programming the Z-Tree code and Simone Feusi for helping us with the data. We appreciate the helpful comments of Thorsten Hens and the participants of the V Workshop LabSi on Experimental Economics. Financial support by the University Research Priority Programme "Finance and Financial Markets" of the University of Zurich the national center of competence in research "Financial Valuation and Risk Management" is gratefully acknowledged. The national centers in research are managed by the Swiss National Science Foundation on behalf of the federal authorities.

[a]Swiss Banking Institute, University of Zürich, Plattenstrasse 32, CH-8032 Zürich, Switzerland.

E-mail: vlcek@isb.unizh.ch, wang@isb.unizh.ch

1 Introduction

The disposition effect refers to the observation that investors tend to sell winning stocks while they have a disposition to keep losing stocks. This observation has been made by a series of articles, most notably Shefrin and Statman (1985), Odean (1998) and Weber and Camerer (1998). Moreover, Odean (1998) shows that the prices of the winner stocks investors have sold, keep on rising, whereas the prices of the loser stocks that investors have not sold, keep falling. Therefore, investors would have earned more money, had they behaved differently.

Different explanations for this puzzle can be found in the literature, including explanations based on traditional finance theories, such as portfolio rebalancing, transaction costs and capital gains taxes. Behavioral explanations have also been proposed, such as prospect theory, belief in mean reverting asset prices, and the justification hypothesis. We conduct experiments to shed light on the validity of the proposed explanations.

The first research question we address, is whether disposition behavior is a disguised fixed-mix strategy, which is consistent with traditional portfolio theory. In a setting where the investment opportunity set is constant, an expected utility maximizer with constant relative risk aversion rebalances his portfolio in each period, based on a fixed-mix strategy (see Samuelson (1969) and Merton (1969)). Therefore when prices rise (fall) he sells (buys) the security, and it may appear that he realizes gains more often than losses.

The majority of the existing research on the disposition effect is performed in terms of units of assets sold (or hold). However, it is not clear in this context, whether the disposition effect is caused by rebalancing because the two may coincide in certain cases. In our experiment we ask the subjects to allocate their current wealth to a risky and a risk-free asset in each period. This allows us to compare the observed investment strategies explicitly with a fixed mix strategy and to draw further conclusions about purchasing behavior.

Our design facilitates the calculation of a fixed-mix strategy. Hence, if we do not observe a fixed-mix portfolio strategy, it implies that the subjects deliberately choose not to do so, and not because they have calculation difficulties to implement the rebalancing strategy. In this case, we can rule out rebalancing as an motivation for the disposition effect.

The most prominent behavioral hypothesis to explain the disposition effect is the S-shaped value function of prospect theory. Disposition behavior may arise if a gain (loss) moves the investor to his risk averse (seeking) part of the value function so that he is inclined to reduce (increase) his position in the risky assets. However, in their theoretical contributions Hens and Vlcek (2005) and Barberis and Xiong (2006) doubt that prospect utility together with a fixed reference point can explain disposition behavior. It is therefore of primary interest to assess this hypothesis empirically.

Thaler and Johnson (1990) observe in their experiments that subjects take more risk after a gain and less risk after a loss unless they have a chance to break even, which they coined as "house-money" and "break-even effects". At the first sight, these seem to contradict with prospect theory, but originally prospect theory was developed for one-shot decision making. In a dynamic setting the assumption about the reference point is crucial. The risk preference in the current period depends on whether prior gains and losses are integrated into the current payoffs. The authors explain their observations with prospect theory and the fact that individuals do not integrate consecutive losses, so that they are very sensitive to each new loss, whereas they do integrate gains, so that they are more tolerant to potential losses after prior gains.

To test the predictability of prospect theory we characterize the subjects in our sample according to prospect theory. We estimate their coefficients of risk and loss aversion, and their coefficients describing the impact of probabilities on the subjects' decisions. To this aim we perform, in addition to the financial market experiment, a lottery experiment. Then we relate the preference parameter estimates to the observed investment decisions.

Another argument to explain the disposition effect is that investors (erroneously) believe in mean-reverting asset prices, i.e. they believe that today's losers will outperform today's winners and that the winners of today are the losers of tomorrow. Based on such beliefs investors sell winners and hold losers. We control for the beliefs of the subjects by using an experimental design, where stock prices are determined exogeneously by a binomial process. The participants know all the parameters of the process and are informed about the independence of returns of past stock prices and their changes. We implement the design by a price generating mechanism, described bellow in detail, that accentuates the randomness of stock prices. Many of the participants really do perceive the stock price process as random. In a questionnaire filled in after the pilot study, most subjects affirm that they perceive the price process to be random.

Zuchel (2001) suggests an explanation for the disposition effect based on the justification hypothesis. It states that individuals stick to previous unsuccessful actions because they feel the need to justify or to rationalize their decisions. People are reluctant to admit, to themselves or others, that the prior decisions were incorrect. To (re)affirm the correctness of earlier decisions they become even more committed to them, which is refered to as escalation of commitment or entrapment[1]. Applied to the disposition effect this means that investors hold a losing stock because they do not want to admit that the initial purchase was a mistake. They sell winning stocks, to realize gains, implying that they have made a good initial decision.

In our financial market experiments we introduce a treatment, where subjects are asked to justify explicitly their decisions. This may make the subjects feel monitored and hence reluctant to admit that their past decisions were bad. Therefore, they are expected to stick stronger to their previous unsuccessful decisions. The supposed treatment effect is to intensify disposition behavior.

We use a multinomial logit model to analyze the the investment decisions, coded as a categorical variable. The categories are "increase in the fraction" (or "buy"), "same fraction" ("hold") or "decrease in the fraction of wealth invested in the risky asset" ("sell"). Our main findings are that investment decisions are significantly explained by the investor's performance and past stock price changes. Other factors, as estimates of prospect theory preference parameters, the order of the tasks and the justification treatment have no significant impact on the subject's portfolio decisions.

On average, our subjects stick to their previous asset allocations, when they are in the loss zone. In the gain zone, however, they invest according to a contrarian strategy, i.e. they increase their holdings in the risky asset after its price fell and they decrease it, after the price rose.

The observed behavior in our experiments is consistent with studies using financial market data, which suggests that our results are externally valid. Choe, Kho, and Stulz (1999) report that individual investors in Korea exhibit short-run contrarian behavior. Grinblatt and Keloharju (2001) find that the propensity to sell stocks of Finnish households is positively related to recent returns and that this propensity to sell is damped when the household is in the loss zone.

[1] Psychological research in this area deals with the question why, and under what circumstances individuals irrationally stick to, or even intensify, losing actions. See Staw (1997) for an overview of the literature, and Brockner (1992) for details on the justification hypothesis.

The fixed-mix investment strategy chosen in the loss zone and the contrarian strategy observed in the gain zone both imply selling winners and holding losers in terms of numbers of assets bought or sold. Therefore our results cannot rule out the possibility that the disposition effect in the loss zone is motivated by rebalancing. However, our findings concerning the behavior in the gain zone are at odds with investing according to a fixed-mix strategy. Therefore we conclude that the disposition effect cannot be explained by rebalancing, in general.

Our findings are also partially compatible with the house money effect documented by Thaler and Johnson (1990), in the sense that people can be more risk-seeking after gains. In our experiments, if the investment is in the gain zone, the subjects are more speculative and active than when the investment is at loss. In particular, they increase the risky positions when they are ahead and after the price has recently fallen.

We find clear evidence for reference point dependent behavior: the subjects behave differently when they are in the gain zone, than when they are in the loss zone. However, their portfolio decisions cannot be predicted by their estimates of prospect theory parameters, although we get similar estimates as Tversky and Kahneman (1992).

We hypothesize that the justification treatment in the financial market experiment makes subjects reluctant to admit that they made bad investments decisions in the past, and therefore, makes them reluctant to realize losses. However this hypothesis is rejected. The justification treatment does not make a significant difference in investment behavior. The inspection of the contents of the justifications suggests that some participants may believe in mean reverting asset prices. But it seems that this belief does not explain the disposition effect, because this hypothesis is not compatible with the observed fixed-mix strategy in the loss zone. If anything, the belief in mean-reversion may explain the contrarian gambling strategy in the gain zone.

In the next section we describe the experimental setting. In section 3 we present our results, that are followed by a discussion in section 4. Section 5 concludes.

2 Experiments

This section first describes the experiments in general, and then focuses on the different tasks.

The computerized experiment was conducted in the laboratories of the University of Zurich, using the software z-Tree (Fischbacher (1999)). Each of the three sessions lasts for approximately 2 hours including 30 minutes of instructions.[2] 59 students from the University of Zurich and the Swiss Federal Institute of Technology Zurich (ETHZ) participated in the experiment. The subjects were studying several fields, including economics, psychology and engineering, among others. The average payoff of a participant was CHF 31 (approximately USD 25).[3]

In each session the subjects have to complete three tasks. The first task is called the lottery experiment. The subjects are asked to compare binary lotteries and to reveal certainty equivalents. We call the second and third tasks financial market experiment 1 (FME 1) and 2 (FME 2), respectively. As the names indicate, the subjects participate during these tasks in two stylized financial market games, where they have to make portfolio decisions. The difference between FME 1 and FME 2 is that in one of them, the justification condition, the subjects have to give reasons for their decisions explicitly, whereas in the control condition, they do not have to do so.

In each session we divide the subjects into two groups, called "Group 1" and "Group 2". The subjects are assigned randomly to the two groups and they do not know about the grouping. In the first financial markets task the subjects in Group 1 play the game without justification. In the meantime the subjects in Group 2 play under the justification treatment. Then, in the second financial market task, the participants in Group 1 have to justify their decision, whereas the others play the control version. The structure of each session is illustrated in Table 1.

A brief description of the tasks is presented bellow; for a complete description see the instructions on the web.[4]

[2]We conduct three sessions: the first on March 23, 2006, and two sessions on June 22, 2006.

[3]We calibrated the experiments so that the average participant received a compensation comparable (by hour) to a Swiss student salary. Final payoffs ranged from roughly CHF 19.10 to CHF 50.70 (USD 15 and USD 42, respectively).

[4]http://www.phd-finance.unizh.ch/People/Vlcek.html .

Group 1	Group 2
Lottery Task Preference Parameters	Lottery Task Preference Parameters
Financial Market 1 Portfolio Allocation (Not justify)	Financial Market 1 Portfolio Allocation (Justify)
Financial Market 2 Portfolio Allocation (Justify)	Financial Market 2 Portfolio Allocation (Not justify)

Table 1: *Structure of the Experiments. In each session we assign the subjects randomly to two groups. First, all subjects participate in the Lottery Experiment. This yields us information about their preferences. Then, in the first Financial Market Experiment (FME) the subjects in Group 1 play the game without justification. In the meantime the subjects in Group 2 play the justification treatment. In the second FME, the participants in Group 1 have to justify their decision, whereas the others play the control version. The FMEs yield us data about the subjects' portfolio choices.*

2.1 The Lottery Experiment

We conduct the lottery experiment in order to elicit the degree of risk aversion, loss aversion and probability weighting, which can be captured using the parametrization of prospect theory by Tversky and Kahneman (1992). Our lottery design and parameter estimation methods are based on Glaser (2001).

The subjects are confronted with different hypothetical lottery questions. To estimate the risk-aversion parameters in prospect theory, we elicit the amount z_a that makes the subjects indifferent between the lotteries $(x_{a1}, 0.5; x_{a2}, 0.5)$ and $(z_a, 0.5; 0, 0.5)$, where $x_{a1} > x_{a2} > 0$ are known to the subjects. Since this type of task is relatively difficult, we design an algorithm, to guide the subjects.[5] We adjust z_a iteratively so that the subjects only have to state their preferences between two well-defined lotteries. Then we can estimate the amount of z_a from their answers. A typical trial of such a lottery question is shown in in Figure 1.

To estimate the loss aversion parameter, we adopt a similar procedure to

[5]This algorithm is described in more detail in the Appendix.

Please Choose a Lottery

Lottery A	A fair coin is thrown. If heads appear you win 10 CHF, if tails occurs, you win 5 CHF.
Lottery B	A fair coin is thrown. If heads appear you win 15 CHF, if tails occurs, you win 0 CHF.

Lottery A ☐
Lottery B ☐
Indifferent ☐

Figure 1: *Example of a Lottery Experiment Display. This is a stylized version a of a screenshot of a typical display. The subjects are presented the two alternatives, lotteries A and B. Bellow they compare the alternatives by clicking in the appropriate box.*

elicit the z_b, that makes the subjects indifferent between the lotteries $(x_b, 0.5; -x_b, 0.5)$ and $(z_b, 0.5; 0.0.5)$, where x_b is given. In order to estimate the probability weighting parameter, we ask the subjects to state their willingness to pay for lotteries of the type of $(x_c, p; 0, p)$, where x_c and p are known to the subjects. A typical question for such a lottery question is "State the maximal amount of money you would like to pay to participate in the lottery". For more details on the lottery design and procedure see Section 3.1.1 and the Appendix. Table 2 shows the different lottery questions we present to the subject in a random order.

The subjects get paid for this task a fixed amount of CHF 36 (about USD 30). They are given this amount in form of an initial endowment for the following financial market experiments.

We choose to pay a flat fee instead of choice-contingent monetary incentives for this task, because we want to control the initial endowment for the next financial markets tasks, and to avoid risk-hedging behavior across the two types of tasks. Moreover, previous studies suggest that for the type of lottery questions we use in our study, there are no significant differences between the subjects who actually played the lotteries and those who did not play, but just received a flat fee (see Camerer (1989) and Camerer and Hogarth (1999)).

2.2 The Financial Market Experiments

In order to analyze the portfolio decisions, we perform, two rounds of financial market experiments. Each round consists of ten periods.

At the beginning of each round, each subject receives an initial endowment of 10'000 Experimental Currency Units (ECU)[6], which comes from the payment of the previous lottery task. In each period, the subject has to allocate his current wealth to one riskless asset labelled as "Cash", yielding zero interests, and one risky asset, labelled as "Asset A", which follows a binomial process with $P(Up) = P(Down) = 0.5$ and gross returns $R_U = 1.25$ and $R_D = 0.8$. All parameters are constant over time and known by the participants.

This design implies that investors are price takers. Such a design is appropriate for our research, since we analyze the behavior of small individual investors. It is worth noting that the prices of asset A are random. We stress this fact in the instructions and add explicitly, that moreover, they are independent of the behavior of the subjects, and, that they are also independent of past asset prices and their changes. We implement the random process by asking the subjects to throw a dice by themselves. More details are described bellow.

The fraction invested in the risky asset can neither be negative, nor exceed unity. Hence short-sales are not allowed. The default allocation to the risky asset is 0%. The fraction of wealth not invested in the risky asset is hold in ECU cash. The design allows us to compare the observed behavior with a fixed-mix strategy.

Figure 2 shows a typical example of what the subject sees on the scree at the beginning of a period.

On the screen the subject is informed about the period number and his current holdings. For asset A, the subject is shown the value of the current position (in ECU), its change with respect to the previous period, the fraction of wealth invested in asset A and the number of assets he holds; in addition the subjects also sees the current price of this asset and the change in the

[6]550 ECU correspond to 1 CHF, which in turn corresponds to about 0.82 USD.

Period: 3 of 11

Current Positions

Position	Value	Change	Fraction of Wealth	Number	Price	Change
Asset A	6'250	+25%	56%	50	125	+25%
ECU Cash	5'000	−50%	44%			
Wealth	11'250	+12.5%				

Investment Decision

Position	Fraction of Wealth in %	Number	Value
Asset A	**0**	0	0
ECU Cash	100		10'000

Figure 2: *Illustration of a Financial Market Experiment Display. This is a stylized version a of a screenshot of a typical display. On the screen the subject is informed about the period number and his current holdings. For asset A, the subject is shown the value of the current position (in ECU), its change with respect to the previous period, the fraction of wealth the position in asset A constitutes and the number of assets he holds; further the current price of this asset and the change in the price with respect to the previous period. The the value of his cash holdings, its change with respect to the previous period, and the fraction of wealth the position in ECU cash constitutes are shown to the subject. He can also observe his wealth position which is the sum of the two previous positions. In the lower part of the screen the subject makes the investment decision for the current period. In the highlighted field he fills in the fraction of his wealth, in percent, he wants to invest in asset A.*

price with respect to the previous period. The value of the cash holdings, its change with respect to the previous period, and the fraction of wealth in ECU cash constitutes are also shown to the subject. He can also observe his current wealth position which is the sum of the two previous positions.

The subject has the possibility to click on information buttons that pop up a new window. In this window he can see a graph displaying the historical path of his positions, together with a table that includes the precise values. An illustration is given in the instructions.

In the lower part of the screen the subject enters the investment decision for the current period. In the highlighted field he can fill in the fraction of his wealth, in percentage, he wants to invest in asset A. By clicking on a calculate-button (not shown in the Figure), the remaining entries in the table are calculated: the fraction of wealth held in ECU cash, the associated number of asset and the ECU value of each position. The subject has the possibility to modify his decision, and inspect different scenarios. After making the final decision, the subject clicks on the confirmation button (not shown in the Figure), and wait for the next period.

As soon as all participants have made their investment decisions, the price of asset A for the next period will be determined by throwing a six-sided dice.

If the number shown on the dice is even, the price of asset A rises, otherwise the price falls. This new price of asset A is displayed on the screen, together with all its consequences. The subject makes a new portfolio decision.

In order to make sure that the subjects perceive the stock price movement as truly random, they throw the dice themselves. At the end of each period one subject is chosen to throw the dice, monitored by the experimentator. The number on the dice that appears determines the price for the second period. All subjects within a session face the same stock price realizations. The subjects are chosen sequentially to throw the dice according to the terminals they are sitting at.

In the tenth period the subject makes his last portfolio decision for this FME. Then the last price of asset A is determined. This price and the last portfolio decision determine together the terminal wealth of the subject. At the end of the experiments, the terminal wealth is calculated in Swiss Francs for each subject and paid out in cash.

Before performing the experiment, we ask the subjects to answer several control questions, in order to make sure that they understand well the experimental setting.

2.2.1 The Justification Treatment

The two rounds of investment are independent, i.e. the subjects starts with a new endowment and decisions taken in the first round have no impact on the second round.

We adopt a within-subject design for the justification treatment. Each subject has one round with justification questions and one round without. The order is randomized.

The only difference of the justification treatment is that the subject has to justify explicitly his investment decision in each period. He can choose from a menu listed bellow.[7]

1. I think the price of asset A will rise
2. I think the price of asset A will fall
3. After a loss I want to take less risk
4. After a loss I want to take more risk
5. After a gain I want to take less risk
6. After a gain I want to take more risk
7. I want to interlock my gain(s)
8. I want to compensate my loss(es)
9. Other reason

Again, we stress to the subjects that there are no objectively "wrong" or "correct" justification and that she should state what she thinks and/or feels.

The subject can choose more than one reason. He can also check on the "other reason" box and fill in his own reason. The first two items are addressed on expectations about the evolution of the stock price. Item three to six are related to changing risk aversion after a prior gain or loss, i.e. the prospect theory argument. The seventh is related to realization of gains in general, whereas the eighth is related to the break-even effect.

[7] The screen looks similar to the one presented in the figure above. The menu with the proposed justifications is right to the decision-block. See the instructions for a screenshot.

The price determination is the same as in the control version and the experiment lasts for 11 periods. The subjects are confronted with the same payoff structure.

3 Results

In the first part of this section we describe the estimation of the prospect theory parameters from the lottery task. Then we present the results for the portfolio decisions.

3.1 Preference Parameters

3.1.1 Estimation Method

The aim of the lottery task is to elicit prospect theory preference parameters. We base our estimations on a methodology used by Glaser (2001). We confront the subjects with 10 hypothetical choice situations, described below. First we estimate for each subject the parameters of the prospect theory value function, then the parameter of the probability weighting function.

We assume that the subjects' preferences are described by prospect theory[8] as suggested by Kahneman and Tversky (1979) and follow the parametric function for the value function by Tversky and Kahneman (1992)[9]

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\beta(-x)^{\alpha} & \text{if } x < 0 \end{cases}, \text{where } \alpha, \beta \geq 0 \qquad (1)$$

Note that we allow the value function to be convex (concave) in gain (loss) domain, i.e. $\alpha > 1$.

First we estimate the value function in the gain domain, i.e. the parameter α. For each subject we elicit the amount z_a^i, in order to be indifferent between

[8]See the Appendix for a short introduction to prospect theory.

[9]In the two sessions conducted on June 22, 2006, we allow for different risk aversion parameters in the gain and loss domain, α^G and α^L respectively. Therefore we introduce four additional lottery questions for the elicitation of the risk aversion parameter in the loss domain. Using a Wilcoxon signed-rank test (p-value = 0.28) we cannot reject the hypothesis that both distributions are the same. Similar results are obtained when using a sign test for testing the hypothesis that the median of the differences is zero (p-value= 0.47). These results justify the assumption that $\alpha^G = \alpha^L = \alpha$. See the Appendix for more details.

two lotteries $A_a = (x_{a1}, 0.5; x_{a2}, 0.5)$ and $B_a = (z_a^i, 0.5; 0, 0.5)$, where $x_{a1} > x_{a2} > 0$ are known to the subjects. We do this for $k = 1, \ldots, K$, $K = 4$ different situations, varying the amounts x_{a1} and x_{a2} (see Table 2 for details).

It follows from prospect theory that for each question $v(x_{a1}) + v(x_{a2}) = v(z_a^i)$.[10] We fit the subject's risk aversion parameter α^i by minimizing the sum of the absolute value of the normalized difference between the prospect utility of the two lotteries as implied by the subject's answers and the postulated functional form.[11] The estimator for each subject's risk aversion parameter is

$$\widehat{\alpha}^i = arg \min_{\alpha_j} \Big\{ \sum_{k=1}^{K} \mid \frac{(x_{a1k})^{\alpha_j} + (x_{a2k})^{\alpha_j} - (z_{ak}^i)^{\alpha_j}}{x_{a1k} + x_{a2k}} \mid \Big\}. \quad (2)$$

We find the estimates numerically using predetermined values of α, $\alpha_j = \{0, 0.005, \ldots, 5\}$.

In order to estimate the loss aversion parameter β, we elicit the amount of z_b^i, s.t. that the subjects is indifferent between the lotteries $A_b = (x_b, 0.5; -x_b, 0.5)$ and $B_b = (z_b^i, 0.5; 0, 0.5)$. For $z_b^i < 0$ the estimator for the subject's loss aversion is $\hat{\beta}^i = \frac{(x_b)^{\alpha^i}}{(x_b)^{\alpha^i} - |z_b^i|^{\alpha^i}}$, where α^i, as estimated above. If $z_b^i \geq 0$ then $\hat{\beta}^i = \frac{(x_b)^{\alpha^i} - (z_b^i)^{\alpha^i}}{(x_b)^{\alpha^i}}$.[12] These two parameters characterize the value function. Next we elicit the parameter of the decision weights γ.

As suggested by Tversky and Kahneman (1992) we assume the following parametric form for the decision weights:

$$w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}}, \text{ for some } 0 \leq \gamma \leq 1. \quad (3)$$

We use a certainty equivalent method to estimate the parameter γ. Each subject has to state the maximum amount of money z_c^i, she would pay for a lottery $A_c = (x_c, p; 0, p)$. It follows that $w(p) = \frac{v(z_c^i)}{v(x_c)}$. Note that the parameters of $v(x)$ are known from above. In the 5 different questions we vary the amount x_c and the probability p. We use the method of minimizing the absolute differences, as described above. We find the estimates numerically using predetermined values of γ, $\gamma_j = \{0, 0.005, \ldots, 1\}$.

[10]To avoid cluttering notation, we skip in our notation the preference parameter as

	Subjects are indifferent between $(x_{a1}, 0.5; x_{a2}, 0.5)$ and $(z_a, 0.5; 0, 0.5)$			
			mean	median
risk aversion	x_{a1}	x_{a2}	z_a	z_a
α	45	5	80	56
	30	10	52	45
	10	5	20	16
	10	1	13	12
	Subjects are indifferent between $(x_b, 0.5; -x_b, 0.5)$ and $(z_b, 0.5; 0.0.5)$			
loss aversion			mean	median
β	x_b		z_b	z_b
	30		-1	-1
	Subjects are indifferent between $(x_c, p; 0, p)$ and z_c,			
			mean	median
probability	x_c	p	z_c	z_c
weighting	100	0.98	49	50
γ	30	0.7	13	11
	1000	0.001	114	2
	100	0.9	46	50
	50	0.1	5	4

Table 2: *Parameters for the elicitation of the risk aversion parameter and answers. This table shows the payoffs used for the elicitation of α, β and γ. The means and medians of the stated answers are given in the last two columns.*

3.1.2 Estimation Results

Some of the answers given by the participants are inconsistent. We assume that these errors are non-systematic, as e.g. caused by inexperience or inattention, and exclude those answers from our analysis.[13]

For the subsequent analysis of the FME it is important to have estimates for *all* preference parameters. Therefore we exclude subjects who do not fulfil this requirement.[14] This is the case for subjects, for whom we do not have estimates of β.

We code $\hat{\beta}^i$ as missing whenever a subject gives an answer $z_b^i \geq | 30 |$ in the respective lottery question (four subjects), or whenever the estimate of β is infinite. The first case implies that the subjects prefers dominated lotteries. The latter occurs when $z_b^i < 0$ and $\alpha^i = 0$. A Subject whose answers vary a lot, in the sense that some answers are close to the expected value of the proposed lottery A_a and others differ substantially, have an $\alpha = 0$. Totally we exclude 38 out of 820 single answers and 13 out of 59 subjects from our analysis.

We summarize our estimates in Table 3. The median value of the risk aversion coefficient α, loss aversion β and probability weighting parameter γ are 0.72, 1.00 and 0.64, respectively.

Except for the loss aversion parameter our estimates are very similar to those obtained by other authors, e.g. Tversky and Kahneman (1992).

3.2 Investment Decisions

In our model we categorize the investment decisions into three categories. The categories are "increase in the fraction", "same fraction" and "decrease in the fraction of wealth invested in the risky asset". For convenience we label them as "buy", "hold" and "sell".[15]

arguments, i.e. we write $v(x)$ for $v(\alpha^i, x)$

[11]Alternatively we could minimize the squared difference. In that case outliers would have more weight. Therefore we choose to minimize the absolute errors.

[12]Note that if $z_b^i \leq 0$, then $\hat{\beta}^i > 1$, else $0 < \hat{\beta}^i < 1$; i.e. we impose the restriction $\beta \geq 0$.

[13]Interestingly, the majority of the inconsistent answers were given to the first question, suggesting that they may be caused by inexperience. See the appendix for details.

[14]Note that we have already excluded single answers as discussed above.

[15]Note that the variables are observed for different subjects and different periods. For readability we skip the indices in this section.

Parameter	median	25 percentile	75 percentile	mean	StD
α (risk aversion)	0.72	0.49	0.92	0.69	0.26
β (loss aversion)	1.00	0.69	1.39	1.27	1.13
γ (prob. weighting)	0 .64	0.49	0.94	0.66	0.25

Table 3: *Estimates of Preference Parameters. This Table presents our estimates for the coefficient of risk aversion, α, the coefficient of loss aversion, β, and the parameter of the probability weighting function, γ. The first column shows the medians, which are followed by the 25th and 75th percentiles. The last two columns present the means and standard deviations of the estimates.*

We use a multinomial logit model to estimate the probability of each choice. In our model, we include 7 explanatory variables. The variable *gain* takes on the value 1, if the subject's current wealth exceeds the initial endowment, and 0 otherwise. Note the importance of the assumption that the reference point, relative to which the gains and losses are measured, is the initial wealth. Given the experimental design, we think that the initial endowment is a natural reference point. The variable *up* takes on the value 1, if the current price of the risky asset exceeds last period's price, and 0 otherwise. It quantifies the impact of stock price movements on the subject's portfolio decisions. Recall that in the chosen design all parameters of the stock price process are constant and known. Therefore, it suffices to include a binary variable that captures the direction of the price change. In order to measure the treatment effect, we include the variable $justify$ that takes on the value 1 if the treatment version is performed, and 0 if the control version is conducted. The variable $secondFME$ controls for the order of the tasks. It takes the value 1 if the second FME is performed and 0 if it is the first. Further we include the estimates of the preference parameters α, β, γ, as described above.

3.2.1 Description of Investment Decisions

In this section we describe the investment decisions of the subjects. Our data set consists of 1012 observations of stock prices and 920 observations of individual investment decisions. In each round of the investment task the initial price of the risky asset is 100 ECU. The lowest observed price is 26.21

ECU, which overall occurred 13 times. The highest value is 156.25 ECU, attains 17 times. The median is 80 ECU, the 25th and 75th percentiles are 64 ECU and 100 ECU, respectively. Since the relative size of the stock prices changes is fixed, we are mainly interested in the direction of the price movement. The price of the risky asset rises 371 times and it falls 549 times.

All subject start with an initial wealth of 10000 ECU. The largest wealth position attained is 15625 ECU, the lowest 2621.44 ECU. The median is 9040.79 ECU, the average wealth is 8685.52 ECU, with a standard deviation of 2092.72 ECU. Moreover the subjects were 212 times in the gain zone, 127 breaking even and 673 times in the loss zone.

The mean terminal wealth is 8624.84 ECU (standard deviation 2215.80 ECU). The median is 8680.39 ECU. The maximal and minimal attained terminal wealths are 4096 ECU and 13067.45 ECU, respectively.

Subjects achieve this performance by investing on average 61% of their wealth in the risky alternative (standard deviation 36%). The median allocation in the risky stock is 50%. Interestingly this corresponds to the optimal investment strategy of an expected utility maximizer with log utility.

Subject decrease their relative holdings in the risky asset 178 times, increase it 258 times and choose a fixed-mixed strategy 392 times. The changes in the portfolio decision range from -1 to 1. The average change in the allocation is +0.2 (standard deviation of 0.23) and the median is 0.

The subjects' behavior changes, depending on their performance and on the stock price movements. The results are summarized in Table 4 and illustrated in Figure 3. In the loss zone[16], after a decline in the price of the risky asset, the subjects mostly choose a fixed-mix strategy (52.5% of the cases), whereas in 33.8% cases they increase the fraction of their wealth invested in the risky asset, and in 13.7% cases they decrease it. It is important to note that in our experiments the default for the fraction invested in the risky asset is 0%. Therefore the choice of a fixed-mix strategy is a deliberate choice of the subject. After the price of the risky asset rises subjects maintain their allocation unchanged in 58.8% of the cases, in 23.6% they sell and in 17.6% they buy.

As shown, when the subjects are in the gain zone, i.e. current wealth exceeds the initial endowment, and when the stock price declined, the most frequently observed decision is to buy (69.0%), followed by holding and selling

[16]Note, that we code the situation where $W_t = W_0$ as a loss. If we code it as a gain the results are practically identical (not presented here) .

Performance	Price	Decision	Freq.	Percent	Cum.
$W_t \leq W_0$	Down	Sell	63	13.67	13.67
		Hold	242	52.49	66.16
		Buy	156	33.84	100.00
$W_t \leq W_0$	Up	Sell	43	23.63	23.63
		Hold	107	58.79	82.42
		Buy	32	17.58	100.00
$W_t > W_0$	Down	Sell	11	15.49	15.49
		Hold	11	15.49	30.99
		Buy	49	69.01	100.00
$W_t > W_0$	Up	Sell	61	53.51	53.51
		Hold	32	28.07	81.58
		Buy	21	18.42	100.00

Table 4: *Observed frequencies of investment decisions. This table presents empirical frequencies of portfolio decisions, in dependence of the subject's performance and stock price movements.*

(both 15.5%). After the price of the risky alternative went up, however, the most frequently chosen decision is to sell (53.5%), followed by holding (28.1%) and buying (18.4%).

Hence, we observe a contrarian behavior for investors. This behavior is accentuated if the subject is in the gain zone, i.e if $W_t > W_0$.

There seems to be no pattern for the preference parameters.[17] This fact is illustrated in Figure 4. There we plot the preference parameters α, β and γ against the changes in the fraction invested in the risky asset.[18] We do not observe any obvious patterns. Neither the sign nor the size of the changes in portfolio allocations are affected by the value of the preference parameters. In the next section we estimate a formal model, in order to quantify the relationships and to formally test hypotheses.

[17]Neither the justification treatment, nor the order of the task, nor the period number seem to have an impact on the subjects investment decisions either.

[18]For this illustration, it is convenient to use changes in the fraction of wealth invested in the risky asset instead of *bhs*. The main observations remain unchanged.

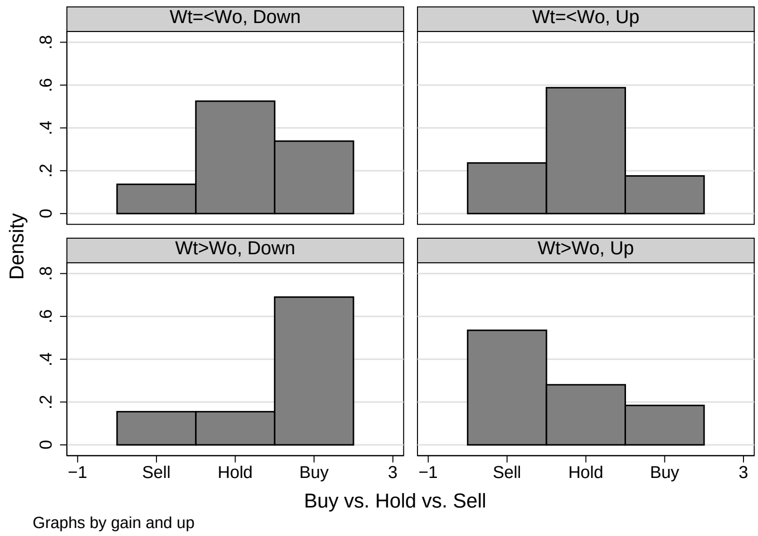

Figure 3: *Histograms for investment decisions. The portfolio decisions are coded as buy, hold, and sell. Four histograms, depending on the subjects' performance and stock price movements are presented. The two upper panels show the portfolio decisions, for the situations, where subjects are in the loss zone. The two lower panels document the portfolio choices for the situations, where subjects are in the gain zone. The left panels show the decisions when the stock price declined, whereas the right panels for the case, when it rose.*

3.2.2 Estimates

Formally, under the logit assumption about errors, the model for portfolio choice can be written as

$$P(Y_{it} = j) = \frac{e^{\boldsymbol{b}_j' \boldsymbol{x}_{it}}}{\sum_{k=0}^{J} e^{\boldsymbol{b}_k' \boldsymbol{x}_{it}}}, \tag{4}$$

where Y_{it} is the choice made by the ith individual in period t, j denotes the category of the choice, i.e. $j = \{buy, hold, sell\}$ and $\boldsymbol{x}_{it}$ is the vector of explanatory variables. After transforming the model into terms of log odds ratios, $\log \frac{P(Y_{it}=m)}{P(Y_{it}=n)}$, the coefficients $\boldsymbol{b}$ are estimated by pseudo-maximum likelihood.

We choose as the base category, the denominator of the log odds ratios,

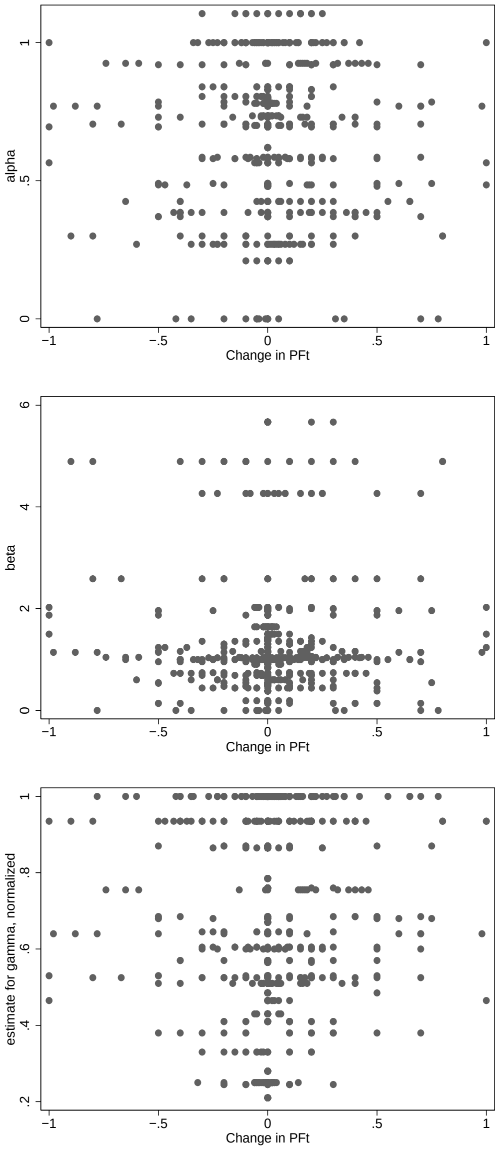

Figure 4: *Scatterplots of preference parameters and changes in the fractions invested in the risky asset. We present three scatterplots relating preference parameters and changes in the fraction invested in the risky asset,* PF_t*. The first panel shows the changes in the portfolio weights for different values of the risk aversion coefficient* α*, the second for the coefficient of loss aversion* β*, and the last for the parameter of the probability weighting function* γ*.*

the decision to hold. This is equivalent to the normalization $\boldsymbol{b}_{hold} = \mathbf{0}$. [19] [20]

We assume that portfolio decisions are independent across subjects given that they price takers, but not necessarily within a subject. Therefore, in order to capture the dynamic aspect, we allow for possible serial correlations.

The results of the multinomial logistic regression are presented in Table 5. As mentioned above, the dependent variable *bhs* takes on the values *buy*, *hold* and *sell*. We use the following explanatory variables: the variable *gain*, that indicates, whether the investor is in the gain or loss zone, and the variable *up*, an indicator for the stock price movement. Further we control for idiosyncrasies, represented by the preference parameter estimates α, β and γ.[21] We include a treatment effect, $justify$, and we control for the order of the task with the $secondFME$ indicator variable.

Since we allow for dependencies within the subjects, we performed a pseudo-maximum estimation. The sample consists of 828 observations. We can reject the hypothesis that all coefficients are jointly 0 (Wald chi2(14) = 80.16, Prob>chi2 = 0.0000). The pseudo $R^2 = 0.0836$.

The base category is *hold*. In the upper panel we present the estimates for the log of the comparison between the probability of selling and holding. The coefficients for *gain* and *up* are both positive and highly significant ($p < 0.01$), whereas all other explanatory variables have no significant impact on the investment decisions of the subjects.[22]

In the lower panel of Table 5 we present the estimates for the log of the comparison between the probability of buying and holding. The coefficients for *gain* and *up* are positive and negative, respectively, and highly significant ($p < 0.01$), whereas all other explanatory variables have no significant impact.

In Table 6 we present the coefficients for the comparison of all possible log

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[19] Since probabilities sum to one, there is need to estimate one coefficient less, which justifies the normalization.

[20] Of course, any other category could have been chosen as the base category. Note, that this would have yielded different estimates for the coefficients, but would have had no impact on the predicted probabilities; being in this sense equivalent. If there is potential ambiguity about the base category, we will index the coefficients explicitly with the base category, in the following way: $\boldsymbol{b}_{m|n}$, which indicates the vector of coefficients for the comparison of category m with the base category n.

[21] Note that we treat the labels *alpha* and α as synonyms. The same applies to the other preference parameters.

[22] Note that the model is in terms of log odds. However, log odds have very little meaning. Therefore the interpretation will be done bellow, in terms of more intuitive odds ratios, marginal effects or predicted probabilities.

Variable	Coefficient	(Std. Err.)
Equation 1 : Sell		
gain	1.603**	(0.355)
up	0.552**	(0.212)
alpha	-0.940	(0.887)
beta	0.056	(0.240)
gamma	0.011	(0.969)
justify	0.288	(0.219)
secondFME	-0.192	(0.220)
Intercept	-0.911	(1.164)
Equation 2 : Buy		
gain	1.543**	(0.317)
up	-1.126**	(0.295)
alpha	-0.326	(0.747)
beta	0.073	(0.194)
gamma	0.604	(0.876)
justify	0.083	(0.198)
secondFME	-0.222	(0.192)
Intercept	-0.590	(0.957)

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 5: *Estimation results: Multinomial logistic regression for the dependent categorical variable bhs, which takes on the values buy, hold and sell. The explanatory variables are: the indicator variable gain, taking on the value 1 if the subject's current wealth exceeds the initial endowment, and zero otherwise; the indicator variable up, taking on the value 1 if the stock price increased with respect to the previous period, and zero otherwise; the preference parameter estimates alpha, beta and gamma, as described above; the indicator variable* $justify$*, taking on the value 1 if the treatment version is conducted, and zero otherwise; and the indicator variable* $secondFME$*, controlling for the order of the task. The standard errors are adjusted for clustering on individuals. The base category is hold. In the upper panel we present the estimates for the log of the comparison between the probability of selling and holding; in the lower panel between buying and holding. The log pseudolikelihood = -795.03, the Wald chi2(14) = 80.16, implying a p-value of* 0.0000.

odds ratios. The results confirm what we see above: only the independent variables *gain* and *up* have a significant impact on the investment decisions.

The first column shows the coefficients b_j for the log odds ratios. These are followed by the z statistic and its p-value. To facilitate the interpretation of the coefficients we present in the fourth column the factor changes e^{b_j}. These factor changes indicate, how the *odds* are expected to change, for a *unit* change in the independent variable x_j, holding all other variables constant.[23] In the last column we present the expected change in the odds for a standard deviation change in x_j.

A unit change in the variable *gain*, representing the move from the loss into the gain zone, increases the odds of selling vs. holding by a factor of roughly 5. That is, as compared with the probability of sticking to the past investment decision, the probability of decreasing the holdings in the risky asset is 5 times higher. The same is true for the odds of buying vs. holding. Interestingly, the odds comparing selling and buying are not significantly affected by the *gain* variable. Hence the fact of being in the loss or gain zone does determine whether the investor chooses a fixed-mix strategy, or not, but does not affect the odds of buying vs. selling.

A rise in the stock price, i.e. a unit change in the variable *up*, significantly increases the probability of selling and decreases the probability of buying: the odds of selling vs. buying increase by a factor of 5.35 and the odds of selling vs. holding increase by a factor of 1.74. The ratio of the probability to buy and the probability to hold decreases by a factor of 3 for a unit change in *up*. That is, holding all other variables constant, our model predicts contrarian behavior.

We do not describe in detail the impacts of the remaining variables, since they have no significant impact on the investment decision. Note however, that factor changes, both for unit changes and standard deviation changes are close to 1 and hence have no impact on the odds.

Above we report z-statistics for individual coefficients, determining the log odds ratios. Other interesting questions are, whether independent variables have an impact on the dependent variable, and whether the categories of the dependent variable are appropriately chosen.

To test the hypothesis that an independent variable has no effect on the dependent variable requires to test that its coefficients are equal to zero in all

[23] This interpretation of the odds ratio assumes that the other independent variables have been held constant, but does not require that they be held constant at specific values.

Variable	Odds comparing		b	z	$P >\| z \|$	e^b	e^{bStdX}
gain	Sell	-Buy	0.060	0.300	0.764	1.062	1.025
	Sell	-Hold	1.603	4.512	0.000	4.966	1.950
	Buy	-Hold	1.543	4.874	0.000	4.677	1.902
up	Sell	-Buy	1.678	3.612	0.000	5.353	2.236
	Sell	-Hold	0.552	2.600	0.009	1.737	1.303
	Buy	-Hold	-1.126	-3.821	0.000	0.324	0.583
justify	Sell	-Buy	0.205	1.469	0.142	1.228	1.108
	Sell	-Hold	0.288	1.316	0.188	1.334	1.155
	Buy	-Hold	0.083	0.417	0.676	1.086	1.042
secondFME	Sell	-Buy	0.030	0.176	0.860	1.031	1.015
	Sell	-Hold	-0.192	-0.874	0.382	0.825	0.908
	Sell	-Hold	-0.222	-1.157	0.247	0.801	0.895
alpha	Sell	-Buy	-0.614	-1.348	0.178	0.541	0.853
	Sell	-Hold	-0.940	-1.060	0.289	0.391	0.784
	Sell	-Hold	-0.326	-0.437	0.662	0.722	0.919
beta	Sell	-Buy	-0.017	-0.162	0.871	0.983	0.981
	Sell	-Hold	0.056	0.232	0.816	1.057	1.064
	Sell	-Hold	0.073	0.376	0.707	1.076	1.084
gamma	Sell	-Buy	-0.593	-1.352	0.176	0.553	0.863
	Sell	-Hold	0.011	0.011	0.991	1.011	1.003
	Sell	-Hold	0.604	0.689	0.491	1.829	1.162

Table 6: *Estimated coefficients for all comparisons among outcomes and factor changes. The first column shows the estimated coefficients b_j for the log odds ratios, followed by the z statistic and its p-value. We present in the fourth column the factor changes e^{b_j}. In the last column we present the expected change in the odds for a standard deviation change in x_j.*

but one odds ratios, i.e. to test the hypothesis that the kth variable has no impact on the investment decision, we test $H_0: \ b_{k,sell|hold} = b_{k,buy|hold} = 0$.[24]

As Table 7 illustrates, the effect of the indicator variable *gain* on the investors' investment decisions is highly significant ($p < 0.01$). So is the effect of the stock price changes ($p < 0.01$). The results show that there is no significant treatment effect and that the order of the task has no impact neither, indicating, that spill-over is not an issue. We reject the hypothesis, that the prospect theory preference parameters α, β and γ, have a significant impact on the portfolio decisions, both each variable on its own and as a group.

Variable	chi2	df	P>chi2
gain	24.467	2	0.000
up	14.605	2	0.001
alpha	1.972	2	0.373
beta	0.202	2	0.904
gamma	2.256	2	0.324
justify	2.675	2	0.262
secondFME	1.360	2	0.506
set 1: alpha beta gamman	4.903	6	0.556

Table 7: *Wald tests for independent variables. Wald test of the null hypothesis that the coefficients of the independent variable equal zero across all comparisons of the categories of the dependent variable. The columns indicates the categories contrasted, the chi-squared value, degrees of freedom, and the p-value of test. In the lower panel we consider the preference parameters together.*

If none of the independent variables significantly affects the odds of two outcomes, the outcomes are indistinguishable with respect to the variables in

[24]In the multinomial logit model we have $\ln\left(\frac{P(y=m|\boldsymbol{x})}{P(y=b|\boldsymbol{x})}\right) = \boldsymbol{x}\boldsymbol{b}_{m|b}$. Therefore, it must hold that $\boldsymbol{b}_{b|b} = \mathbf{0}$.

the model (Anderson (1984)). Testing the hypothesis that outcomes m and n are indistinguishable corresponds to the hypothesis $H_0: \; b_{1,m|n} = \ldots = b_{K,m|n} = 0$, where K is the number of independent variables. If two outcomes are indistinguishable with respect to the variables in the model, then one can obtain more efficient estimates by combining them.

The results of Wald tests for combining outcome categories, testing that all coefficients, except intercepts, associated with given pair of outcomes are 0, are reported in Table 8.

We can reject the hypothesis that the categories buy, hold and sell are indistinguishable with respect to the variables in our model (p-value = 0.000), i.e. that we could get better results, combining categories.

Categories tested		chi2	df	$P > chi2$
Sell-	Buy	26.361	7	0.000
Sell-	Hold	43.025	7	0.000
Buy-	Hold	35.368	7	0.000

Table 8: *Wald tests for combining categories. Results of Wald tests to combine categories. Rows represent all contrasts among dependent variable categories. The columns indicates the categories contrasted, the chi-squared value, degrees of freedom, and the p-value of test.*

Above, our model of portfolio decisions is estimated in terms of log odds ratios, which have very little intuitive meaning. Therefore, we perform the interpretation of our results in terms of predicted probabilities and their changes. These are presented in Table 9.

In order to illustrate the impact of the different explanatory variables on portfolio decisions we compute discrete and marginal changes.[25] We analyze the effect of each explanatory variable separately, holding the remaining independent variables constant at their medians.[26]

[25]The marginal change is the partial derivative of the predicted probability with respect to the independent variables. The discrete change is the difference in the predicted value as one independent variable changes values while all others are held constant at specified values.

[26]The medians of the independent variables are: $m(gain) = 0$, $m(up) = 0$, $m(alpha) = 0.718$, $m(beta) = 1$, $m(gamma) = 0.643$, $m(justify) = 0.5$, and $m(secondFME) = 0.5$. For other constellations, e.g. holding all other variables at their mean, we get very similar

Table 9 indicates in the first column the variable, the effect of which is studied. It is followed by the specific values and the differences that are considered. Then, the average absolute discrete change or marginal effect is presented. The last 3 columns show the (differences in) predicted probabilities and marginal effects for selling, buying and holding, respectively.

The first 3 rows describe the impact of the variable *gain*. Holding all other independent variables constant at their medians, our model predicts a probability of 12% for selling if the investor is in the loss zone, i.e. if $gain = 0$. The probability for buying and holding are 35% and 53%, respectively.

If the investor is in the gain zone, the probabilities for selling and buying nearly double to 22% and 59%, respectively, whereas the probability of sticking to the previous fraction falls by a factor 3 to 19%. In absolute terms, the probability to sell to purchase increase by 10% and 24%, respectively, whereas the probability to hold decreases by 34%; resulting in a absolute value average change of 23%.

After the price of the risky asset declined, i.e. $up = 0$, the probabilities for selling, buying and holding are 12%, 35% and 53%. After the stock price rose, the probability for selling doubles (25%); the probability for buying falls sharply to 13%, and the probability for holding remains at a similar level (62%).

Note that the median of the variable *gain* is zero. Therefore, these values apply to the case where the investor is in the loss zone. However, we observed above, that the effect of the *up* variable is strongest if the investor is in the gain zone. Holding the variable *gain* constant at 1 and all others at their medians our model predicts the following probabilities (not shown in Table 9): after a decline in the stock price, the probability of selling is 22%, the probability of buying is 59%, and the probability of holdind is 19%. After the price rose, the probability of selling (50%, +28%), and buying (25%, -34%) change drastically, whereas the probability of holding (25%, +6%) remains practically unchanged. The average of the absolute value of the changes is 23%.

The remaining explanatory variables have no significant impact on the investors portfolio decisions, which results in small, or in some cases even negligible, changes in predicted probabilities and marginal effects.

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results.

			Avg.Chg	Sell	Buy	Hold
gain	from:	x=0	0	0.122	0.345	0.533
	to:	x=1	0	0.220	0.587	0.193
	dif:	0→1	0.226	0.098	0.241	-0.339
up	from:	x=0	0	0.122	0.345	0.533
	to:	x=1	0	0.247	0.131	0.622
	dif:	0→1	0.143	0.125	-0.215	0.089
alpha	from:	x=min	0	0.198	0.361	0.441
	to:	x=max	0	0.092	0.330	0.578
	dif:	min→max	0.091	-0.106	-0.031	0.137
		MargEfct	0.081	-0.087	-0.034	0.121
beta	from:	x=min	0	0.119	0.331	0.550
	to:	x=max	0	0.134	0.413	0.452
	dif:	min→max	0.065	0.015	0.082	-0.097
		MargEfct	0.011	0.003	0.014	-0.017
gamma	from:	x=min	0	0.132	0.289	0.579
	to:	x=max	0	0.113	0.396	0.491
	dif:	min→max	0.071	-0.019	0.106	-0.087
		MargEfct	0.091	-0.024	0.136	-0.112
justify	from:	x=0	0	0.109	0.342	0.549
	to:	x=1	0	0.136	0.348	0.515
	dif:	0→1	0.022	0.027	0.007	-0.034
secondFME	from:	x=0	0	0.127	0.367	0.506
	to:	x=1	0	0.116	0.325	0.559
	dif:	0→1	0.036	-0.011	-0.042	0.053

Table 9: *Discrete and marginal changes. We indicate, in the first column the variable, the effect of which is studied. Then the table shows the specific values and the differences that are consider, followed by the average absolute discrete change or marginal effect is presented. The last 3 columns show the (differences in) predicted probabilities and marginal effects for selling, buying and holding, respectively.*

4 Discussion

Our main findings are that investment decisions can be significantly predicted by the investor's own performance and past stock price changes. Other factors, as estimates of prospect theory preference parameters, the order of the tasks and a treatment, which imposes the explicit justification of the decisions, have no significant impacts on the subjects' portfolio decisions. On average, our subjects stick to their previous asset allocations, when their investments are in the loss zone. In the gain zone they invest according to a contrarian strategy. In this section we discuss in more depth our results. The first issue we address is their robustness. Further we analyze the justifications that the subjects give in the treatment version of the investment task. Then we explore the implications of our results for the proposed explanation for the disposition effect.

4.1 Robustness

Our results are robust to modifications of the base model presented above. The main results are insensitive to alternative definitions of the variables as well as the in- or exclusion of variables. Moreover the estimates of the significant coefficients do not vary much with such modifications.[27]

In our base model, we define the variable $gain = \mathbb{I}_{W_t > W_0}$. This implies that we code a zero position as a loss. Our results do not change if we treat a zero position as a gain. If instead of using an indicator variable for the performance of the investor, we use the variable $perform$, defined as the difference between the actual wealth and the initial endowment, we get similar results.[28]

An alternative specification of our model is to introduce classes for investors' characteristics. We do not observe any apparent patterns in the prospect theory parameter estimates; whether we consider them separately, or as groups. Moreover, except for β, there are no natural bounds for a convenient classification of the individuals. Therefore, we modify our base model only with respect to β. As a variant, we estimate the model using indicator variables for the case, where a loss hurts more than an equivalent

[27]For details on the alternative specification and on the results see our homepage: http://www.phd-finance.unizh.ch/People/Vlcek.html.

[28]For the ease of interpretation we prefer to state the basic version in terms of the the indicator variable *gain*.

gain ($\beta > 1$), the case where its importance is equal ($\beta = 1$) and where gains are more important than losses ($\beta < 1$). However, the findings do not differ.

Including in our model a time trend as an explanatory variable does not alter the main findings. The estimated coefficients for the trend are negative for the odds ratio of both sell vs. hold and buy vs. hold. They are significantly different from zero. This implies that the subjects stick stronger to their previous decisions as time goes by, which can be interpreted as evidence for learning.[29]

In further modifications we include various interaction terms. In particular we interact the treatment indicator variable and the preference parameters with the *gain* variable. Our conclusions do not change for these alternative specifications.

Defining the dependent variable as the fraction of wealth invested in the risky asset, PF_t, instead of the categorical variable bhs, does not alter the main findings.

In order to control for unobserved idiosyncrasies, we estimate a model with individual fixed effects. We exclude the preference parameters α, β and γ from the model because of collinearity. For the same reason we use the variable $perform$ instead of $gain$. We drop observations for subjects who do not have observations in all categories of the dependent variable, because otherwise the model would be misspecified. Totally 26 subjects are excluded form the analysis.

The analysis yields significant coefficients for the variables $perform$ and *up*. They have very similar effects on the portfolio decisions as in the base model. Most of the individual fixed effects have significant coefficients. This indicates that there are some unobserved, individual specific factors that can help explaining investment behavior and the observed heterogeneity. However, as the above results suggest, these are not the preference parameter estimates α, β and γ.[30]

[29] However, the time series in our data set are too short, to infer whether in the limit investors choose a fixed-mix strategy.

[30] We suggest that the absence of a relation between α, β, γ and the subjects' portfolio decisions should be investigated in more depth, before concluding that prospect theory is inappropriate to explain investor behavior. A possible extension is to use alternative parametrizations of the value function as e.g. suggested by DeGiorgi, Hens, and Levy (2004).

4.2 Justifications

One of the unobserved, individual specific factors mentioned above may be the participants expectations about future returns. Indeed, we have some indications from the answers given in justification treatments supporting this hypothesis.[31]

The most frequently given justification is "I think the price of asset A will rise" (28%), followed by "I want to compensate my loss(es)" (17%), "Other reason" (15%) and "After a loss I want to take more risk" (13%). The other proposed justification were chosen less frequently (less than 7%).

Although we do not reward the participants for giving the justifications, we have evidence that the subjects give truthful answers.[32] This evidence arises from comparing the stated justifications and the corresponding actions. For example, when subjects state that they belief the stock price will rise, they increase the fraction of wealth invested in the risky asset on average by 17%. When they state that they think the stock price will decline, they *de*crease their holdings by 15%. Consistent justifications and actions are observed for all justifications, except for the argument of compensating losses. Moreover, we find that the differences between the average change in the fraction invested in the risky asset, given a particular justification, and the change in the invested fraction, when this particular justifications is not given, has the expected sign and is significant at a 10% level in seven out of nine cases.

The first two justifications, both at which linked to expectations of future stock prices, account for one third of the statements. This suggests that beliefs about future returns play an important roll for investment decisions. Although, we designed an experiment, where stock prices are random and the stock price generating mechanism is chosen as to make subjects perceive it really that way, we are apparently not able to control the expectations of all the participants.[33]

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[31] A detailed description of the justifications treatment can be found in section 2.2.1.

[32] Besides the fact that it is quite difficult to design an appropriate reward scheme to give subjects incentives to state the *true* justifications, paying them for their justifications would offer them a possibility to hedge their decisions taken in the financial market, and therefore possibly distort our results. Hence we choose not to reward them for the justifications.

[33] However, many of the participants really do perceive the stock price process as random. In the questionnaire filled in after the pilot study, 19 out of 20 subject affirm that they perceived the price process to be random, thanks to the price generating mechanism using

We find that the subjects are overly optimistic about the price movement, although we try hard to show the i.i.d. characteristic of the binomial price process by asking to throw the dice themselves. An unfounded optimism manifests itself in the first period: 56% of the subjects state that they think the price of the risky asset will rise, as opposed to only 3% thinking it will decline. They are also relatively optimistic after they see the price went down. In this case 36% of the subjects think the price will rise, whereas only 3% think it will go down. A similar pattern holds after they see an up movement or two consecutive down movements. Interestingly we observe gambler's fallacy because the expectations are significantly different after they see two consecutive up movements (only 15% think the price will go up, and 19% think the price will go down) as compared to when they see only one up movement (30% think the price will go up and 8% think the price will go down).

4.3 Explanations for the Disposition Effect

To our knowledge, this is the first study that explicitly compares the trading strategies chosen by investors with a fixed-mix strategy.[34] Our analysis is performed in relative terms, i.e. in terms of fractions of wealth invested in the risky alternative, whereas previous studies analyze the number of assets purchased or sold. We find that investors choose a fixed mix investment strategy when they are in the loss zone and a contrarian strategy when they are in the gain zone. Both observed strategies imply selling winners and holding losers in terms of numbers of assets bought or sold. Therefore our results indicate, at least for the loss zone, that documented disposition behavior can be triggered by rebalancing.[35] However, our findings concerning the behavior in the gain zone are at odds with a fixed-mix strategy.[36] Therefore we

the dice.

[34]Odean (1998) controls for rebalancing in an indirect way: he analyzes the sub-sample, consisting of trades where the whole position was sold off, arguing that those trades cannot be motivated by rebalancing. He finds that even when controlling for rebalancing investors are prone to the disposition effect. However, we do not limit ourselves to positions that are completely sold off. Moreover, our design allows us to analyze purchasing behavior.

[35]It would be interesting to investigate whether the decision variable plays a role. One could perform the same experiment with the decision variable being the number of assets bought or sold and explore whether the same behavioral patterns are observed.

[36]Note that the unconditional mean (and median) portfolio decision is to hold. However, this seeming evidence for fixed-mix strategy arises because subjects are proportionally

conclude that the disposition effect cannot be explained by rebalancing.

Our observations are consistent with studies using financial market data, which suggests that they are externally valid. Choe, Kho, and Stulz (1999) report that individual investors in Korea exhibit short-run contrarian behavior. Grinblatt and Keloharju (2001) perform logit regressions to study the Finnish stock market and report that households' propensity to sell stocks is positively related to recent returns and that this propensity to sell is damped when the household is in the loss zone.

The findings are also compatible with the house money effect documented by Thaler and Johnson (1990). The authors observe in their experiments that participants do not integrate consecutive losses. This implies for our experimental setting, that after a loss, subjects edit the subsequent decision situation exactly as the previous one. Hence they choose the same investment strategy, which results in a fixed-mix strategy. Further we observe, as Thaler and Johnson (1990), that subjects "gamble" when they are ahead. They do so according to a contrarian strategy.

We find clear evidence for reference point dependent behavior: subjects invest differently when they are in the gain zone, than when in the loss zone. However, their portfolio decisions cannot be explained by our estimates of prospect theory parameters.

Because the focus of our research is individual trading behavior, we opt for a shorter elicitation method based on Glaser (2001) than studies that concentrate on preference parameters. Nevertheless, our estimates of the preference parameters are, except for β, similar to those obtained by other authors, in particular by Tversky and Kahneman (1992). This indicates, that although we use less lotteries the estimates for the coefficients are still reasonable.

We find that the coefficient for risk aversion, α, does not differ significantly for the gain and loss zone and that only one subject has an $\alpha > 1$.[37] For the loss aversion coefficient we get different results than reported by most authors. The median for our sample is 1, which implies that almost half of our subjects are not loss averse, and pay more attention to the positive payoffs. We use only one lottery to measure the degree of loss aversion. Although it is not the focus of this paper, it would be interesting to study how the measurement of loss aversion can be affected by various structures

more often in the loss zone.

[37]An $\alpha > 1$ implies risk-seeking in the gain zone and risk aversion in the loss domain.

of lottery questions. Our findings concerning γ are compatible with those found in the literature.

Based on cognitive dissonance theory, Zuchel (2001) proposes that the disposition effect can be explained by the self-justification hypothesis. Namely, the investors are reluctant to admit that they made bad investments decisions in the past, and therefore, makes them reluctant to realize losses.

To test this hypothesis, we introduce a within-subject justification treatment by asking the subjects to provide reasons for their allocation decisions each period. We did not observe any treatment-effect on investment behavior. However, in future experiments, one can test whether alternative justification treatments can make a difference, e.g., to let the subjects decide for other people vs. for themselves.

A further inspection of the justifications suggests that some participants did fall into gambler's fallacy. Although the mean-reversion hypothesis has been rejected by some previous studies (Weber and Camerer (1998)), it deserves more careful investigation. Explicit elicitation of price expectations like what we have done in this study would be helpful for such an investigation. In general, our results indicate that this hypothesis is not compatible with the observed fixed-mix strategy in the loss zone. However, it is possible that the beliefs explain the contrarian gambling strategy in the gain zone.

In summary, we present evidence that investors measure their gains relative to their initial wealth, and that this reference point together with past stock price changes determine the portfolio choices. When they are in the loss zone they choose a fixed-mix strategy, which suggests that they do not integrate subsequent losses. When they are in the gain zone, they gamble according to a contrarian strategy, possibly based on belief in mean reverting asset prices.

5 Conclusions

We conduct controlled experiments in order to analyze individuals' trading behavior. We observe the disposition effect in terms of units of assets sold and purchased. Additional analysis in terms of fractions of wealth invested in the risky asset yields further insights: subjects choose a fixed-mix investment strategy in the loss zone and a contrarian strategy in the gain zone. Our analysis shows clear evidence for reference point dependent behavior. The observed portfolio decisions are in line with the house money effect. We reject the hypotheses that rebalancing, prospect theory with a fixed reference point, or the justification hypothesis explain the disposition effect.

A Appendix

A.1 Prospect Theory

According to prospect theory, the overall value of a prospect is given by the sum of the subjective values of the outcomes weighted by the agent's decision weights associated with the probability of the outcome. The overall value of a prospect yielding gain x with probability p, and loss y with probability $1-p$, is given by: $V(x,p;y,1-p) = w(p)v(x)+w(1-p)v(y)$. The decision weights w measure the impact of events on the desirability of prospects. According to the authors, the decision weights take the following form

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{\frac{1}{\gamma}}}, \text{ for some } 0 \leq \gamma \leq 1. \tag{5}$$

The value function v assigns to each outcome x a number $v(x)$, which reflects the subjective value of that outcome. The key features of prospect theory are that outcomes are coded into gains and losses, that losses hurt more than gains and that risk-taking behavior differs for gains and losses. Based on empirical evidence, Tversky and Kahneman (1992) proposed a two part power function

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\beta(-x)^{\alpha} & \text{if } x < 0 \end{cases}. \tag{6}$$

The parameter β is the coefficient of loss aversion and reflects the fact that losses hurt more than equivalent gains, which is true for all $\beta > 1$. Using data from their experiments, the authors estimated β to be equal to 2.25. The coefficient α measures the agent's risk aversion and takes on values between zero and one. The authors estimated α to be equal to 0.88. Observe that, in the domain of gains, i.e. $x \geq 0$, the value function is concave, implying that the agent is risk-averse, whereas in the domain of losses the function is convex, i.e. the investor prefers to gamble instead of facing a sure loss. We assume that all parameters are constant over time.

A.2 Algorithm

Typically subjects perceive this task as very difficult.[38] Therefore in our experiments we use an indirect way to elicit this answer. At any one time we confront the subjects with two lotteries, which they have to compare, and use an algorithm to find out the answer we are ultimately interested in, by gradually restricting the possible values z_a^i can take on.

The algorithm works as follows. Suppose we want to elicit the amount of money z_a^i, that makes the ith subject indifferent between the two lotteries $A_a = (x_{a1}, 0.5; x_{a2}, 0.5)$ and $B_a = (z_a^i, 0.5; 0, 0.5)$, where $x_{a1} > x_{a2} > 0$ are known to the subjects. Then we first confront the subject with the two lotteries A_a and $B_{a1} = (0, 0.5; 0, 0.5)$. The subject has to state which of the two he prefers. Subjects also have the option to state that they are indifferent. Typically subjects prefer lottery A_a, implying that 0 is a first lower bound, l_1^i, for z_a^i. Next we confront the subjects with two lotteries A_a and $B_{a2} = (10x_{a1}, 0.5; 0, 0.5)$. Typically subjects prefer the latter, yielding a first upper bound, u_1^i, for z_a^i. Next, the two lotteries A_a and $B_{a3}^i = (\frac{u_1^i - l_1^i}{2}, 0.5; 0, 0.5)$ are compared. Note that the payoffs of the B lotteries depend on past choices of the subject.

If the subject prefers A_a, the positive payoff of lottery B_{ak}^i, where k indicates the number of the proposed B lottery, determines the new lower bound for z_a^i, while the upper bound remains unchanged; if B_{ak}^i is preferred a new upper bound, keeping the earlier lower bound, is set. If the subject states that she is indifferent, we know that z_a^i equals the payoff proposed by the B_{ak}^i lottery. The algorithm stops either when the subject states that she is indifferent, or when $u_k^i - l_k^i \leq 2$. The latter case yields $z_a^i = \frac{u_k^i - l_k^i}{2}$.

One such a completed algorithm is called one (lottery) question. In each question the first payoff of the B_{a1} lottery is 0 and the one of B_{a2} equals $10x_{a1}$. These two payoffs are chosen enough broadly, such that all subjects' answers are captured. On the other hand they are chosen narrowly enough, so that the algorithm never lasts more than 10 iterations.

[38]Subjects find it more natural to state certainty equivalents, i.e. the amount z, such that they are indifferent between a lottery and this amount, or to compare two lotteries.

A.3 α^G vs. α^L

Using a Wilcoxon signed-rank test (p-value = 0.28) we cannot reject the hypothesis that both distributions are the same. Our conclusion does not change even if we exclude all α^G and α^L that equal zero, that may bias our results (p-value=0.86). Similar results are obtain for testing the hypothesis that the median of the differences is zero (p-value= 0.47; exclude all α^G and α^L that equal zero p-vlaue= 1) or that the mean of the differences is zero (p-value= 0.28; exclude all α^G and α^L that equal zero p-vlaue= 0.75).

A.4 Inconsistent Answers

Some subjects in our sample do not behave as economic theory predicts. In particular, some of them occasionally prefer dominated alternatives. For example, one subject states that he is indifferent between the lotteries $A_{13} = (10, 0.5; 1, 0.5)$ and $B_{13} = (x_{13}, 0.5; 0, 0.5)$ if $x_{13} = 9$. Note however, that lottery A_{13} strictly dominates lottery B_{13} since it yields in both states a higher gain.

Another example for a non-conform behavior related to dominance, is a subject who answers $x_9 = 25$, when being asked for the amount x, s.t. he is indifferent between the lottery $A_9 = (10, 0.5; 5, 0.5)$ and $B_9 = (x_9, 0.5; 0, 0.5)$. However, he states later that he is indifferent between lotteries $A_{13} = (10, 0.5; 1, 0.5)$ and $B_{13} = (x_{13}, 0.5; 0, 0.5)$ if $x_{13} = 25$. Note that A_9 is strictly better than A_{13} since in the bad case its payoff is strictly higher, while yielding the same gain in the good state. Hence there is a contradiction in the answers of the subject, who indirectly states that the lotteries, for him, have the same value.

Since prospect theory was designed for cases for which no dominated alternatives appear, it makes little sense to estimate the prospect theory parameters for those cases. In fact, if still doing so, we get in such cases generally a risk aversion parameter $\alpha = 0$ and an infinite loss aversion. In order to elicit the subjects' loss aversion, β, we asked them to state the amount x_{10} such that he is indifferent between lotteries $A_{10}(30, 0.5; -30, 0.5)$ and $B_{10}(x_{10}, 0.5; 0, 0.5)$. We exclude the observation when $x_{10} >\mid 30 \mid$.

For the elicitation of the probability weighting function parameter, γ, we ask each subject five questions of the type: "you are given a lottery that pays of an amount a with probability p and nothing otherwise. What is the maximum amount you are willing to pay to participate in this lottery?" We exclude all answers that are bigger than a.

We assume that the described errors are non-systematic, as e.g. caused by the inattention of the subjects, and exclude the answers from our analysis.

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