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The disposition effect and investor experience

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ABSTRACT

We examine whether investing experience can dampen the disposition effect, that is, the fact that investors seem to hold on to their losing stocks to a greater extent than they hold on to their winning stocks. To do so, we devise a computer program that simulates the stock market. We use the program in an experiment with two groups of subjects, namely experienced investors and undergraduate students (the inexperienced investors). As a control procedure, we consider random trade decisions made by robot subjects. We find that though both human subjects show the disposition effect, the more experienced investors are less affected.

1. Introduction

The disposition effect is the anomaly that investors seem to hold on to their losing stocks to a greater extent than they hold on to their winning stocks (Schlarbaum et al., 1978; Shefrin and Statman, 1985; Weber and Camerer, 1998). For instance, data from a consulting retail brokerage house revealed that stocks with positive returns were 68% more likely to be sold than those with negative returns (Odean, 1998). The disposition effect is lessened if there is financial counseling (Taylor, 2000; Shapira and Venezia, 2001), and it is heightened for inexperienced investors (Grinblatt and Keloharju, 2001; Coval and Shumway, 2005; Feng and Seasholes, 2005; Locke and Mann, 2005; Dhar and Zhu, 2006), though that is still unsettled (Chen et al., 2007). Here, we investigate the relationship between the disposition effect and investing experience using a "framed field experiment" (Harrison and List, 2004).

Tests proving the disposition effect in actual markets (such as those in the works above) cannot be conclusive because investor decisions cannot be controlled in there. For that reason, lab experiments can be more illuminating in that they can be designed to match individual investors' trading decisions with the prices at which they buy or sell stocks. In stark contrast with the above studies using actual data, when it comes to the lab the disposition effect may be even higher for experienced investors (like in the "artefactual field experiments" of Haigh and List (2005) and of Abbink and Rockenbach (2006)). That can be explained by either the curse of knowledge ("the more you know, the worse you become at using that knowledge") (Camerer et al., 1989), the desire to avoid regret (Barber and Odean, 1999), or simply by the fact that an experiment is too simplistic.

Because it is possible that the relationship between the disposition effect and investing experience can be dependent on experiment design, here we try to remedy such a deficiency by developing a computer program that mimics the stock market while retaining the characteristic that investor decisions cannot influence the (exogenous) stock prices. We use the program in an experiment with two groups of subjects, namely experienced investors and undergraduate students (the inexperienced investors). As a control procedure, we also consider random trade decisions made by robot subjects. We thus set a more complex experimental environment than does a typical experiment while preserving the control characteristics that are the edge of the experimental method. As a result, we find the disposition effect in human subjects, and also that experienced investors are less prone to the effect, which is in line with most of the evidence discussed above for actual data.

Harrison and List (2004) put forward the following taxonomy to classify experiments: (1) conventional lab experiment; (2) artefac-

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Table 1
Selected recent work related to the disposition effect and investor experience.

Author	Result
Menkhoff and Nikiforow (2009)	Fund managers who have strong incentives to learn efficient behavior and who do not endorse the behavioral finance view, end up failing to learn, thus suggesting that many behavioral finance patterns are rooted in human behavior and difficult to be overcome by learning
Chang (2008)	Evidence of the disposition effect in investors of the Taiwanese warrant markets
Kliger and Kudryavtsev (2008)	The reference point updating process of the disposition effect is more reactive to events when information flow is low and prices are sensitive to market fluctuations. Agents facing numerous alternatives consider those that have caught their attention
Lee et al. (2008)	Evidence of the disposition effect in internet-based stock trading
Goetzmann and Massa (2008)	A panel of individual investor trading records shows that exposure to a portfolio of stocks held by disposition-prone investors explains cross-sectional differences in daily returns
Hales (2007)	Investors are motivated to agree unthinkingly with information that suggests they might make money on their investment, but disagree with information that suggests they might lose money
Hedesstrom et al. (2007)	In an internet-based survey of fictitious choices among fund categories, home bias and a diversification heuristic were unaffected by previous stock market investment experience
Garvey and Murphy (2004)	Data on a US proprietary stock-trading team provide evidence of the disposition effect

tual field experiment; (3) framed field experiment; and (4) natural field experiment. As observed, ours is a framed field experiment, which is also an artefactual field experiment but with field context in the task and information set used by the subjects.

Table 1 presents the main results of selected recent work related to the disposition effect and investor experience; the reader may wish to consider the references therein for a more comprehensive account of the vast literature on the subject.

The rest of this paper is organized as follows. Section 2 presents the three measures of the disposition effect employed in this work, Section 3 details the design of the experiment, Section 4 presents the characteristics of the subjects participating in the experiment, Section 5 reports results, and Section 6 concludes the study. A sensitivity analysis of the results is presented in an Appendix.

2. Measures of the disposition effect

Experimental studies typically track the disposition effect whenever subjects sell more (less) stocks as the sale price is above (below) either the purchasing price or the previous price (Weber and Camerer, 1998). However, such a measure can be misguiding in the presence of bull–bear market cycles. For instance, in a bull market a stock sold is more likely to be a winner. Here investors might rationally think that rising prices will tend to persist in future, thereby making sense to sell winners (Da Costa et al., 2008). Since our experiment is run in an artificial market we consider the measure of the disposition effect commonly used in real-world markets (Odean, 1998) that is able to take market cycles into account. However, Odean's measure is not without problems, as discussed below. For that reason, we also assess the disposition effect in our experiment by two other measures: that of Weber and Camerer (1998), and a more recent one suggested by Dhar and Zhu (2006).

Odean's measure considers the actual and potential trades of investor i during a sample period. Potential trades refer to stocks in a portfolio that were not sold but that could have been either winners or losers. The proportion of gains realized (PGR_i) and proportion of losses realized (PLR_i) are computed as

$$PGR_i = \frac{N^i_{gr}}{N^i_{gr} + N^i_{gp}}, \quad PLR_i = \frac{N^i_{lr}}{N^i_{lr} + N^i_{lp}} \tag{1}$$

where N^i_{gr} (N^i_{lr}) is the number of trades by investor i with a realized gain (loss), and N^i_{gp} (N^i_{lp}) is the number of potential trades for investor i with a gain (loss).

The disposition effect (DE) of investor i is then

$$DE_i = PGR_i - PLR_i \tag{2}$$

where $-1 \leqslant DE_i \leqslant 1$. A positive value of DE_i indicates that a smaller proportion of losers is sold if compared with the proportion of winners sold, in which case investor i exhibits the disposition effect.

The definition in Eq. (2) can be evaluated by the t-statistic

$$t = \frac{PGR_i - PLR_i}{SE_i} \tag{3}$$

where the standard error SE_i is

$$SE_i = \sqrt{\frac{PGR_i(1 - PGR_i)}{N^i_{gr} + N^i_{gp}} + \frac{PLR_i(1 - PLR_i)}{N^i_{lr} + N^i_{lp}}}. \tag{4}$$

One disadvantage of Eq. (2) is that the PGR_i and PLR_i measures are sensitive to portfolio size and trading frequency (Odean, 1998). They are likely to be smaller for investors who hold larger portfolios and trade frequently because those portfolios contain a larger number of stocks with capital gains and capital losses. This problem gets more serious as the measures are employed in cross-sectional analyses.

Thus we also employ two other measures of the disposition effect that are not sensitive to portfolio size and trading frequency. The first one is precisely the measure of Weber and Camerer (1998), which considers the difference between the number of trades with realized gains by investor i and the number of trades with realized losses relative to the number of all trades, that is,

$$DE_i = \frac{N^i_{gr} - N^i_{lr}}{N^i_{gr} + N^i_{lr}} \tag{5}$$

where $-1 \leqslant DE_i \leqslant 1$. If the number of trades with realized gains matches the number of trades with realized losses there is no disposition effect. The other measure is that of Dhar and Zhu (2006):

$$DE_i = \frac{N^i_{gr}}{N^i_{lr}} - \frac{N^i_{gp}}{N^i_{lp}} \tag{6}$$

3. Experiment design

To run our experiment we employ the computer program that simulates the stock market called SimulaBolsa®, which was developed by one of us (J.M.). Fig. 1 shows the program's main menu. The program generates an individual report for all the decisions made by the subjects throughout the simulation period. The output can thus allow one to get informed about variables, such as the number of stocks bought and sold each period, and individual portfolio composition at the end of a period.

The program was fed with actual data for stock prices taken from the Sao Paulo stock exchange (Bovespa) for the 5-year period from January 1997 to December 2001. The program also included

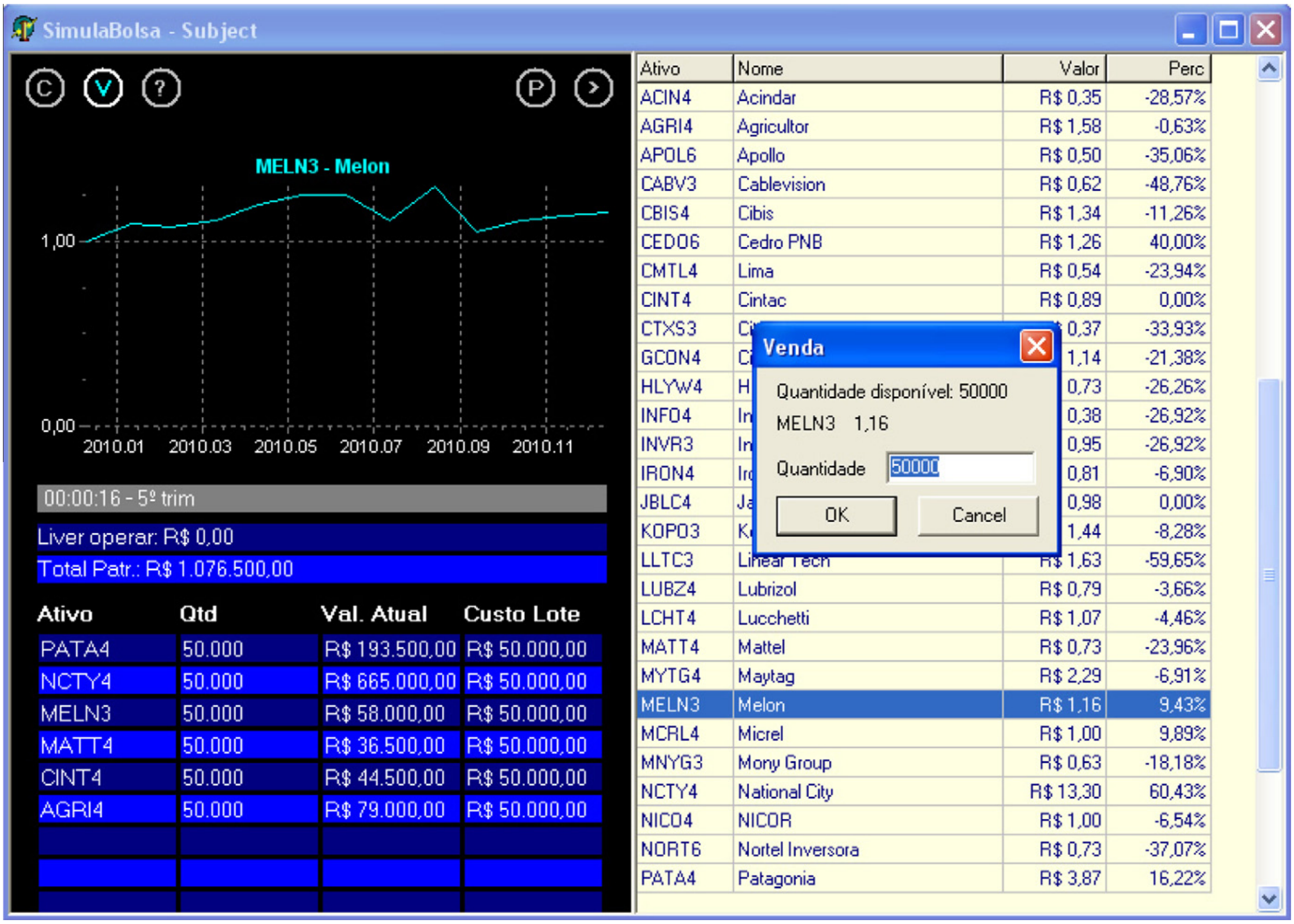

Fig. 1. Main menu of the stock market simulator we devised to run the experiment.

indicators based on fundamental analysis taken from Economatica®. However, subjects were not informed about the period involved, and the companies' real names were replaced with fictitious ones. The stock prices were deflated by the Brazilian GDP deflator (called IGP-DI), and corrected for dividends and other occurrences. Then the prices were normalized so that each stock cost one Brazilian *real* (R$ 1) at the beginning of the experiment. Because prices (purchasing prices equaling selling prices) were fixed by the simulator, the whole stock market was exogenous to each subject. Each subject was then considered as a small trader, and their actions did not influence prices.

On the main screen of the program (Fig. 1) each subject was endowed with initial assets worth R$ 300,000, which could be allocated in either cash or stocks of 28 companies. Money for real was not involved. Before getting started, subjects received instructions about the simulation. They were told a story about managing the portfolio of a teenage boy's best friend who died of cancer. The story aimed at promoting emotional engagement with the play, to compensate for the fact that no real money was involved. Subjects were then asked to manage the investment portfolio over 20 periods using the program, and their buy and sell decisions had to be made at the beginning of each period. Decisions were to be reached within a 3 min time limit. After this limit, the simulation screen switched for the next one. The subjects could eventually compare their decisions during the experiment with the actual stock prices announced by the program. Subjects performed a total 7429 transactions, which is equivalent to 5 years of actual data (Table 2).

Table 2
Descriptive statistics of the subjects participating in the simulation.

Subject	Investors	Students	Robots	All subjects
Sample	26	38	50	114
Average stocks in portfolio	6.1	7.2	8.2	6.7
Total trades	1644	2737	3048	7429
Average number of trades	63.23	72.03	60.96	65.2
Cumulative returns (%)	230.8	201.6	65.2	149.8
Bovespa index cumulative returns (%)	178.3			

4. Subject characteristics

Stock investors with a minimum of 2 years of experience were sampled from consulting retail brokerage houses located in Florianopolis, Brazil. From the 26 subjects that ended up participating in the experiment, 9 reported more than 5 years of experience, while 17 reported from 2 to 5 years. The inexperienced investors were sampled from economics and business administration students of the Federal University of Santa Catarina, also located in Florianopolis. The students had already taken "Capital Markets" in the previous term. A total 38 student subjects participated. The experiment with students was conducted during two sessions run in the second term of 2007. The sessions were located at the university's Stock Market Lab. The Lab has 40 computers arranged in individual tables with no possible communication between users. Thus, one subject's screen could not be seen by others. The students' sessions took approximately 90 min each. The experiment with professional investors was run in the course of several sessions performed in their own workplaces to comply with their time availability. The sessions took 90 min as well. In all experiments, subjects were allowed to ask for directions from the tutor.

After the end of the sessions we calculated the measures of the disposition effect as in Section 2. To control the experiment, we also considered 50 robot subjects that were programmed to randomly buy or sell stocks through a uniform distribution (see Miller, 2008 and references therein). Then we calculated the disposition effect for the robots as well. This procedure aimed at checking whether the effect was really caused by some type of cognitive illusion of the human brain, as commonly asserted. After all, if robots also exhibited the disposition effect it should be explained by some type of emergence property resulting solely from the dynamics of the experiment; in other words, the effect had nothing to do with cognitive illusion.

The final sample of 26 investors and 38 students did not include those subjects with neither gains nor losses throughout the experiment, and also those that spent less than 30 min in the simulation. We thought that such subjects were not really engaged with the experiment.

5. Results

Table 2 shows the descriptive statistics of the three types of subjects. As can be seen, the average number of trades carried out by the investors was less than that of students (difference = 8.8, $t = 1.53$, p-value = 0.13). For both human subjects the total average returns beat the actual returns in the Bovespa index (over the period January 1997 to December 2001). Moreover, the returns of human subjects were by far greater than the returns made by the robots.

Table 3 shows the details of the calculation of the disposition effect using Eq. (2) for each of the three groups of subjects as a whole. The t-statistic for both groups of human subjects was $t = 11.39$. This figure matches those commonly found in the studies with actual data described in Section 1. As can be seen in Table 3, though both human groups exhibited the disposition effect, the effect was lessened for the experienced investors. The robots did not show the disposition effect, thus suggesting that the common explanation by some type of human cognitive bias makes sense.

Table 4 shows the descriptive statistics for the disposition effect calculated separately for each individual using Eq. (2). It also shows two tests (parametric and nonparametric) for the distribution of the effect along with a test for the normality of the distribution (Jarque–Bera). The t-statistic tests the hypothesis of zero mean, while the nonparametric Wilcoxon Z-statistic tests whether the median of the distribution is zero. Table 5 repeats the calculations considering the definition in Eq. (5), while Table 6 considers the measure represented by Eq. (6).

As can be seen, the results in Tables 4–6 are very similar. In Tables 4 and 6, the disposition effect is significant at 1% for students and students and investors taken together, and significant at 5% for the investors alone. Yet the effect is overall significant at 1% in Table 5. Apart from the investors in the definition (6) in Table 6, the Jarque–Bera test could not reject the normality hypothesis. For the robots, the hypothesis could be rejected (Tables 4 and 6), but such subjects did not exhibit the disposition effect, as seen. The row at the bottom in Table 6 also shows that a little bit more than 26% of the subjects did not exhibit the disposition effect; this finding matches that of Dhar and Zhu (2006) for actual data, where 20% of individuals did not present the effect.

To investigate the influence of experience on the disposition effect, we first run a simple linear regression between the disposition effect (using the definitions in Eqs. (2), (5), and (6)) and investing experience, that is,

$$DE_i = \alpha + \beta X_i + \mu_i \tag{7}$$

where experience is tracked by the dummy variable X_i, which takes on the value $X_i = 1$ for the subjects with 2 or more years in stock markets (investors), and $X_i = 0$ for subjects with experience below 2 years (students). Table 7 shows that the disposition effect is reduced as the years of experience grow (negative slope coefficient); however, the coefficient is nonsignificant.

Table 3
The disposition effect for the groups of subjects using Eq. (2).

Subject	Group of investors	Group of students	Both human groups	Group of robots
N_{gr}	346	693	1039	544
N_{lr}	179	314	493	581
N_{gp}	1434	2239	3673	3894
N_{lp}	1265	2085	3350	3845
PGR	0.1944	0.2364	0.2205	0.1280
PLR	0.1240	0.1309	0.1283	0.1317
DE	0.0704	0.1055	0.0922	−0.0037
SE	0.0127	0.0104	0.0081	0.0071
t-Statistic	5.51***	10.10***	11.38***	−0.52

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 4
The disposition effect for individual subjects using Eq. (2).

Subject	Investors	Students	All human subjects	Robots
Number of subjects	26	38	64	50
Mean	0.0790	0.0913	0.0863	−0.0100
Median	0.0739	0.0848	0.0814	−0.0072
Maximum	0.4093	0.4198	0.4198	0.1018
Minimum	−0.2232	−0.4371	−0.4371	−0.1891
Standard deviation	0.1562	0.1724	0.1649	0.0610
Jarque–Bera	0.35	4.69	3.39	7.63**
t-Statistic (mean = 0)	2.57**	3.26***	4.19***	−1.15
Wilcoxon Z-statistic (median = 0)	2.18**	3.21***	3.93***	0.74
Subjects with $DE > 0$ (%)	69.2	76.3	73.4	48

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 5
The disposition effect for individual subjects using Eq. (5).

Subject	Investors	Students	All human subjects	Robots
Number of subjects	26	38	64	50
Mean	0.2916	0.3708	0.3386	−0.0155
Median	0.3968	0.3333	0.3333	−0.0238
Maximum	0.8182	0.8889	0.8889	0.5000
Minimum	−0.5000	−0.2727	−0.5000	−0.5238
Standard deviation	0.3502	0.2890	0.3150	0.2650
Jarque–Bera	1.13	0.32	1.39	1.17
t-Statistic (mean = 0)	4.25***	7.91***	8.60***	−0.41
Wilcoxon Z-statistic (median = 0)	3.34***	4.90***	5.93***	0.28
Subjects with $DE > 0$ (%)	80.8	89.5	85.9	42

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 6
The disposition effect for individual subjects using Eq. (6).

Subject	Investors	Students	All human subjects	Robots
Number of subjects	26	38	64	50
Mean	1.4165	1.8919	1.6988	0.0410
Median	1.0179	1.1016	1.1016	−0.0290
Maximum	9.6923	15.0952	15.0952	2.1935
Minimum	−3.1310	−8.5417	−8.5417	−0.7679
Standard deviation	2.9427	4.4986	3.9217	0.6000
Jarque–Bera	5.64	13.05***	33.34***	21.80***
t-Statistic (mean = 0)	2.45**	2.59**	3.45***	0.48
Wilcoxon Z-statistic (median = 0)	2.08**	3.21***	3.76***	0.12
Subjects with $DE > 0$ (%)	69.2	76.3	73.4	48

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 7
The disposition effect and investing experience (Eq. (7)).

Disposition effect	Eq. (2)	Eq. (5)	Eq. (6)
Constant	0.0913***	0.3708***	1.8919***
Experience ($\geqslant$2 years)	−0.0123	−0.0792	−0.4754
R squared n = 64	0.002	0.015	0.004

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 8
The disposition effect and investing experience (Eq. (8)).

Disposition effect	Eq. (2)	Eq. (5)	Eq. (6)
Constant	0.0913***	0.3708***	1.8919**
Experience (2–5 years)	0.0344	0.0076	0.4716
Experience (>5 years)	−0.1006*	−0.2433**	−2.2641*
R squared n = 64	0.064	0.075	0.049

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

To remedy such a shortcoming, we run the following multiple regression:

$$DE_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \mu_i \tag{8}$$

where $X_{1i} = 1$ is the dummy for subjects with 2–5 years of experience ($X_{1i} = 0$ otherwise), and $X_{2i} = 1$ is the dummy for subjects with more than 5 years of experience ($X_{2i} = 0$ otherwise). Table 8 shows that the disposition effect tends to be reduced for subjects with more than 5 years in stock markets. Parameter β_2 was significant at 5% for the definitions in Eqs. (5) and (6), and was significant at 10% for the measure given by Eq. (2).

Moreover, we test for the difference between the disposition effects of the two experienced groups only. Using the definitions in Eq. (2), (5), and (6), we then run the following regression:

$$DE_i = \alpha + \beta X_i + \mu_i \tag{9}$$

where the level of experience is tracked by the dummy variable X_i, which takes on the value $X_i = 1$ for the subjects with more than 5 years in stock markets, and $X_i = 0$ for the subjects with 2–5 years of experience. Table 9 shows that the difference between the two groups was significant. The slope coefficient was negative for all the three different definitions of the disposition effect. It was significant at 5% for the definition in Eq. (2), 10% for that in Eq. (5), and 1% for that in Eq. (6).

Table 9
The disposition effect between the two groups of experienced subjects (Eq. (9)).

Disposition effect	Eq. (2)	Eq. (5)	Eq. (6)
Constant	0.1257***	0.3784***	2.3635***
Experience (>5 years)	−0.1350**	−0.2509*	−2.7357**
R squared n = 26	0.176	0.121	0.203

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

6. Conclusion

Does investor experience dampen the disposition effect? Most studies using actual data answer "yes". However, this answer conflicts with the results found in lab experiments. Tests proving the disposition effect in actual markets cannot be conclusive because investor decisions cannot be controlled in there. Control characteristics are an advantage of the experimental method, though results can still be dependent on experiment design, mainly if the experiment is too simplistic.

Here, we consider that possibility and thus devise a more elaborated experiment through a computer program that mimics the stock market while retaining the control characteristics. In line with the actual data studies, our "framed field experiment" found that the disposition effect is reduced if investors have more than 5 years of experience in stock markets.

The disposition effect is commonly attributed to a cognitive illusion of the human brain. To evaluate such a proposition we consider not only professional investors and students in our experiment, but also robots. Do robots dream of winning stocks? If they do, the phenomenon has to be explained by some type of emergence property resulting from the dynamics of the experiment, rather than by human brain imperfections. We find that robots do not exhibit the effect, and thus we cannot dismiss that the phenomenon is really caused by cognitive illusion.

Appendix A. Sensitivity analysis

We conducted a slightly modified experiment setup 2 years time after the first experiment described in the main text. Its major features were:

- ten assets were considered, rather than the 28 assets used in the first experiment;
- each subject was endowed with R$ 300,000 at the beginning of the experiment;
- all stock prices and company names were different from the first experiment's prices and names;
- as in the first experiment, subjects who made neither gains nor losses throughout the experiment were dropped from the sample;
- those who spent less than 10 min in the experiment were excluded from the sample;
- as in the first experiment, the sample of inexperienced investors was drawn from students of business administration of the Federal University of Santa Catarina. The students had already coursed "Capital Markets" in the previous term. The experiment with the students was conducted in one session run during the first term of 2009;
- the experiment with professional investors was run in the course of several sessions that were conducted in their own workplaces to comply with their time availability, during the second semester of 2009;

Table 1A
Descriptive statistics of the subjects participating in the extra simulation.

Subject	Investors	Students	Robots	All human subjects
Sample	16	21	30	37
Total trades	695	841	1708	1536
Average number of trades	43.44	40.05	56.93	41.51

Table 2A
The disposition effect for the groups of subjects using Eq. (2).

Subject	Group of investors	Group of students	Both human groups	Group of robots
N_{gr}	103	136	239	302
N_{lr}	96	124	220	331
N_{gp}	588	503	1091	1312
N_{lp}	590	794	1384	1368
PGR	0.1491	0.2128	0.1797	0.1871
PLR	0.1399	0.1350	0.1372	0.1948
DE	0.0092	0.0778	0.0425	
SE	0.01895	0.01973	0.01359	0.01366
t-Statistic	−0.56	0.48	3.94***	3.13***

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 3A
The disposition effect for individual subjects using Eq. (2).

Subject	Investors	Students	All human subjects	Robots
Number of subjects	16	21	37	30
Mean	0.0282	0.1261	0.0837	−0.0092
Median	−0.0249	0.1500	0.0313	−0.0007
Maximum	0.4857	0.7083	0.7083	0.1096
Minimum	−0.1410	−0.3913	−0.3913	−0.1553
Standard deviation	0.1439	0.2954	0.2440	0.0701
Jarque–Bera	24.67***	0.28	2.20	1.09
t-Statistic (mean = 0)	0.78	1.96*	2.09**	−0.72
Wilcoxon *Z*-statistic (median = 0)	0.13	1.70*	1.64*	0.43
Subjects with *DE* > 0 (%)	43.75	66.7	56.8	50.0

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 4A
The disposition effect and investing experience (Eq. (7)).

Disposition effect	Eq. (2)
Constant	0.1261* (*p*-value = 0.06)
Experience (⩾2 years)	−0.0979 (*p*-value = 0.19)
R squared	0.041

Regression with White heteroskedasticity-consistent standard errors and covariance, $n = 37$.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

- stock investors with a minimum of 2 years of experience were sampled from two different consulting retail brokerage houses located in Florianopolis, Brazil. From the 20 subjects that ended up participating in the experiment, six reported more than 5 years of experience, while 10 reported 2–5 years of experience. Four subjects were excluded from the sample because one did not make any sell transaction and three belatedly reported to have less than 2 years of experience. Also, one subject misreported to have more than 5 years of experience, but in fact he had only 3 years. So, he was reallocated from the more than 5 years of experience to the 2–5 years of experience group. Descriptive statistics are presented in Table 1A.

Table 5A
The disposition effect and investing experience (Eq. (8)).

Disposition effect	Eq. (2)
Constant	0.1261* (*p*-value = 0.06)
Experience (2–5 years)	−0.0594 (*p*-value = 0.49)
Experience (>5 years)	−0.1621** (*p*-value = 0.02)
R squared	0.059

Regression with White heteroskedasticity-consistent standard errors and covariance, $n = 37$.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 6A
The disposition effect between the two groups of experienced subjects (Eq. (9)).

Disposition effect	Eq. (2)
Constant	0.0667 (*p*-value = 0.24)
Experience (>5 years)	−0.1027* (*p*-value = 0.09)
R squared	0.127

Regression with White heteroskedasticity-consistent standard errors and covariance, $n = 16$.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 7A
The disposition effect and years of investing experience.

Disposition effect	Eq. (2)
Constant	0.1155** (*p*-value = 0.04)
Years of experience	−0.0134* (*p*-value = 0.07)
R squared	0.047

Regression with White heteroskedasticity-consistent standard errors and covariance, $n = 37$.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

The results were similar to those of the benchmark experiment, and are described in the tables above. Shorter samples were responsible for less statistical significance, however. The disposition effect was nonsignificant among the investors, both as a group and individually (Tables 2A and 3A). Despite that, the effect still affected less the investors (negative slope) (see Table 4A). Also, (see Table 5A) shows that the more experienced investors were less affected by the disposition effect if compared with the investors with experience between 2 and 5 years (negative slope).

In order to directly compare the two groups of investors we run a simple regression based in Eq. (9), as in the benchmark experiment. The results in Table 6A show that the difference between the two groups of investors is significant. The group of investors with less market experience (2–5 years) presents a disposition effect of 0.0667, while in the more experienced group (>5 years) the coefficient (which represents the differential effect) is −0.1027 and significant at 10%.

We also run a simple linear regression between the disposition effect (as in Eq. (2)) and years of investing experience, instead of using dummies as in Eqs. (7) and (8). We show the results in Table 7A. In the benchmark experiment we did not collect such data (subjects were only checked as to whether they had no experience, more than 2 years, or more than 5 years of experience). We detect the presence of heteroskedasticity in the variance–covariance matrices of the regressions presented in Tables 4A–7A, but the problem was properly corrected by the technique of White.

References

Abbink, K., Rockenbach, B., 2006. Option pricing by students and professional traders: a behavioural investigation. Managerial and Decision Economics 27, 497–510.

Barber, B.M., Odean, T., 1999. The courage of misguided convictions. Financial Analysts Journal 55, 41–55.

Camerer, C., Loewenstein, G., Weber, M., 1989. The curse of knowledge in economic settings: an experimental analysis. Journal of Political Economy 97, 1232–1254.

Chang, C.-H., 2008. The impact of behavioral pitfalls on investors' decisions: the disposition effect in the Taiwanese warrant market. Social Behavior and Personality 36, 617–634.

Chen, G.M., Kim, K., Nofsinger, J., Rui, O., 2007. Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. Journal of Behavioral Decision Making 20, 425–451.

Coval, J.D., Shumway, T., 2005. Do behavioral biases affect prices? Journal of Finance 60, 1–34.

Dhar, R., Zhu, N., 2006. Up close and personal: investor sophistication and the disposition effect. Management Science 52, 726–740.

Da Costa Jr., N., Mineto, C., Da Silva, S., 2008. Disposition effect and gender. Applied Economics Letters 15, 411–416.

Feng, L., Seasholes, M.S., 2005. Do investor sophistication and trading experience eliminate behavioral biases in financial markets? Review of Finance 9, 305–351.

Garvey, R., Murphy, A., 2004. Are professional traders too slow to realize their losses? Financial Analysts Journal 60, 35–43.

Goetzmann, W.N., Massa, M., 2008. Disposition matters: volume, volatility, and price impact of a behavioral bias. Journal of Portfolio Management 34, 103–125.

Grinblatt, M., Keloharju, M., 2001. What makes investor trade? Journal of Finance 56, 589–616.

Haigh, M.S., List, J.A., 2005. Do professional traders exhibit myopic loss aversion? An experimental analysis. Journal of Finance 60, 523–534.

Hales, J., 2007. Directional preferences, information processing, and investors' forecasts of earnings. Journal of Accounting Research 45, 607–628.

Harrison, G.W., List, J.A., 2004. Field experiments. Journal of Economic Literature 42, 1009–1055.

Hedesstrom, T.M., Svedsater, H., Garling, T., 2007. Determinants of the use of heuristic choice rules in the Swedish premium pension scheme: an internet-based survey. Journal of Economic Psychology 28, 113–126.

Kliger, D., Kudryavtsev, A., 2008. Reference point formation by market investors. Journal of Banking and Finance 32, 1782–1794.

Lee, H.-J., Park, J., Lee, J.-Y., Wyer Jr., R.S., 2008. Disposition effects and underlying mechanisms in e-trading of stocks. Journal of Marketing Research 45, 362–378.

Locke, P.R., Mann, S.C., 2005. Professional trader discipline and trade disposition. Journal of Financial Economics 76, 401–444.

Menkhoff, L., Nikiforow, M., 2009. Professionals' endorsement of behavioral finance: does it impact their perception of markets and themselves? Journal of Economic Behavior and Organization 71, 318–329.

Miller, R.M., 2008. Don't let your robots grow up to be traders: artificial intelligence, human intelligence, and asset-market bubbles. Journal of Economic Behavior and Organization 68, 153–166.

Odean, T., 1998. Are investors reluctant to realize their losses? Journal of Finance 53, 1775–1798.

Schlarbaum, G.G., Lewellen, W.G., Lease, R.C., 1978. Realized returns on common stocks investments: the experience of individual investor. Journal of Business 51, 299–325.

Shapira, Z., Venezia, I., 2001. Patterns of behavior of professionally managed and independent investors. Journal of Banking and Finance 25, 1573–1587.

Shefrin, H., Statman, M., 1985. The disposition to sell winners too early and to ride losers too long: theory and evidence. Journal of Finance 40, 777–790.

Taylor, L., 2000. The Disposition Effect: Do New Zealand Investors Keep Their Mistakes? Coursework Masters Thesis in Finance, University of Otago.

Weber, M., Camerer, C.F., 1998. The disposition effect in securities trading: an experimental analysis. Journal of Economic Behavior and Organization 33, 167–184.