Discussion Papers In Economics And Business

Disposition Effect and Diminishing Sensitivity:

An Analysis Based on a Simulated Experimental Stock Market

Youki Kohsaka

Grzegorz Mardyla

Shinji Takenaka

Yoshiro Tsutsui

Discussion Paper 13-02-Rev.2

Graduate School of Economics and
Osaka School of International Public Policy (OSIPP)
Osaka University, Toyonaka, Osaka 560-0043, JAPAN

Disposition Effect and Diminishing Sensitivity:

An Analysis Based on a Simulated Experimental Stock Market

Youki Kohsaka

Grzegorz Mardyla

Shinji Takenaka

Yoshiro Tsutsui

Discussion Paper 13-02-Rev.2

December 2013

Graduate School of Economics and
Osaka School of International Public Policy (OSIPP)
Osaka University, Toyonaka, Osaka 560-0043, JAPAN

Disposition Effect and Diminishing Sensitivity: An Analysis Based on a Simulated Experimental Stock Market*

Youki Kohsaka†
Grzegorz Mardyla‡
Shinji Takenaka§
Yoshiro Tsutsui¶

Abstract

We experimentally investigate the existence of the disposition effect and diminishing sensitivity as its potential cause. Our approach includes three key characteristics: (i) An environment closely resembling actual stock markets; (ii) Individual-specific reference prices; (iii) A direct test of diminishing sensitivity as a cause of the disposition effect. We find strong support for the existence of the disposition effect as an independent hypothesis. This is an improvement over previous studies, which tested this hypothesis only jointly with others. Our results also strongly point to diminishing sensitivity, of the type postulated by prospect theory, being a source of the disposition effect.

JEL classification codes: G02
Keywords: disposition effect, diminishing sensitivity, investor behavior, experimental economics

---

* An earlier version of this paper was presented at the 6th annual meeting of Association of Behavioral Economics and Finance, and at a conference held at Hosei University. We are grateful to the participants of those events for their useful comments. We also express gratitude to Hiroshi Izawa, Jie Qin and Shunichiro Sasaki for helpful comments and constructive collaboration during the early stages of this project.
† Waseda University Center for Finance Research, Email: kohsaka@aoni.waseda.jp
‡ Kinki University Faculty of Economics, Email: greg@kindai.ac.jp
§ Japan Center for Economic Research, Email: s.takenaka@jcer.or.jp
¶ Osaka University Graduate School of Economics, Email: tsutsui@econ.osaka-u.ac.jp

1. Introduction

The purpose of this paper is to test the existence and causes of the disposition effect. Empirical evidence indicates that individual investors exhibit a greater propensity to realize gains than to realize losses, thereby causing them to incur excessive losses. Numerous informal "investing advice" books have been written on how to avoid the trap of being unable to cut one's losses early. Such informal publications are based mostly on casual observations and often themselves suffer from representativeness biases. In this paper we attempt to carefully examine the disposition effect in an experimental setting, in order to discover how psychologically difficult it really is for human traders to sell stocks at a loss, and to shed some light on the underlying causes of that difficulty.

There are two basic strands of extant research on this topic. The first one involves empirical investigations of real-world financial transaction data, while the second consists of laboratory experiments. Papers in the first strand analyze data from various securities markets around the world. Some representative empirical work, all of which confirms the existence of the disposition effect in various markets, includes: Odean (1998) – U.S. stock market; Grinblatt and Keloharju (2001) – Finnish stock market; Coval and Shumway (2005) – The Chicago Board of Trade; Shumway and Wu (2006) – Shanghai stock market; Fogel and Berry (2006) – 176 members of the American Association of Individual Investors; Misumi at al. (2007) – Tokyo Stock Exchange; and Choe and Eom (2009) – South Korean futures index market.[1] Concerning the second

[1] Choe and Eom (2009) find in addition that individual investors are much more susceptible to the disposition effect than institutional or foreign investors.

strand of literature, the disposition effect has also been demonstrated in laboratory experiments conducted mainly on a university students in various locations, including: Weber and Camerer (1998) – Germany; Chui (2001) – Macau; Kirchler et al. (2005) – Austria; Rubaltelli et al. (2005) – Italy; Vlcek and Wang (2007) – Switzerland; and Shiroshita (2009) – Japan.

Empirical analyses of the disposition effect are valuable, since they directly test for the existence of the effect in real-world financial markets. Experimental research, on the other hand, while it cannot guarantee external validity, has the undisputed merit of allowing for a strict control over, and accurate design of, the environment in which stocks are traded. On top of that, individual investor information, which is vitally important yet difficult or impossible to obtain in empirical research, can be acquired relatively easily in experimental studies. In our case, this information includes individual-specific reference points, individual degrees of diminishing sensitivity, and the personal and demographic attributes of subjects. Economic experiments, besides offering another avenue to test for the existence of the disposition effect, thus also permit an opportunity to investigate the effect's potential *causes*.

In order to show why this is important, observe that there exist a multitude of candidate explanations for the apparent prevalence of the disposition effect. These include:

(1) The shape of the value function from Kahneman and Tversky's (1979) prospect theory, which implies that agents are risk averse in the domain of gains and risk loving in the domain of losses. In this paper, we refer to this phenomenon simply

as “diminishing sensitivity”.

(2) Belief in reversion to the mean: If investors believe that stocks trading at a loss will rebound in the future with high enough probability, then holding on to such stocks might be optimal.

(3) Portfolio rebalancing: Investors might wish to maintain a constant cash value of certain stocks in their portfolios. This would lead them to rationally hold on to, or perhaps buy still more of, losing stocks.

(4) Transaction costs: All else equal, selling losing stocks entails higher per-unit transaction costs. This, in turn, implies that holding on to them is the smart thing to do.

(5) Psychologically-motivated reasons, such as mental accounting, regret aversion, and self-control (Shefrin and Statman (1985)).

(6) Tax reasons: Although early research on the disposition effect (Shefrin and Statman (1985), Lakonishok and Smidt (1986), Odean (1998)), following Constantinides’ (1984) exposition of a rational loss realization model, pointed to tax-related issues as a possible cause, tax exemption rules associated with capital losses would seem to preclude a tax-motivated disposition effect.

Odean (1998) conjectured that diminishing sensitivity might bring about the disposition effect. While demonstrating the effect’s existence in a large data sample, he excluded a number of other factors as its possible sources. In particular, Odean’s (1998) results do not support the trading costs hypothesis, which is shown to be inconsistent with the disposition effect; investors in his sample sell winners more frequently than they sell losers, regardless of transaction costs. Also, by eliminating from his analyses trades that might have been motivated by a desire to rebalance, he effectively controlled for portfolio rebalancing. Odean (1998), while initially reluctant to reject belief in mean reversion as a potential cause of the disposition effect, refers later to his complementary paper based on the same sample of investors (Odean (1999)). In that paper he finds that the investors tend to buy stocks that have outperformed the market in the past, whereas a belief in mean reversion would imply the exact opposite.

In a related study, an experiment by Weber and Camerer (1998) finds that participants are significantly more inclined to buy stocks trading at a loss as opposed to those trading at a gain. The authors attribute these findings to prospect theory, yet do not exclude belief in mean reversion or, more generally, the misperception of stochastic processes, as probable reasons for the effect.

It has long been suspected that the convexity of prospect theory's value function in the domain of losses might account for the disposition effect. This suspicion, however, has itself come to be questioned recently. Kaustia (2010) parameterizes cumulative prospect theory's S-shaped value function (Tversky and Kahneman (1992)) to show that propensity to sell is highest at the reference point (purchase price) and declines when either gains or losses inflate. Oddly enough, the model predicts that in most cases holding any stock is more beneficial than selling. On the other hand, Kaustia (2010) finds empirically, using Finnish transaction data, that the propensity to sell a stock does not decline as paper gains or losses increase, but rather is increasing or constant in the domain of gains and insensitive to returns in the domain of losses. In other words, there is a discontinuity (a "jump") in investors' attitudes towards selling exactly at a point where capital gains are zero. Given this evidence, he concludes that the S-shaped value function cannot predict the pattern of realized returns found in the data and hence that the disposition effect is unlikely to be driven by prospect theory preferences.

Barberis and Xiong (2009) study theoretically the trading behavior of an investor with prospect theory preferences and conclude (in the first part of their study) that for a significant range of parameter values, prospect theory predicts investors will be more inclined to sell stocks with losses than to sell stocks with gains – exactly opposite to what the disposition effect leads to.[2]

Both Barberis and Xiong (2009) as well as Kaustia (2010) employ a carefully calibrated prospect theory-type value function and show that it does NOT lead to the disposition effect. This finding sent a shockwave throughout the behavioral finance community, spurring whole new streams of research in the area.

One alternative disposition effect explanation that has surfaced recently is realization utility theory. The actions of selling and buying stocks result in changes in the internal constitution of an investor's wealth, NOT in changes in the investor's overall wealth level. Hence, it is problematic that the mere act of stock trading, in and of itself, should be considered as an event capable of generating any extra utility.

Both of the two studies cited above make clear distinctions between the evaluation period for changes in an investor's wealth/utility levels and the stock trading time intervals. Barberis and Xiong (2009), after first modeling a "traditional" wealth-level

[2] Hens and Vlcek (2011) derive an analogous result.

utility-maximizing investor and concluding that such an investor would not be prone to the disposition effect, proceed with a simulation exercise based on the premise that any act of buying or selling stocks generates a prospect theory-type “utility surge” and report significant disposition effect incidence as a result. Barberis and Xiong (2012) term this type of utility function “realization utility” and propose a linear specification, on which they subsequently base their theoretical and computational modeling exercise.

In a related study, Henderson (2012) utilizes a Tversky-Kahneman (1992) S-shaped value function to solve for an asset-liquidation optimization problem of a realization utility investor. Her model predicts that disposition effect becomes more pronounced as convexity of the value function in the loss domain increases.

Importantly, the prevalence of the disposition effect is not extreme in Henderson (2012) – investors do sell at a loss voluntarily. The predictions of her model are thus closer to (nonetheless, still an order of magnitude higher than) observed empirical and experimental results on the intensity of the disposition effect. And her predictions are more accurate than those stemming from several competing theories, which are capable of producing only a very strong version of the disposition effect wherein investors never voluntarily realize losses.

The theory of realization utility has also been experimentally validated by Frydman et al. (2012) with an fMRI study. They report that ventral striatum exhibits a positive response when subjects realize capital gains.

The theory of realization utility is not the only recently debated candidate for explaining the disposition effect. Meng (2012) focuses on the prospect theory reference point and shows with a simulation exercise similar to Barberis' and Xiong's (2009) that the disposition effect obtains readily once we redefine the reference point by a rationally expected return rate (above the riskless interest rate) rather than by a status quo level. On the other hand, Li and Yang (2013) build a general equilibrium model to endogenously solve for the risky asset return rate. Again, using a Tversky-Kahneman (1992) value function, they find that diminishing sensitivity does predict a disposition effect.

Summarizing recent research efforts aimed at explaining the disposition effect with prospect theory-related arguments, we recognize two distinct lines of reasoning. The first line focuses on the effects of the kink at the reference point of the value function, associated with loss aversion. In this case, prospect theory is found to explain the disposition effect in Meng (2012) (conditional on the reference point being sufficiently high above the risk-free rate), as well as in Barberis and Xiong (2012) (in which the effect is caused by the realization utility function). The second line of reasoning emphasizes diminishing sensitivity – the convexity of the value function in the domain of losses. In this case as well, prospect theory is found to be a persuasive explanation for the disposition effect, be it through the introduction of realization utility in Henderson (2012), or in the stylized extension of a general equilibrium model in Li and Yang (2013).

This paper attempts to examine whether diminishing sensitivity can explain the disposition effect without resorting to any specific theory. Such an attempt has been a longstanding challenge ever since the seminal paper by Shefrin and Statman (1985).

Our approach has three key characteristics. First, we use data generated through an experiment designed to mimic as closely as possible a real-world security market – our data is thus very similar to actual stock market data. The simulated market in our experiment lasts for four weeks. It is open for four and a half hours each trading day – exactly like the Tokyo Stock Exchange (TSE). Our market is open in the evening hours to facilitate frequent trading. We use real-world historical price data for 10 stocks from the TSE, edited from tick data so that the prices are updated every two minutes.[3] Participants in our experimental market may trade during any time the market remains open. Remuneration for participating in the experiment is proportional to the earnings (or losses) they acquire through trading. Thus we may assert that any results obtained through the experiment mimic closely those of a real world stock market.

Second, our method directly tests whether or not diminishing sensitivity leads to the disposition effect. We do this by eliciting the degree to which subjects are prone to display diminishing sensitivity, and correlating this with the strength of the disposition effect they exhibit in trading. To this end, we perform supplemental experiments to measure our subjects' degrees of risk aversion in the domains of gains and losses. This method allows a more general inquiry into the potential causal relation between diminishing sensitivity and the disposition effect. Without the need to rely on a particular theory, our method offers a direct test of the hypothesis that diminishing sensitivity causes the disposition effect.

The third characteristic of our study is related to Odean's (1998) observation that

[3] This method guarantees that subjects will be able to trade at their desired price.

testing for the disposition effect is equivalent to testing a joint hypothesis about the disposition effect's existence and the location of the agents' reference points. Assuming a particular value for the reference price – e.g. first purchase price, last purchase price, weighted average purchase price, etc. – has been the standard practice used in empirical research on the disposition effect. This practice does constitute a type of robustness check of the results obtained, but it ignores the possibility of heterogeneity in reference points across investors. To address this problem, we solicit individual participants' reference points using a questionnaire survey, and use the obtained values when computing gains and losses. In effect, our method constitutes an independent test for the disposition effect, not merely a test of the joint hypothesis described by Odean.

In addition to the three features outlined above, our setup also allows us to exclude both taxes and transaction costs as potential explanations for the disposition effect.

Our analyses, employing the techniques spelled out above, clearly confirm the existence of the disposition effect, and point to diminishing sensitivity as being one of its causes. We also examine the potential link between individual time preferences and the incidence and strength of the disposition effect and find, contrary to expectations, that higher discount rates are associated with a weakening of the disposition effect.

The rest of this paper is arranged as follows. In the next section we describe the experimental design and methods. In Section 3, we explain the techniques used to analyze the data. In Section 4 we report our main results and robustness checks involving subjects' personal attributes; we also verify that our results remain unaffected when alternative values are substituted for individual reference points. Our examination of the relationship between time discounting and the disposition effect is also contained in Section 4. We offer conclusions in Section 5.

2. Experimental Design and Procedures

The main experiment in our design is called the "Stock Trading" experiment, in which participants buy and sell shares in a simulated stock market. We also conduct two supplemental experiments: the "Insurance Buying" experiment and the "Lottery Selling" experiment, which we use to measure participants' risk aversion in the domains of losses and gains.

2.1. Stock Trading Experiment

2.1.1. Outline of the Experiment

The "Stock Trading" experiment required its participants to buy and sell shares of 10 companies in a simulated stock market accessed through the internet. Each participant was given an initial endowment of virtual shares and virtual cash with which to trade. The market lasted for four weeks, and was open for four hours and thirty minutes every day from 18:00 through 22:36 (with a six minute break from 20:00 to 20:06).[4]

The stock price data we used is authentic mid-price tick data from the past, edited so that it is updated every two minutes.[5] In this way, we avoid any possible negative

[4] The six minute break replicates the lunchtime break from 11:00 through 12:30 instituted on the Tokyo Stock Exchange.

[5] Specifically, we randomly selected ten high-liquidity stocks traded on the Tokyo Stock Exchange and for each extracted 33 days worth of tick data from "Nikkei Tick Data". We subsequently created for each of the ten stocks a vector of mid-quotes corresponding to those observed at the mid-quotes of 2-minute intervals in the original data file, and used morning period mid-quote data for the 18:00 through 20:00 experiment trading period, and afternoon mid-quote data for the 20:06 through 22:36

auto-correlation issues resulting from the bid-ask spread, which we might have encountered if we had used actual execution prices. Subjects in our experiment were guaranteed that their trades are going to be carried out exactly at the prices shown on their monitors, and that those prices are not in any way affected by their own, nor by other subjects' quantities demanded or quantities supplied.[6] Short-selling and negative cash positions were not allowed. We performed a simple linear transformation on the price data to preclude the possibility of identification of actual stocks by the participants.

The initial endowment of each participant consisted of 10 shares of each of the ten stocks and a cash allotment of 10,000,000p ("points"). Participants had access to a transaction panel (Figure 1), where they received information on the present composition of their portfolios, stock prices and cash holdings. The panel also allowed them to make buy and sell orders, which were immediately executed: for instance, by changing the number of shares in the "After Transaction" column and clicking on the "Execute Trade" button, a corresponding order is completed. Traders in our experiment also had access to graphs representing both past price paths (closing quotes) up to the present day, and the same-day price paths, starting from the opening bell until the present time.[7] There were no dividends or transaction costs, nor were there any taxes. This differs from real world markets but has the benefit of excluding from our analysis the above-mentioned factors as possible explanations for the disposition effect.

---

trading period.

[6] Consequently, experiment participants emulate small individual investors facing a highly liquid market.

[7] On the first day of the experiment, data from the preceding five trading days is made available.

2.1.2. Compensation Structure

Participants received three types of compensation. The first type depended on the number of days they logged on to the experiment homepage throughout its duration. In addition to ¥30 (The exchange rate was around ¥90 per $1 as of the time this experiment was conducted.) for each day a subject logged on, a subject was entitled to a bonus payment of a few thousand yen if they accessed the system on at least 18 days.[8] The second type of compensation was commensurate with the final portfolio return – for each percentage point of the return on a subject's portfolio, ¥180 were awarded. In case of negative returns, the resulting losses were subtracted from bonus payment awarded for regular logging on to the experiment homepage described above.[9] The third payment type was a ¥30,000 "winner prize" awarded to the participant whose final holdings at the end of the experiment were the highest. This prize was instituted to facilitate frequent trading activity and hence to generate enough experiment data. Experiments such as ours suffer, due to the inherent funding limits, from the problem of providing monetary incentives high enough to mimic real world activities. A chief characteristic of our experimental design is participants' ability to engage in stock trading anyplace where they have access to the internet, at the time of their choosing during the one month duration of the experiment. This differs substantially from majority of economic laboratory experiments. Participants in such experiments are

[8] These bonus payments are: ¥1,800 for logging on between 18 and 22 days, ¥2,600 for logging on between 23 and 27 days, and ¥3,600 for logging on 28 days (every day of the experiment).

[9] Should the resulting yen amount turn out to be negative, relevant subjects were to receive ¥0. However, there were no such cases.

confined in the laboratory environment and have no choice as to the time and place, in which to decide and act. Moreover, constant surveillance by experimenters makes neglecting to participate in the experiment very difficult. Since our experiment participants do not need to cope with such unusual and strenuous conditions, it is plausible to expect that they might be tempted to slack off on participation. The ¥30,000 winner prize, whilst being affordable in terms of experimenters' budget constraints, is large enough to serve as an effective trading incentivization device.[10] This type of incentive scheme, though it might not be an exact imitation of real world conditions, does resemble actual stock trading in that it allows for a possibility of quite high returns.

2.1.3. Basic Experiment Data

Participants were recruited (with the assistance of an internet research company) from among individual investors with previous stock trading experience, defined as having recent history of trading at least once per month on the stock market. The average age of the participants was 41.94 years (SD=10.74; For males 41.03, SD＝10.98, for females 44.38, SD=10.06). Detailed attributes of the experiment participants are summarized in Table 1. The most numerous age groups were people in their 30s, followed by 40s, with a few participants in their 60s and 70s. Employment income earners comprised about half of the pool of subjects. Four of the male participants were self-employed. Household income ranged from slightly below 3 million yen to 15 million yen. Finally,

[10] As we report below in section 4.2, this incentive structure resulted in ample trading activity and hence, an adequate amount of valid experiment data.

the real-world trading frequency reported by subjects was most commonly "roughly once a week" or "almost daily", each of these accounting for over 30% of the total.

On January 24th 2010, all the subjects were gathered together at a computer laboratory at the Osaka University campus, where the experiment was thoroughly explained. On the same day, the supplemental risk aversion estimation experiments (detailed below) and the questionnaire survey (designed to elicit individual reference points) were conducted. From Monday January 25th 2010 through Sunday February 21st 2010, the simulated stock market was open for trading every evening between the hours 18:00 and 22:36.

2.2. Diminishing Sensitivity Measurement Experiment

Measurements of individual diminishing sensitivity levels were carried out by means of two simple experiments. The "Insurance Buying Experiment" was implemented to estimate individual risk aversion levels in the loss domain. The "Lottery Selling Experiment" was implemented to estimate risk aversion levels in the gain domain.

2.2.1. Insurance Buying Experiment

In this experiment, each subject was asked whether they were willing to purchase insurance at various prices displayed on the monitor. Given an initial endowment of assets, the insurance – if purchased – guarantees a payment equivalent to the value of assets in case these are lost or damaged. This design in effect allows the experimenters to estimate the degree of a participants' risk tolerance in the domain of losses.

The details of the experiment are as follows. A subject is first presented with an initial endowment of ¥2,000. Then, an amount of potential damage and the probability of its occurrence are displayed along with a proposed insurance premium. The subject chooses whether to purchase the insurance or to decline it. There are four categories of potential damage (¥100, ¥400, ¥1200, ¥2000) while the probabilities of their occurrence are set constant at 50%. The insurance premiums (along with corresponding premium rates, equal to the premium sum divided by the damage total) are displayed in random order. An example screenshot is shown in Figure 2. This procedure is repeated 30 times in a row for each category corresponding to the four potential damage totals, starting from the lowest ¥100.

Thus, each subject goes through 120 yes-or-no queries. After that, the computer randomly chooses one of the 120 queries, which is then used to determine the actual payment.[11]

2.2.2. Lottery Selling Experiment

Individual levels of risk aversion in the domain of gains were estimated via the "Lottery Selling Experiment". In this experiment the subjects were asked whether they were willing to sell a lottery ticket at a proposed price. Each ticket has a 50% chance of winning a prize. The prize falls into one of four categories: ¥100, ¥400, ¥1200, ¥2000. A

[11] If a subject had in fact purchased insurance for the randomly chosen query, they were given the option to avert any potential damage by actually paying the premium. In the case when they had not purchased the insurance, the subject had to pay the amount of damage (in case it occurred), which was subtracted from their initial endowment. The endowment was left intact whenever no damage actually occurred. Whether the damage in fact occurred or not was selected randomly by the computer with independent probability of 50%.

participant's task is to answer "yes" or "no" to 30 choice problems for each of the four categories. The procedures as well as settlement of payments are analogous to those employed in the "Insurance Buying Experiment".[12]

2.3. Questionnaire Survey

The survey was conducted mainly to elicit reference prices, but we also included questions pertaining to subjects' preferences and demographic attributes. Here, we constrain ourselves to the description of our main purpose – identification of individual reference points.

In the questionnaire, hypothetical stock prices paths for two cases – a rising price path and a declining one – spanning 6 discrete time periods are presented. For each point in time, hypothetical buy and sell transactions along with resulting positions in the stock in question are shown. Furthermore, a 7^{th} period price is shown along with 8 different ways to calculate paper gains and paper losses for the relevant stock. Subjects are then requested to choose a method of calculation closest to their own.[13] The choices available for a reference point are: (1) the first purchase price; (2) FIFO: first-in, first-out; (3) the last purchase price; (4) LIFO: last-in, first-out; (5) the highest purchase price; (6) the lowest purchase price; (7) weighted average purchase price; (8) weighted average purchase price minus average profit/loss for the portion of shares sold in the

[12] Out of 120 choice sub-tasks, one was selected randomly by the computer. If the subject chose to sell the lottery ticket in that sub-task, they received an amount of money specified therein. In the opposite case – when the subject had chosen to not sell – the computer drew the lottery and payments were decided depending upon whether a winning ticket or a losing ticket was drawn. In the former case the subject was paid the prize, while in the latter they received nothing.

[13] There was also an additional item corresponding to a "none of the above" option, where a subject was asked to describe in detail their method of calculation.

interim time.

3. Method of Analysis

3.1. Degree of Risk Aversion

We restrict our explanation here to the case of Insurance Buying Experiment, wherein we used computational methods exactly analogous to those used in the Lottery Selling Experiment.

First, we compute for all experiment participants their individual insurance values. When specific insurance policies are ordered starting from the cheapest policy and going up in value to the most expensive one, we would expect to observe any given subject first choosing “buy” a few times, at some point switching to “not buy”, and then continuing to choose “not buy” for the remaining cases. We define “individual insurance value” as the average of the two values between which the switch occurs. It is however conceivable, and indeed turns out to be the case that, some subjects switch multiple times. In these cases, we estimate a LOGIT regression model for the 30 proposed insurance prices where we assign a “1” to each “buy” decision and a “0” to each “not buy” decision. The individual insurance value is then defined as the one corresponding to 0.5 in the regression.

The absolute risk aversion (ARA) coefficient for the *i*th subject is defined and calculated according to the following formula due to Cramer et al. (2002).

$$ARA_i = \frac{az - p_i}{\frac{1}{2} \times (az^2 - 2ap_i z + p_i^2)} \tag{1}$$

Here, a is the probability of winning equal to 0.5, z is the damage amount, and p_i is the "individual insurance value". As there are four different z values, we take an arithmetic average of those to get the final ARA coefficient values.[14]

3.2. The Estimation Model

Estimation of the disposition effect and its potential relationship with diminishing sensitivity is performed with a LOGIT analysis. The dependent variable $SELL_{i,j,t}$ is defined as follows. For each subject i we first look for all instances (measured in two-minute units) in which any trades were recorded. The subscript t then corresponds to the ordinal location of a trade, when trades are ordered chronologically. $SELL_{i,j,t}$ is set to 1 whenever a subject i sells a stock j at a time t and to 0 otherwise. The independent variable $LOSS_{i,j,t}$ is set to 1 whenever a stock j in a subject i's portfolio is trading at a loss at a time t, and to 0 otherwise. The regression model is thus

Model 1 : $$SELL_{i,j,t} = \alpha + \beta_1 \cdot LOSS_{i,j,t} + \varepsilon_{i,j,t}, \quad (2)$$

where α and β_1 are the regression coefficients and $\varepsilon_{i,j,t}$ is the error term. β_1 will be negative if the disposition effect obtains; that is, if the tendency to sell is stronger in the domain of gains than it is in the domain of losses.

Next, we test for diminishing sensitivity as a potential cause of the disposition effect. It is plausible that as the degree of diminishing sensitivity increases, the disposition effect becomes stronger. The absolute value of the coefficient β_1 from equation (2) would in this case increase with the degree of diminishing sensitivity. The regression model in this case is

---

[14] Four subjects in total appeared to either answer Yes/No randomly, or reverse the "Yes's" and the "No's". We exclude these subjects from all regressions.

$$\text{Model 2}: SELL_{i,j,t} = \alpha + (\beta_{11} + \beta_{12} \cdot DS_i) \cdot LOSS_{i,j,t} + \varepsilon_{i,j,t}$$
$$= \alpha + \beta_{11} \cdot LOSS_{i,j,t} + \beta_{12} \cdot DS_i \cdot LOSS_{i,j,t} + \varepsilon_{i,j,t}. \quad (3)$$

We expect β_{12} to be negative if diminishing sensitivity is indeed a cause of the disposition effect. We use here two alternative variables to represent diminishing sensitivity. The first one, *DS*1, is the degree of risk tolerance (the negative of risk aversion) in the domain of losses, which corresponds to a measure of convexity of the value function. The second one, *DS*2, is the risk tolerance degree in the domain of losses relative to its counterpart in the domain of gains, defined as risk aversion coefficient in the domain of gains minus risk aversion coefficient in the domain of losses. This second relative measure of diminishing sensitivity might be a more appropriate one, given that the disposition effect itself is essentially a relative measure of the extent to which winners are more likely to be sold than losers.

4. Results

4.1. Reference Points

We use each experiment participant's individual reference point, estimated from the questionnaire survey data outlined above. Table 2 summarizes our findings on the reference points: reference points for the domain of gains are in rows, while those for the domain of losses are in columns. For instance, the "1" in the left-uppermost cell of the table indicates that one person chose the first purchase price as their reference point for both the gain and the loss domains. Thus we find most subjects choosing a weighted average of purchase prices for their reference points, noting that many of them take into account profits for the portion of shares sold in the interim. We also note that most respondents selected the same reference points for both the loss and the gain domains.

4.2. Results of the Stock Trading Experiment

Throughout 28 days of the experiment and across 49 participants, we recorded a total of 3,527 sell transactions and 4,005 buy transactions – roughly 153 trades per subject, 5.5 trades per subject per day. Out of the 10 stocks traded, the most frequently traded stock was traded 1,639 times, and the least popular one 430 times, while the corresponding figures for remaining eights stocks were between 527 and 839. We observe thus an overall abundance of trading activity, with one stock topping all the others in popularity. Out of all sell orders, 1,620 (45.9%) were profitable while 1,357 (38.5%) were accompanied by losses. The remaining 550 (15.6%) trades were zero-profit transactions. For the case of buy orders, 622 (15.58%) additional purchases were recorded in the gain domain, and 1,108 (27.7%) additional purchases in the loss domain, while 2,275 (56.8%) additional purchases were recorded on zero-profit accounts.

Final asset value scores, when compared with the initial benchmark of 10,000,000 points, averaged an approximate 70,000 point loss (SD=34,000), with the highest scoring subject winning a profit of some 80,000 points and the biggest loser incurring some 88,000 points in losses.

4.3. Results of the Risk Attitudes Measurement Experiment

The average absolute risk aversion coefficient across all subjects was –0.0014 in the

Lottery Selling Experiment and –0.0031 in the Insurance Buying Experiment. Subjects thus exhibit apparently risk loving attitudes, on average. This outcome most likely originates from small stakes used in the simple lottery tasks employed to estimate risk attitudes.

When we subtract the risk tolerance coefficient measured in the Lottery Selling Experiment from the one measured in the Insurance Buying Experiment, we obtain 0.00168, which is significant at a 5% level. We conclude therefore that our subjects exhibit more risk-loving behavior in the domain of losses as opposed to the domain of gains.

4.4. Incidence of the Disposition Effect – LOGIT Regressions

In Table 3 we present a summary of the LOGIT analysis using the individual-specific reference points from the questionnaire survey. The first panel reports pooled results for all ten stocks. The "Model 1" section reports estimation results for formula (2). The coefficient for the losing-stocks variable $LOSS$ is significantly negative at 1%, revealing a tendency to avoid the realization of losses. The "Model 2 (1)" section adds the $DS1 \cdot LOSS$ as an explanatory variable in the regression. Again, the $LOSS$ coefficient is negative at a 1% significance level. Together with the results of "Model 1", this implies reluctance on the part of subjects to get rid of losing stocks, and thereby the existence of disposition effect. Furthermore, the coefficient for the $DS1 \cdot LOSS$ variable is also negative and statistically significant at a 1% level. For the alternative measure of diminishing sensitivity used in "Model 2 (2)", the coefficient of interest is again negative and statistically significant at the 1% level. These results support the hypothesis that diminishing sensitivity is a cause of the disposition effect; the higher the degree of diminishing sensitivity, the more reluctant investors are to sell losing stocks.

With the exception of stock #8, we obtain analogous statistically significant results for the *LOSS* coefficients when we perform the regressions for individual stocks (not reported here). Regarding the interaction term with the diminishing sensitivity variable *DS*1, the coefficients are all negative except for stock #8, and significantly negative except for stocks #8, #1 and #5. When *DS*2 is substituted for the diminishing sensitivity variable, the interaction term coefficients are negative except for stock #9, and significantly negative except for stocks #3 and #9. Hence we conclude that for most cases our results are consistent with the disposition effect hypothesis, and that diminishing sensitivity is one source of the effect. In other words, these outcomes are not driven by the special characteristics of any one stock in subjects' portfolios, but are a prevalent tendency evident throughout the entire stock spectrum.

4.5. Accounting for Participants' Demographic and Personal Attributes

We next check whether results reported in the previous section are replicated when we take into account participants' individual demographic and personal traits. The particular attributes we include in our analyses are gender, age, household income, and stock trading experience.

Table 4 summarizes the results. In a nutshell: (1) The disposition effect obtains even when individual attributes are accounted for; (2) Cross-term coefficients for the losing stocks term *LOSS* and both diminishing sensitivity terms *DS*1 and *DS*2 are negative and statistically significant. Clearly, higher diminishing sensitivity produces a more pronounced disposition effect.

A look at the control variables tells us that women are less prone to selling losing stocks. Also, propensity to sell grows stronger with both age and income, albeit in a diminishing manner. Finally, those with more real world trading experience tend to sell stocks more frequently.

4.6. Alternative Reference Points

In the analyses reported thus far we have used the individual-specific reference points elicited from the participants through a carefully tailored questionnaire survey. It is prudent to verify whether the results thus obtained are changed when other, arbitrarily chosen reference prices are employed. For completeness, we performed this verification exercise for all subjects for each of the eight reference points specified above in Section 2.3, for both “Model 1” and “Model 2”. The findings do not differ much from the main results reported above. In Table 5 we show the estimation results for two out of eight possible reference prices – weighted average purchase price (WA1), and first-bought first-sold (FIFO). These findings corroborate previous empirical studies that report robustness of the disposition effect with respect to a variety of assumptions on reference points.

4.7. Time Discounting and the Disposition Effect

The ongoing debate about the relationship between prospect theory and the disposition effect needs to address the potential effects of time preferences on investors' reluctance to realize losses. Time preferences – in particular, individual discount rates – are likely to influence the timing of trades. Although many intertemporal decision making models assume, for tractability and simplicity, no discounting at all, it is plausible that individual discount rates could interact with the disposition effect. Henderson (2012) conjectures that "the inclusion of time discounting would be likely to give an incentive to delay losses further, contributing to an even more pronounced disposition effect". In fact, Barberis and Xiong (2012), show in their model that for a strong disposition effect to obtain, sufficiently high time discount rates are required, in combination with realization utility. In this section we attempt to supplement these theories with an empirical test of the hypothesis that investors with higher time discount rates exhibit stronger disposition effects.

We elicited participants' time discount rates using a questionnaire accompanying the experiment. In the questionnaire, a subject is presented with a series of binary choice tasks, in which they must choose between receiving a payment of ¥10,000 in 90 days (option "A"), or a payment of ¥X in 97 days (option "B"). The latter amount X is varied from the minimum of ¥9,981 through eight values, increasing gradually to the maximum of ¥10,574; these correspond to effective annual rates of return of –10% to +300%. Usually, the respondents choose the ¥10,000 option at low interest rates, but as the imputed interest rate rises, they ultimately switch to the increasingly attractive "X" option.[15] The individual respondents' discount rates can be inferred by estimating the interest rate at which respondents are indifferent between the delayed receipt of ¥X and the more immediate receipt of ¥10,000. The present study employed procedures of measurement and analysis of time-discount rates similar to those outlined in Kimball, Sahm, and Shapiro (2008). We estimated the gross discount rate for each respondent according to a lognormal distribution function. This estimation method enabled us to obtain the interest rates between which a subject switched his choice from option "A" to "B" for each respondent, including those who stuck either to option "A" or to "B" for all given choices. We term the time discount rates estimated using this method "*TD*1." Similarly, in another series of eight binary choices, participants chose between receiving ¥10,000 in one month, or an amount ¥X ranging from ¥9,500 (for an annual rate of –5%) through ¥14,000 (for an annual rate of +40%) in 13 months. The discount rates corresponding to this task are termed "*TD*2."

Estimation results for equation (3) with added *TD*1***LOSS* (*TD*2***LOSS*) cross-term coefficients are presented in Table 6. Subjects' individual attributes, such as gender, age and income, are added to the regression equations here as control variables. The results remain unchanged if we omit these variables.

The *LOSS* coefficients are negative and significant in all cases, confirming the incidence of the disposition effect. The coefficients for *DS*1***LOSS* and *DS*2***LOSS* are again negative and significant. However, both the *TD*1 and *TD*2 cross-term *LOSS* coefficients are significantly positive, denying the intuition that higher time-discount

[15] We excluded from this analysis 3 cases wherein respondents switched multiple times between ¥10,000 and ¥X.

rates lead to fewer instances of selling losers. The fact that the signs of the control variables' coefficients are identical to those in the diminishing sensitivity *DS* estimates reported in Table 4 provides additional credibility to our findings.

In Table 7, we report estimation results for the cases in which the *DS*1**LOSS* and *DS*2**LOSS* cross-term coefficients are omitted from the estimated formula reported in Table 6. In other words, Table 7 presents results for estimation of equation (3) in which the *DS*1 and *DS*2 data have been replaced with *TD*1 and *TD*2. Again, the findings we report here include the control variables on the right hand side of the equation, but they remain unchanged if we omit them.

Our basic results concerning time discounting and the disposition effect remain unchanged in this new regression. The *LOSS* coefficients are significantly negative (confirming the existence of the disposition effect), while the cross-term coefficients for all combinations of *TD*1, *TD*2 and *LOSS* are significantly positive. The impact of control variables remains practically unaltered as well.

These findings contradict both Henderson's (2012) conjecture and Barberis' and Xiong's (2012) theoretical result that higher individual time-discount rates lead to stronger disposition effects.

5. Conclusions

The economic experiment reported in this paper adds to a substantial body of work on the existence of the disposition effect and its potential causes. While numerous experimental studies exist on the topic, the distinguishing feature of our approach is the close similarity of our experimental environment with real-world stock markets. For a span of 28 days, participants of our simulated stock market bought and sold shares in 10 stocks, the prices of which were taken from actual past market data. Participants' remuneration was commensurate with profits and losses incurred from buying and selling stocks. On top of that, a winner's prize was awarded to the most successful trader. As a result, we acquired ample trading data, with a total of 7,532 transactions. Our experimental environment has the additional merit of allowing us to control for a range of conditions. For instance, the absence of taxation and transaction costs eliminates the need to consider those effects.[16]

The greatest merit of our experiment lies in the fact that we were able to extract two additional types of information from our participants. First, we pinpointed each participant's individual reference point using a questionnaire survey we conducted before the experiment. This information is impossible to acquire in empirical studies, and to the best of our knowledge, no previous experimental studies even attempted to acquire it. Accordingly, we succeeded in testing an *independent* hypothesis about the existence of the disposition effect, not merely a joint hypothesis of the disposition effect and a particular reference point.

Our second finding regards the source of the disposition effect, which we were able to assess by measuring participants' risk aversion in both domains (gains and losses) in our two supplementary experiments. We find that diminishing sensitivity is a cause of the disposition effect, as the latter becomes stronger whenever either (i) behavior in the

---

[16] However, we can eliminate neither the "portfolio rebalancing" nor the "regression to the mean" arguments as potential causes of the disposition effect, as we were unable to control for these.

domain of losses becomes more risk-loving, or (ii) behavior in the domain of losses compared to behavior in the domain of gains becomes more risk-loving.

Our approach, in contrast to previous studies, also has the merit of being a *direct* examination of diminishing sensitivity as a potential cause of the disposition effect. Odean (1998) deduces that diminishing sensitivity brings about the disposition effect in an *indirect* manner. He shows by elimination that alternative explanations do not fully account for the disposition effect, which persists even after these factors are taken into account.

We demonstrate directly with our LOGIT analyses that the disposition effect exists *and* that diminishing sensitivity is one of its causes. This result remains valid even when we use a variety of alternative reference points for prices.

The debate over whether prospect theory can explain the disposition effect has heated up recently. It has been convincingly argued by both Barberis and Xiong (2009) and Kaustia (2010) that the traditional economic interpretation of a Tversky and Kahneman (1992) value function, wherein the sheer act of stock trading does not lead to changes in utility levels as long as consumption remains unchanged, will not generate the disposition effect. In contrast, arguments based on prospect theory readily produce the disposition effect in a series of recent studies. In Barberis and Xiong (2012) and in Henderson (2012), the effect is generated by realization utility. In Li and Yang (2013), a prospect theory-based extended general equilibrium model with endogenous returns generates the effect. A modification of the value function reference point, which uses the expected excess return rate as the reference point, yields the disposition effect in

Meng (2012).

The two theoretical studies most closely related to ours, Henderson (2012) and Li and Yang (2013), point to diminishing sensitivity as the vital link between prospect theory and the disposition effect. In both papers, the larger the degree of diminishing sensitivity, the more prominent the disposition effect. This is consistent with our empirical findings, though we admit that it was not our intent in this project to verify the validity of either of the theories mentioned above. In order to fully validate those theories, it is necessary to design experiments based on hypotheses aimed at clearly distinguishing between the various theories. This task remains a challenge for further research.

We also find, interestingly, that higher individual discount rates do not lead to stronger disposition effects; in fact, the opposite appears to be true, a result that negates the conjectures of both Henderson (2012) and Barberis and Xiong (2012). However, our time discounting analysis is a tentative one, and as such should be regarded with caution. In contrast to our elicitation of risk attitudes through a rigorous economic experiment, the time discount rates were estimated from participants' responses to a simple questionnaire. On top of that, the discount rates were estimated in the gains domain only. Appelt et al. (2011) provide evidence for a lack of consistency in discount rates across the gain/loss domains. A more thorough examination of the potential links between time preferences and the disposition effect is another avenue for future research.

References

Appelt, K. C., D. J. Hardisty, and E. U. Weber (2011) “Asymmetric Discounting of Gains and Losses: A Query Theory Account,” *Journal of Risk and Uncertainty*, 43, 107-126.

Barberis, N., and W. Xiong (2009) “What Drives the Disposition Effect? An Analysis of a Long-Standing Preference-Based Explanation,” *Journal of Finance,* 64, 751–784.

Barberis, N. and W. Xiong (2012) “Realization Utility,” *Journal of Financial Economics*, 104, 251–271.

Choe, H., and Y. Eom (2009) “The Disposition Effect and Investment Performance in the Futures Market,” *Journal of Futures Markets,* 29, 496-522.

Chui, P. M. W. (2001) “An Experimental Study of the Disposition Effect: Evidence from Macau,” *Journal of Psychology and Financial Markets*, 2, 215–221.

Constantinides, George M. (1984) "Optimal Stock Trading with Personal Taxes: Implications for Prices and the Abnormal January Returns," *Journal of Financial Economics*, 13(1), 65-89.

Coval, J. D., and T. Shumway (2005) “Do Behavioral Biases Affect Prices?” *Journal of Finance,* 60, 1-34.

Cramer, J.S. J. Hatog, N. Jonker, and C. M. Van Praag (2002) “Low Risk Aversion Encourages the Choice for Entrepreneurship: An Empirical Test of a Truism,” *Journal of Economic Behavior & Organization*, 48, 29-36

Fogel S. and T. Berry (2006) “The Disposition Effect and Individual Investor Decisions: The Roles of Regret and Counterfactual Alternatives,” *Journal of Behavioral Finance*, 7(2), 107–116.

Frydman, C., N. Barberis, C. Camerer, P. Bossaerts, and A. Rangel1 (2012) “Using Neural Data to Test A Theory of Investor Behavior: An Application to Realization Utility,” NBER Working Paper 18562.

Grinblatt, M. and M. Keloharju (2001) “What Makes Investors Trade?” *Journal of Finance*, 56, 589–616.

Henderson, V. (2012) “Prospect Theory, Liquidation, and the Disposition Effect,” *Management Science*, 58, 445–460.

Hens, T. and M. Vlcek (2011) “Does Prospect Theory Explain the Disposition Effect?”

Journal of Behavioral Finance, 12(3), 141–157.

Kahneman, D. and A. Tversky (1979) "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47, 263–291.

Kaustia, M. (2010) "Prospect Theory and the Disposition Effect," *Journal of Financial and Quantitative Analysis*, 45, 791-812.

Kimball, M. S., C. R. Sahm, and M. D. Shapiro (2008) "Imputing Risk Tolerance from Survey Responses" *Journal of the American Statistical Association*, 103, 1028-1038.

Kirchler, E., B. Maciejovsky, and M. Weber (2005) "Framing Effects, Selective Information, and Market Behavior: An Experimental Analysis," *Journal of Behavioral Finance*, 6 (2), 90–100.

Lakonishok, J. and S. Smidt (1986) "Volume for Winners and Losers: Taxation and Other Motives for Stock Trading," *Journal of Finance*, 41, 951–974.

Li, Y. and L. Yang (2013) "Prospect Theory, the Disposition Effect, and Asset Prices," *Journal of Financial Economics*, 107, 715–739.

Meng, J. (2012) "Can Prospect Theory Explain the Disposition Effect? A New Perspective on Reference Points," http://ssrn.com/abstract=1851883.

Misumi, T., T. Shumway, and H. Takahashi (2007) "On the Behavior of Investors from a Behavioral Finance Viewpoint: Evidence from the Trades of Japanese Individual Investors," mimeo.

Odean, T. (1998) "Are Investors Reluctant to Realize Their Losses?" *Journal of Finance*, 53, 1775–1798.

Odean, T. (1999) "Do Investors Trade Too Much?" *American Economic Review*, 89(5), 1279-1298.

Rubaltelli, E, S. Rubichi, L. Savadori, M. Tedeschi, and R. Ferretti (2005) "Numerical Information Format and Investment Decisions: Implications for the Disposition Effect and the Status Quo Bias," *The Journal of Behavioral Finance*, 6 (1), 19–26.

Shefrin, H. and M. Statman (1985) "The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence," *Journal of Finance*, 40, 777–790.

Shiroshita, K. (2009) "Kishitsu-Koka (Disposition Effect)," in Shiroshita, K. and H. Moriyasu eds., *Nihon Kabushiki Shijō no Tōshi Kōdō Bunseki (Analysis of Investment Behavior in Japanese Stock Market)* Chpt. 7, 139-159, Chuokeizai-Sha, (in Japanese).

Shumway, T. and G. Wu (2006) “Does Disposition Drive Momentum?” mimeo.

Tversky, A. and D. Kahneman (1992) “Advances in Prospect Theory: Cumulative Representation of Uncertainty,” *Journal of Risk and Uncertainty*, 5, 297–323.

Vlcek, M. and M. Wang (2007) “The Disposition Effect in the Lab,” Working Paper, University of Zurich.

Weber, M. and C.F. Camerer (1998) “The Disposition Effect in Securities Trading: An Experimental Analysis,” *Journal of Economic Behavior and Organization*, 33, 167–184.

Table 1: Summary of Experiment Participants' Attributes

Participants were recruited (with the assistance of an internet research company) from among individual investors with previous stock trading experience, defined as having recent history of trading on the stock market at least once per month.

	Male		Female		Total	
	n	%	n	%	n	%
age_group						
20-29	3	8.60%	1	7.70%	4	8.30%
30-39	16	45.70%	4	30.80%	20	41.70%
40-49	9	25.70%	5	38.50%	14	29.20%
50-59	5	14.30%	1	7.70%	6	12.50%
60-69	0	0.00%	2	15.40%	2	4.20%
70-	2	5.70%	0	0.00%	2	4.20%
Total	35	100.00%	13	100.00%	48	100.00%
JOB						
civil servant	1	2.90%	0	0.00%	1	2.10%
business executive	2	5.70%	1	7.70%	3	6.30%
administrative staff	1	2.90%	0	0.00%	1	2.10%
office staff	2	5.70%	3	23.10%	5	10.40%
technical staff	10	28.60%	0	0.00%	10	20.80%
sales/customer service	4	11.40%	2	15.40%	6	12.50%
other salaried worker	2	5.70%	0	0.00%	2	4.20%
teacher	1	2.90%	0	0.00%	1	2.10%
medical expert	1	2.90%	0	0.00%	1	2.10%
self-employed	4	11.40%	0	0.00%	4	8.30%
other part-time	2	5.70%	0	0.00%	2	4.20%
homemaker	1	2.90%	4	30.80%	5	10.40%
working homemaker	0	0.00%	2	15.40%	2	4.20%
unemployed	1	2.90%	1	7.70%	2	4.20%
other	3	8.60%	0	0.00%	3	6.30%
Total	35	100.00%	13	100.00%	48	100.00%
INCOME_GROUP (unit: 10,000yen)						
<100	1	2.90%	0	0.00%	1	2.10%
100-200	0	0.00%	1	7.70%	1	2.10%
200-300	1	2.90%	0	0.00%	1	2.10%
300-400	3	8.60%	2	15.40%	5	10.40%
400-500	5	14.30%	1	7.70%	6	12.50%
500-600	5	14.30%	3	23.10%	8	16.70%
600-700	5	14.30%	0	0.00%	5	10.40%
700-800	2	5.70%	2	15.40%	4	8.30%
800-900	6	17.10%	0	0.00%	6	12.50%
900-1000	4	11.40%	1	7.70%	5	10.40%
1000-1500	1	2.90%	0	0.00%	1	2.10%
1500-	1	2.90%	3	23.10%	4	8.30%
unknown	1	2.90%	0	0.00%	1	2.10%
Total	35	100.00%	13	100.00%	48	100.00%
FREQ_TRADE (about once in ~)						
a month	9	25.70%	0	0.00%	9	18.80%
half a month	2	5.70%	6	46.20%	8	16.70%
a week	11	31.40%	5	38.50%	16	33.30%
daily	13	37.10%	2	15.40%	15	31.30%
Total	35	100.00%	13	100.00%	48	100.00%

Table 2: Questionnaire Survey of Reference Points – Summary of Results

This table summarizes the results of a questionnaire survey conducted to elicit individual reference points. It reports the number of subjects corresponding to each combination of reference points. Each row represents a reference point for the domain of gains and each column represents a corresponding reference point for the domain of losses. The labels for each reference point are as follows. FIRST: first purchase price; FIFO: first-in first-out; LAST: last purchase price; LIFO: last-in first-out; HIGH: highest purchase price; LOW: lowest purchase price; WA1: weighted average purchase price; WA2: weighted average purchase price minus average profit/loss for the portion of shares sold in the interim time NULL: no response.

		LOSS									
		FIRST	FIFO	LAST	LIFO	LOW	WA1	WA2	OTHER	NULL	TOTAL
GAIN	FIRST	1									1
	FIFO		2						1		3
	LAST		2	1							3
	LOW					1					1
	WA1			1	1		15	1		1	19
	WA2							21			21
	OTHER						1				1
	TOTAL	1	4	2	1	1	16	22	1	1	49

Table 3: Summary of LOGIT Regressions Using Individual-Specific Reference Points

This table shows regression results for two models – "Model 1" and "Model 2". Data for this analysis consists of trade records for all the stocks in subjects' portfolios. The dependent variable *SELL* takes a value of 1 whenever a sell transaction occurs, and 0 otherwise. The variable *LOSS* is set equal to 1 whenever a stock is trading at a loss and 0 otherwise. Whether the stock in question is actually trading at a loss is determined via a subject-specific reference point elicited through a questionnaire survey. Whenever such determination was not possible, the corresponding data was excluded from the analysis. Diminishing sensitivity coefficients *DS1* and *DS2* used for Model 2 (1) and Model 2 (2) are defined as *DS1 = (–1) * (Degree of Risk Aversion in the Insurance Buying Experiment)* and *DS2 = (–1) * (Degree of Risk Aversion in the Insurance Buying Experiment) – (–1) * (Degree of Risk Aversion in the Lottery Selling Experiment)*, respectively. *** indicates coefficients which are significant at the 1% significance level.

	Model 1			Model 2					
				(1)			(2)		
	coef.	z		coef.	z		coef.	z	
LOSS	-0.748	-19.64	***	-0.528	-10.39	***	-0.555	-13.10	***
DS1·LOSS				-58.274	-6.23	***			
DS2·LOSS							-46.192	-9.13	***
Constant	-1.151	-46.07	***	-1.151	-46.07	***	-1.151	-46.07	***
Pseudo R^2	0.02			0.02			0.03		
Number of Observations	19451			19451			19451		
Marginal Effects									
LOSS	-0.110	-19.91	***	-0.106	-19.60	***	-0.106	-19.53	***
DS1				-3.609	-6.23	***			
DS2							-2.846	-9.11	***

Table 4: Summary of LOGIT Regressions Including Individual Attributes

This table reports results of regressions for "Model 1" and "Model 2" with experiment subjects' personal attributes added as independent variables. The dependent variable *SELL* takes a value of 1 whenever a sell transaction occurs, and 0 otherwise. The variable *LOSS* is set equal to 1 whenever a stock is trading at a loss and 0 otherwise. Whether the stock in question is actually trading at a loss is determined via a subject-specific reference point elicited through a questionnaire survey. Whenever such determination was not possible, the corresponding data was excluded from the analysis. *FEMALE* is a dummy variable equal to 1 for females and 0 for males, *AGE* is the age variable and *INCOME* is the income variable. *FREQ_TRADE_dummy* is the dummy variable with values assigned according to subjects' real-world market trading experience. Diminishing sensitivity coefficients *DS1* and *DS2* used for Model 2 (1) and Model 2 (2) are defined as *DS1 = (–1) * (Degree of Risk Aversion in the Insurance Buying Experiment)* and *DS2 = (–1) * (Degree of Risk Aversion in the Insurance Buying Experiment) – (–1) * (Degree of Risk Aversion in the Lottery Selling Experiment)*, respectively. **, *** indicate coefficients that are significant at the 5% and 1% significance level, respectively.

	Model 1			Model 2					
				(1)			(2)		
	coef.	z		coef.	z		coef.	z	
LOSS	-0.719	-18.30	***	-0.608	-11.28	***	-0.604	-13.68	***
DS1 ·LOSS				-31.804	-2.95	***			
DS2 ·LOSS							-29.091	-5.36	***
FEMALE	-0.726	-13.64	***	-0.660	-11.44	***	-0.672	-12.55	***
AGE(x0.01)	5.164	3.66	***	4.459	3.12	***	0.045	3.21	***
AGE^2(x0.0001)	-6.851	-4.81	***	-6.155	-4.27	***	-5.975	-4.21	***
INCOME(x0.01)	-0.127	-10.77	***	-0.124	-10.46	***	-0.115	-9.66	***
$INCOME^2$(x0.0001)	0.001	11.10	***	0.001	10.84	***	0.001	10.14	***
FREQ_TRADE_dummy	(against "once/month")			(against "once/month")			(against "once/month")		
once in half a month	-0.804	-8.15	***	-0.827	-8.34	***	-0.833	-8.44	***
once a week	-0.454	-6.01	***	-0.487	-6.39	***	-0.456	-6.09	***
daily	-0.011	-0.16		-0.013	-0.20		0.018	0.28	
Constant	-0.842	-2.59	***	-0.693	-2.11	**	-0.813	-2.53	***
Pseudo R^2	0.063			0.064			0.065		
Number of Observations	19345			19345			19345		

	Model 1			Model 2					
				(1)			(2)		
Marginal Effects	coef.	z		coef.	z		coef.	z	
LOSS	-0.099	-18.61	***	-0.099	-18.55	***	-0.098	-18.46	***
DS1				-1.880	-2.96	***			
DS2							-1.714	-5.37	***
FEMALE	-0.100	-13.74	***	-0.091	-11.50	***	-0.092	-12.62	***
AGE(x0.01)	-0.148	-5.58	***	-0.157	-5.89	***	-0.130	-4.89	***
INCOME(x0.01)	-0.016	-10.72	***	-0.015	-10.39	***	-0.014	-9.58	***
FREQ_TRADE_dummy	(against "once/month")			(against "once/month")			(against "once/month")		
once in half a month	-0.111	-8.17	***	-0.114	-8.36	***	-0.115	-8.46	***
once a week	-0.062	-6.02	***	-0.067	-6.41	***	-0.063	-6.10	***
daily	-0.001	-0.16		-0.002	-0.20		0.003	0.28	

Table 5: LOGIT Regressions Results Summary under Weighted Average Purchase Price WA1 and under the First-Bought First-Sold FIFO Rule as Reference Points

Panels A and B report regression results for "Model 1" and "Model 2" for the case when individual-specific reference points are replaced with the weighted average purchase price and the first-bought first-sold FIFO rule (i.e. shares which are purchased first are also sold first) as a reference point, respectively. The distinction between the domain of gains and the domain of losses is accordingly revised to reflect this change in the reference point. For details, please refer back to Table 3.

Panel A: Weighted Average Purchase Price WA1

	Model 1			Model 2					
				(1)			(2)		
	coef.	z		coef.	z		coef.	z	
LOSS	-0.792	-21.01	***	-0.550	-10.87	***	-0.594	-14.20	***
DS1 ·LOSS				-63.230	-6.83	***			
DS2 ·LOSS							-47.883	-9.51	***
Constant	-1.133	-45.68	***	-1.133	-45.68	***	-1.133	-45.68	***
Pseudo R^2	0.02			0.03			0.03		
Number of Observations	19992			19992			19992		

Marginal Effects	coef.	z		coef.	z		coef.	z	
LOSS	-0.114	-21.34	***	-0.111	-20.93	***	-0.112	-20.94	***
DS1				-3.908	-6.82	***			
DS2							-2.948	-9.48	***

Panel B: The First-Bought First-Sold FIFO

	Model 1			Model 2					
				(1)			(2)		
	coef.	z		coef.	z		coef.	z	
LOSS	-0.794	-20.93	***	-0.511	-10.10	***	-0.582	-13.94	***
DS1 ·LOSS				-74.417	-7.94	***			
DS2 ·LOSS							-53.295	-10.28	***
Constant	-1.147	-46.96	***	-1.147	-46.96	***	-1.147	-46.96	***
Pseudo R^2	0.02			0.03			0.03		
Number of Observations	19992			19992			19992		

Marginal Effects	coef.	z		coef.	z		coef.	z	
LOSS	-0.114	-21.25	***	-0.111	-20.79	***	-0.113	-20.99	***
DS1				-4.400	-7.92	***			
DS2							-3.138	-10.23	***

Table 6: Summary of LOGIT Regressions Including the Time Discount Rates TD1 and TD2 Cross-Terms with LOSS besides the Diminishing Sensitivity and LOSS Cross-Terms.

This table reports regression results for "Model 2" (equation (3)) with TD1*LOSS and TD2*LOSS cross-term coefficients added to the equation.

	Model 2											
	(1)			(2)			(3)			(4)		
	coef.	z		coef.	z		coef.	z		coef.	z	
LOSS	-0.733	-12.94	***	-0.696	-12.43	***	-0.787	-16.50	***	-0.758	-15.93	***
DS1 ·LOSS	-53.751	-4.68	***	-54.319	-4.80	***						
DS2 ·LOSS							-58.260	-9.17	***	-64.167	-9.78	***
TD1 ·LOSS(x0.01)	0.193	7.56	***				0.292	10.41	***			
TD2 ·LOSS(x0.01)				1.306	6.42	***				2.307	9.76	***
FEMALE	-0.561	-9.51	***	-0.607	-10.42	***	-0.555	-10.12	***	-0.601	-11.18	***
AGE(x0.01)	2.251	1.55		5.090	3.52	***	2.069	1.46		5.597	3.96	***
AGE^2(x0.0001)	-3.882	-2.65	***	-6.691	-4.59	***	-3.313	-2.31	**	-6.720	-4.72	***
INCOME(x0.01)	-0.169	-13.63	***	-0.135	-11.24	***	-0.161	-13.08	***	-0.125	-10.51	***
$INCOME^2$(x0.0001)	0.002	14.03	***	0.001	11.68	***	0.002	13.68	***	0.001	11.17	***
FREQ_TRADE_dummy	(against "once/month")			(against "once/month")			(against "once/month")			(against "once/month")		
once in half a month	-0.924	-9.21	***	-0.837	-8.41	***	-0.943	-9.47	***	-0.842	-8.51	***
once a week	-0.708	-9.06	***	-0.515	-6.76	***	-0.673	-8.84	***	-0.451	-6.04	***
daily	-0.136	-1.98	**	-0.053	-0.80		-0.114	-1.67	*	-64.167	0.16	
Constant	0.127	0.38		-0.794	-2.38	**	0.015	0.04		-1.129	-3.45	***
Pseudo R^2	0.071			0.066			0.074			0.070		
Number of Observations	19277			19345			19277			19345		

Table 7: Summary of LOGIT Regressions Including the Time Discount Rates TD1 and TD2 Cross-Terms with LOSS instead of the Diminishing Sensitivity and LOSS Cross-Terms.

This table reports regression results for "Model 2" (equation (3)) with TD1*LOSS and TD2*LOSS cross-term coefficients replacing the DS1*LOSS and DS2*LOSS coefficients.

	Model 2											
	(1)			(2)			(3)			(4)		
	coef.	z		coef.	z		coef.	z		coef.	z	
LOSS	-0.986	-21.81	***	-0.988	-21.26	***	-0.889	-18.88	***	-0.849	-17.99	***
TD1 ·LOSS(x0.01)	0.0023	10.28	***				0.156	6.44	***			
TD2 ·LOSS(x0.01)				0.01809	9.44	***				1.010	5.22	***
FEMALE							-0.670	-12.32	***	-0.719	-13.45	***
AGE(x0.01)							339.530	2.37	**	6.047	4.22	***
AGE^2(x0.0001)							-5.027	-3.48	***	-7.656	-5.31	***
INCOME(x0.01)							-0.171	-13.77	***	-0.138	-11.50	***
$INCOME^2$(x0.0001)							0.002	14.09	***	0.001	11.84	***
FREQ_TRADE_dummy							(against "once/month")			(against "once/month")		
once in half a month							-0.877	-8.83	***	-0.800	-8.09	***
once a week							-0.643	-8.34	***	-0.460	-6.09	***
daily							-0.111	-1.63		-0.042	-0.63	
Constant	-1.167	-46.36	***	-1.153	-46.06	***	-0.142	-0.43		-1.000	-3.03	***
Pseudo R^2		0.029			0.027			0.069			0.065	
Number of Observations		19290			19358			19277			19345	

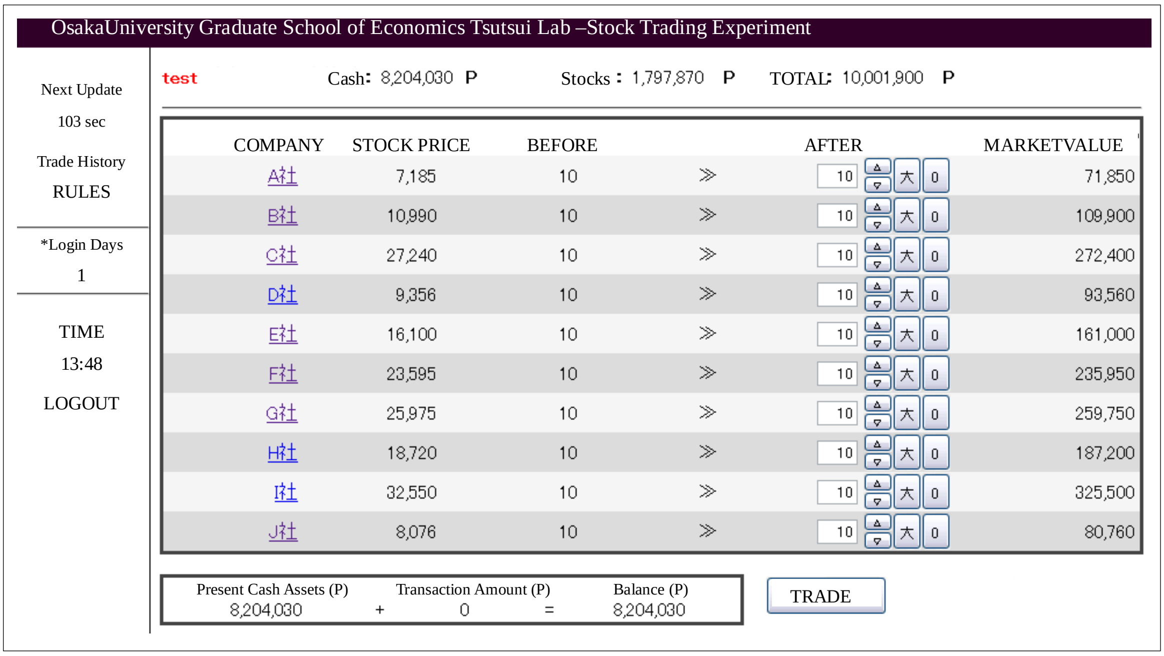

Figure 1: Screenshot of the Transaction Panel (translated from Japanese)

The screenshot in the figure above provides information on the present composition of the subjects' portfolios, stock prices and cash holdings. Subjects use it also to order their buy and sell transactions, which are immediately executed. For instance, by changing the number of shares in the "AFTER" transaction column and clicking on "TRADE", a corresponding order is completed.

Figure 2: Screenshot from the “Insurance Buying Experiment” (edited from Japanese)
The display for this experiment shows an amount of potential damage with the probability of its occurrence as well as an insurance premium offer. The subject chooses either to purchase the insurance (”yes”) or to decline it (”no”).