Splitting the Disposition Effect: Asymmetric Reactions Towards "Selling Winners" and "Holding Losers"*

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Abstract: The disposition effect describes investors' common tendency of quitting a winning investment too soon and holding on to losing investments too long. Since Shefrin and Statman (1985), the two sides of the disposition effect, i.e. "selling winners" and "holding losers", have been assessed as one coherent bias. High-disposition investors are usually modeled to sell their winners quickly while almost never selling losers, while low-disposition investors are assumed to behave in the opposite way. Investigating both account level field data as well as data from a controlled laboratory experiment, we however show that individual investors' reactions towards "selling winners" and "holding losers" are completely independent, meaning that the disposition effect is better depicted as two separate biases, investors' "preference for cashing-in gains" and their "loss realization aversion". Furthermore, investors' individual preferences towards both sides are also stable over tasks and time so that both biases can be seen and modeled as individual personality traits.

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1 Introduction

The disposition effect describes investors' common tendency of selling a winning investment too soon and holding on to losing investments too long (Shefrin and Statman 1985). Previous literature has documented the disposition effect for various tasks and investor types, including individual as well as professional investors. (See e.g. Odean 1998, Weber and Camerer 1998, Genesove and Mayer 2001, and Garvey and Murphy 2004 for evidence regarding individual stock market investors, student subjects in an individual choice experiment, house holders, and professional stock market investors, respectively.) Lately, research has shifted from studying aggregate behavior towards investigating individual behavior, especially relating individual disposition effect with investors' sophistication (see, e.g. Dhar and Zhu 2006, Feng and Seasholes 2005, Seru, Shumway and Stoffman 2007, and Leal, Armada and Duque 2008).

From its definition ("selling winners too soon – holding losers too long"), the disposition effect consists of two sides, one concerning gains and the other concerning losses. In research on the disposition effect the two sides of the biases are treated as symmetric. While a non-disposition investor is unbiased in his selling decisions, a high-disposition investor is usually assumed to both selling winners quickly and to be reluctant to realize losers. There is some indication in the literature that both sides of the effect are not perfectly correlated, e.g. Feng and Seasholes (2005) show that experience and sophistication have different effects on the behavior in the gain and loss domain (see Dhar and Zhu 2006 for related findings). However, a thorough investigation of the dependency of behavior in the gain and in the loss domain based on individual level data is still missing.

Using field as well as experimental data, we show that investors' reactions towards capital gains are uncorrelated to their reactions towards capital losses, indicating that the disposition effect should be better classified as two separate biases. In a more detailed analysis, we find that both sides of the disposition effect are not merely random but stable on an individual level, which classifies both biases as stable personality traits. Investors who are extremely reluctant to sell their losers in one year in our field data study or one task of the individual choice experiment also appear to be reluctant in later years or other tasks, respectively. We also find that learning attenuates the effects over time and that certain investor characteristics affect and explain investors' reactions towards gains and losses.

Our results are important both for research and practical applications. In research, these findings are especially useful for multi-agent models that focus on the relationship between individual biases and market measures, e.g. Grinblatt and Han (2005). In practice, banks providing investment advice to their customers could especially benefit from our contribution.

As indicated, we use two different data sets, i.e. research methodologies. First, we analyze trading behavior of actual stock market investors. Our field data is based on purchase and selling transactions of about 3,000 individual investors from a German online broker covering the period from January 1997 to April 2001. We are also provided with some personal characteristics concerning these investors (age, gender, investment experience, income, and investment strategy). Second, we analyze individual level disposition effects in an individual choice experiment. The experiment consists of two parts that are separated by a four-week interval to test for time stability. In each part of the experiment, our 113 student subjects are confronted with two different individual choice tasks. The tasks are especially designed to measure individual disposition effects and differ in multi-dimensions to capture a broad spectrum of how disposition effects might emerge. While the first task is similar to the stock market design of Weber and Camerer (1998), the second task consists of sequences of simple lottery choices framed as a housing task.

Both methodologies have advantages and disadvantages. The most important benefits of the field data analysis are that it deals with the population we really want to study, i.e. individual investors, and that it spans more than four years of data. However, it is generally difficult to distinguish whether certain effects in the field, or certain individual behaviors, are driven by biased preferences or biased expectations. The laboratory, on the other hand, gives us the opportunity to control for different explanations, especially expectations, so that we are able to compare actual behavior to a strict rational benchmark. The experiment, in addition, also allows us to study research questions for which there is no field data available, i.e. stability across tasks. Drawbacks of the experimental method are the short time interval between the two parts of the experiment, and the fact that our subjects are students instead of real investors. We believe that the combination of both methodologies, i.e. field and experiment, eliminates most concerns and alternative explanations and therefore provides a strong robustness check for all our findings.

Our analysis is conducted in the following way: For both data sets, we measure the extent to which an investor exhibits the disposition effect as the difference between proportions of winners and losers realized. Proportions of winners (losers) realized are calculated as the number of times an investor sells at a gain (loss), divided by the number of opportunities to do so (see e.g. Odean 1998). We replicate known results showing that both investors in the field and subjects in the individual choice tasks tend to sell their winners far more often than their losers. In the field, winners are 50 % more likely to be realized, while in the experiment, winners are twice as likely to be cashed in. As our main contribution we find, that those investors selling their winners too soon are not the same investors who hold their losers too long. The two sides of the disposition effect are thus not entangled with one another which is true for both settings.

In the next step, we apply a stability analysis within tasks, across tasks, and across time by correlating individual attitudes in the gain and loss domain across different years in the field, different rounds of the same task, different tasks, or different parts of the experiment, respectively. Our results suggest that the two, independent building blocks of the disposition effect, i.e. investors' attitude for cashing in their gains quite quickly and their loss realization aversion, are indeed stable for all the tested dimensions. In accordance with prior research (see e.g. Dhar and Zhu 2006 and Shumway and Wu 2006) we also find that individual disposition effects decrease with trading experience. Investors who are engaged in frequent trading realize their winners more and their losers less readily.

The paper is structured as follows. In section 2, we review related literature and constitute our hypotheses. We describe our field data set, as well as the experimental design and procedure, in section 3. Section 4 discusses our results and section 5 draws conclusions.

2 Related Literature and Hypotheses

The term "disposition effect" dates back to Shefrin and Statman (1985). Stock market investors exhibit the tendency to sell their winning stocks too early and hold on to their losing stocks too long.[2] Since Shefrin and Statman (1985), the disposition effect has been replicated in a variety of different economic settings, such as stock markets, housing markets, or economic experiments. It has also been replicated for different investor types, including individual investors as well as professionals, and for many different countries.

Heisler (1994) documents the disposition effect among small speculators in the U.S. treasury bond futures market. He shows that these investors hold trades with an initial paper loss significantly longer than trades that show an initial profit. Odean (1998) uses individual level discount broker data to discover that individual stock market investors in the U.S. stick to their loser stocks while selling their winner stocks. He also shows that rational explanations, like stock market mean reversion, portfolio rebalancing, or trading costs, do not seem to drive the results. Odean's findings have been replicated for the Australian (Brown, Chappel, da Silva Rosa, and Walter 2002), Chinese (Chen, Kim, Nofsinger, and Rui 2007), Finnish (Grinblatt and Keloharju 2001), and Israeli (Shapira and Venezia 2001) stock markets.

While these studies mainly investigate trading behavior of individual investors, there is another stream of literature which looks at behavioral biases among professionals. Garvey and Murphy (2004) show that U.S. proprietary stock traders hold on to their losers too long and sell their winners too soon. Coval and Shumway (2005) find that Chicago Board of Trade proprietary traders take above-average afternoon risk to recover from morning losses, a behavior related to the disposition effect. Disposition effects for professional future traders are documented by Frino, Johnstone, and Zheng (2004), Locke and Mann (2005), as well as Locke and Onayev (2005).

The disposition effect, however, does not only apply to financial markets, but also to different economic situations, such as housing markets or economic experiments. Genesove and Mayer (2001) find a disposition effect in the housing market in downtown Boston in the 1960s. Weber and Camerer (1998) investigate the disposition effect within an individual choice experiment and show that it is mainly driven by their subjects' unwillingness to close a position at a loss. Once subjects are forced to close all their positions in each trading period, but later given the opportunity to reopen them, the ef-

[2] See Barberis and Xiong (2008) for a detailed formal discussion on the relation between prospect theory and the disposition effect.

fect weakens significantly. Weber and Zuchel (2005) document that risk taking after gains and losses is highly affected by economic frames. When subjects are confronted with a stock market frame, they tend to exhibit the disposition effect. If the same decision is presented in a lottery frame, however, risk taking after gains exceeds risk taking following losses.

Different from the previous literature, our paper focuses on the two sub-effects contributing to the disposition effect, i.e. the behavior on the gain side vs. the behavior on the loss side. Besides replicating the mere existence of the disposition effect (hypothesis 1), hypothesis 2 therefore asks for symmetry of the effect in the gain and loss domain. The question is whether investors who exhibit the disposition effect do so because they sell winners too early, losers too late, or both:

Hypothesis 1: Individual investors realize their gains quicker than they realize their losses.

Hypothesis 2: Investors who exhibit the disposition effect tend to both sell their winners too early and their losers too late.

Whether or not we find symmetry, we need to check for stability to show that individual differences across investors are not merely random but stable personality traits. To our knowledge, there is no study that compares individual level disposition effects and its two building blocks across different settings, e.g. the stock and the housing market. In addition, it is quite unclear whether individual biases are stable within tasks, e.g. across different market regimes, and across time. Some evidence that the disposition effect might be time stable comes from Shumway and Wu (2006), who analyze individual account data from a Chinese brokerage firm. The authors document that individual investors' disposition effects, measured using one year of data, forecast these investors' disposition effects in subsequent years.

For testing stability within tasks, we first analyze whether experimental subjects who exhibit a relatively strong disposition effect, preference for cashing-in gains, or loss realization aversion within one round of a task are also highly affected in other rounds of the same task. Second, we test whether individual level effects are stable across the two different tasks. Furthermore, by repeating the experiment four weeks later and by analyzing our field data set, we are able to test for time stability. Our three stability hypotheses are therefore the following:

Hypothesis 3a: (Stability within tasks) Preferences for cashing-in gains and loss realization aversions are stable within tasks.

Hypothesis 3b: (Stability across tasks) Preferences for cashing-in gains and loss realization aversions are stable across different tasks.

Hypothesis 3c: (Stability across time) Preferences for cashing-in gains and loss realization aversions are stable across time.

We also investigate whether and how learning attenuates individual investors' tendencies for selling winners and holding losers. Although individual level disposition effects might be time stable on a relative level, it might be that investors learn over time, thus lowering the disposition effect on aggregate. Learning might be induced by the performance penalty investors have to pay when exhibiting this bias (Camerer 1990). Recent literature tests whether the disposition effect diminishes with increasing investment sophistication, using proxies like investment size, trading frequency, age, wealth, or professional occupation. Evidence on this issue, however, is mixed. While Brown et al. (2006), Dhar and Zhu (2006), Grinblatt and Keloharju (2001), Shapira and Venezia (2001), and Shumway and Wu (2006) claim that sophistication indeed weakens the disposition effect, Chen et al. (2007) find an opposite effect for the Chinese market. We apply hypothesis 4 to test for learning within tasks and over time both with our field data and our experimental data set:

Hypothesis 4: Learning decreases disposition effects on aggregate. While investors hold on to their winners more often, they are more likely to sell their losers.

3 Data

3.1 Field Data

Our field data study is based on three data sets: A data set containing purchase and selling transactions of 3,079 individual investors from a German online broker covering the period of January 1997 to April 2001, a second data set containing voluntarily self-reported investor characteristics collected by the online broker when the investor opened the account (age, gender, investment experience, income, and investment strategy), and a third data set containing price information from Datastream on the securities traded.

(insert table 1 about here)

Table 1 presents descriptive statistics of those 2,978 investors who enter our analysis. We consider all investors who traded in stocks listed in Euro or German Marks. The table also provides descriptive statistics on trades and portfolios. Note that, since our investors hold an average (median) number of only 5.52 (4.29) stocks in their portfolios, they seem largely indifferent to diversification. More information on our field data set can be found in Glaser (2003).

3.2 Experimental Data

We measure individual level disposition effects in two different individual choice treatments: A multiperiod investment task similar to Weber and Camerer (1998) and a framed housing task. In the following we explain these experimental designs as well as the experimental procedure in detail.

3.2.1 Task 1: Stock Market Design

We call the first treatment "stock market design" because of its affinity to a stock market – although the terms "stock" and "market" are actually not used in the experiment to avoid framing effects. The treatment covers three rounds, with each round consisting of 14 periods, numbered period -3 to 10. Our subjects trade in six different goods, labeled good 1 to 6. To facilitate comparison of results across subjects, all subjects are faced with the same price paths, meaning that price paths are fixed for each round of the treatment. We vary the order in which subjects pass through rounds 1 to 3 and the labels for the six goods in each round to prevent subjects from noticing that they are all playing an identical game. The purpose of periods -3, -2, and -1 is only to provide price information, therefore our subjects are allowed to purchase and sell units of the six goods starting only at period 0. In period 0, our subjects are given 2,000 units of experimental currency, but no units of any of the six goods. Over the following ten periods, i.e. period 0 to 9, they can use their endowment to buy units of the six goods, or sell units if they possess any. The only restrictions to our subjects' transactions are that their money account as well as the number of units held for each of the six goods have to remain nonnegative. In period 10 the round ends and subjects are informed about the final value of the goods. Figure 1 shows the computer screen for this task.

(insert figure 1 about here)

Every period, each of the six goods changes in value. Starting at 100 units of experimental currency, the price either increases by 6 % or decreases by 5 %, while the probability with which a good increases in value is constant over the whole round. Price changes are independent from previous price changes of that good, as well as current and previous price changes of all other goods. While subjects are informed how price changes are calculated, and that probabilities are constant, they are not told what the probabilities of the six goods actually are. As they are not provided with a priori probabilities they cannot rely on simple Bayesian updating, but rather have to deal with ambiguity. Probabilities are chosen to replicate three different kinds of market regimes: an upward moving market, a neutral market, and a downward moving market. Under the neutral market regime we have two goods exhibiting a negative trend (probabilities for price increase 40 % and 45 %), two goods set up to oscillate around the starting price of 100 (probabilities 50 %), and two goods with an upward moving trend (probabilities 55 % and 60 %). The upward and downward moving markets are similar to the neutral market, but omit the one good with the lowest or highest probability of price increase and exchange it with another good offering the same probability as the best or worst good, respectively.

While our subjects are not informed about the real probabilities underlying the six goods, they could heuristically derive simple probability estimates by counting the number of times a certain good increased in value and dividing this measure by the number of periods played. A good that moved up in value more often than it decreased in value is likely to move up again while a good that decreased in value most of the time is likely to expect another price downturn. In period 0, subjects could assess the underlying probabilities by analyzing price changes in periods -3 to 0. In period 1, subjects should update these probability estimates based on the additional price change between period 0 and 1.

Probability estimates thus change each period – and so should allocations. Depending on a subject's risk aversion, a variety of different strategies could be optimal. If a subject is risk neutral or risk averse, he or she should never buy or hold any units of a good with a current subjective probability estimate for further price increases lower than 45.45 %.[3] Ignoring diversification effects, or assuming risk neutrality, a subject should invest only in the highest priced good. If there are multiple goods sharing the highest price, the subject should divide his endowment equally over these goods. An optimal strategy thus generally requires that a subject holds on to the goods that moved up in value, and thus probably show unrealized gains, and to sell the goods that decreased in value and show unrealized losses. Hence, a disposition effect is a clear mistake under our design.

To determine a subject's payout for this task, one round is chosen randomly. We calculate the subject's wealth at the end of period 10 as the sum of his or her money account and the current value of holdings in goods. Payout equals 0.2 % of this sum.

3.2.2 Task 2: Housing Design

The second individual choice task, which we call "housing design", is distinct from the first one in a multitude of dimensions. While we try to avoid framing in the stock market treatment, our housing treatment is based on a real life background story. Another difference is that in our housing treatment, subjects only need to decide when to sell, while in the stock market treatment both purchasing and selling decisions have to be made. Finally, our second individual choice task does not rely on probability updating so that rational strategies are easier to discover and implement. As the housing treatment is less time consuming than the stock market treatment, we play a total of six rounds. Price paths are again the same for all subjects, and the order in which subjects pass through rounds 1 to 6, as well as the house labels, are again assigned randomly. Figure 2 shows the computer screen of the treatment.

(insert figure 2 about here)

Our subjects are told that they have just inherited five different houses from a distant relative. They neither want to inhabit these houses themselves, nor rent them to other people, but instead want to sell them during the next five years, i.e. between 2005 and 2010. Hence they need to decide each year if and which houses they want to sell. Once a house is sold, the subject can never repurchase it, and houses that are not sold in 2009 are sold automatically in 2010 for their current price. The market

[3] If the probability estimate is 45.45 %, the expected price change is just $0.4545 \cdot 0.06 + 0.5454 \cdot -0.05 = 0$.

value of each of the five houses is € 200,000 in 2005. In subsequent years each house price either increases or decreases by € 30,000. Subjects are told that price changes are independent of previous price changes and, as all houses are situated in different residential areas, price changes are independent across houses. They are also informed that probabilities of price increases and decreases are equal for all houses but abate over time. If a subject decides not to sell a house in 2005, it increases in value with a probability of 65 %. In 2006, this probability decreases to 55 %, while it drops to 50 %, 48 %, and 45 % over the years 2007 to 2009.

From a normative point of view, the game can be split into in a sequence of lotteries, which offer either a gain or a loss of € 30,000. Similar to the stock market treatment, normative strategies depend on risk aversion. While almost all subjects should be willing to play the first lottery, which offers a 65 % chance of winning, a risk neutral subject would quit the lottery sequence for 2007 or 2008. Holding a house longer than 2008 can only be explained by risk seeking. Note that unrealized gains and losses, which are building blocks of the disposition effect, do not affect – or by changing current wealth only marginally affect – rational strategies in this treatment. Subjects should sell their houses regardless of their current price, since the lottery is the same for every price level. Exhibiting the disposition effect in this task becomes costly if a subject sells a winner too early, and thus misses a lottery with a high probability of winning, or holds on to a loser too long and thus accepts a lottery which he or she normally would refuse to play, e.g. a lottery with negative expected payoff.

We determine a subject's payout for this task by randomly choosing one of the six rounds and calculating total revenues. Payout equals 0.0002 % of this sum.

3.2.3 Procedure

The experiment was conducted in May and June 2005 at the University of Mannheim and consisted of two parts. We chose a four-week interval between the first and the second part for testing time stability. Both parts of the experiment included the stock market treatment and the housing treatment, but subjects were not told that they were going to repeat exactly the same tasks.

Our analysis is based on 78 male and 35 female students, who participated in both parts of the experiment.[4] Approximately half of all subjects studied economics and business administration, while the other half's fields of study were not related to economics, e.g. computer science, sociology or law. The average age was 24, the average academic year was 3.2. The experiment was conducted in a computer laboratory using the experimental software zTree (Fischbacher 2007). To ensure that everyone understood the rules and computer screens, subjects had to go through short tutorial sessions. The average processing time was approximately 45 minutes for each part of the experiment. The average payout was € 12.32, with a standard deviation of 40 cents. A translation of the German instructions can be found in the appendix.

4 Results

4.1 Definition of Variables

In the field and both individual choice treatments, we calculate individual disposition effects based on the number of times an investor sells at gains or losses. Results are nevertheless unchanged if we base individual disposition effects on the amounts realized. Instead of only counting how many times an investor sells for a gain or a loss, we relate actual sales to selling opportunities as done by Odean (1998). Doing this ensures that our results are not affected by a lack of selling opportunities. Proportions of winners realized (PWR) and proportions of losers realized (PLR) are calculated the following way:

$$(1) \qquad \text{PWR} = \frac{\#\text{of sales at gain}}{\#\text{of selling opportunities at gain}}$$

$$(2) \qquad \text{PLR} = \frac{\#\text{of sales at loss}}{\#\text{of selling opportunities at loss}}$$

The individual level disposition effect is just the difference between these two variables and is thus specified as

$$(3) \qquad \text{DE} = \text{PWR} - \text{PLR}\,.$$

[4] We excluded twelve subjects who only participated in the first part of the experiment. Their behavior in the first part, however, did not differ from the other subjects' behavior.

DE measures vary between –1 and 1. Investors with a measure of 1 quit an investment every time it contains an unrealized gain, while they never quit investments with unrealized losses. Hence, they exhibit the strongest possible disposition effect. The opposite is true for investors with a DE measure of –1, while a measure of 0 means that the investor does not base his or her selling decisions on unrealized gains and losses.

In the field, selling opportunities are only counted on those days where the investor decides to sell at least one of his or her stocks. This procedure is similar to Odean (1998) and Grinblatt and Keloharju (2001), and tries to control for the fact that some investors in the field might monitor their portfolios more regularly than others. We count a selling opportunity at a gain (loss) for each stock in the investor's portfolio trading at a price above (below) the average purchase price. For each stock the investor actually sells, we count a sale at a gain or at a loss, as appropriate. Results are robust if we alternatively define the reference point as the first, the most recent, or the highest purchase price.

In the stock market treatment, we derive individual level disposition effects by analyzing our subjects' selling behavior through periods 1 to 9. Although robust under different specifications, we again apply the weighted average purchase price as a reference point. We count a selling opportunity at a gain (loss) whenever a subject owns at least one unit of the good in question, with the price of the good being above (below) the average purchase price. Whenever a subject decides to sell one or more units of the good, we count a sale.

In the housing treatment, we measure our subjects' disposition effects over the years 2006 to 2009. In each round and each year we count a selling opportunity at a gain (loss) whenever the house is still in the subject's possession and its value is above (below) its starting price of € 200,000. If the subject actually decides to sell the house, we count a sale at a gain or loss, as appropriate.

4.2 Disposition Effect on Aggregate

We test whether investors in the field or subjects in our experimental treatments exhibit the disposition effect, i.e. hypothesis 1. On average, individual investors in our field data set utilize their opportunities to sell in 30 % of all cases if the stock is in the gain domain. If the stock, conversely, trades below the average purchase price, its selling frequency drops to 20 %. The average investor therefore exhibits a disposition effect of approximately 0.09. Compared to our result, Odean (1998) reports an aggregated disposition effect of 0.05 for U.S. discount broker clients. Besides a general disposition effect, we also detect a remarkable heterogeneity among investors. Of those 2,614 investors for which we are able to calculate the disposition effect[5] a significant majority of 1,711 investors (65.46 %) is positively affected (p = 0.0000 using a binomial test). Nevertheless, a considerable number of 903 investors (34.54 %) exhibit a behavior unaffected by or even opposite to the disposition effect, selling losers more frequently than winners.

In the experiment, if subjects are unaffected by unrealized gains and losses and apply a random trade strategy, we expect an average DE measure of 0 in all treatments.[6] Table 2 shows mean PWR, PLR, and DE measures. .

(insert table 2 about here)

Subjects use their selling opportunities in the stock market treatment following gains almost twice as regularly as they use their selling opportunities following losses. They also sell their houses in the housing treatment almost twice as often if the house price exceeds the starting price of € 200,000 than if it is below its starting price. Hence, disposition effects in our experiment are even stronger than disposition effects in the field. Our findings are comparable to the results reported in Weber and Camerer (1998). While using a different method for calculating disposition effects, Weber and Camerer report that 59 % of all shares sold in their experiment were winners, 36 % losers, and 5 % trading at break-even prices. In our experiment, the majority of subjects exhibit positive individual level disposition effects, although in all tasks a considerable number of subjects, varying between 24 (21.24 %) and 50 (44.25 %), follow the opposite strategy. The number of subjects with positive disposition effects is significantly higher than 50 % for all tasks but the stock market design in the second part of the experiment. It should also be noted that by exhibiting the disposition effect, our subjects leave money on

5 PWR and PLR measures are only defined for those investors who have at least one selling opportunity at a gain or at a loss.

6 Sometimes it can be rational to sell a good with unrealized capital gains. This is the case if during a round another good catches up in price and is now as likely to increase in value as the good that is already in the subject's possession. If this is the case, the subject could sell some of the units of the good he already possesses and buy units of the other good to decrease his portfolio risk.

the table. The strategies our subjects play lead to an average payout of € 12.32, compared to a payout of € 13.28 if the simple heuristic strategy were applied.

4.3 Symmetry

While, in accordance with Dhar and Zhu (2006), we find individual differences among all investigated measures, we still do not know how these individual differences relate to each other: Are those investors with a pronounced tendency to sell their winners early the same investors who are extremely reluctant to sell their losers (hypothesis 2)?

(insert figure 3 about here)

At a first glance, PWR and PLR measures in the field are indeed positively and significantly correlated, as shown in the left-hand graph of figure 3. Spearman's correlation coefficient between PWR and PLR equals 0.31 ($p = 0.0000$). Investors who realize their winners frequently thus also sell their losers relatively often.

This correlation, however, could be artificially generated by the general definition of PWR and PLR. Since Odean (1998), both measures are usually calculated as the number of sales divided by the number of selling opportunities at gains or losses, respectively, with selling opportunities only counted on those days where the investor sells at least one of his stocks. If, however, investors normally only sell one stock on each selling day and some investors hold larger portfolios than others, these investors also generate many selling opportunities compared to actual sales. This in turn leads to PWR and PLR measures being negatively correlated to portfolio size.[7]

To control for the possible influence of portfolio size on PWR and PLR, we regress both measures on logarithmic portfolio size using a two-sided censored Tobit regression. Portfolio size is therefore defined as the number of different stocks in the investor's possession. The residuals of this regression constitute the part of PWR or PLR which cannot be explained by differences in portfolio size. The resulting correlation of residuals is shown in the right-hand graph of figure 3: there is no interde-

[7] As a simple example, think of an investor who has N stocks in his portfolio. All stocks trade above the reference point and are thus considered as winners. If on each selling day the investor only sells shares in one of his stocks, his PWR measure equals 1/N. Thus, under these strong assumptions, PWR is a strictly decreasing function of the number of different stocks in the portfolio.

pendence between proportions of winners realized and proportions of losers realized after controlling for portfolio size. Spearman's rank correlation equals 0.00 (p = 0.8655).

Again, our experiment may serve as a robustness check. In our experimental treatments, we control for portfolio size in the way that every subject is assigned the same initial endowment. Portfolio sizes therefore differ only marginally. Figure 4 plots PWR and PLR measures for both the stock market and the housing treatment.

(insert figure 4 about here)

It reveals that there is no systematic correlation between PWR and PLR. Spearman's rank correlation coefficients are with both -0.13 economically and statistically insignificant (p = 0.1691 and p = 0.1587).

To sum up, we find strong evidence of individual differences concerning the disposition effect as well as its two building blocks: realization of winners and loss realization aversion. Most importantly, we find that investors who sell their winners frequently are not the same investors who hold their losers until they have caught up with the purchase price. An investor with a certain level of disposition effect might, for example, exhibit the bias to this amount, because he never sells his losers or because he always sells his winners right away. In both cases the investor shows only one side of the disposition effect, i.e. loss realization aversion or a tendency for cashing in his gains immediately, while his behavior concerning gains or losses, respectively, may be close to rationality.

4.4 Relative Stability within Tasks, across Tasks, and across Time

We test for relative stability of the two building blocks of the disposition effect within tasks, across tasks, and across time, i.e. hypotheses 3a, 3b, and 3c. To disentangle stability from learning, we define the disposition effect as being stable if investors exhibiting a relatively strong disposition effect in one year of the field data sample period, or round, task, or part of the experiment, also belong to the high disposition effect group in all other years, another round of the same task, another task, or the next part of the experiment, respectively. Hence, stability does not necessarily mean that investors do not learn over time. It only means that – if investors learn at all – learning does not change the ranking of investors.

The field gives us the opportunity to perform an in-depth analysis of stability across time, i.e. hypothesis 3c. By comparing individual disposition measures across years, over the whole sample period we obtain average time intervals between one and three years. Over years, of course, individual investment strategies, wealth levels, or expectations may change, which in turn affect individual stability. If we nevertheless find significant correlations in individual disposition measures across years, this should be a convincing finding for stability across time. Table 3 reports the results of the correlation analysis.

(insert table 3 about here)

First, the table reveals that both proportions of winners realized and proportions of losers realized are highly and significantly correlated with average correlation coefficients of 0.40 for PWR and 0.37 for PLR measures. Furthermore, correlations of PWR and PLR indeed decrease over the length of the time interval, supporting our assumption that external influences, like changing investment strategies or changes in wealth levels, impact selling behavior over time.

One might worry, however, that this stability is driven by an effect already discussed in section 4.3: As PWR and PLR measures are affected by portfolio size, portfolio size could also serve as an external stabilizer for these measures. Stable portfolio sizes thus could enforce stable disposition effects: If an increase in portfolio size leads to more selling opportunities, but does not affect the number of sales on a selling day, PWR and PLR drop by a certain percentage. Hence, if an investor in all years manages a relatively small (big) portfolio, PWR and PLR should be relatively high (low) in all years. To control for the stabilizing impact of portfolio size we perform additional robustness checks for all considered measures. In a first robustness check we regress PWR and PLR on logarithmic portfolio size using a censored Tobit regression, and correlate only the resulting residuals. We do not report the results, as correlations decrease only by a small amount..

In the next paragraphs, we examine our experimental data. We begin by testing for stability within tasks, i.e. hypothesis 3a. Table 4 shows correlation coefficients as well as p-values in parentheses for the three different market regimes in the stock market design of the first and the second part of the experiment.

(insert table 4 about here)

The table reveals that PWR and PLR measures are highly correlated across rounds. For PWR measures, all correlation coefficients are higher than 0.5. We perform the same tests for the second individual choice treatment and obtain similar results.

Stability across tasks (hypothesis 3b) is investigated by comparing individual disposition effects across both individual choice tasks for *the same part* of the experiment. On the other hand, we test for stability across time (hypothesis 3c) by analyzing changes in individual level disposition effects *between* the first and second parts.[8] Again, test statistics are based on Spearman's rank correlation coefficients. Table 5 documents the results.

(insert table 5 about here)

Each correlation matrix can be split up into three different parts. The upper left-hand and the lower right-hand section of each matrix show correlations across tasks for the first and second parts of the experiment. Correlation coefficients across time are documented in the lower left-hand section. For individual level PWR (PLR), we find significant correlations across tasks, with correlation coefficients of 0.15 (0.30) for the first and 0.0.29 (0.34) for the second part of the experiment. Correlations across time for the same task are even stronger with coefficients of 0.73 (0.47) for the stock market and 0.38 (0.53) for the housing treatment.

Summing up, we find consistent evidence for stability within tasks, across tasks, and across time. Stability across time is supported by both experimental and field data, while our tests for stability within and across tasks are only based on our individual choice experiments. We conclude that individual attitudes for selling winners and holding losers do not vary much within tasks, over tasks, or over time, but appear rather to be a stable personal characteristic.

4.5 Learning, sophistication and other determinants of the disposition effect and its sub-effects

Relative stability does not necessarily mean that investors do not learn within a task or over time. While an investor might throughout the entire field data sample period, in all rounds of a task, or both parts of the experiment belong to the high disposition effect group, learning may nevertheless decrease individual biases in this and all other groups. We test for learning, i.e. hypothesis 4, in two

[8] Note that the two parts of the experiment are separated by a four-week interval.

different ways. Firstly, we utilize our field data set and test whether investors in the field learn over years. Therefore we test whether in the second half of the sample period, individual investors' disposition effects are closer to 0. Secondly, we analyze our experimental data and test for learning within tasks, i.e. over rounds, and learning over time, i.e. between the first and second parts of the experiment. We consequently test whether individual disposition effects decrease over rounds or between the first and second parts of the experiment. We test for sophistication and other effects by running a regression with PWR, PLR, and DE as dependent variables.

We begin by looking at our field data. We test empirically whether investors starting with positive disposition effects, are, over the years, able to reduce their tendency to sell winners and hold losers. In addition, we also test whether those investors starting at negative DE measures sell their winners more and their losers less often as time progresses. Table 6 presents the results.

(insert table 6 about here)

As hypothesized, both investor groups learn over time and correct their behavior towards a selling strategy not based upon aggregated capital gains or losses. While the positive DE group decreases its average DE measure significantly from 0.29 to 0.10, the average DE measure of the negative DE group shows a significant increase from -0.21 to -0.02. A ranksum test reveals, however, that even after learning, investors starting at positive initial DE measures exhibit significantly higher disposition effects than investors starting at negative levels ($p = 0.0000$). While learning, positively affected investors decrease their proportions of winners realized and increase their proportions of losers realized, and vice versa for negatively affected investors.

To ensure our findings are not biased by portfolio size, as discussed in subsections 4.3 and 4.4, we again perform two different robustness checks. First, we regress PWR, PLR, and DE on portfolio size using two-sided censored Tobit regressions and analyze the residuals only. Second, we calculate individual disposition effects not as the difference, but as the ratio between PWR and PLR. Table 6 documents means as well as p-values for those measures in the four right-hand columns. As all effects retain their signs and are still highly significant, we confirm our preceding results.

In the second step, we test whether subjects in our experiment learn within tasks, i.e. whether individual disposition effects decrease from round to round, resp. from the first part of the experiment to the second part. We first compare individual level disposition effects in the first round(s) played by a subject with his or her disposition effects in later rounds.

(insert table 7 about here)

As table 7 reveals, subjects reduce their individual disposition effects significantly in the housing treatment as well as the second part of the stock market treatment. The attenuation of the disposition effect is based on both a reduction of subjects' tendencies to sell winners too quickly and an increase in subjects' willingness to sell their losers.

Second, we test whether subjects in the experiment similar to investors in the field also learn over time, i.e. between the first and the second part of the experiment. Table 8 documents average DE, PWR, and PLR measures as well as p-values.

(insert table 8 about here)

Although the disposition effect is present in both parts of the experiment, individual level DE measures decrease considerably over time. Subjects, again, reduce their bias by both selling losers more often and winners less often.

Having found an effect of learning, we finally want to shed some light on which factors might influence the effects. We regress proportions of winners realized, proportions of loser realized, and individual disposition effects in the field on trading habits and individual characteristics. We also present results for the overall individual disposition effect, to indicate that gain as well as loss side can be responsible for the effect. For the regression analysis we use ordinary least squares as well as censored Tobit regressions.

(insert table 9 about here)

Our regression analysis provides us with three significant explanatory variables for individual level disposition effects, and effects for the gain and loss side. Individual disposition effects decrease with income and the total number of trades during the sample period, but increase if an investor follows an aggressive trading strategy. Compared to the average DE measure of 0.09, the reported effects are, with coefficients of -0.03 or 0.04, also economically significant. Table 9 reveals that rich investors exhibit lower disposition effects mainly because they sell their losers more often, while their PWR decreases only insignificantly. Trading experience, on the other hand, reduces individual investors' tendencies for selling winners and increases their willingness to sell losers. Finally, investors following aggressive investment strategies cash in their winners much more frequently than other investors. Concerning losers, however, these investors exhibit trading habits that equal those of all others.

5 Discussion

The combination of our field data set and our laboratory experiment allows us to derive several new insights concerning individual level disposition effects. Splitting the disposition effect into its two components, i.e. investors' tendencies for cashing in winners and their reluctance to sell losers shows that, on an individual level, the two sides of the disposition effect are not systematically related. Those investors exhibiting a strong tendency to quit winning investments quickly are not necessarily the same investors who stick to their losing ones. Instead, some investors seem to be particularly biased towards "cashing in", while others cannot overcome their "loss realization aversion". This finding of general asymmetry constitutes an antithesis to how the disposition effect is usually depicted in behavioral finance models (see e.g. Grinblatt and Han 2005).

We also show that these individual differences are not merely random but stable on an individual level within tasks, across tasks, and across time. Investors' attitudes towards winners and losers thus appear as stable personality traits. Unaffected by this general stability, we also find that learning within tasks and over time reduces the magnitude of this bias. Finally, in a regression analysis based on our field data set, we highlight possible determinants of the above-mentioned heterogeneity. We find that individual investors with high incomes are more likely to sell their losers, while investors following aggressive investment strategies tend to realize their winners more frequently. Trading experience, on the other hand, makes investors sell their winners less and their losers more often.

By proving evidence on general stability and learning, our paper sets the foundations for previous as well as future research concerning the identification of disposition effect investors, the causes of the disposition effect, its impact on market prices and volume, and possible counteractive measures. However, while investors might be individually classified as being either more or less affected by the disposition effect, one should be aware that the disposition effect actually constitutes two separate and uncorrelated biases. On an individual level, investors often either appear to have a preference for cashing in winners quickly or are reluctant to sell losers, while they behave quite rational concerning the other side of the disposition effect..

Based on our findings, it might also be of value to further investigate why certain investors are so interested in selling their winners or are so reluctant to sell their losers, i.e. an in-depth analysis on the interdependence between an investor's personal characteristics as studied in psychology, financial sophistication, etc. on one side and his investment decisions on the other. The question is whether those people exhibiting above-average investment biases do so due to a lack of understanding of the market they trade in or the game they play, a lack of general or specific financial sophistication, or emotional reactions unrelated to rational decision making. The impact of frequent trading on investment sophistication in particular requires further research.

For practitioners in finance and banking it should be valuable information that their customers' individual disposition effects are indeed stable over tasks and time. Practitioners could apply this information in two different ways: They might either identify biased investors and help them to counter their investment mistakes by providing specific information or by offering learning tools, e.g. via the internet. Customers who are aware of this additional service could be willing to pay a premium for good investment advice. Conversely, financial engineers might use our findings to create financial products that exploit their customers' loss realization aversion. Products e.g. might be framed in a way that mentally traps and hinders customers to disinvest in the future.

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Table 1: Descriptive statistics (field)

This table summarizes the data used in our field data study. We report investor characteristics, information on their trading behavior, and their portfolio size. While our data set contains 3,079 individual investors, only 2,978 investors trade in Euro or German Mark and are therefore considered in our analysis. Investor characteristics were collected by the discount broker when the investors opened their accounts. Investment experience and income were collected in ranges or categories, respectively.

Investor characteristics			
# of accounts in dataset			2,978
Age in years	Mean		40.92
	Median		39.00
	Std. dev.		10.24
	# of obs.		2,463
Gender	Female	144	(4.84 %)
	Male	2,834	(95.16 %)
	# of obs.	2,978	(100.00 %)
Investment experience	0 – 5 years	1,024	(43.95 %)
	5 – 10 years	1,256	(53.91 %)
	10 – 15 years	15	(0.64 %)
	Over 15 years	35	(1.50 %)
	# of obs.	2,330	(100.00 %)
Income in thousand German Marks	0 – 50	140	(12.83 %)
	50 – 100	469	(42.99 %)
	100 – 150	314	(28.78 %)
	150 – 200	101	(9.26 %)
	Over 200	67	(6.14 %)
	# of obs.	1,091	(100.00 %)
Investment strategy	High current profits	67	(2.87 %)
	No strategy	1,247	(53.45 %)
	Retirement savings	112	(4.80 %)
	Short term capital gains	77	(3.30 %)
	Speculative	360	(15.43 %)
	Well-balanced	470	(20.15 %)
	# of obs.	2,333	(100.00 %)

Trades		
# of trades	Mean	82.85
	Median	44.00
	Std. dev.	133.23
Trading volume in Euro	Mean	536,206
	Median	142,769
	Std. dev.	1,794,121

Portfolios		
# of stocks per month	Mean	5.52
	Median	4.29
	Std. dev.	4.72
Portfolio value per month	Mean	36,088
	Median	14,675
	Std. dev.	93,149

Table 2: Disposition effect on aggregate (experiment)

The table reports mean values for proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) for both tasks and both parts of the experiment. The next two columns report the number of subjects exhibiting DE measures higher than, smaller than, or equal to zero. P-values in the right-hand column are based on binomial tests.

Part	Treatment	Mean PWR	Mean PLR	Mean DE	# DE > 0	# DE ≤ 0	p
First	Stocks	0.38	0.14	0.24	83	30	0.0000
	Housing	0.46	0.20	0.26	89	24	0.0000
Second	Stocks	0.28	0.21	0.07	63	50	0.1294
	Housing	0.40	0.24	0.15	80	33	0.0000

Table 3: Correlations of PWR and PLR measures (field)

This table reports Spearman's rank correlation coefficients between individual level proportions of winners realized (PWR)and between proportions of losers realized (PLR) over years, i.e. between 1997 (year 1) and 2000 (year 4), for our field data study. P-values are given in parentheses.

PWR	Year 1	Year 2	Year 3	Year 4
Year 1	1.00			
Year 2	0.40 (0.0000)	1.00		
Year 3	0.32 (0.0000)	0.48 (0.0000)	1.00	
Year 4	0.27 (0.0000)	0.40 (0.0000)	0.53 (0.0000)	1.00

PLR	Year 1	Year 2	Year 3	Year 4
Year 1	1.00			
Year 2	0.39 (0.0000)	1.00		
Year 3	0.35 (0.0000)	0.40 (0.0000)	1.00	
Year 4	0.33 (0.0000)	0.34 (0.0000)	0.40 (0.0000)	1.00

Table 4: Correlations of PWR and PLR measures within the first and second parts of the stock market treatment (experiment)

The table reports Spearman's rank correlation coefficients between individual level proportions of winners realized (PWR) and between proportions of losers realized (PLR) over rounds 1 to 3 in the stock market treatment for the first and second parts of the experiment. P-values are given in parentheses.

PWR, 1	Round 1	Round 2	Round 3
Round 1	1.00		
Round 2	0.62 (0.0000)	1.00	
Round 3	0.63 (0.0000)	0.61 (0.0000)	1.00

PWR, 2	Round 1	Round 2	Round 3
Round 1	1.00		
Round 2	0.68 (0.0000)	1.00	
Round 3	0.75 (0.0000)	0.64 (0.0000)	1.0000

PLR, 1	Round 1	Round 2	Round 3
Round 1	1.00		

PLR, 1	Round 1	Round 2	Round 3
Round 1	1.00		

Round 2	0.31 (0.0009)	1.00	
Round 3	0.32 (0.0009)	0.39 (0.0000)	1.00

Round 2	0.61 (0.0000)	1.00	
Round 3	0.58 (0.0000)	0.35 (0.0005)	1.0000

Table 5: Correlations of PWR measures across tasks and time (experiment)

The table reports Spearman's rank correlation coefficients between proportions of winners realized (PWR) and between proportions of losers realized (PLR) for the stock market treatment and the housing treatment, and the first and second parts of the experiment. P-values are given in parentheses.

PWR		First part		Second part	
		Stocks	Housing	Stocks	Housing
First part	Stocks	1.00			
	Housing	0.15 (0.1079)	1.00		
Second part	Stocks	0.73 (0.0000)	0.18 (0.0536)	1.00	
	Housing	0.26 (0.0062)	0.38 (0.0000)	0.29 (0.0017)	1.00

PLR		First part		Second part	
		Stocks	Housing	Stocks	Housing
First part	Stocks	1.00			
	Housing	0.30 (0.0011)	1.00		
Second part	Stocks	0.47 (0.0000)	0.28 (0.0028)	1.00	
	Housing	0.28 (0.0027)	0.53 (0.0000)	0.34 (0.0003)	1.00

Table 6: Learning over time (field)

This table shows mean values for proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) for both those investors starting at positive and those starting at negative disposition effects. Mean values are reported separately for the first (1997 to 1998) and second (1999 to 2000) halves of the field data sample period. The first three entries report mean values for standard PWR, PLR, and DE measures, with DE defined as the difference between PWR and PLR. The next three columns report mean values of residuals of PWR, PLR, and DE resulting from a two-sided censored Tobit regression using portfolio size as the single explanatory variable. The last column shows mean values for an alternative disposition effect measure which is calculated as PWR / PLR. P-values are based on signtests which compare individual measures for the first and the second part of the sample period.

		Mean PWR	Mean PLR	Mean DE	Mean PWR r.	Mean PLR r.	Mean DE res.	Mean alt. DE
Positive	97 – 98	0.43	0.14	0.29	0.07	-0.05	0.22	3.24
DE	99 – 00	0.31	0.20	0.10	0.01	-0.01	0.03	2.60
	p	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000
Negative	97 – 98	0.17	0.38	-0.21	-0.13	0.16	-0.23	0.51
DE	99 – 00	0.20	0.22	-0.02	-0.03	0.03	-0.05	1.23
	p	0.0456	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 7: Learning within tasks (experiment)

This table shows mean values for proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) for the stock market and the housing treatment. Mean values are reported separately for the first and second parts of the experiment as well as for first round(s), i.e. round 1 in the stock market and rounds 1 to 3 in the housing treatment, and later rounds, i.e. rounds 2 and 3 in the stock market and rounds 4 to 6 in the housing treatment. P-values are based on signtests which compare individual measures between the first round(s) and later rounds.

		Stock market treatment			Housing treatment		
		Mean PWR	Mean PLR	Mean DE	Mean PWR	Mean PLR	Mean DE
First part	First round(s)	0.40	0.14	0.27	0.50	0.20	0.30
	Later rounds	0.38	0.15	0.23	0.48	0.24	0.24
	p	0.2754	0.0519	0.1713	0.3468	0.1204	0.0407
Second part	First round(s)	0.33	0.23	0.11	0.39	0.24	0.15
	Later rounds	0.27	0.21	0.08	0.41	0.29	0.12
	p	0.0092	0.5429	0.0898	0.2060	0.0009	0.0297

Table 8: Learning over time (experiment)

This table shows mean values for proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) for the stock market and the housing treatment. Mean values are reported separately for the first and second parts of the experiment. P-values are based on signtests which compare individual measures between both parts.

	Stock market treatment			Housing treatment		
	Mean PWR	Mean PLR	Mean DE	Mean PWR	Mean PLR	Mean DE
First part	0.38	0.14	0.24	0.46	0.20	0.26
Second part	0.28	0.21	0.07	0.40	0.24	0.15
P	0.0000	0.0018	0.0000	0.0035	0.0000	0.0003

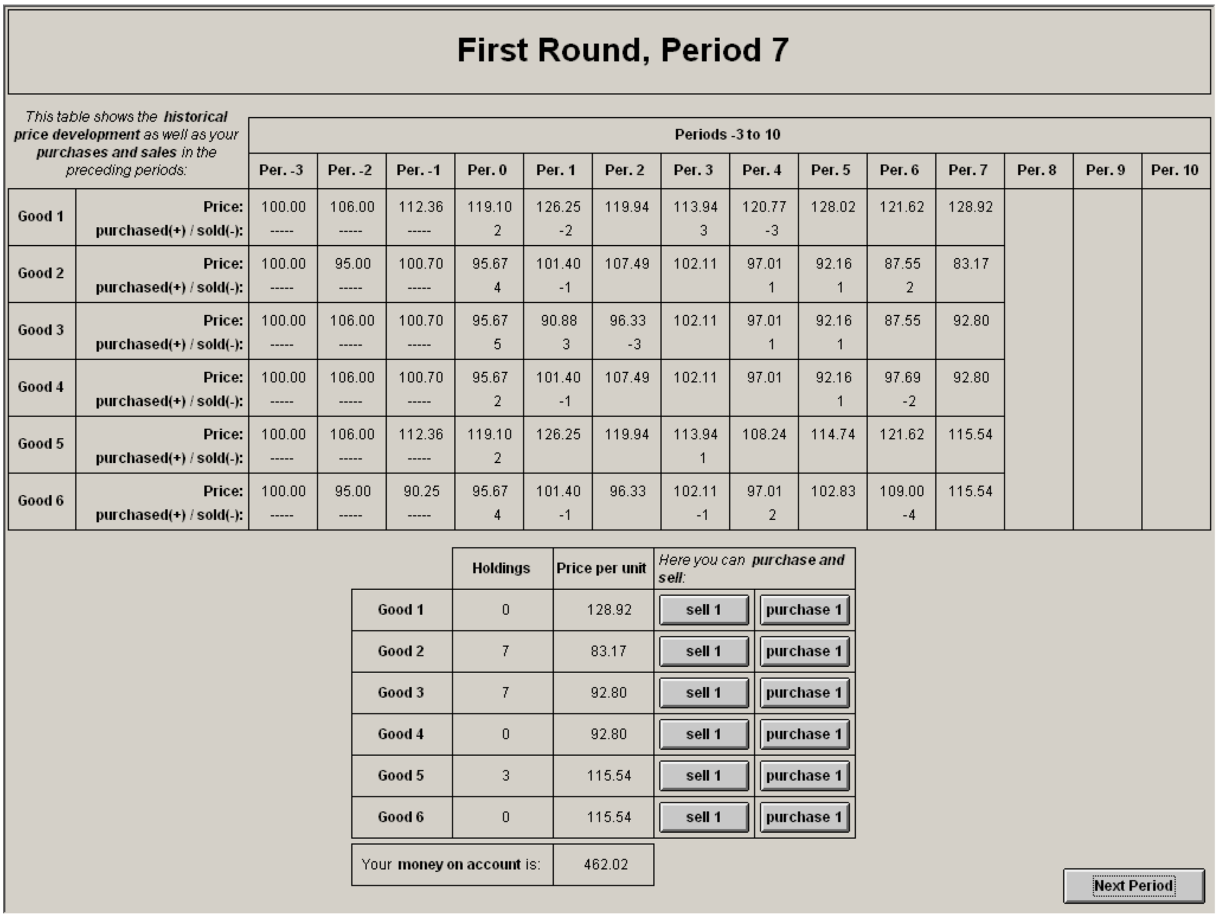
Table 9: Determinants of PWR, PLR, and DE measures (field)

The table documents the results of simple ordinary least squares regressions as well as two-sided censored Tobit regressions. We regress proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) on individual characteristics and trading habits. P-values are given in parentheses.

	PWR		PLR		DE	
Explanatory variable	OLS (bin.)	Tobit (bin.)	OLS (bin.)	Tobit (bin.)	OLS (bin.)	Tobit (bin.)
Age	-0.01	-0.01	-0.02	-0.02	-0.00	-0.00
(logarithm)	(0.820)	(0.790)	(0.403)	(0.431)	(0.954)	(0.980)
Gender	-0.01	-0.01	-0.02	-0.02	0.02	0.02
(dummy; men = 1)	(0.814)	(0.720)	(0.611)	(0.604)	(0.629)	(0.624)
Investment experience > 5 years	-0.02	-0.03	-0.02	-0.02	-0.01	-0.01
(dummy)	(0.038)	(0.036)	(0.172)	(0.233)	(0.624)	(0.593)
Income > 100,000 DM	-0.01	-0.01	0.02	0.02	-0.03	-0.04
(dummy)	(0.301)	(0.336)	(0.064)	(0.081)	(0.025)	(0.025)
Aggressive investment	0.04	0.04	-0.00	-0.01	0.04	0.04
strategy (dummy)	(0.001)	(0.001)	(0.699)	(0.677)	(0.008)	(0.008)
Retirement savings	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01
(dummy)	(0.320)	(0.293)	(0.622)	(0.595)	(0.741)	(0.745)
Trades	-0.02	-0.02	0.02	0.03	-0.03	-0.03
(logarithm)	(0.003)	(0.005)	(0.042)	(0.003)	(0.009)	(0.008)
Average portfolio size	-0.25	-0.26	-0.23	-0.24	-0.02	-0.02
(logarithm)	(0.000)	(0.000)	(0.000)	(0.000)	(0.172)	(0.171)
Constant	0.83	0.861	0.63	0.61	0.21	0.21
	(0.000)	(0.000)	(0.000)	(0.000)	(0.103)	(0.105)
# of observations	846	846	832	832	819	819
R^2	0.53		0.36		0.05	
F	117.08		57.46		5.23	
χ^2		582.05		297.16		41.56
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Figure 1: Computer screen for stock market design

The figure shows a translation of the computer screen for the stock market treatment. The rows in the upper table represent the six goods, the columns represent periods -3 to 10. Cells in the upper table contain two types of information: The upper figure is the price of the corresponding good in this period. The number underneath shows how many units of this good the subject purchased (positive number) or sold (negative number) in this period. The first column in the bottom table shows the subject's current holding of the six goods. In the next column you again see the current price per unit of the corresponding good. Next to the prices, the lower table contains twelve buttons, labeled "sell 1" and "purchase 1" which the subject could click for purchasing and selling single units of the six goods. Below the small table you see the current money account. If the subject decided to continue to the next period, he could click on the "Next Period" button at the lower right-hand corner of the screen. The screen was explained to subjects in a preceding tutorial session.



First Round, Period 7

This table shows the **historical price development** as well as your **purchases and sales** in the preceding periods:		Periods -3 to 10													
		Per. -3	Per. -2	Per. -1	Per. 0	Per. 1	Per. 2	Per. 3	Per. 4	Per. 5	Per. 6	Per. 7	Per. 8	Per. 9	Per. 10
Good 1	Price:	100.00	106.00	112.36	119.10	126.25	119.94	113.94	120.77	128.02	121.62	128.92			
	purchased(+) / sold(-):	-----	-----	-----	2	-2		3	-3						
Good 2	Price:	100.00	95.00	100.70	95.67	101.40	107.49	102.11	97.01	92.16	87.55	83.17			
	purchased(+) / sold(-):	-----	-----	-----	4	-1			1	1	2				
Good 3	Price:	100.00	106.00	100.70	95.67	90.88	96.33	102.11	97.01	92.16	87.55	92.80			
	purchased(+) / sold(-):	-----	-----	-----	5	3	-3		1	1					
Good 4	Price:	100.00	106.00	100.70	95.67	101.40	107.49	102.11	97.01	92.16	97.69	92.80			
	purchased(+) / sold(-):	-----	-----	-----	2	-1				1	-2				
Good 5	Price:	100.00	106.00	112.36	119.10	126.25	119.94	113.94	108.24	114.74	121.62	115.54			
	purchased(+) / sold(-):	-----	-----	-----	2			1							
Good 6	Price:	100.00	95.00	90.25	95.67	101.40	96.33	102.11	97.01	102.83	109.00	115.54			
	purchased(+) / sold(-):	-----	-----	-----	4	-1		-1	2		-4				

	Holdings	Price per unit	*Here you can **purchase and sell**:*	
Good 1	0	128.92	sell 1	purchase 1
Good 2	7	83.17	sell 1	purchase 1
Good 3	7	92.80	sell 1	purchase 1
Good 4	0	92.80	sell 1	purchase 1
Good 5	3	115.54	sell 1	purchase 1
Good 6	0	115.54	sell 1	purchase 1
Your **money on account** is:		462.02		

Next Period

Figure 2: Computer screen for housing design

The figure shows a translation of the computer screen for the housing treatment. The rows in the table represent the five houses the subject inherited. Columns represent years 2005 to 2010. Cells in the table contain two types of information: The upper entry is the price of the house in the corresponding year. If the subject decided to sell the house in a particular year the comment “sold” appears underneath the price. Beneath the table you see a row containing the probabilities of price increases for all years. The bold probability is the current one. Next to the table you see 5 buttons labeled “sell house 1” to “sell house 5” which the subject could click to sell the corresponding house. If the subject decided to continue to the next year, he could click on the “Next Year” button at the lower right-hand corner of the screen. The screen was explained to subjects in a preceding tutorial session.

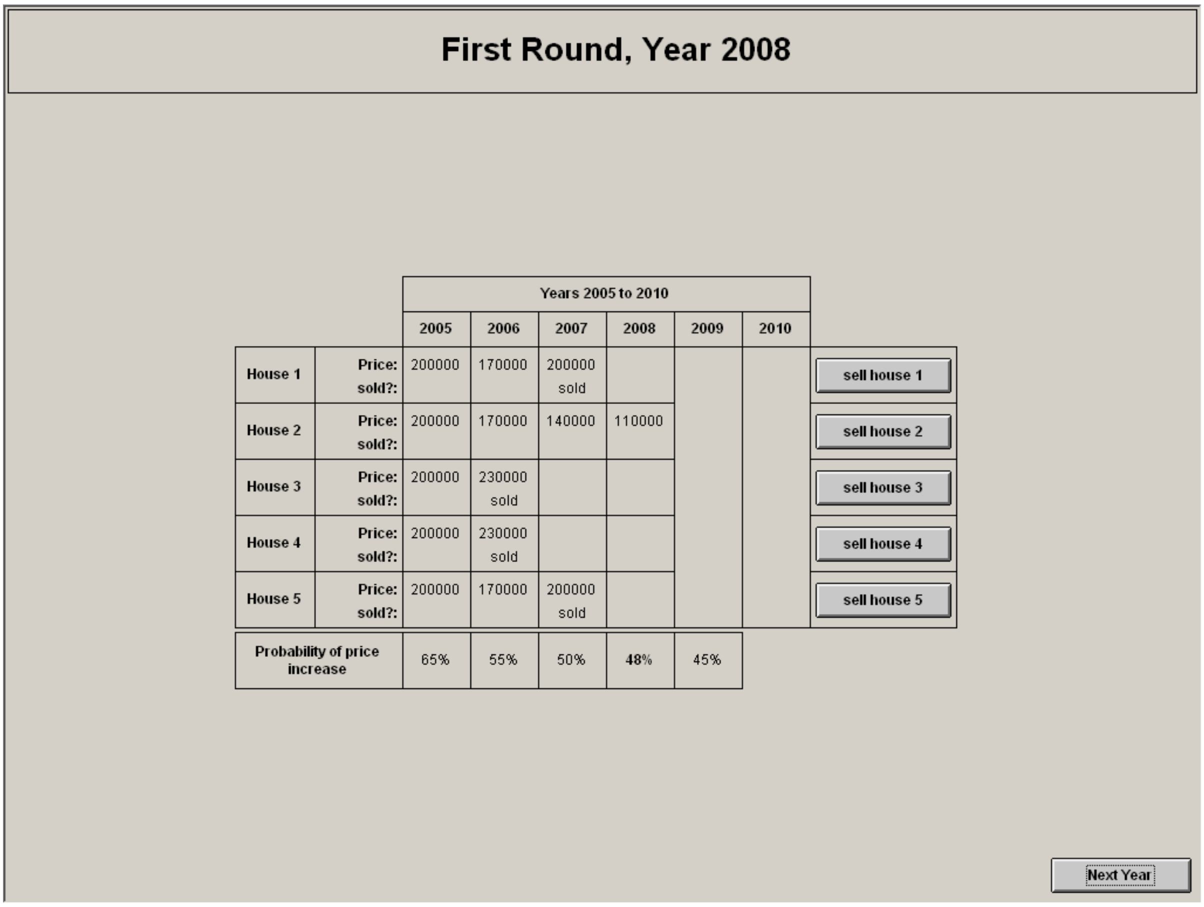


Figure 3: Correlations between PWR and PLR measures (field)

The graphs plot the correlation between proportions of winners realized (PWR) and proportions of losers realized (PLR) for the field data study. Each dot stands for an investor's PWR / PLR combination. Black dots mark individual level disposition effects (DE) higher than 0, while negative or zero disposition effects are market by white dots. The left-hand graph shows the correlation between standard PWR and PLR measures as defined in section 4.1. The right-hand graph plots the same correlation for PWR and PLR residuals resulting from a two-sided censored Tobit regression using portfolio size as the single explanatory variable.

Uncontrolled PWR and PLR | Controlled PWR and PLR

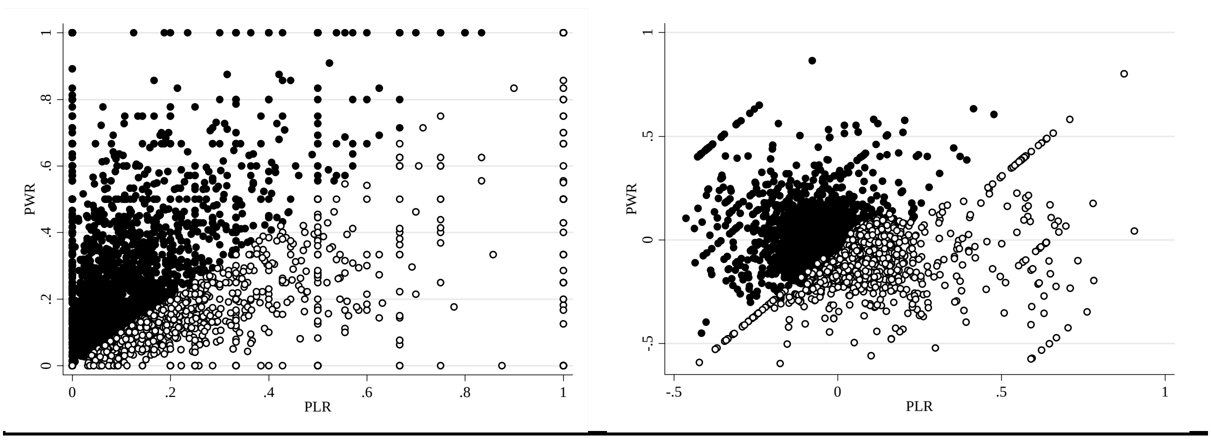


Figure 4: Correlations between PWR and PLR measures (experiment)

The graphs plot the correlation between proportions of winners realized (PWR) and proportions of losers realized (PLR) for both experimental treatments. Each dot stands for a subject's PWR / PLR combination. Black dots mark individual level disposition effects (DE) higher than 0, while negative or zero disposition effects are market by white dots.

Stock market treatment | Housing treatment