〔論　　　文〕

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Who Learns Well from Boosting?
――Heterogeneous Treatment Effects on the Disposition Effect* ――

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1　Introduction

With the deepening of research in behavioral economics, it has become widely known that irrational behavioral biases and heuristics drive our decisions. Behavioral biases and heuristics can prevent us from getting the desired results. For example, people tend to draw statistically incorrect conclusions, such as the Linda problem[1)] (Tversky and Kahneman (1983)), or make different judgments about the same event depending on the salience of the information (see Kahneman (2012)). The prospect theory (Kahneman and Tversky (1979)), in which the shape of the value function under uncertainty is assumed to be concave for profits and convex for losses, is a representative model that explains how such irrational decision-making occurs.

One of the typical biases thought to be explained by prospect theory is the disposition effect, which is the tendency of an investor to realize winning positions rather quickly while holding on to losing positions (Odean (1998)). According to the assumptions of prospect theory, investors are risk-loving in the loss domain and, therefore, reluctant to realize valuation losses. Alternatively, in the profit domain, they are risk-averse and therefore tend to realize valuation gains immediately, resulting in the disposition effect. The disposition effect inevitably leads to lost opportunities, which is not an optimal investment behavior. Some researches show that the disposition effect negatively affects investment performance (Seru *et al.* (2010), Locke and Mann (2005)).

The purpose of the present paper is to deal with our behavioral biases and achieve better welfare. Behavioral insights, such as nudging and boosting based on behavioral economics, can be helpful to manage our biases in decision-making. Among these approaches, considering behavioral insights in

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1) Linda problem is an example of a conjunction fallacy that originated with Tversky and Kahneman (1983). The conjunction fallacy occurs when it is assumed that specific conditions are more probable than a single general one. Tversky and Kahneman (1983) argue that most people get this problem wrong because they use a heuristic procedure called representativeness to make judgments.

investment is an essential issue because it can reduce the economic disadvantages caused by behavioral biases. A good example of boosting approaches in investment behavior is Ando (2021). She shows through experiments that the disposition effect can be mitigated on average by teaching investors the importance of cutting their losses.

Although the results of Ando (2021) are significant as they show that boosting is effective for trading behavior, they are still insufficient for actual application to financial literacy education. This inadequacy is due to the fact that Ando (2021) lacks a perspective on the differences in effects caused by the heterogeneity of individuals who receive boosting. Behavioral interventions can improve people's well-being, but the effect of the intervention depends on their heterogeneity.[2)] Behavioral insights are not always a panacea, and it is essential to clarify when cases work and when they do not. The study by Ando (2021) should also clarify the effects of heterogeneity.

Against this background, this study extends the work of its companion paper, Ando (2021), to examine the implication of investor heterogeneity for the treatment effects of education on the disposition effect. To conduct this examination, I use the same dataset as Ando (2021) and focus on individual attributes such as gender, cognitive ability, and investment experience that studies have reported as direct determinants of the disposition effect and examine the effect of these attributes on boosting. Ando (2021) used a difference-in-difference (DD) approach to analyze uniform treatment effects. In contrast, I use a difference-in-difference-in-difference (DDD) approach to explicitly address which individual attributes increase or decrease the effect of boosting.

The results of my experiment can be summarized as follows: the effect of boosting on the disposition effect is not uniform across individual attributes. First, the experiment shows a more substantial reduction in the disposition effect through educational treatment when the investor's cognitive ability is higher. Second, investors with more than three years of investment experience show a more significant decrease in the disposition effect after boosting than investors with no investment experience. However, for investors with only one or two years of investment experience, boosting increases the disposition effect, contrary to its intention. These results indicate that considering investors' cognitive ability and investment experience is essential when analyzing the treatment effect of boosting because these factors influence the effectiveness of education. Additionally, education in the very early stages of investment (i.e., no experience) is essential to encourage investors to make rational decisions as investors with no investment experience can learn more effectively about the necessity of cutting losses than investors with one or two years of investment experience. I have clarified the effect of the treatment on the disposition effect, but I have not analyzed the effect on performance because behavioral change takes more time to have a long-lasting effect on trading performance.

The remainder of this paper is organized as follows: In Section 2, I provide an overview of the relevant studies and present the position of this study. Section 3 presents the experimental design.

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2) For example, applying the same tax policy to different countries or regions will have different effects. Patients who take the same medicine will have different results that depend on their age and medical history. The organization of the Ministry of the Environment, Government of Japan, BEST (2019), states: "Effective examples of using behavioral insights in other countries may not always work out in the same way in Japan because cultures, customs, and other aspects are different."

The data are described in Section 4. In Section 5, I describe the model used for the analysis. Section 6 presents the effects of individuals' attributes on the education treatment of the disposition effect. Section 7 presents a summary of this study and topics for future studies. Note that this study uses the experimental data of Ando (2021) to deepen her research. For this reason, the experimental design, tools, intervention methods, and data sets described in Chapters 3 and 4 below are all the same as those of Ando (2021), the source of the citation.

2 Literature Review and Contribution

2.1 Disposition effect

The disposition effect is a well-known behavioral bias in which investors dispose of profitable positions early while holding losing positions longer (Odean (1998)). As with other heuristics and biases, the disposition effects can lead to irrational decision-making under uncertainty. Seru *et al.* (2010) showed that investors with lower disposition effects have higher investment performance.

The extent of the disposition effect varies between individuals, and many empirical studies exist on its determinants. For example, Grinblatt *et al.* (2012) show that investors with higher IQs demonstrate a smaller disposition effect. Moreover, Rau (2014) shows that the disposition effect is more significant for women. Vaarmets *et al.* (2019) find that the disposition effect is smaller for investors with higher levels of education. However, two opposing arguments exist on the effect of investment experience. Some studies show that investment experience effectively reduces the disposition effect (e.g., Da Costa *et al.* (2013), Dhar and Zhu (2006)). However, one study argues that the disposition effect does not depend on investment experience (Frazzini (2006)).

Recently, two types of studies have emerged concerning treatment methods to reduce the disposition effect. One uses institutional devices as the treatment. For example, Fischbacher *et al.* (2017) show that stop-loss orders effectively reduce the disposition effect. Ando (2021) uses boosting to point out that teaching people the importance of cutting their losses can reduce their disposition effect. These studies show that the treatment can mitigate the disposition effect, but they do not show how much the treatment differs among heterogeneous individuals.

2.2 Nudging and boosting

Two contrasting approaches to behavioral change are nudging and boosting. Nudging is an intervention designed to guide people in a particular direction while maintaining freedom of choice (Thaler and Sunstein (2008)). Nudging takes advantage of people's cognitive deficiencies to encourage them to make better decisions.[3] Typical examples of nudging are changing the default option to encourage pension enrollment (Beshears *et al.* (2006)) or encouraging people to choose healthier foods by making the information as clear and simple as possible (Van Gestel *et al.* (2018)). Nudging can help improve decision-making in health and wealth. However, a criticism of nudging is that it undermines people's autonomy by deliberately using their irrationality to influence their choices (Wilkinson (2013), Saghai (2013)) and reducing their ability to make autonomous decisions

3) Nudging is based on the philosophy of libertarian paternalism. Thaler and Sunstein (2008) defined the concept as: "A nudge, as we will use the term, is any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives."

(Hausman and Welch (2010), Selinger and Whyte (2012)).

Boosting has emerged as an alternative behavioral approach to this criticism (Hertwig and Grüne-Yanoff (2017), Grüne-Yanoff *et al.* (2018)). Boosting is a policy approach that allows people to improve their competencies and literacy and develop decision-making capabilities on their initiative (BEST: Japan's national Behavioral Sciences Team (2019)). The focus of boosting is on interventions that help people develop their independence by developing existing abilities or instilling new ones. Examples of boosting are teaching statistical literacy to enhance the ability to scrutinize potentially manipulated information, teaching citizens the symptoms and coping strategies for myocardial infarctions and strokes, or providing a simple and highly efficient decision tree that supports decisions under uncertainty (Grüne-Yanoff and Hertwig (2016)).

Nudging assumes somewhat mindless, passive decision-makers hostage to a rapid and instinctive automatic system (Thaler and Sunstein (2008)). By contrast, boosting assumes a decision-maker whose competencies can be improved by enriching skills and decision tools. Using Kahneman's (2012) definitions of two different ways in which the brain forms thoughts, nudging uses the unconscious System 1 and boosting uses the concept of training under the contemplation System 2.[4)]

Grüne-Yanoff and Hertwig (2016) show that boosting contains at least three approaches. The first is to foster risk competence in situations where risks are known and measurable. The second is to identify the limited core of factual and procedural smart knowledge that constitutes health, risk, dietary, or financial literacy and to boost people's competence by teaching them these domain-specific ABCs. The third approach is to build and teach simple, intuitive, and efficient heuristics to support decisions in various situations for which knowledge about risks is incomplete and uncertain. Considering these three approaches, this study uses investment behavior as the best area to apply boosting.

2.3 Experimental market

There are two types of experimental markets: an artificial market consisting entirely of computer simulations and a simulated experimental market in which humans also participate in transactions. Artificial markets help with investigating the effect of institutional design on the market. For example, Yagi *et al.* (2011) use an artificial market to analyze the effect of short-selling regulations on the stock market. NASDAQ uses an artificial market to examine the effect of changes in nominal tick size on investors (Darley and Outkin (2007)). On the other hand, the simulated experimental market is a suitable experimental environment for analyzing investor behavior (Ando (2021)). For example, Ueda *et al.* (2008) show that professional traders have a weak disposition effect by comparing individual investors in a simulated market.

An experimental market provides a pure measure of traders' behavior than a real market, with more control over irrelevant variables that might affect the results. However, some studies have

4) The dual-process theory helps us understand how we make decisions. The theory assumes that "thinking has two modes: fast thinking and slow thinking." The terms System 1 and System 2 were coined by Stanovich and West (2000) and popularized by Kahneman (2012). System 1 is intuitive, fast, automatic, effortless, implicit, and emotional. System 2 is slower, more cautious, and logical and requires effort and energy.

pointed out that the experimental market is not a perfect representation of the actual market. For example, in the experiment conducted by Corgnet *et al.* (2018), investors made decisions in a setting that was very different from an actual market and that the prices of the traded asset could have only three values. In experimental studies, it is essential to construct a market as close to reality as possible in terms of pricing and trading, even while using a controlled mechanism that enables the measurement of the target data alone (Ando (2021)).

2.4 Contribution

Many studies have examined the relation between the disposition effect and individuals' attributes or abilities. Very few studies have examined methods to mitigate the disposition effect through direct treatments, and even then, they have not considered the effect of investor heterogeneity. For example, Ando (2021) uses a DD approach to show that education reduces the education disposition effect on average but does not specify how education works for individual investors. This study contributes to this work by extending Ando's (2021) analysis, in other words, by using a DDD approach to show in more detail that the treatment effect of education on the disposition effect is not uniform when the different attributes of individuals are considered.

Furthermore, this study contributes to the analysis of boosting by using experimental methods. While many analyses use behavioral insights, few studies have explored the effects of boosting on behavioral biases in investors' behavior. This study, along with Ando (2021), is one of the first to examine boosting on the disposition effect.

Another contribution of this study is its high reproducibility. As Ando (2021) mentioned, in this series of studies, I use an RCT in a well-controlled experimental environment that closely resembles a real market, in which asset prices are endogenously formed by trading just like in a real market. In the experimental virtual market, in addition to the human trader, computer traders follow a trend set in advance by an experimenter to participate in the virtual experimental market. With the coexistence of computer traders, I can repeatedly reproduce almost the same market trend across multiple rounds of the experiment in the virtual market without interfering with the function of forming prices (Ando (2021)).

3 Experiment

3.1 Purpose of the experiment

This experiment aims to clarify the effectiveness of an educational intervention in reducing the disposition effect on a heterogeneous sample of participants. The design and procedures of the experiment are all the same as those of Ando (2021).

3.2 Experimental design

A total of 112 newly recruited employees from a nonfinancial company participated in this experiment. The company's human resources personnel randomly divided participants into two groups. One was the treatment group that received instruction on the importance of a stop-loss order, and the other was a control group without it. Each group traded separately in the experimental market. When heterogeneity influenced the treatment, each participant of both groups showed a different effect.

3.3 A simulated experimental market

As an experimental environment, I used the Virtual Trading Simulation System (VTS^2) developed by the Simplex Institute Inc. VTS^2 is used in financial institutions to train traders or in educational institutions to teach students about markets. Studies have also used VTS^2 as a tool to analyze investment behavior, such as in an experiment by Ueda *et al.* (2008). These authors show that a professional trader has a smaller disposition effect than a retail investor.

VTS^2 is a simulated market that uses an exchange trading mechanism in which prices change depending on the market participants' trading. It has interfaces close to real trading environments to experience the trading mechanisms of exchange transactions. The VTS^2 interface is shown in Figure 1. Participants could check the board in real time on the screen. Besides board information, market news was delivered to all participants simultaneously on the VTS^2 screen. Participants determined the impact of the news on the securities and traded based on their judgment. The news and the corresponding basic price path were created by imitating the past price paths in the real market. Table 1 shows an example of the basic price path that was set and the news that was delivered.[5),6)]

3.4 Trading securities

Participants traded the Nikkei 225 mini in this experiment, a stock-index futures contract based on the Nikkei Stock Average. This futures contract is one of the world's most actively traded. The studies that deal with the disposition effect have typically used stock portfolios. However, the stock portfolio has an asymmetry between cash and the margin in which only short-selling requires a margin, and there may be a difference in investment behavior between bull and bear markets. Alternatively, futures have the advantage of being traded on the same margin regardless of whether buying or selling. There is no need to worry about the effects of market trends on trading behavior when using futures. The analysis of the behavior with a single financial asset is preferable to analyze the treatment effect more clearly.

3.5 Treatment

Locke and Mann (2005) show that professional CME futures traders emphasize the "discipline" of not holding positions with significant valuation losses for a long time to minimize irrational behavioral biases. They also find that adherence to this discipline is associated with trading success. Considering this finding, the following educational treatment was provided only to the treatment group.

> "Based on behavioral insights, professional investors always cut their losses at certain criteria to minimize the negative effects of bias and heuristics. Learn from the efforts of professionals and abide by the following rules: You must not have a paper loss greater than ¥10,000 per one contract of Nikkei 225 mini. Should a paper loss on one contract exceed ¥10,000, you must realize your losses immediately."

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5) The proper nouns used in the news are fictitious so that differences in the prior knowledge of participants in the experiment do not affect them.

6) In addition to the participants, computer traders who trade according to the trends set by the experimenter also participated in the simulated market so that we realized the price movements that were close to the basic price path. However, the final price was determined endogenously by the transactions of all participants.

Figure 1 The VTS² trading interface

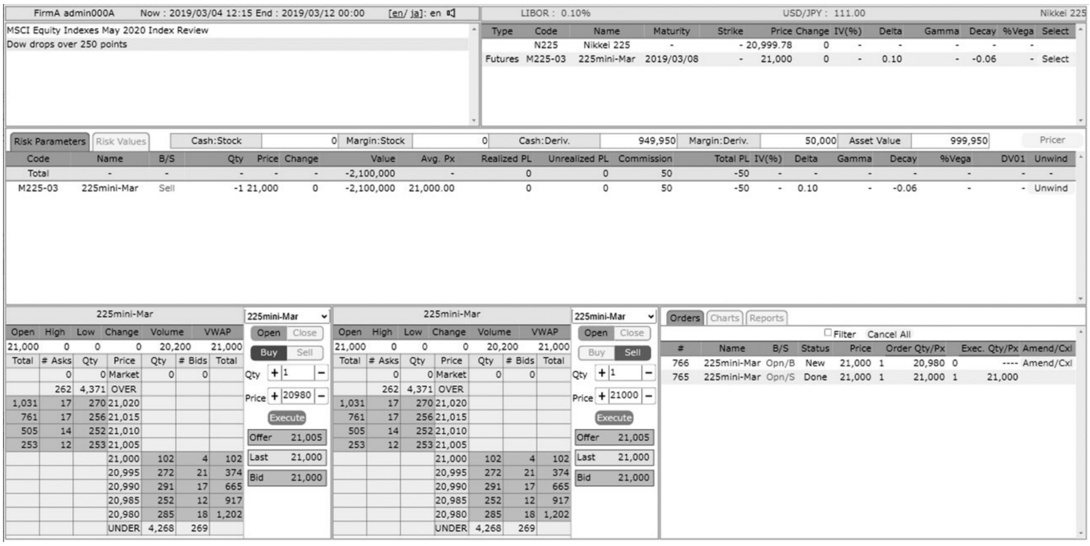

Table 1 Sample of news and index price movements

Date	Headline	Detail	Index
2-Jun	〈January-March GDP growth rate〉 YoY + 0.3%, annualized + 1.2%, exceeding expectations.	The January-March GDP growth rate announced by the Cabinet Office increased by 0.3% from the previous quarter and increased by 1.2% on an annualized basis, exceeding the previous forecast of 0.9%. Both personal consumption expenditure and capital investment grew.	22,159.64
2-Jun	〈Nikkei decline〉 GDP is favorable and the index hits the highest in half a year, but is sold down at the close.	Following the announcement of good GDP, the Tokyo stock market rallied in the morning, and the Nikkei Stock Average reached 22,220 yen for the first time in half a year. However, it closed 70 yen up compared to the previous day.	22,169.66
3-Jun	〈CPI rises 1.5% YoY〉	According to the Ministry of Internal Affairs and Communications, the national consumer price index (excluding fresh food) last month rose 1.5% year-on-year. In the preliminary forecast survey, the median forecast was +1.2%. It has increased year-on-year for the third consecutive month.	22,119.70

The treatment in this study was guidance as part of employee training rather than general education for financial literacy. Therefore, caution should be exercised when applying the treatment to the context of general education, as it might be more coercive than school education. In this regard, Ando (2021) adds that since the individual participant had to decide whether to follow the instruction, examining whether educational instruction can change a behavioral bias is meaningful.

Further, no monetary reward was given based on investment performance in this study. Although this point is controversial, according to Camerer and Hogarth (1999), "whether financial incentives improve performance depends on the type of task and that the presence or absence of financial incentives does not affect performance in market transactions, games, auctions, or risky choices." Hence, Ando (2021) argues that the results of this experiment could be assumed as no different from the results in the real market.

3.6 The experiment procedure

I conducted a total of five experiments (Cases 1 to 5). In each case, all participants were given an equal amount of cash and futures positions before trading. After trading on the market for a certain

Figure 2　Experimental procedure

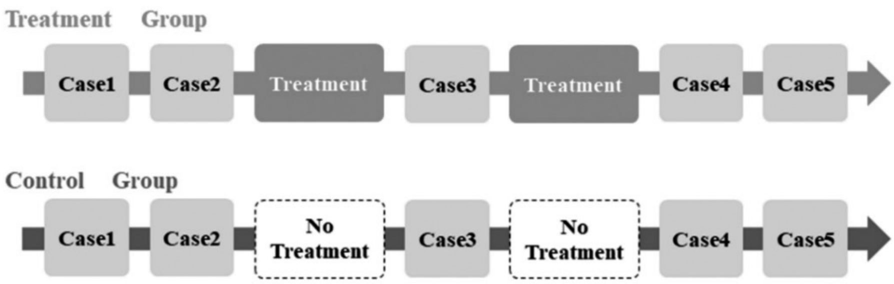

Table 2　Outline of experimental settings

Experience	Time (min)	Initial cash	Initial position	Price (Start)	Price (End)	Daily volatility
Case1	12	1,000,000 JPY	–	21,835	22,670	10.26%
Case2	17	1,000,000 JPY	–	20,000	19,875	6.81%
Case3	11	1,000,000 JPY	5 contracts long of Nikkei 225 mini	22,040	20,400	18.22%
Case4	15	1,000,000 JPY	5 contracts long of Nikkei 225 mini	21,995	22,260	13.39%
Case5	9	1,000,000 JPY	5 contracts long of Nikkei 225 mini	22,000	21,215	23.47%

period, I measured the disposition effect in each case. Case 1 is the benchmark. The treatment was given to the treatment group in Cases 3 and 4 only. I prepared two treatments in case one did not work. In Cases 1, 2, and 5, both treatment and control groups did not receive any treatment. The configuration is shown in Figure 2.

Table 2 shows the time, the initial cash and positions, and the market price in each case. The time for each case is 9 to 17 minutes. The experiment was carried out for two consecutive days for one group. Cases 1 to 3 were the first day, and cases 4 and 5 were the second day. The interval between cases within the same date was about 30 minutes to 2 hours. It took about 19 hours for each group to complete all cases. The schedule was the same for the treatment and control groups so that the time effect could be regarded as common for both groups.

4　Data

4.1　Individual attributes

By conditioning personal attributes, I can investigate how the heterogeneity of individuals influences the effectiveness of the treatment. The questionnaires and tests measured various characteristics of the participants before the experiment. Table 3 shows the descriptive statistics of individual attributes, which is a partial replication of Ando (2021) Table 5 as I am using the exact same data used in Ando (2021).

I measured cognitive ability and grades in mathematics as measures for IQ because the disposition effect might be related to IQ (Grinblatt *et al.* (2012)). Following Corgnet *et al.* (2018), I measured their cognitive ability using the cognitive reflection test (CRT) that was proposed by Frederick (2005). Hanaki (2020) shows the importance of paying attention to differences in participants' cognitive ability in laboratory experiments. Akiyama *et al.* (2017) and Hanaki (2020) have shown in experiments in asset trading games that participants behave differently depending

Table 3 Descriptive statistics of individual attributes

Attribute	Definition	Obs.	Mean	Std. Dev.	Min.	Max.
CRT Score	Score on cognitigve reflection test (CRT, Frederic (2005)) CRT test consists of 3 questions, and the score is from 0 to 3 points. (Unit : Point)	112	1.90	0.98	0.00	3.00
Math Score	Score on math test (a total of 300 for the 3 tests) (Unit : Point)	112	177.44	50.62	51.00	287.00
Risk Aversion	Score on risk aversion test proposed by Ikeda and Tsutsui (2006) (Unit : Point)	112	0.00005	0.00010	−0.0001	0.0003
Experience	Investment experinece in stocks, foreign exchange trading, commodity or sotck futures, or other financial products. (0 : No experience / 1: Have experience)	112	0.21	0.41	0.00	1.00
Female	1: Female / 0: Male	112	0.13	0.34	0.00	1.00
Final Degree	1 : Master's degree and above / 0: Otherwise	112	0.58	0.50	0.00	1.00

Table 4 Statistics of individual attributes (Comparison between groups)

	Control		Treatment		
Attribute	Mean	Std. Dev.	Mean	Std. Dev.	p-value
CRT Score	2.00	0.12	1.80	0.14	0.28
Math Score	179.77	6.27	175.02	7.30	0.62
Risk Aversion	0.000045	0.000013	0.000053	0.000013	0.673
Experience	0.19	0.05	0.22	0.06	0.74
Female	0.21	0.05	0.05	0.03	0.02**
Final Degree	0.58	0.07	0.58	0.07	0.98
Obs.	57		55		

***p <0.01, **p <0.05, *p <0.1.

Table 5 Descriptive statistics for the disposition effect

Variable	Definition	Obs.	Mean	Std. Dev.	Min.	Max.
PGR	The proportion of gain realized High *PGR* represents a tendency to realize profits.	112	0.34	0.16	0.06	0.83
PLR	The proportion of loss realized High *PLR* represents a tendency to realize losses.	112	0.38	0.22	0.00	1.00
DE	Dispositon effect (*PGR* minus *PLR*)	112	−0.04	0.29	−0.80	0.64

on their CRT score. In addition to the CRT test, I conducted a total of three mathematical tests. Each exam had a maximum score of 100 points, and the total for the three tests was 300 points. Each exam question consisted of a calculation and a word problem at the level of high school mathematics (excluding calculus).

I also examined whether the participants had any experience with trading stocks, foreign exchange margins, commodity futures, stock-index futures, options, or other financial instruments because more experienced investors present a smaller disposition effect (Da Costa *et al.* (2013)). Further, I measured some attributes that were thought to be determinants of the disposition effect, such as gender (Feng and Seasholes (2005), Rau (2014), Da Costa *et al.* (2013)), final degree (Vaarmets *et al.* (2019)), and degree of risk aversion (Prates *et al.* (2017)). I used the questionnaire survey that was proposed by Ikeda and Tsutsui (2006) to measure the degree of risk aversion.

Table 4 shows the attribute statistics for each treatment and control group. This table is a partial replication of Ando (2021) Table 6, using the same data as Ando (2021). Except for the female ratio, there was no significant difference between the two groups for each attribute, and I determined that participants were randomly divided.

4.2 Disposition effect

I measured the data on the disposition effect by using the trading logs on the VTS[2]. In this study, I conducted a *PGR-PLR* analysis, a typical method for measuring the disposition effect conducted by Odean (1998). In this analysis, the disposition effect is calculated as the difference between the *PGR* (proportion of gain realized) and the *PLR* (proportion of loss realized). Following Choe and Eom (2009), who use futures contracts, I define the PGR, the PLR, and the disposition effect (DE) as follows:

The proportion of gain realized (*PGR*) and the proportion of loss realized (*PLR*)

$$PGR_i = \frac{N^i_{RealizedGain}}{N^i_{RealizedGain} + N^i_{PaperGain}}$$

$$PLR_i = \frac{N^i_{RealizedLoss}}{N^i_{RealizedLoss} + N^i_{PaperLoss}}$$

Here, for participant i, $N^i_{RealizedGain}$ is the number of days with realized gains, $N^i_{RealizedLoss}$ is the number of trading days with realized losses, $N^i_{PaperGain}$ is the number days with valuation gains, and $N^i_{PaperLoss}$ is the number of days with valuation losses.

The disposition effect (*DE*)

The *DE* of participant i is defined as the difference between the *PGR* and the *PLR*.

$$DE_i = PGR_i - PLR_i$$

A positive *DE* indicates that an investor is more likely to realize gains than losses. The greater the *DE*, the more likely an investor is to realize a winner over a loser. Table 5 presents an overview of the *DE* at the beginning of the experiment (Case 1).

5 Model and methodology

I perform a "difference-in-difference-in-differences" (DDD) approach to identify the treatment effect on the disposition effect according to the attributes of individuals. Specifically, I conduct a DDD estimation with interaction terms between the case dummy and the educational treatment dummy and personal attributes. The estimation equation is as follows:

$$\begin{aligned} Y_{it} = {} & \beta_0 + \beta_1 Treatment_i \\ & + \sum_{t=2}^{5} \beta_t CaseDum_t + \sum_{t=2}^{5} \beta_{t+4} CaseDum_t * Treatment_i \\ & + \sum_{t=2}^{5} \beta_{t+8} CaseDum_t * Treatment_i * Attribute_i + \eta_i + \varepsilon_{it} \end{aligned}$$

The outcome variable Y_{it} is *DE*, *PGR*, and *PLR*. $Treatment_i$ is a dummy variable that equals one when participant i belongs to the treatment group, and zero otherwise. $CaseDum_t$ is a dummy variable that equals one for case t, and zero otherwise. $Attribute_i$ is participant i*'s* attributes measured previously (CRT test scores, math test scores, risk aversion, investment experience, gender, and final degree). These personal attributes are antecedent variables that do not change over the short period of the experiment, so they are not endogenous. η_i is the fixed effect for participant i.

In this experiment, the treatment was carried out in a controlled environment. Therefore, I can estimate the effect of $Attribute_i$ on the treatment effect in each case t without any possibility of endogeneity. Consequently, I can estimate the conditional effect by estimating the DDD coefficients for the interaction terms between $CaseDum_t$, $Treatment_i$, and $Attribute_i$. In other words, the coefficients of most significant interest are those for the triple cross-terms from β_{10} to β_{13}.

6 Results

This survey examines the possibility that the effectiveness of a treatment depends on the attributes of individuals. I ran regressions using the interaction terms between personal attributes and the treatment. The dependent variables with significant effects (CRT test scores and investment experience) are described below. However, the other attributes made no significant difference in the effect of education on the disposition effect (see appendix).

6.1 CRT test scores

Table 6 shows the results of the regression conditional on the CRT test scores. Regarding the *DE*, the DD estimator in Case 3 (first intervention) is significantly negative (coefficient −0.22, standard deviation 0.06). This result indicates that the *DE* can be reduced by the treatment, regardless of the personal attributes, and it is consistent with the results in Ando (2021). The DDD estimator in Case 3 is −0.10 (standard deviation 0.04), indicating that the higher a participant's CRT test score, the more likely the educational treatment would reduce the *DE*. To summarize, these results show that education is more effective for participants with higher cognitive ability. In other words, applying the treatment for the first time reduces the *DE* for a person with a CRT test score of 0 by 0.22 points, and a person with a CRT test score of 1 has an additional 0.10 point reduction. For people with a CRT test score of 3 (perfect score), the treatment reduces the *DE* by 0.52 points.

Concerning the *PGR*, the DDD estimator in Case 3 is −0.03 (standard deviation 0.02), and the *PLR* is 0.07 (standard deviation 0.03). These results indicate that an increase in the *PLR* contributes more to the decrease in *DE* than the decrease in the *PGR*. This result is consistent with the fact that the treatment in this experiment only addresses the loss domain.

This result is consistent with other studies that show that higher cognitive ability (i.e., higher IQ) relates to lower *DE* (Grinblatt *et al.* (2012)). The CRT test requires careful consideration to arrive at the correct answer, as intuitive solutions can lead to mistakes. People with high cognitive ability are good at consciously using System 2. They are inherently less likely to be dominated by the disposition effect caused by System 1. Therefore, if they were taught the importance of cutting their losses, they could easily modify their decision-making and behavior to cut their losses. On the other hand, people with low cognitive ability could have difficulty using System 2. They would not have easily resisted the heuristics caused by System 1 even after receiving the treatment.

In summary, this analysis shows the importance of considering the effect of cognitive ability when educating investors about their behavior. Further, this analysis shows that the mitigating effect of boosting on investment bias depends on the individuals' cognitive ability. This result supports the argument for the need to consider the heterogeneity in individuals' cognitive ability when examining the intervention effects.

6.2 Investment experience

Table 7 shows the analysis results that are conditional on investment experience. Regarding the *DE*, the DDD estimator in Case 3 is 0.43 (standard deviation 0.10). It indicates that participants

Table 6 Results of DDD estimation (CRT test scores)

Dependent variable	*DE*		*PGR*		*PLR*	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Independent variables						
Treatment	−0.06	0.05	−0.05	0.03	0.00	0.03
$CaseDum_2$	0.11	0.04***	0.12	0.02***	0.01	0.03
$CaseDum_3$	0.24	0.05***	0.27	0.02***	0.03	0.04
$CaseDum_4$	0.11	0.05**	0.13	0.02***	0.02	0.04
$CaseDum_5$	0.08	0.05*	0.29	0.02***	0.21	0.04***
DD						
$CaseDum_3 \times Treatment$	−0.22	0.06***	0.01	0.03	0.23	0.05***
$CaseDum_4 \times Treatment$	−0.10	0.06	−0.02	0.03	0.08	0.05
$CaseDum_5 \times Treatment$	0.01	0.06	−0.01	0.03	−0.02	0.05
DDD						
$CaseDum_3 \times Treatment \times CRT$	−0.10	0.04**	−0.03	0.02*	0.07	0.03**
$CaseDum_4 \times Treatment \times CRT$	−0.02	0.04	−0.03	0.02*	−0.01	0.03
$CaseDum_5 \times Treatment \times CRT$	0.05	0.04	−0.01	0.02	−0.06	0.03*
_cons	−0.01	0.04	0.36	0.02***		
No. Obs.	560		556		556	
No. Groups	112		112		112	

***p <0.01, **p <0.05, *p <0.1.

with investment experience have a greater *DE* after the educational treatment than those without investment experience. Since the unconditional treatment effect on the *DE* is −0.30 (standard deviation 0.07), investment experience cancels the treatment effect. The *DE* ranges from −2 to 2, and the DDD term of 0.43 indicates that the investment experience has quite an influence on the educational effect. These results can be summarized as somewhat questionable: education is less effective for participants with prior investment experience.

There are two possible reasons for the reactionary increase in the *DE* when the importance of cutting losses is taught to experienced investors. Either experienced participants might be confused by the instructions to trade differently than usual, or the intervention might be more effective for those without investment experience. In any case, the results show that educating investors while they are still inexperienced might allow them to make rational decisions easily and get better results. Just as the saying goes, "A little knowledge is a dangerous thing," teaching investors that biases and heuristics influence their investment decisions and behavior before they have developed their bad trading habits will contribute to their rational investment. These results highlight that investment experience interferes with intentionally reducing behavioral biases and may be the reason for disagreements in earlier studies. A more detailed analysis of the effect of investment experience on education is still needed.

6.3 Sufficient/insufficient investment experience

The results in subsection 6.2 show that investment experience inhibits the learning effect, contrary to Da Costa *et al.* (2013) and Dhar and Zhu (2006), who show that investment experience effectively reduces the disposition effect. To clarify why the results of this experiment are different from other studies, I conduct a DDD analysis of the effect of investment experience separately for those with sufficient investment experience and those without. Specifically, I use explanatory variables to conduct a regression analysis: the interaction terms between the treatment dummy variable and dummy variable that represent participants with less than three years of investment

Table 7 Results of DDD estimation (Investment experience)

Dependent variable	DE		PGR		PLR	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Independent variables						
Treatment	−0.06	0.05	−0.05	0.03	0.00	0.03
$CaseDum_2$	0.11	0.04***	0.12	0.02***	0.01	0.03
$CaseDum_3$	0.24	0.05***	0.27	0.02***	0.03	0.04
$CaseDum_4$	0.11	0.05**	0.13	0.02***	0.02	0.04
$CaseDum_5$	0.08	0.05*	0.29	0.02***	0.21	0.04***
DD						
$CaseDum_3 \times Treatment$	−0.30	0.07***	−0.02	0.03	0.28	0.05***
$CaseDum_4 \times Treatment$	−0.12	0.06*	−0.04	0.03	0.08	0.05
$CaseDum_5 \times Treatment$	0.02	0.06	0.00	0.03	−0.02	0.05
DDD						
$CaseDum_3 \times Treatment \times Exp$	0.43	0.10***	0.15	0.05***	−0.27	0.08***
$CaseDum_4 \times Treatment \times Exp$	0.11	0.09	0.11	0.05**	0.02	0.07
$CaseDum_5 \times Treatment \times Exp$	−0.03	0.09	−0.01	0.05	0.04	0.07
_cons	−0.01	0.04	0.36	0.02***	0.37	0.03***
No. Obs.	560		556		556	
No. Groups	112		112		112	

***p <0.01, **p <0.05, *p <0.1.

experience, and the interaction terms between the treatment dummy and dummy variable that represent participants with more than three years of investment experience.

Table 8 shows the results of this analysis. The coefficients in the DDD cross-term, including Exp_under3Y, represent the treatment effect for those participants with less than three years of investment experience; the coefficients in the DDD cross-term, including Exp_over3Y, represent the treatment effect for those participants with more than three years of investment experience.[7)]

Regarding the DE, the DDD estimator in Case 3 for Exp_under3Y is 0.53 (standard deviation 0.10). It indicates that participants with investment experience of fewer than three years have a greater DE after the educational treatment than those without investment experience. However, the DDD estimator in Case 3 for Exp_over3Y is −0.61 (standard deviation 0.29). It indicates that participants with investment experience of more than three years have a smaller DE after the educational treatment than those without investment experience. Taken together, these results show that education is more effective for participants with sufficient investment experience, but surprisingly, less effective for participants with little investment experience than for participants with no investment experience.

This more careful analysis shows that the effectiveness of education varies depending on the amount of investment experience. In other words, people with inadequate investment experience are less likely to accept education, while people with sufficient investment experience can use education to their advantage. This result may fill in the blanks as to why other studies have not agreed on the causal effect of investment experience on the disposition effect. One explanation for why the treatment effect varies with investment experience is that the degree of overconfidence varies with investment experience. Menkhoff *et al.* (2013) find that inexperienced investors are

7) The three-year period was set simply for the convenience of the survey, and analyses for other periods will be a future challenge.

Table 8 Results of DDD estimation (Investment experience by the number of years)

Dependent variable	*DE*		*PGR*		*PLR*	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Independent variables						
Treatment	−0.06	0.05	−0.05	0.03*	0.00	0.03
$CaseDum_2$	0.11	0.03***	0.12	0.02***	0.01	0.03
$CaseDum_3$	0.24	0.05***	0.27	0.02***	0.03	0.04
$CaseDum_4$	0.11	0.05**	0.13	0.02***	0.02	0.04
$CaseDum_5$	0.08	0.05*	0.29	0.02***	0.21	0.04***
DD						
$CaseDum_3 \times Treatment$	−0.30	0.06***	−0.02	0.03	0.28	0.05***
$CaseDum_4 \times Treatment$	−0.12	0.06*	−0.04	0.03	0.08	0.05
$CaseDum_5 \times Treatment$	0.02	0.06	0.00	0.03	−0.02	0.05
DDD						
$CaseDum_3 \times Treatment \times Exp\_under3Y$	0.53	0.10***	0.18	0.05***	−0.33	0.08***
$CaseDum_4 \times Treatment \times Exp\_under3Y$	0.12	0.10	0.13	0.05***	0.04	0.08
$CaseDum_5 \times Treatment \times Exp\_under3Y$	0.03	0.10	0.00	0.05	0.00	0.08
$CaseDum_3 \times Treatment \times Exp\_over3Y$	−0.61	0.29**	−0.25	0.15*	0.32	0.23
$CaseDum_4 \times Treatment \times Exp\_over3Y$	0.05	0.29	−0.12	0.15	−0.21	0.23
$CaseDum_5 \times Treatment \times Exp\_over3Y$	−0.69	0.29**	−0.20	0.15	0.45	0.23**
_cons	−0.01	0.04	0.36	0.02***	0.37	0.03***
No. Obs.	556		560		556	
No. Groups	112		112		112	

***$p<0.01$, **$p<0.05$, *$p<0.1$.

overconfident, but the degree of overconfidence may decrease with experience. One possible explanation is that the education was least effective for inexperienced investors because they could not accept the education honestly due to their overconfidence bias. On the other hand, the degree of overconfidence of inexperienced investors were neutral, indicating they show an average effect of education.

7 Conclusion

One of the goals of this study is to experimentally analyze the heterogeneity treatment effect of boosting on the disposition effect by extending the work of Ando (2021). The results show that teaching the importance of cutting losses can reduce the disposition effect and that investors' attributes increase or decrease the effectiveness of the treatment effect. Specifically, the results show that education is more effective for participants with higher cognitive ability or sufficient investment experience. However, one point to note is that education is less effective when the investment experience is halfway through.

The personal attributes that influenced the treatment effect in this study, cognitive ability and investment experience, have been treated as determinants of the disposition effect in other studies. The results indicate that when planning interventions that use behavioral insights, investors should consider the heterogenous effects of personal attributes as determinants of behavioral bias. The results also support the literature that argues the importance of paying attention to differences in participants' cognitive ability in lab and field experiments (Hanaki (2020), Wai *et al.* (2018)).

Another implication of this study is the importance of education for novice investors. As the saying goes, "Strike while the iron is hot"; timing is important in teaching. Educating people before they develop their habits is much more effective than educating people who are halfway through their experience. This observation is equally helpful in investment education. The effect of education may be counterproductive for those with only a limited trading experience of one or two years. Therefore, it is essential to teach investors how to deal with investment heuristics and biases early before they become less educated due to inadequate trading experience. From the perspective of education policy, it is appropriate to encourage them to make rational decisions and build their assets efficiently in the very early stages of investment. On the other hand, it is also essential to provide practical education to those with investment experience because they are more likely to learn.

Finally, I will discuss the topics for future studies. First, an examination of the effects of the educational treatment is important when it specifies criteria not only for cutting losses but also for taking profits because the difference in decision-making between the loss and profit domains causes the disposition effect. Second is the issues that relate to the experimental environment. While no rewards were given in this experiment, as Ando (2021) points out, they could help investigate whether the outcome may change if participants receive a financial return on their investment performance. A further challenge is to find out the difference between boosting and different types of treatments such as nudging and automation (such as stop-loss orders). In addition, in this experiment, the criteria for investment experience is set at "more than/less than three years," but further analysis is needed to determine how much experience will have a positive impact on education about the frequency of investment, investment amount, and experience with investment products.

As financial products become more complex, providing proper education to investors is becoming a significant issue. I hope that experimental markets are used more in the field of behavioral finance and financial education.

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Appendix

This appendix shows the regression results that are conditional on the attributes that did not make much of a significant difference in the effectiveness of education on the disposition effect.

A.1 Math Score

Table A.1 shows the analysis results conditional on the math score. Although not statistically significant, the DDD coefficients in Cases 3 and 4 are negative. Some studies state that cognitive ability can predict a student's math performance (Hilbert *et al.* (2019)), so estimates that use the math score may be similar to the CRT estimates. In other words, higher math scores may be associated with slightly higher educational effectiveness.

A.2 Risk Aversion

Table A.2 shows the results of the analysis that uses risk aversion. Regarding the *PLR*, the DDD coefficient in Case 3 is significantly negative. On the other hand, there is no statistically significant effect regarding the *DE*. Thus, there is no clear evidence that risk aversion affects the treatment's efficiency.

A.3 Gender

Table A.3 shows the results of the analysis based on gender. Regarding the *PLR*, the DDD coefficient in Case 3 for the *PLR* is significantly negative. On the other hand, there is no statistically significant effect regarding the *DE*. Thus, there is no clear evidence that risk aversion affects the treatment's efficiency. This result may help explain the relation between gender and other attributes. Other studies have indicated that women are more risk-averse (Charness and Gneezy (2012)), while others have found that risk aversion is not related to gender (Sarin and Wieland (2016)). However, some studies have shown that cognitive ability is not associated with gender (Primi *et al.* (2018)). In this experiment, the results on gender are similar to those for risk aversion but not those for cognitive ability.

Table A.1 Results of DDD estimation (Math Score)

Dependent variable	***DE***		***PGR***		***PLR***	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Independent variables						
Treatment	−0.06	0.05	−0.05	0.03	0.00	0.03
$CaseDum_2$	0.11	0.04***	0.12	0.02***	0.01	0.03
$CaseDum_3$	0.24	0.05***	0.27	0.02***	0.03	0.04
$CaseDum_4$	0.11	0.05**	0.13	0.02***	0.02	0.04
$CaseDum_5$	0.08	0.05*	0.29	0.02***	0.21	0.04***
DD						
$CaseDum_3 \times Treatment$	−0.21	0.06***	0.02	0.03	0.22	0.05***
$CaseDum_4 \times Treatment$	−0.10	0.06	−0.02	0.03	0.08	0.05
$CaseDum_5 \times Treatment$	0.01	0.06	−0.01	0.03	−0.02	0.05
DDD						
$CaseDum_3 \times Treatment \times Math$	−0.05	0.04	−0.04	0.02**	0.01	0.03
$CaseDum_4 \times Treatment \times Math$	−0.04	0.04	−0.04	0.02**	0.00	0.03
$CaseDum_5 \times Treatment \times Math$	0.02	0.04	−0.02	0.02	−0.04	0.03
_cons	−0.01	0.04	0.36	0.02***	0.37	0.03***
No. Obs.	560		556		556	
No. Groups	112		112		112	

***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table A.2 Results of DDD estimation (Risk Aversion)

Dependent variable	*DE*		*PGR*		*PLR*	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Independent variables						
Treatment	−0.06	0.05	−0.05	0.03	0.00	0.03
$CaseDum_2$	0.11	0.04***	0.12	0.02***	0.01	0.03
$CaseDum_3$	0.24	0.05***	0.27	0.02***	0.03	0.04
$CaseDum_4$	0.11	0.05**	0.13	0.02***	0.02	0.04
$CaseDum_5$	0.08	0.05*	0.29	0.02***	0.21	0.04***
DD						
$CaseDum_3 \times Treatment$	−0.21	0.06***	0.02	0.03	0.22	0.05***
$CaseDum_4 \times Treatment$	−0.09	0.06	−0.01	0.03	0.08	0.05
$CaseDum_5 \times Treatment$	0.01	0.06	−0.01	0.03	−0.02	0.05
DDD						
$CaseDum_3 \times Treatment \times Risk\ Aversion$	0.07	0.04	−0.01	0.02	−0.08	0.03***
$CaseDum_4 \times Treatment \times Risk\ Aversion$	−0.03	0.04	−0.02	0.02	0.00	0.03
$CaseDum_5 \times Treatment \times Risk\ Aversion$	0.02	0.04	0.00	0.02	−0.03	0.03
_cons	−0.01	0.04	0.36	0.02***	0.37	0.03***
No. Obs.	560		556		556	
No. Groups	112		112		112	

***p <0.01, **p <0.05, *p <0.1.

Table A.3 Results of DDD estimation (Gender)

Dependent variable	*DE*		*PGR*		*PLR*	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Independent variables						
Treatment	−0.06	0.05	−0.05	0.03	0.00	0.03
$CaseDum_2$	0.11	0.04***	0.12	0.02***	0.01	0.03
$CaseDum_3$	0.24	0.05***	0.27	0.02***	0.03	0.04
$CaseDum_4$	0.11	0.05**	0.13	0.02***	0.02	0.04
$CaseDum_5$	0.08	0.05*	0.29	0.02***	0.21	0.04***
DD						
$CaseDum_3 \times Treatment$	−0.22	0.06***	0.02	0.03	0.24	0.05***
$CaseDum_4 \times Treatment$	−0.09	0.06	−0.02	0.03	0.08	0.05
$CaseDum_5 \times Treatment$	0.01	0.06	−0.01	0.03	−0.02	0.05
DDD						
$CaseDum_3 \times Treatment \times Female$	0.22	0.18	0.02	0.09	−0.24	0.14*
$CaseDum_4 \times Treatment \times Female$	−0.03	0.18	0.04	0.09	0.04	0.14
$CaseDum_5 \times Treatment \times Female$	0.01	0.18	0.08	0.09	0.04	0.14
_cons	−0.01	0.04	0.36	0.02***	0.37	0.03***
No. Obs.	560		556		556	
No. Groups	112		112		112	

***p <0.01, **p <0.05, *p <0.1.

A.4 Final Degree

Table A.4 shows the analysis results based on the final degree. There are no statistically significant DDD estimates. This result means that the final degree does not affect the treatment's efficiency.

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Table A.4 Results of DDD estimation (Final Degree)

Dependent variable	*DE*		*PGR*		*PLR*	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Independent variables						
Treatment	−0.06	0.05	−0.05	0.03	0.00	0.03
$CaseDum_2$	0.11	0.04***	0.12	0.02***	0.01	0.03
$CaseDum_3$	0.24	0.05***	0.27	0.02***	0.03	0.04
$CaseDum_4$	0.11	0.05**	0.13	0.02***	0.02	0.04
$CaseDum_5$	0.08	0.05*	0.29	0.02***	0.21	0.04***
DD						
$CaseDum_3 \times Treatment$	−0.20	0.08**	0.03	0.04	0.23	0.06***
$CaseDum_4 \times Treatment$	−0.13	0.08*	0.00	0.04	0.13	0.06**
$CaseDum_5 \times Treatment$	0.04	0.08	−0.01	0.04	−0.04	0.06
DDD						
$CaseDum_3 \times Treatment \times Final\ Degree$	−0.01	0.08	−0.02	0.04	−0.01	0.06
$CaseDum_4 \times Treatment \times Final\ Degree$	0.06	0.08	−0.03	0.04	−0.08	0.06
$CaseDum_5 \times Treatment \times Final\ Degree$	−0.05	0.08	0.00	0.04	0.05	0.06
_cons	−0.01	0.04	0.36	0.02***	0.37	0.03***
No. Obs.	560		556		556	
No. Groups	112		112		112	

***p <0.01, **p <0.05, *p <0.1.

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《SUMMARY》

WHO LEARNS WELL FROM BOOSTING?
――HETEROGENEOUS TREATMENT EFFECTS ON THE DISPOSITION EFFECT――

By NOZOMI ANDO

I experimentally examine the heterogeneous treatment effects of investor education on the disposition effect, explicitly focusing on investors' attributes. Using a randomized controlled trial (RCT) under a simulated experimental market environment, I implement the education that teaches (i.e., boosting) investors the practical importance of cutting losses to examine whether educated participants have a mitigated disposition effect. First, such boosting mitigates the disposition effect effectively when investors have high cognitive ability. Second, the effectiveness of the educational treatment depends on the amount of investment experience. Specifically, boosting mitigates the disposition effect for those with zero or more than three years of investment experience, while boosting increases those with one or two years of experience. Furthermore, participants with more than three years of experience significantly reduce their disposition effect by boosting than those with no experience. These results suggest the necessity of considering investors' heterogeneity to design effective investor education.

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