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An Individual Level Analysis of the Disposition Effect: Empirical and Experimental Evidence

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Abstract: We test empirically and experimentally for individual differences, stability, and learning in individual level disposition effects. While we observe the disposition effect on aggregate, the extent to which a single decision maker is affected varies considerably across investors. We find overwhelming evidence for stability of individual disposition effects both within and across tasks, as well as across time. Learning, nevertheless, attenuates the magnitude of the effect strongly within tasks and over time. In accordance with prior research, we document that frequent traders sell their winners less and their losers more often, resulting in lower disposition effects. We also document evidence that the magnitude of the bias depends on the length of the holding period.

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1 Introduction

Behavioral finance builds on the fact that investors in certain situations systematically defy neoclassic theory. Thereby it commonly assumes that individuals exhibit these biases to different degrees and that the magnitude of an individual bias is stable over different market regimes, different economic situations, and time. Biases need to be stable if we want to identify biased investors or if we want to be able to consistently explain its causes. We want to test whether this general stability assumption holds for individual investors. Therefore, we pick one of the most important biases in behavioral finance, the so-called disposition effect.

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 Meyer (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). As for most biases discussed in behavioral finance, it remains unknown whether an investor's tendency of being affected by the disposition effect is actually a stable personality trait, or only temporary behavior strongly influenced by day-to-day changes in mental attitude or mood. By documenting evidence for stability in individual level disposition effects, our paper provides the basis for prior, as well as further research concerning individual differences in the disposition effect, its causes, its impact on market prices and volume, and possible counteractive measures. In science, our findings are especially useful for multi-agent models, like Grinblatt and Han (2005). In practice, banks providing investment advice to their customers could especially benefit from our research.

Our paper aims to investigate individual differences, stability, and learning in the disposition effect, determinants of the disposition effect, and holding period effects. To answer our research questions, we apply a combination of different methodologies. In the first step, we analyze trading behavior of actual stock market investors. Our field data study is based on the 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, income, investment strategy, and investment experience). In the second step, we analyze individual level disposition effects in an individual choice experiment. The experiment consists of two parts which 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 individual choice 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 for 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 our field data set, as well as for each task in the experiment, 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. As expected, we find that both investors in the field and subjects in the individual choice treatments 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 even twice as likely to be cashed in. However, we also find strong heterogeneity among individuals. While most investors are positively affected by the disposition effect, a considerable number of investors act in the opposite way. In the field and in our experiment, about 1/3 of all investors sell their losers more often than their winners, or equally often. In both settings, we also 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.

In the next step, we test for stability within tasks, across tasks, and across time by correlating individual disposition effect measures 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 disposition effect, as well as its two building blocks, i.e. proportions of winners and losers realized, is indeed stable for all the tested dimensions. However, we also find that investors learn within tasks and over time and correct their behavior towards the rational benchmark. In a regression done with our field data set, we find that investors with high incomes sell their losers more often, whereas investors following aggressive investment strategies sell their winners more often than other investors. In accordance with prior research (Dhar and Zhu (2005) and Shumway and Wu (2005)) we also find that individual disposition effects decrease with trading experience. Investors who are engaged in frequent trading realize their winners less and their losers more readily. In a final analysis, we document for both the empirical and the experimental data set that disposition effects decrease considerably over the holding period of a stock, thus supporting the common assumption that individual investors might need some time to accept their losses and to overcome their loss realization aversion (Kahneman and Tversky (1979) and Shefrin and Statman (1985)).

The paper is structured as follows. In section 2 we review related literature concerning the disposition effect 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. This behavior is typically explained by prospect theory (Kahneman and Tversky (1979) and Tversky and Kahneman (1992)) in combination with mental accounting (Thaler (1980, 1985)), using a stock’s purchase price as the reference point. 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. exhibit the disposition effect. 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 (2003)), Chinese (Chen, Kim, Nofsinger, and Rui (2004)), 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 professional investors. 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) as well as Locke and Onayev (2005).

The disposition effect, however, does not only apply to real financial markets, but also to different economic situations such as housing markets or economic experiments. Genesove and Meyer (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 effect 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.

Our paper focuses on research questions largely unanswered. We therefore investigate the disposition effect on the individual level. Firstly, we want to shed some more light on individual differences. Investigating individual differences is not only important for its own sake, but also inevitable for our other research questions. Without variance in the distribution of individual level disposition effects, we are unable to distinguish between investors and thus cannot test for stability, learning, determinants, or holding period effects. We therefore test the following two hypotheses with both our field data set and each experimental treatment:

Hypothesis 1: (Disposition effect on aggregate) Individual investors realize their gains quicker than they realize their losses.

Hypothesis 2: (Individual differences) There are individual differences in how far an investor is affected by the disposition effect.

In addition, as the disposition effect is a two-sided effect, it seems natural to investigate whether we can find symmetry. The question is whether investors who exhibit the disposition effect do so because they sell winners too early, losers too late, or both. We therefore test hypothesis 3:

Hypotheses 3: (Symmetry) Investors that exhibit the disposition effect tend to both sell their winners too early and their losers too late.

The question of whether the disposition effect is a stable bias is also largely unanswered. To our knowledge, there is no study which compares individual level disposition effects across different settings, e.g. the stock and the housing market. In addition, it is quite unclear whether individual level disposition effects 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 (2005), 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. Note, however, that since investors are in the stock market for many years, they are continuously engaged in the same game. We find it therefore desirable to let them alternatively clear their mental accounts and restart the game, thus having no unrealized gains or losses from previous rounds and less overlapping effects. This is exactly what we try to achieve with our experiment. For testing stability within tasks, we analyze whether experimental subjects who exhibit a relatively strong disposition effect within one round of a task are also highly affected in other rounds of the same task. Analyzing our experimental data, we also test whether individual level disposition effects are correlated across 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 4a: (Stability within tasks) Individual level disposition effects are correlated within tasks.

Hypothesis 4b: (Stability across tasks) Individual level disposition effects are correlated across different tasks.

Hypothesis 4c: (Stability across time) Individual level disposition effects are correlated 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)). We apply hypothesis 5 to test for learning within tasks and over time both with our field data and our experimental data set:

Hypothesis 5: (Learning) Learning decreases disposition effects on aggregate.

In addition, our field data set allows us to analyze which factors determine or influence individual level disposition effects. We therefore regress disposition effects on individual characteristics and trading habits. 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. (2003), Dhar and Zhu (2005), Grinblatt and Keloharju (2001), Shapira and Venezia (2001), and Shumway and Wu (2005) find that sophistication indeed weakens the disposition effect, Chen et al. (2004) find an opposite effect for the Chinese market. We test for similar effects in our data set and propose the following hypothesis:

Hypothesis 6: (Determinants) Individual level disposition effects decrease with trading experience.

In a final analysis, we test whether the disposition effect is stable over the holding period of the stock. We hypothesize that, as individual investors might need some time to get used to and accept their losses (See Kahneman and Tversky (1979) and Shefrin and Statman (1985)), they might be more willing to sell a loser if it has been in their mental account for a long time. We therefore propose hypothesis 7:

Hypothesis 7: (Holding Period Effect) Individual level disposition effects decrease over the length of the holding period.

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, income, investment strategy, and investment experience), and a third data set containing price information from datastream on the securities traded.

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 Deutsche Mark. The mean (median) age of investors in our data set equals 40.92 (39.00) years. Approximately 95 % of our investors are male. Investment experience and income were collected in ranges. If we use the midpoint of each range, and 17.5 years or DM 225,000 for the top classes, we obtain an average investor with 5.48 years of investment experience and with a salary of over DM 101,000 (almost € 52,000). In the online broker's questionnaire, 53.45 % of our investors state that they do not follow a specific strategy, while 21.60 % indicate that they are following aggressive strategies, i.e. "high current profits", "speculative", and "short term capital gains". Only a small number of investors, i.e. 4.80 %, state that they are saving for their retirement. The rest, i.e. 20.15 %, wants to follow a well-balanced investment strategy. This information sheds some light on how these investors think about their investments, with aggressive investment strategies probably being most affected by the disposition effect.

Table 1 also provides descriptive statistics on trades and portfolios. As the statistics document, there are few investors on the right hand side of the distribution who hold big portfolios and drive trading volume. The average (median) investor trades 82.85 (44.00) times during the sample period, generating a trading volume of approximately € 536,000 (€ 143,000). As our investors hold an average (median) number of only 5.52 (4.29) stocks in their portfolio, they seem largely indifferent to diversification. The average (median) portfolio has a value of approximately € 36,000 (€ 15,000).

(insert table 1 about here)

More information on our field date set can be found in Glaser (2003).

3.2 Experimental Data

We measure individual level disposition effects, both in a multiperiod investment task similar to Weber and Camerer (1998) and Weber and Welfens (2005), and a framed housing task. In the following we explain these experimental designs as well as the experimental procedure in detail.

3.2.1 Individual Choice 1: Stock Market Design

The first treatment is an individual choice task. We call this 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 non-negative. In period 10 the round ends and the subjects are informed about the final value of the six 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 (round 1), a neutral (round 2), and a downward moving market (round 3). Table 2 gives an overview on probabilities used in the three different rounds for each of the six goods.

(insert table 2 about here)

Under the neutral market regime we have two goods exhibiting a negative trend, two goods set up to oscillate around the starting price of 100, and two goods with an upward moving trend. The upward and downward moving markets are similar to the neutral market, but omit the one good that shows the worst or best price trend and exchange it with another good offering the same trend as the best or worst good respectively. As an example, figure 2 shows the price paths generated for round 1 of the first part of the experiment.

(insert figure 2 about here)

While our subjects are not informed about the real probabilities underlying the six goods, they could heuristically derive simple probability estimators 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 %.[2] Ignoring diversification effects, or assuming risk neutrality, a subject should invest only in the highest priced good. If there are a couple of 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

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

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 payoff 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 Individual Choice 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. In addition, 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 3 shows the computer screen of the treatment.

(insert figure 3 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 on themselves, nor rent them to other people, and 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 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, optimal strategies depend on risk aversion. While almost all subjects would 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. The first part took place on May 17 – 19, the second part four weeks later on June 13 – 17. 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.[3] 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. To ensure that everyone understood the rules and computer screens, subjects had to go through short tutorial sessions. The average processing time was approximately 50 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.

[3] 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.

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 calculated as

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

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. Table 3 shows mean PWR, PLR, and DE measures of individual investors in our field data set.

(insert table 3 about here)

On average, individual investors 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 US discount broker clients. Dhar and Zhu (2005) repeat the analysis on the individual level similar to our study and document an average DE measure of 0.21.

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[4] a majority of 1,711 investors (65.46 %) are positively affected. 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. The p-value given in table 3 is based on a binomial test and shows that positively affected investors nevertheless still clearly dominate the field.

For our experiment, we could compare the distribution of individual level disposition effects with two different benchmarks: 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. If

[4] PWR and PLR measures are only defined for those investors who have at least one selling opportunity at a gain or at a loss. If an investor has no opportunity to sell either winners or losers, we cannot calculate his or her DE measure because we have no information about his or her reactions towards gains or losses.

subjects, on the other hand, follow a simple heuristic strategy and always hold the good(s) with the highest price or sell all houses in the year 2008, we expect low and most of the time even negative DE measures.[5, 6] Table 4 shows mean PWR, PLR, and DE measures, as well as DE measures which would arise from this simple heuristic strategy. It also reports the number of subjects exhibiting positive and negative or 0 disposition effects as well as p-values based on binomial tests.

(insert table 4 about here)

Table 4 provides strong evidence of a disposition effect. Subjects use their selling opportunities in the stock market treatment following gains almost twice as regularly as they do 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 (1998) 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. In unreported tests we also confirm that the disposition effect is present in all but one round of the stock market design and all but one round of the housing task. The rounds that lead to insignificant disposition effects are nevertheless exceptional rounds, as a rational strategy would lead to extremely low DE measures of -0.83 and -0.56. Compared to the rational benchmark, disposition effects are highly significant for all tasks, both parts, and all rounds of the experiment. It should also be noted that by exhibiting the

[5] 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 the subject already possesses. If this is the case, the subject should sell some of the units of the good he already possesses and buy units of the other good to decrease his portfolio risk.

[6] As this strategy underlies strong assumptions concerning our subjects' rationality, their mathematical capabilities, and their risk attitudes, and in addition is strongly path dependent, we do not want to put too much weight on this benchmark. As our subjects' trading behavior is obviously not driven by rational considerations, we believe that the 0 benchmark is a much better comparison.

disposition effect, our subjects leave money on 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 Individual Differences and Symmetry

The disposition effect does not affect all investors to the same extent. Consistent with hypothesis 2 we find instead strong individual differences concerning how far an investor is influenced by this bias. Figures 4 to 6 show the distributions of PWR, PLR, and DE measures for our field data study and the two individual choice tasks.

(insert figures 4 to 6 about here)

The distributions document quite strongly that investors react differently given unrealized gains. While some investors never sell their winners and thus exhibit PWR measures of 0, other investors sell their winners whenever they have an opportunity to do so, resulting in PWR measures of 1. Compared to PWR measures, distributions of PLR measures put more weight on the left hand side of the scale. While almost all investors avoid selling for a loss, it is striking that many investors do not sell for a loss at all during the whole sample period or the entire treatment, and thus show the strongest possible degree of loss realization aversion.

When comparing distributions of PWR and PLR measures, one gets the idea that holding on to losers too long is more common among investors than selling winners too soon. We test this hypothesis using a robust Levene test for the equality of variances. Table 5 shows the results.

(insert table 5 about here)

As expected, individual differences are much more pronounced when investors are faced with opportunities to sell their winners, while it is much more difficult to distinguish between investors based on their loss realization aversion. Only for the housing treatment is the difference in standard deviations insignificant. This insignificance, however, is solely present in the first part of the experiment. In the second part, also in the housing treatment, standard deviations of PWR measures are significantly higher than standard deviations of PLR measures.

While 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 3)? If this is the case, we would expect a negative relationship between proportions of winners realized and proportions of losers realized.

(insert figure 7 and table 6 about here)

As documented in the left-hand graph of figure 7 and the first row of table 6, PWR and PLR measures in the field are positively and significantly correlated. Investors who realize their winners frequently also sell their losers relatively often. This correlation, however, could be artificially generated by our definition of PWR and PLR. Both measures are 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 e.g. investors normally only sell one stock on each selling day and some investors hold larger portfolios than others, these investors also generate a lot of selling opportunities compared to actual sales. This in turn leads to relatively low PWR and PLR measures.[7] To control for the possible influence of portfolio size on PWR and PLR, we regress both measures on logarythmic portfolio size using a two-sided censored Tobit regression. Portfolio size is therefore defined as the number of different stocks in the investor's portfolio. The residuals of this regression constitute the part of PWR or PLR which cannot be explained by portfolio size. The resulting correlation of residuals is shown in the right-hand graph of figure 7. As documented in the graph and tested in the second row of table 6, there is no correlation between proportions of winners realized and proportions of losers realized after controlling for portfolio size.

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. Figure 8 plots PWR and PLR measures for both the stock market and the housing treatment. Table 7 provides Spearman's rank correlation statistics.

(insert figure 8 and table 7 about here)

[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.

It reveals that there are no systematic correlation between PWR and PLR. While the sign is as expected, correlation coefficients are insignificantly small. We therefore repeat the same analysis for both parts of the experiment and find that only in the housing treatment of the first part of the experiment there is a significantly negative correlation between the two measures. In the other treatments correlations are insignificantly negative, or in the case of the housing treatment in the second part of the experiment, even positive.

To sum up this section, 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. Although most investors are affected by the disposition effect, a considerable number of investors acts in the opposite way, i.e. they tend to hold winners and to sell losers. Analyzing the two building blocks, we find strong heterogeneity concerning realization of winners and a more common agreement across investors that losses should not be realized. Furthermore, 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 exhibit the bias to this amount, because he never sells his losers while holding on to his winners for longer, or because he always sells his winners while also frequently selling his losers. In both cases the investor only shows 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 individual level disposition effects within tasks, across tasks, and across time, i.e. hypotheses 4a, 4b, and 4c. 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. By comparing individual level disposition effects 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 alter and complicate our stability analysis. If we nevertheless find significant correlations in individual level disposition effects across years, this should be a convincing finding for stability across time. Table 8 reports the results of the correlation analysis.

(insert table 8 about here)

Firstly, the table reveal that both proportions of winners realized, as well as proportions of losers realized, are highly and significantly correlated with average correlation coefficients of 0.40 for PWR and 0.37 for PLR measures. Cronbach alphas are 0.66 and 0.62 respectively.[8] In addition, pairwise correlations as well as Cronbach alphas show that consistency in behavior within a task is stronger for gains than for losses. Hence, consistent with our findings in section 4.3, it is easier to distinguish among investors by their attitude concerning realization of winners. Realization of losers, on the other hand, is so unpopular that differences across investors are less obvious and changes in rank occur more frequently. As a direct result of stability in PWR and PLR measures, individual level disposition effects are also stable over the sample period. Investors who exhibited a high disposition effect in 1997 are also likely to exhibit a relatively high disposition effect in the year 2000. The average correlation is 0.32 with a Cronbach alpha of 0.66. Furthermore, correlations of DE, 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 stability 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 could be affected by portfolio size, portfolio size could also serve as an external stabilizer for these measures. As a result, stable portfolio sizes could also lead to 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. As DE measures are defined as the difference between PWR and PLR, they also decrease. 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, PLR, and DE on logarythmic 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. For a second robustness check, we redefine how we calculate disposition effects. Instead of calculat-

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[8] In questionnaire studies designed to measure personality traits, Cronbach alphas higher than 0.7 are often regarded as acceptable reliability coefficients. See Nunnally (1978). As our studies were however neither intended nor designed to measure the disposition effect as one single underlying characteristic, and we are faced with a multitude of external influences in the field, we may even accept lower degrees.

ing DE as the *difference* between PWR and PLR, we now calculate it as PWR *divided by* PLR. This alternative DE measure is unaffected by symmetric changes in proportions of winners and losers realized and should thus not be biased by portfolio size. However, correlation coefficients for this measure are even higher than for our standard DE measure.

In the next paragraphs, we examine our experimental data. We begin by testing for stability within tasks, i.e. hypothesis 4a. Table 9 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 9 about here)

As the table reveals, PWR, PLR, and DE measures across rounds are highly correlated. For DE and PWR measures, all correlation coefficients are significantly higher than 0.5. Cronbach alphas for DE measures are 0.80 for the first and 0.84 for the second part of the experiment, which means that behavior in all rounds is highly inter-correlated and all DE measures seem to capture the same underlying personal characteristic.[9] The magnitude of the effect is particularly suprising if one considers that the three rounds are set up with different underlying probabilities for price increases and totally different price paths. We perform the same tests for the second individual choice treatment and obtain similar results. Under the housing design, correlation coefficients of DE measures last from 0.19 to 0.76 with Cronbach alphas of 0.89 and 0.88. In the two experimental treatments, as in our field data study, correlations and Cronbach alphas for PWR measures are again higher than for PLR measures.

Stability across tasks (hypothesis 4b) 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 4c) by analyzing changes in individual level disposition effects *between* the first and second parts.[10] Again, test statistics are based on Spearman’s rank correlation coefficients. Table 10 documents the results.

(insert table 10 about here)

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9 Glaser, Langer, and Weber (2005) calculate correlation coefficients of various overconfidence measures within tasks and find correlations to a similar degree. Their correlation coefficients vary between 0.92 and 0.19, while Cronbach alphas in their study vary between 0.96 and 0.59.

10 Note that the two parts of the experiment are separated by a four week interval.

Each correlation matrix can be split up into three different parts. The upper left-hand and the lower right-hand part 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 part of each matrix. For individual level disposition effects, we find significant correlations across tasks, with correlation coefficients of 0.23 for the first and 0.36 for the second part of the experiment. Correlations across time for the same task are even stronger with coefficients of 0.67 for the stock market and 0.44 for the housing treatment. Even a combination of different individual choice tasks and different points in time leads to statistically and economically significant correlations. For the whole DE matrix, we get a Cronbach alpha of 0.70.

Summing up, we find striking 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 solely based on our individual choice experiments. We conclude that individual level disposition effects do not vary within tasks, over tasks, or over time, but appear rather to be a stable personal characteristic. As individual differences are not just randomly generated, we are now ready to analyze the determinants of systematic heterogeneity.

4.5 Learning

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 disposition effects in this and all other groups. We test for learning, i.e. hypothesis 5, in two 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. Distinct from the field, subjects in the experiment should regularly sell their losers and stick to their winners, resulting in negative DE measures. We consequently test whether individual disposition effects decrease over rounds or between the first and second parts of the experiment.

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 11 presents the results.

(insert table 11 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 perform two different robustness checks. Firstly, we regress PWR, PLR, and DE on portfolio size using two-sided censored Tobit regressions and analyze the residuals only. Secondly, we calculate individual disposition effects not as the difference, but as the ratio between PWR and PLR. All measures should be unaffected by portfolio size effects. Table 11 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. We therefore compare individual level disposition effects in the first round(s) played by a subject with his or her disposition effects in later rounds. In the stock market treatment we compare DE, PWR, and PLR measures in the first round with measures in the second and third round. In the housing treatment we compare disposition effects in the first three rounds with disposition effects in the later three rounds.

(insert table 12 about here)

As table 12 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, i.e. PWR measures, and an increase in subjects’ willingness to sell their losers, i.e. PLR measures.

In a final test we question whether subjects in the experiment also learn over time, i.e. between the first and the second part of the experiment. Table 13 documents average DE, PWR, and PLR measures as well as p-values.

(insert table 13 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.

To sum up this section, we find strong evidence for learning within tasks and over time, supporting hypothesis 5. Depending on the initial sign of their bias, investors in the field either learn to sell their losers or winners more often while lowering their selling frequency for winners or losers respectively. In the laboratory, conversely, we discover a general tendency towards lower disposition effects within tasks and over time. Both, investors in the field and subjects in the experiment, thus try to reach the rational benchmark.

4.6 Determinants

After documenting stable individual differences in sections 4.3 and 4.4, we now want to shed some light on which factors might determine these differences. Consequently, we regress proportions of winners realized, proportions of loser realized, and individual disposition effects in the field on trading habits and individual characteristics. For the regression analysis we use ordinary least squares as well as censored Tobit regressions. The Tobit regressions control for the fact that PWR and PLR measures cannot be bigger than 1 or smaller than 0, as well as DE measures beeing between 1 and -1. Table 14 documents the results.

(insert table 14 about here)

Our regression analysis provides us with three significant explanatory variables for individual level disposition effects: 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 14 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, decreases 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, they exhibit trading habits which equal those of all others.

Although similar effects have been reported in Dhar and Zhu (2005), as well as Shumway and Wu (2005), in our view the interpretation of these findings is still problematic: Dhar and Zhu (2005) and Shumway and Wu (2005) interpret income and trading volume as proxies for financial sophistication and therefore conclude that more sophisticated investors are less affected by the disposition effect. While one might accept that income indeed proxies for education, we are particularly apprehensive about the interpretation of trading experience. As Barber and Odean (2000) document, individual investors suffer a tremendous performance penalty for excessive trading. One should thus not characterize active trades as being more sophisticated in general. An alternative interpretation might be that trading experience is a double-edged sword: Although investors in general suffer from their trading activity, they might nevertheless learn to avoid other behavioral bias, such as the disposition effect.

4.7 Holding Periods

If investors need time to accept their losses and to overcome their loss realization aversion, as proposed by Kahneman and Tversky (1979) and Shefrin and Statman (1985), we should expect an attenuation of the disposition effect over the length of the holding period of a stock. To test this hypothesis, we recalculate individual proportions of winners realized, proportions of losers realized, and disposition effect measures in the field based on holding periods. We report results for reference points defined as average purchase prices and holding periods calculated as the average time that the shares of the considered stock are in the investor's portfolio. All results are nevertheless robust if we apply the first purchase price and the first purchase day, the most recent purchase price and the most recent purchase day, or the highest purchase price and the corresponding purchase day as reference points or holding periods. Figure 9 shows the results for the first 30 days and for a four years period for our field data set.

(insert figure 9 about here)

In both graphs, PWR and PLR measures decrease over the length of the holding period. Because PWR measures decrease to a stronger extent, the difference between both measures, i.e.

the disposition effect, also attenuates. The disposition effect is nevertheless still present even after a four year holding period.

(insert table 15 about here)

Table 15 tests our graphical findings using Spearman's rank correlation coefficients. Rank correlations are calculated for PWR, PLR, and DE on one side and the length of the holding period on the other side. For all measures and both periods, rank correlations are economically and statistically significant.

A second test is based on our experimental data set. We analyze whether individual subjects' disposition effects in the stock market treatment are influenced by a good's average holding period. In contrast to our field data set, real time intervals between periods in the lab are very small. Nevertheless, subjects might perceive the number of periods between transactions, as well as the number of obtained feedbacks, as something similar to real time intervals. Figure 10 shows the development of individual proportions of winners realized and proportions of losers realized for different holding periods and the first and the second part of the stock market treatment. Table 16 reports Spearman's rank correlations between PWR, PLR, and DE measures and the length of the holding period.

(insert figure 10 and table 16 about here)

In the lab, similar to the field, PWR measures decrease over the length of the holding period. PLR measures increase significantly in the first part of the experiment, while in the second part they remain largely unchanged. As a result, DE measures in both parts are the lower the longer the holding period of the good.

5 Conclusion

The combination of our field data set and our laboratory experiment allows us to derive a couple of new insights concerning individual level disposition effects. On average, investors in the field, sell their winners in 30 % and their losers in only 20 % of all selling opportunities. Subjects in the lab, on the other hand, tend to exhibit even stronger disposition effects, holding their losers twice as long as their winners. On an individual level, however, the degree to which investors are affected by this bias varies considerably. While most investors exhibit the disposition effect to some degree, approximately 1/3 display the reverse effect. Splitting the disposition effect into its components, i.e. proportions of winners and losers realized, reveals that investors react quite heterogeneously with respect to gains, while loss realization aversion is a common mistake across almost all investors. Furthermore, our test for symmetry 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.

A major goal of our paper was to investigate whether the disposition effect is stable within tasks, across tasks, and across time. We answer these questions by correlating individual level disposition effects as well as proportions of winners and losers realized across different rounds of one and the same task in the experiment, across different tasks of the same part, across different parts, and across years in our field data set. We find that subjects exhibiting high level disposition effects in one round of one individual choice task also tend to belong to the high-disposition-effect group in all other rounds of the same task. In addition, individual disposition effects seem to be stable across the two individual choice tasks, across different parts of the experiment, and across different years in our field data study, thus providing strong evidence of stability across tasks and time. The same is true for proportions of winners and losers realized.

Although our investors' tendency to be affected by the disposition effect seems stable on a relative level, we find that learning within tasks and over time reduces the magnitude of this bias. While the disposition effect is present in both halves of the field data sample period, as well as all rounds and both parts of the experiment, investors in the second half of the sample period, later rounds, or the second part of the experiment display a lesser bias. In our field data study, we find that those investors starting with a positive disposition effect decrease their bias over time, while those investors with a negative initial disposition effect also drift towards the no-disposition effect benchmark. In our experiment, in which investors should sell their losers and hold their winners, we observe a significant reduction of individual disposition effects within tasks and over time.

In a regression analysis based on our field data set, we try to highlight possible determinants of the above mentioned heterogeneity. We therefore regress individual disposition effects as well as proportions of winners and losers realized on individual characteristics and trading habits. We find that individual investors with high incomes sell their winners more often, resulting in lower disposition effects. Investors following aggressive investment strategies tend to realize their winners frequently and exhibit relatively high disposition effects. What is maybe most remarkable, and also most interesting to discuss is our finding that trading experience makes investors sell their winners less and their losers more often. While we know from Barber and Odean (2000) that investors pay a severe performance penalty for frequent trading, we hypothesize that although frequent trading is a bias itself, it may nevertheless help in learning to avoid other investment bias, such as the disposition effect.

In a final analysis we test for a holding period effect. Investors might need some time to accept their paper losses and to overcome their loss realization aversion, as proposed by Kahneman and Tversky (1979) and Shefrin and Statman (1985). In accordance with this hypothesis we are be able to detect an attenuation of the disposition effect over the length of the holding period for both our field data and our experimental study. While investors over the length of the holding period reduce the frequency at which they sell their winners, the proportion of losers realized reduces much more slowly, and in the experiment even increases.

By proving evidence on individual differences, stability, and learning within individual level disposition effects, 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. While investors might be classified as being either more or less affected by the disposition effect, one should note that individual level disposition effects could be caused by either both or only one side of the bias, i.e. immediate gain realizations or loss realization aversion. Agent based models in particular, such as that of Grinblatt and Han (2005), should take these effects into account. Based on our findings, it might also be of value to further investigate why certain investors exhibit the disposition effect and others not, i.e. an in-depth analysis on the interdependence between an investor's personal characteristics, financial sophistication, etc. on one side and his investment decisions on the other. The question is whether those people exhibiting above-average disposition effects 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.

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Table 1: Descriptive statistics (emp.)

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 Deutsche Mark and are therefore considered in our analysis. Investor characteristics were collected by the discount broker when the investors opened their accounts. Investment experience, income, and investment strategies 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	TDM 0 – 50	140	(12.83 %)
	TDM 50 – 100	469	(42.99 %)
	TDM 100 – 150	314	(28.78 %)
	TDM 150 – 200	101	(9.26 %)
	Over TDM 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 per investor	Mean	82.85
	Median	44.00
	Std. dev.	133.23
	# of obs.	2,919
Trading volume per investor in Euro	Mean	536,206
	Median	142,769
	Std. dev.	1,794,121
	# of obs.	2,919

Portfolios		
# of stocks per investor per month	Mean	5.52
	Median	4.29
	Std. dev.	4.72
	# of obs.	2,919
Portfolio value per investor per month in Euro	Mean	36,088
	Median	14,675
	Std. dev.	93,149
	# of obs.	2,914

Table 2: Probabilities of price increases over rounds (exp.)

The table shows the probabilities of price increases for each good in each round of the stock market design. Probabilities of price decreases are just the remainders, i.e. 100 % - probabilities of price increases.

	Round 1 (upward moving)	Round 2 (neutral)	Round 3 (downward moving)
Good 1	45 %	40 %	40 %
Good 2	50 %	45 %	40 %
Good 3	50 %	50 %	45 %
Good 4	55 %	50 %	50 %
Good 5	60 %	55 %	50 %
Good 6	60 %	60 %	55 %

Table 3: Disposition Effect on aggregate (emp.)

This table shows mean values for proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) in our field data study. Individual DE measures are simply calculated as the difference between PWR and PLR. We also report the number of investors exhibiting DE measures higher than, smaller than, or equal to zero. The p-value is based on a binomial test on the hypothesis that half of all investors are positively affected.

Mean PWR	Mean PLR	Mean DE	# DE > 0	# DE ≤ 0	p
0.30	0.20	0.09	1,711	903	0.0000

Table 4: Disposition Effect on aggregate (exp.)

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. Individual DE measures are again calculated as the difference between PWR and PLR. The column “Rational DE” shows DE measures which would arise from a simple heuristic strategy where a subject in the stock market design always holds the good(s) with the highest price, and in the housing design sells all his houses in the year 2008. 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 on the hypothesis that half of all subjects are positively affected.

Part	Treatment	Mean PWR	Mean PLR	Mean DE	Rational DE	# DE > 0	# DE ≤ 0	p
First	Stocks	0.38	0.14	0.24	-0.44	83	30	0.0000
	Housing	0.46	0.20	0.26	-0.18	89	24	0.0000
Second	Stocks	0.28	0.21	0.07	-0.44	63	50	0.1294
	Housing	0.40	0.24	0.15	-0.19	80	33	0.0000

Table 5: Test for the equality of variances between PWR and PLR measures (emp. & exp.)

The table reports mean and median values for proportions of winners realized (PWR) and proportions of losers realized (PLR) as well as standard deviations for our field data study, the stock market and the housing treatment. The p-value is based on a robust Levene test for the equality of variances. For the Levene test, we replace the mean with the median to correct for asymmetric distributions.

Treatment	Measure	Mean	Median	Standard deviation	p
Field	PWR	0.30	0.22	0.25	0.0000
	PLR	0.20	0.13	0.23	
Stocks	PWR	0.33	0.30	0.24	0.0000
	PLR	0.18	0.15	0.14	
Housing	PWR	0.43	0.40	0.20	0.3326
	PLR	0.22	0.21	0.18	

Table 6: Correlations between PWR and PLR measures (emp.)

This table reports Spearman's rank correlation coefficients between individual investors' proportions of winner realized (PWR) and proportions of losers realized (PLR) as well as p-values for our field data study. The first row shows the correlation between standard PWR and PLR measures as defined in section 4.1. The second row reports the same information for PWR and PLR residuals resulting from a two-sided censored Tobit regression, using portfolio size as the single explanatory variable.

Type	ρ	p
Uncontrolled	0.31	0.0000
Controlled	0.00	0.8655

Table 7: Correlations between PWR and PLR measures (exp.)

The table shows Spearman's rank correlation coefficients between individual subjects' proportions of winners realized (PWR) and proportions of losers realized (PLR), as well as p-values for both experimental treatments.

Treatment	ρ	p
Stocks	-0.13	0.1691
Housing	-0.13	0.1587

Table 8: Correlations of PWR, PLR, and DE measures (emp.)

This table reports Spearman's rank correlation coefficients between individual level proportions of winners realized (PWR), between proportions of losers realized (PLR), and between individual disposition effects (DE) 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

DE	Year 1	Year 2	Year 3	Year 4
Year 1	1.00			
Year 2	0.36 (0.0000)	1.00		
Year 3	0.29 (0.0000)	0.37 (0.0000)	1.00	
Year 4	0.22 (0.0000)	0.29 (0.0000)	0.39 (0.0000)	1.00

Table 9: Correlations of PWR, PLR, and DE measures within the first and second parts of the stock market treatment (exp.)

The table reports Spearman's rank correlation coefficients between individual level proportions of winners realized (PWR), between proportions of losers realized (PLR), and between individual disposition effects (DE) 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		
Round 2	0.31 (0.0009)	1.00	
Round 3	0.32 (0.0009)	0.39 (0.0000)	1.00

PLR, 1	Round 1	Round 2	Round 3
Round 1	1.00		
Round 2	0.61 (0.0000)	1.00	
Round 3	0.58 (0.0000)	0.35 (0.0005)	1.0000

DE, 1	Round 1	Round 2	Round 3
Round 1	1.00		
Round 2	0.59 (0.0000)	1.00	
Round 3	0.57 (0.0000)	0.59 (0.0000)	1.00

DE, 2	Round 1	Round 2	Round 3
Round 1	1.00		
Round 2	0.72 (0.0000)	1.00	
Round 3	0.73 (0.0000)	0.54 (0.0000)	1.00

Table 10: Correlations of PWR measures across tasks and time (exp.)

The table reports Spearman's rank correlation coefficients between proportions of winners realized (PWR), between proportions of losers realized (PLR), and between individual disposition effects (DE) 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

DE		First part		Second part	
		Stocks	Housing	Stocks	Housing
First part	Stocks	1.00			
	Housing	0.23 (0.0157)	1.00		
Second part	Stocks	0.67 (0.0000)	0.30 (0.0014)	1.00	
	Housing	0.27 (0.0040)	0.44 (0.0000)	0.36 (0.0001)	1.00

Table 11: Learning over time (emp.)

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 12: Learning within tasks (exp.)

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 13: Learning over time (exp.)

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 14: Determinants of PWR, PLR, and DE measures (emp.)

The table documents the results of simple ordinary least squares regressions as well as a two-sided censored Tobit regressions. We regress individual proportions of winners realized (PWR), individual 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	
Dependent 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	-0.02	-0.03	-0.02	-0.02	-0.01	-0.01
years (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

Table 15: Influence of the holding period (emp.)

The table reports Spearman's rank correlation coefficients between proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) on one side, and the length of the holding period on the other side. Correlations are calculated separately for the first thirty trading days and over a 48 month period.

	PWR		PLR		DE	
Period	ρ	p	ρ	p	ρ	p
First 30 days	-0.76	0.0000	-0.51	0.0037	-0.55	0.0017
Over four years	-0.93	0.0000	-0.94	0.0000	-0.41	0.0036

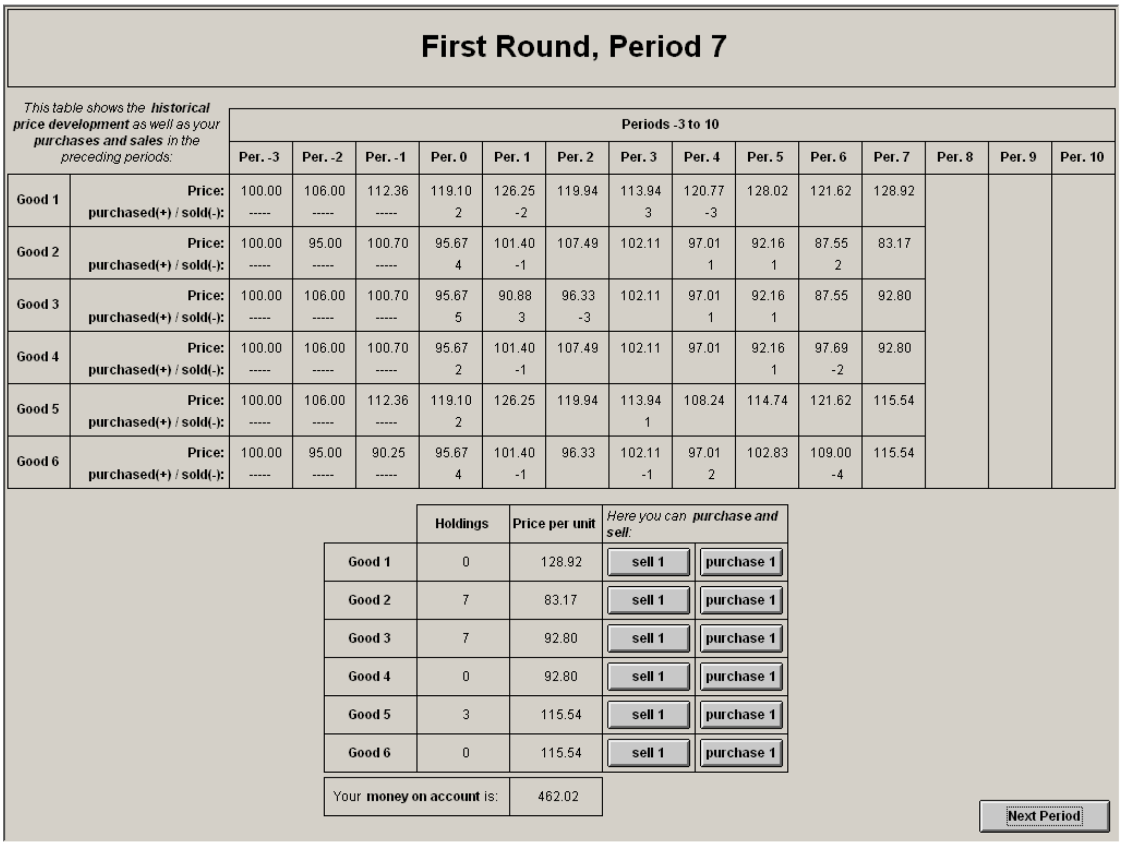
Table 16: Influence of the holding period (exp.)

The table reports Spearman's rank correlation coefficients between proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) for the stock market treatment on one side, and the length of the holding period on the other side. Correlations are calculated separately for the first and the second part of the experiment.

	PWR		PLR		DE	
	ρ	p	ρ	p	ρ	p
First part	-0.85	0.0037	0.65	0.0581	-0.98	0.0000
Second part	-0.58	0.0992	0.02	0.9661	-0.73	0.0246

Figure 1: Computer screen for stock market design

The figure shows a translation of the computer screen for the stock market treatment. 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: Price paths, first part, round 1

The figure shows the price paths for all six goods traded in the first round of the stock market treatment in the first part of the experiment.

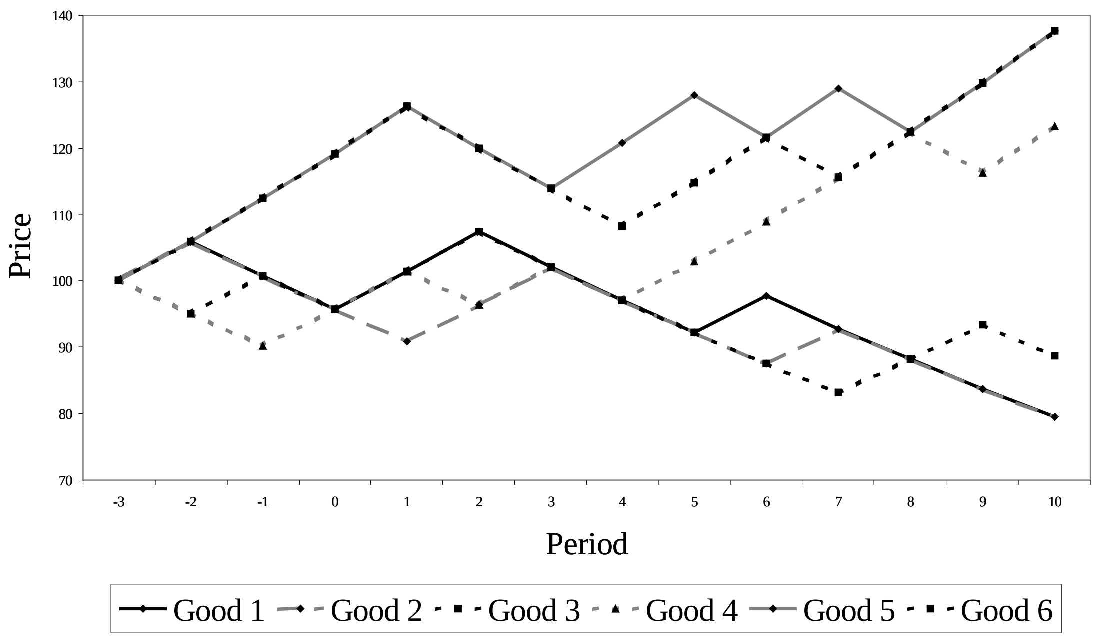


Figure 3: Computer screen for housing design

The figure shows a translation of the computer screen for the housing treatment. The screen was explained to subjects in a preceding tutorial session.

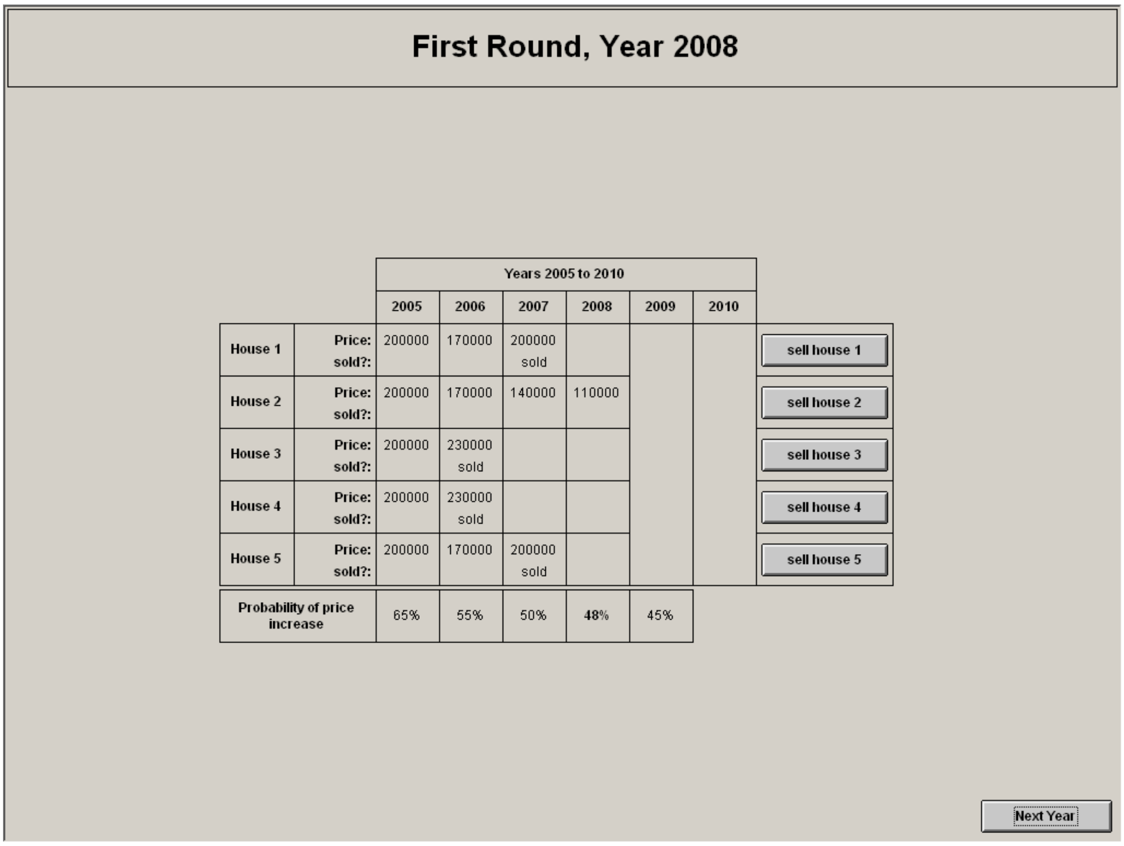
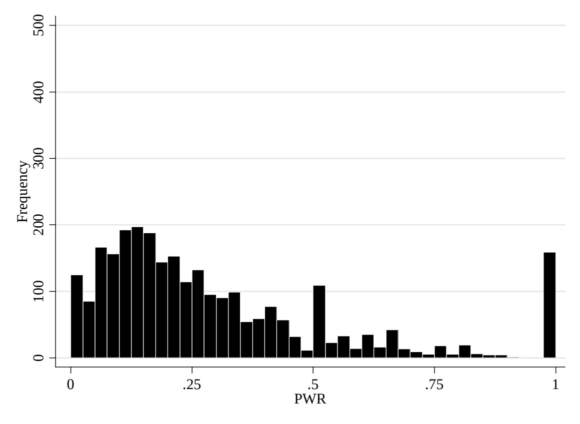
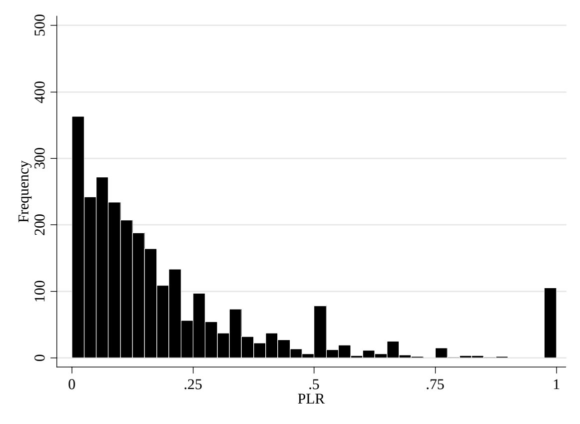


Figure 4: Distributions of PWR, PLR, and DE measures (emp.)

The histograms show the distributions of proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) in the field data study. Individual DE measures are calculated as the difference between PWR and PLR.





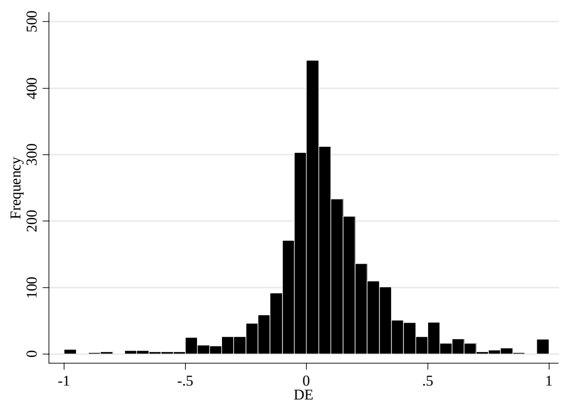


Figure 5: Distributions of PWR, PLR, and DE measures in the stock market design (exp.)

The histograms show the distributions of proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) in the stock market design. PWR and PLR are calculated as the mean between the first and second parts of the experiment. Individual DE measures are calculated as the difference between PWR and PLR.

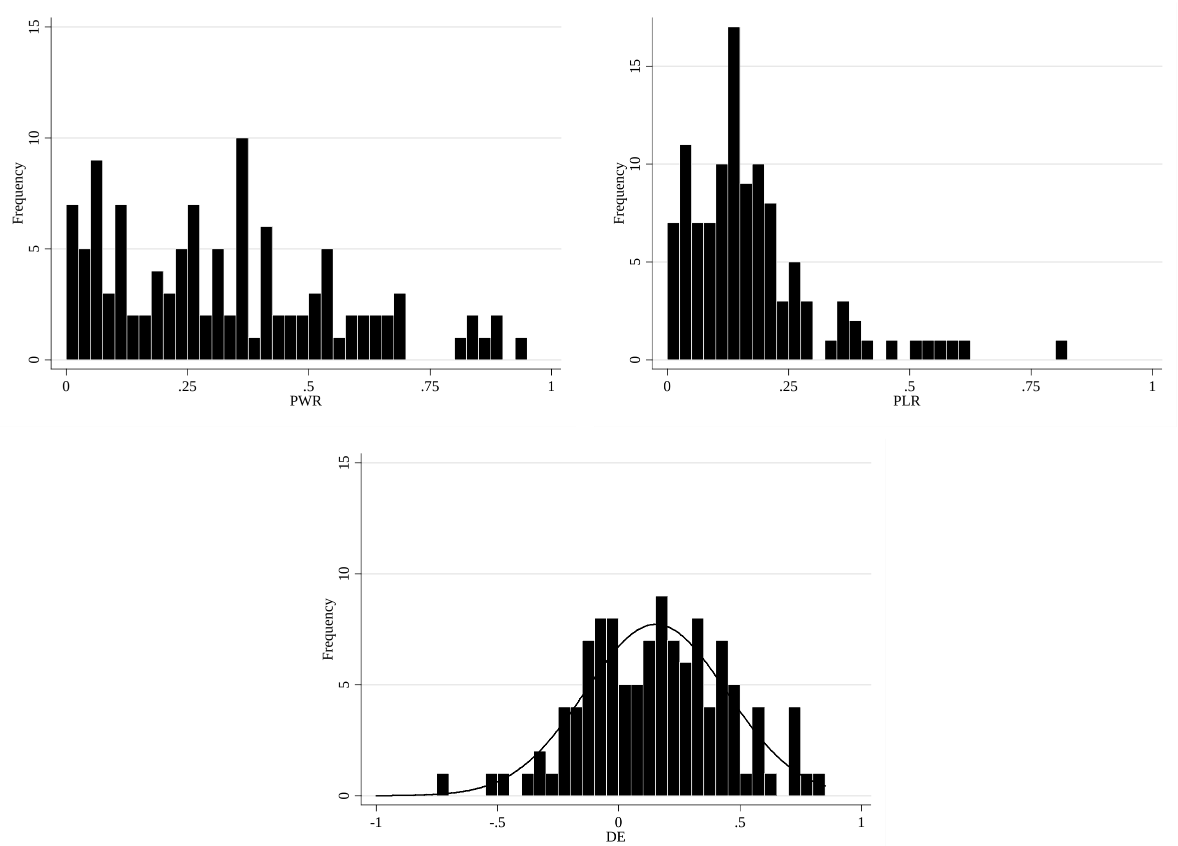


Figure 6: Distributions of PWR, PLR, and DE measures in the housing design (exp.)

The histograms show the distributions of proportions of winners realized (PWR), proportions of losers realized (PLR), and individual level disposition effects (DE) in the housing design. PWR and PLR are calculated as the mean between the first and second parts of the experiment. Individual DE measures are calculated as the difference between PWR and PLR.

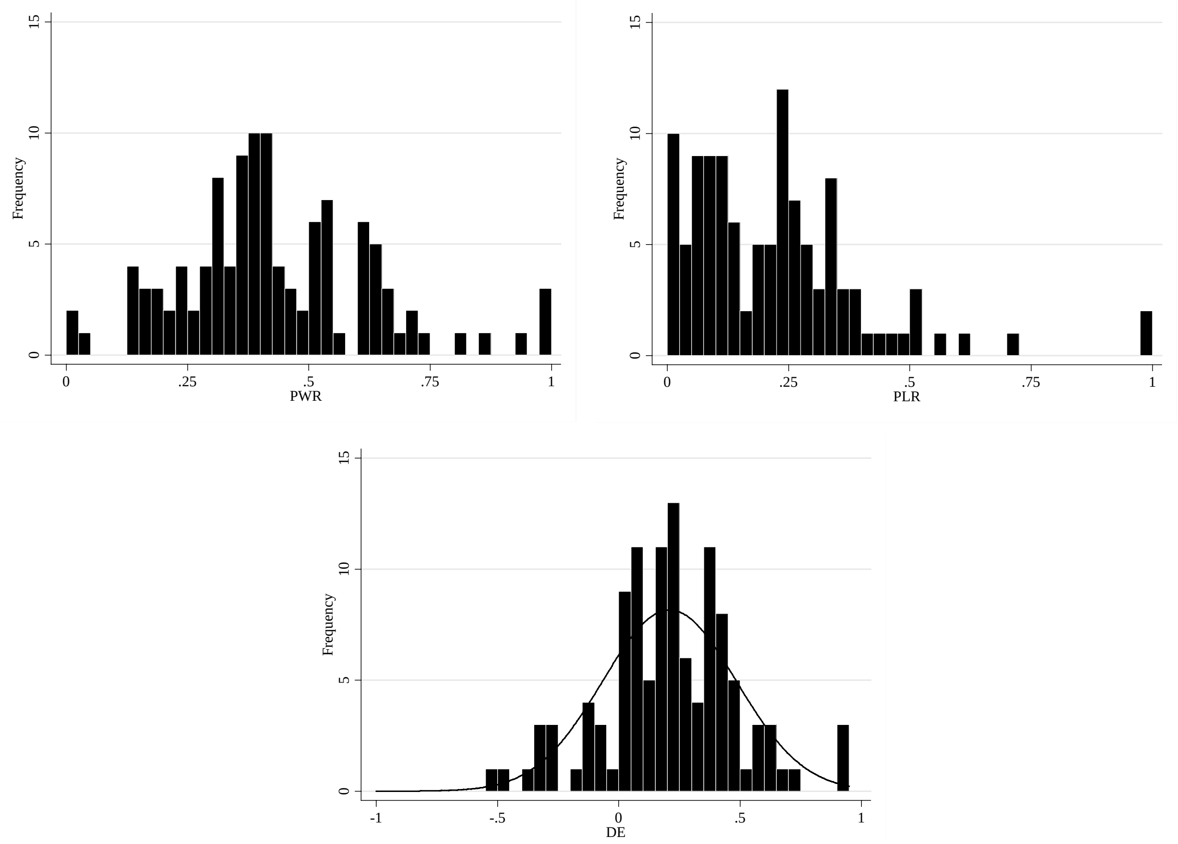


Figure 7: Correlations between PWR and PLR measures (emp.)

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 0 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

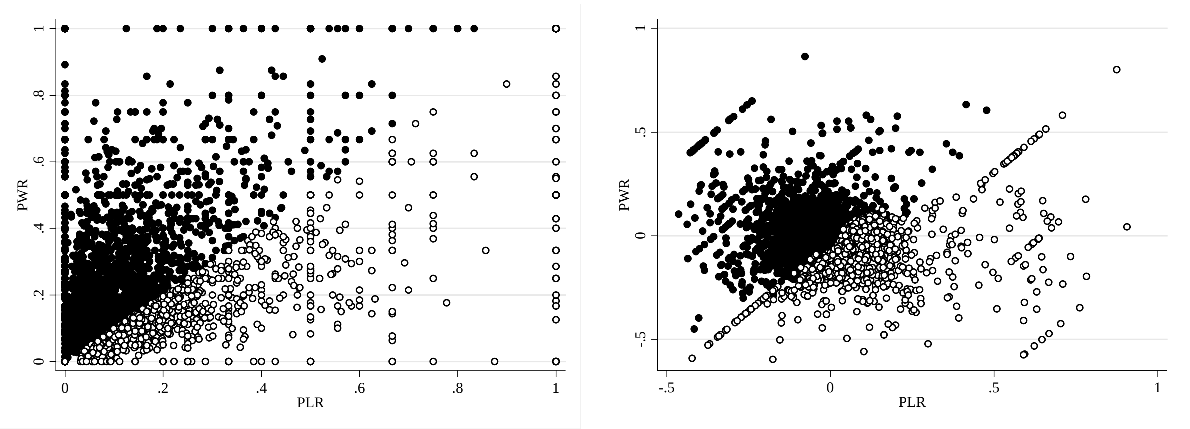


Figure 8: Correlations between PWR and PLR measures in the stock market design (exp.)

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 0 disposition effects are market by white dots.

Stock market treatment | Housing treatment

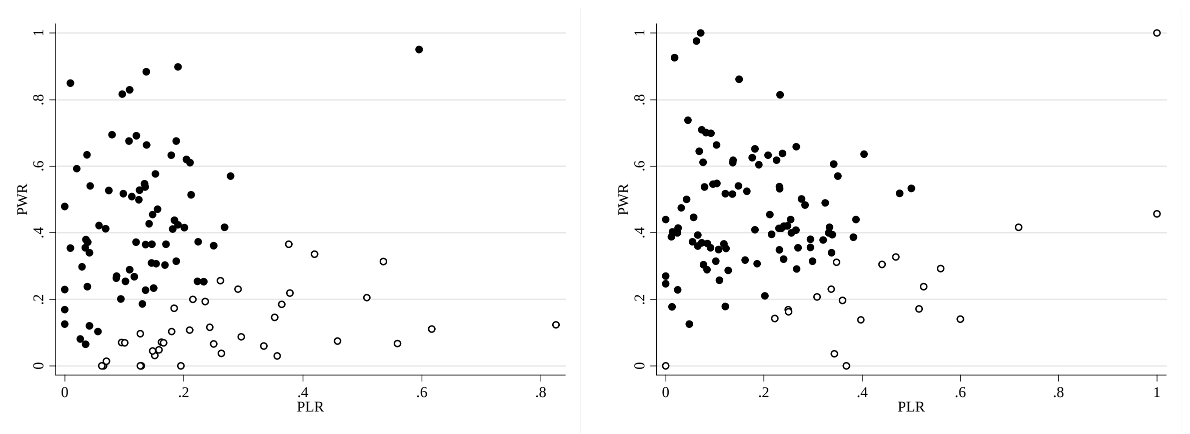


Figure 9: Influence of the holding period (emp.)

The graphs show proportions of winners realized (PWR) and proportions of losers realized (PLR) for different holding periods of the stock. The left-hand graph shows the development of daily PWR and PLR measures over short holding periods between 0 and 30 days. The right-hand graph shows monthly PWR and PLR measures over holding periods between 0 and 48 months. Individual disposition effects (DE) are not displayed explicitly, but can be assessed as the gap between PWR and PLR for each holding period.

First 30 days | Over four years

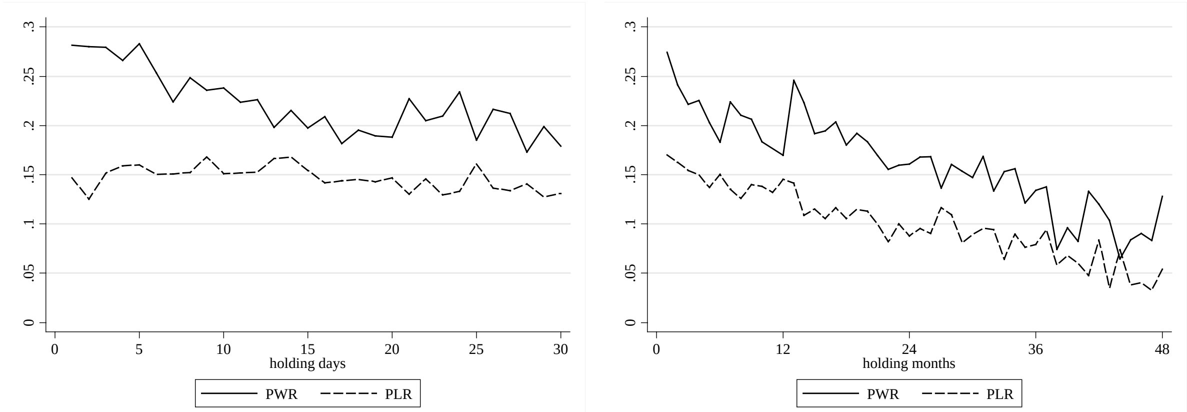
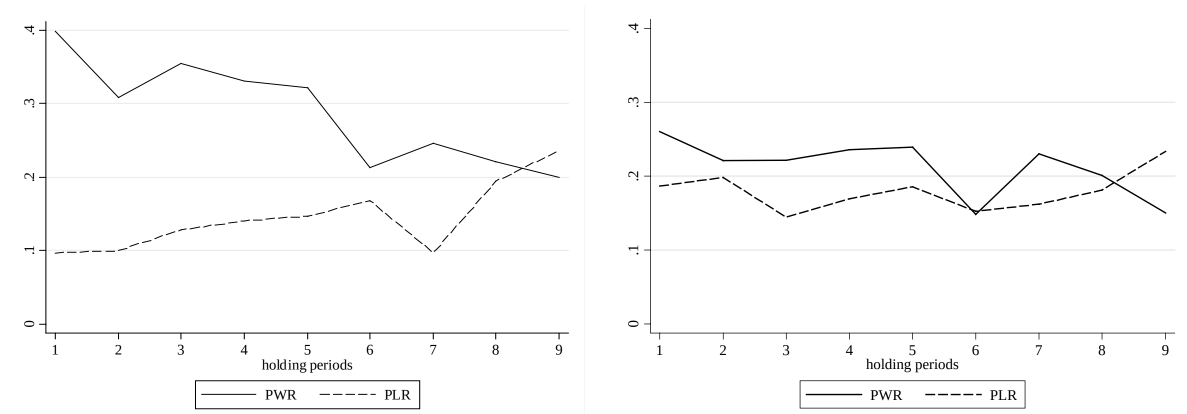


Figure 10: Influence of the holding period (exp.)

The graphs show proportions of winners realized (PWR) and proportions of losers realized (PLR) for different holding periods of the goods. The left-hand graph shows the development of PWR and PLR measures for the stock market treatment in the first part of the experiment. The right-hand graph shows the same information for the second part of the experiment. Individual disposition effects (DE) are not displayed explicitly, but can be assessed as the gap between PWR and PLR for each holding period.

First part | Second part



Appendix A: Instructions for Individual Choice 1: Stock Market Design (translated from German)

This is the first of two games. On the following pages, the procedure of the game will be explained. Please read these instructions carefully. Your financial reward partly depends on your success in this game.

In this game you can trade in six different goods: Good 1 to good 6. The game consists of a total of 14 periods (periods -3 to 10) and will be repeated three times. During periods -3 to -1 you will only receive information on the price development of the six goods during these three periods; you may neither purchase nor sell them.

In period 0 you will receive 2,000 monetary units, but no goods. You can use this money to purchase goods in the following 10 periods (period 0 to 9). In addition, you may also sell goods you own.

Starting at a price of 100 monetary units in period –3, the price of each good will change each period, either increasing by 6 % or decreasing by 5 %. Each of the 6 goods has its own individual probability of increase in price. These probabilities are constant within the 14 periods of the game. You will not be told the individual probabilities of each good.

Price changes in one period are independent of price changes in previous periods and price changes of one good are independent of price changes of all other goods.

The game will be played three times. Individual probabilities remain constant during one game but differ between the three repetitions of the game, which means that individual probabilities for price increases as well as actual price changes are determined randomly in each of the 3 runs.

You will receive your financial reward after the second experiment. To determine the reward, one of the 3 repetitions will be chosen at random. Your payout will depend on your final wealth at the end of this run, i.e. period 10. It will equal 0.2 % of your final wealth, which in turn will be calculated as the amount remaining in your money account plus the current value of your goods.

On the following pages we show you the various components on the computer screen.

(In the following we present the text of the computer tutorial.)

You are looking at the game screen. At the top you can see that this is a “test run.” Next to this is the period number. As explained in the instructions you start in period 0. Please click “OK”.

The rest of the screen is divided into two parts: In the upper part you can see a big table showing price developments of goods 1 – 6, as well as your purchases and sales across previous periods. Underneath you see a smaller table containing the number of goods you currently hold, current prices, buttons for purchasing and selling, and the amount of money remaining in your account.

Please study the upper table first. The rows in this table represent the 6 goods, the columns represent periods -3 to 10. Since you are in period 0, only the columns for periods -3 to 0 contain entries. The 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 you have purchased (positive number) or sold (negative number) in this period.

For example: Examine the entries regarding good 1 in the first row of the table. As you see, the price of the good changed from 100 in period -3 to 106 and 100.70 in periods -2 and –1 respectively, and to 95.67 monetary units in period 0. Since you were not allowed to buy and sell the good during periods -3 to -1 (the game starts in periods 0) you see the entry “----“ in the row “bought(+) / sold(-)”. Since you have not yet bought anything in period 0, there is no entry in “bought(+) / sold(-)” in this period either. As soon as you purchase a good, you will be able to see the number of units bought (positive number) or sold (negative number) here.

Next, please look at the smaller table on the bottom half of the screen. The first column shows your current holding of the 6 goods. Since you currently do no possess any goods, all entries are “0”. In the next column you again see the current price per unit of the corresponding good. Please compare the prices shown in this table with period 0 prices in the upper table. Next to the prices, the lower table contains two buttons, labeled “sell 1” and “purchase 1” for each of the 6 goods. Below the small table you see your current money account. Since you have yet not purchase anything, your account contains 2,000 monetary units.

Please test the procedure by purchasing some units of good 1. To do so click repeatedly on the “purchase 1” button for good 1, in the lower table. As you can see, that the number of units increases by one with each click, while your money account simultaneously decreases by the price of the good. In addition, the number of units bought in period 0 is documented in the upper table in the row “bought(+) / sold(-)”. Now that you have bought several units you can of course sell them back. To do this just click on the button “sell 1”. The number of units of the particular good decreases by one with each click, while your money account simultaneously increases by the current price of the good.

When you have finished making your purchases and sales, you can move on to the next period, i.e. period 1, by clicking on the “next period” button in the bottom right-hand corner of the screen. As soon as you click on “next period”, the prices of the 6 goods change in the bottom table. Moreover, another column is added to the upper table. Please move on to period 1! Note how the screen has changed. As you can see, the price of good 1 has risen to 101.40. In the game, you could now purchase and sell again, however, we will shorten this procedure for demonstration purposes. Please click on “OK” to switch to period 10.

We have skipped periods 2 to 9 and are now in the final period, period 10. As you can see, the upper table is now completely filled in. In addition, the buttons to purchase and sell are no longer there. Since this is the last period, and prices will not change any more, there is no opportunity to sell or buy. Please leave the test run now and start the real game by clicking on the button “end of test run” in the bottom right-hand corner of the screen.

Appendix B: Instruction for Individual Choice 2: Housing Design (translated from German)

You are now in the second game. On the following pages we will explain the procedure. Please read these instructions carefully. Your financial reward will partly depend on your success in this game.

For this game please imagine that you have recently (in 2005) inherited 5 houses from a distant relative. You neither want to live in these houses yourself nor rent them out. Instead you want to sell them by the year 2010 at the latest. Therefore, you need to decide each year whether and which of the houses you want to sell. Houses that have not been sold by the end of 2009 are automatically sold in 2010. Houses, once sold, cannot be repurchased again.

In the year 2005, each of the 5 houses has a value of € 200,000. These prices will however change every year: In each year, house prices either increase by € 30,000 or decrease by € 30,000. After your decision in the year 2005, the probability for a price increase is 65 %. Following your decision in 2006 the probability is 55 %. After 2007 there is a 50 % change of a price rise, and after 2008 and 2009 the probability drops to 48 % and 45 % respectively. Since the houses are situated in 5 different residential areas, price changes are independent of one another. In addition, price changes do not depend on changes in previous years.

You will play this game a total of 6 times, and will receive your financial reward after the second experiment. To determine the reward, one of the 6 runs will be chosen randomly. Your payout will be based on your final wealth at the end of this run, i.e. in the year 2010. It equals 0.002 % of your final wealth, which in turn will be calculated as the sum of the prices at which you sold your 5 houses.

On the following pages you will be shown the various components on the computer screen.

(In the following we present the text of the computer tutorial.)

You are looking at the game screen. At the top you can see that this is a “test run.” Next to this is the year. As explained in the instructions you start in 2005. Please click OK.

In the center of the screen you see a table. The rows of this table represent the 5 houses you have inherited: House 1 to house 5. The columns represent the 6 years of the game: 2005 to 2010. Since you are now in the year 2005, there are only entries in the first column. Next to the columns you can also see 5 buttons which can be used to sell your houses at their current values. Under the table you see the probabilities of price increases.

There are two types of information in the cells: The upper entry is the price of the house in the corresponding year. If you sell your house in a particular year you see the comment “sold” underneath the price. Since you have not yet sold a house, there are currently no entries underneath the prices. Beneath the table you see a row containing the probabilities of price increases for the following 5 years. The bold probability is the current one. For example, if you decide in 2005 not to sell a specific house, there is a 65 % chance that the price of this house will increase by 2006. Next to the table you see 5 buttons labeled “sell house 1” to “sell house 5”. If you want to sell one or more houses at their current prices, you just need to click on the corresponding button. As soon as you sell a house you will see the remark “sold” in the table.

Please test the procedure by clicking the corresponding button and selling one of the houses. After the sale, the comment “sold” will appear underneath that house’s price. Please click on the button “next year” in the bottom right-hand corner of the screen to move on to the year 2006.

As you can see, another column has been added to the table. There is a new price for each house yet to be sold. Additionally, you can see in the row “probabilities for price increases” that the current probability is now 55 %. Now, in the year 2006, you again need to decide whether and which of the houses you want to sell at their current values. As this is only a demonstration, we will now skip to the final year, 2010. Please click “Ok”. The table is now completely filled in. In addition, the five buttons for selling houses 1 to 5 are no longer there. Since you are in the final year, the houses that you have not yet sold will now be sold automatically. Please leave the test run now and start the real game by clicking on the button “end of test run” in the bottom right-hand corner of the screen.

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