Intention-Based Disposition Effect in Experimental Asset Markets with Long Horizon

Zvika Afik[1] Yaron Lahav[2] Liran Maymoni[3]

Abstract

Prior experimental studies of the disposition effect use experiments that are 14-20 period long. We use data gathered from experimental asset markets with a long horizon and call trading market rules. The long horizon eliminates experimental aberrations such as the 'end-game' effect. Furthermore, the call trading market rules reveal information on traders' intentions (willingness to sell) which are often hidden when only transaction data is used and observations are affected by market prices. Our results show that the disposition effect is present among the majority of traders, especially among those who trade less frequently. We find a positive relationship between the disposition effect and *CRT* scores, yet there are no statistically significant differences between genders. Finally, we show that momentum trading reduces the disposition effect whereas the net effect of trade that is based on fundamental values is small and statistically insignificant.

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[1] Senior lecturer, Department of Business Administration, Ben-Gurion University of the Negev, P.O. Box 653 Beer-Sheva 84105, Israel. Email: afikzv@som.bgu.ac.il.
[2] Corresponding author, Senior Lecturer, Department of Business Administration, Ben-Gurion University of the Negev, P.O. Box 653 Beer-Sheva 84105, Israel. Email: ylahav@som.bgu.ac.il.
[3] Department of Business Administration, Ben-Gurion University of the Negev, P.O. Box 653 Beer-Sheva 84105, Israel. Email: liran.maymoni@gmail.com.

1. Introduction

The disposition effect is defined as the tendency of investors to hold their losing stocks too long while selling their winning stocks too soon. This effect was first introduced by Shefrin and Statman (1985), who provide four possible reasons for its occurrence: prospect theory (Kahneman and Tversky, 1979), self-control (Thaler and Shefrin, 1981), mental accounting (Thaler, 1985) and the desire to seek pride and avoid regret (Thaler, 1980).

These possible explanations are all behavioral, because they assume some level of irrationality among investors, thus the disposition effect could be a significant cause for deviations of asset prices from their “rational” intrinsic values. This is probably among the main motivations of researchers to explore the disposition effect - it is relevant to behavioral and “classical” finance and economics researchers, and to practitioners, for the understanding of market behavior.

Shefrin and Statman (1985) spark a large volume of work aimed at finding evidence to the disposition effect existence and measuring its impact on investors’ decisions and market outcome. Some of the work uses real data on individual investors (Odean, 1998; Shapira and Venezia, 2001; Dhar and Zhu, 2006; Chen et al., 2007 and Frino et al., 2015) and on aggregate market level (Shefrin and Statman, 1985; Lakonishok and Smidt, 1986 and Ferris et al., 1988). One benefit of using such data is the ability to characterize the behavior of real investors over time. However, actual market data analysis might be inconclusive because some parameters cannot be controlled, among them are those suggested as possible reasons for the effect.

Laboratory experiments, on the other hand, can offer controlled environments to study subjects’ trading decisions. Prior laboratory experiments examine the disposition effect using various trading mechanisms. In some, stock prices are pre-determined exogenously (Weber and Camerer, 1998; Chui, 2001; Weber and Welfens, 2007; Da Costa et al., 2008 and Rau, 2014), while others use call market (CM) trading rules (Oehler et al., 2003; Kirchler et al., 2005) or continuous double auction (CDA) (Oehler et al., 2003). Most experimental work confirms the disposition effect.

To our opinion, there are some limitations to the experimental design used in prior research. One of them is the relatively short horizon of trade – lasting between 14 to 20 periods. We believe that short-term trade might introduce unwarranted biases and therefore is improper to replicate the field, mainly because short-horizon trade triggers strategic behavior based on the known future value of the stock in the last period. In experimental asset markets with long horizon, on the other hand, the “end-game” effect is minimized and therefore trade decisions should be closer to the field.

In this paper, we use data from experimental asset markets with a long-horizon to test the existence of the disposition effect among market participants. The data is taken from Hoshihata et al. (2018), which includes markets that utilize CM and CDA trading rules. However, in our work, we use the data generated with the CM rules only, for reasons explained below.

In general, CDA trading rules replicate an open book, where traders can post buy and sell orders executing bilateral transaction, during a fixed period of time (usually 240 seconds, 60 seconds in Hoshihata et al., 2018). Alternatively, according to the CM trading rules, traders can submit only one buy and/or one sell orders (or none), in each period. The computer then executes the transactions according to a unique equilibrium (or market) price determined by an intersection of supply and demand. Consequently, those willing to buy for a price higher than the equilibrium price purchase from those willing to sell for a price lower than the equilibrium price.

For the purpose of this study, certain market characteristics of these trading rules provide an important advantage to the CM. The key weakness of the CDA data generated by Hoshihata et al. (2018) is the quantity constraint to a single stock in each buy and sell order. This obscures the actual volume that traders wish to sell. Furthermore, in general, transaction prices in CDA do not necessarily represent traders' willingness to buy or sell. In the CM, on the other hand, traders submit the maximum (minimum) prices they are willing to pay (accept) and quote as many units of the asset as they wish to buy or sell. As a result, the data obtained in the CM design can be regarded as traders' willingness to buy and sell before a market price is revealed.

Measuring the disposition effect of individuals based on actual market prices may result in biased results. Consider a trader operating in a market under the CDA trading rules, who purchased a stock for, say, 50 points a few periods ago, and it is now worth 30. The trader wishes to sell the stock and decides to do so for 30 at the beginning of the next period. However, the first asking price during the next period turns out to be 55 and the trader sells for this price. The data generated in this case would show a quick sell, consistent with the disposition effect, while the trader was already willing to sell for less, at a loss. Under the CM trading rule, data for this trader would show willingness to sell for 30, which better represents the trader's preferences.

In this paper we use Hoshihata et al. (2018) data, of six sessions, each 100-period long, of experimental asset markets with CM trading rules. This dataset enables us to measure the disposition effect revealed by willingness to sell and to study the relations of the effect with individual gender, Cognitive Reflection Test (CRT) score, and personal trading characteristics while controlling for market features.

Our results show the existence of the disposition effect in long-horizon experimental asset markets, using Hoshihata et al. (2018) experimental data and measures suggested by Odean (1998). The difference in the disposition effect between traders' willingness to sell and their actual transactions is statistically insignificant. Our results also show that the disposition effect is present among both male and female traders with no significant difference. CRT scores are positively correlated with the disposition effect, implying that those with a higher tendency of rational thinking are more prone to the disposition effect. Finally, the disposition effect is higher among those who trade less frequently. We also find effects of market price pattern and investment behavior which we describe in detail below.

2. Literature Review

Our literature review on the disposition effect begins with the seminal paper of Shefrin and Statman (1985), who introduce the effect, provide four possible behavioral reasons and conduct some empirical analysis using real market data. They also show that the disposition effect cannot be fully explained by tax advantage of year-end winning stock selling avoidance.

The literature on the disposition effect can be divided into three groups: the first offers theoretical explanations for the disposition effect, the second uses real market data to provide empirical evidence for the occurrence of the effect, and the third is experimental.

2.1. Theory

According to Shefrin and Statman (1985), the disposition effect is motivated by the *S*-shaped value function of Kahneman and Tversky's (1979) Prospect Theory, Thaler's (1985) Mental Accounting, self-control and the asymmetry between seeking pride and avoiding regret. According to the Prospect Theory, individuals' value function corresponds differently to relative wins and losses. Investors are risk-averse toward gains and risk-seeking toward losses. In mental accounting, when individuals purchase a certain stock, a mental account is open. When the stock is sold, the account is closed. Individuals are reluctant to close the account at a loss. The search for pride and the tendency to avoid regret lead to investors' desire to sell winners (and be proud by realizing profits) and keep losers (and avoid the regret of losing with the hope of a future price increase). Finally, self-control is described as an ongoing intra-person conflict between the rational self and the emotional self. Investors may determine investment rules that are supposed to govern their decisions following a price change. The more emotional investors tend to dismiss their own pre-determined decision to sell if the stock price decreases to a certain point. On the other hand, they most likely execute a pre-determined decision to sell if the stock price increases.

A number of theoretical studies that follow Shefrin and Statman (1985) examine how prospect theory drives the disposition effect. Barberis and Xiong (2009) develop a trading model which includes investors with prospect theory preferences. They find that when a portfolio performance is evaluated on an annual basis, prospect theory does not necessarily lead to the disposition effect among traders. Li and Yang (2013) propose a general equilibrium dynamic model that use prospect theory to explain trade behavior, pricing and volume. They find that effective risk aversion is affected by stock returns for traders with a ‘prospect’ utility function. This connection may generate the disposition effect or reduce it, depending on the characteristics of the utility function and the asset returns’ pattern.

Zuchel (2011) suggests that the disposition effect can be explained by the self-justification hypothesis, known as cognitive dissonance theory. Accordingly, investors find it hard to admit that they have made a wrong investment decision in the past, and for this reason, they are unwilling to realize their losses.

2.2. Empirical

In general, empirical studies on the disposition effect can be divided into two groups: those conducted on individual data, and those performed using aggregated market data. We start with prominent examples of the latter type. Shefrin and Statman (1985) are the first to use stock and mutual funds trading data to demonstrate the existence of the disposition effect, and find that tax consideration alone cannot explain it. Lakonishok and Smidt (1986) distinguish the non-tax responses from the tax responses among traders using abnormal volumes from NYSE and AMEX stocks. They find more volume for winner stock in both groups. In addition, and as predicted by tax consideration for the tax responses group, the abnormal volumes for loser stock is higher than normal in December, while for winners it is higher than normal in January. Ferris et al. (1988) also use trading volumes and document higher volumes during price increases and lower volumes during price decreases. Surprisingly, in their study the disposition effect remains significant even in December, despite the tendency of sophisticated investors to realize a tax-loss at the end of the year.

Several papers demonstrate the disposition effect using individual data. Odean (1998) is probably the first to use database of 10,000 investors’ accounts from a large brokerage house, showing that the average investor is prone to the disposition effect. Odean (1998) introduces new measures: the proportion of gains realized and the proportion of losses realized (PGR and PLR respectively) relative to potential gain/loss sales. PGR and PLR overcome measuring bias during asymmetric price trends, e.g. when prices increase most of the time and measurement ignores potential sales - even a random trade might seem like a disposition effect. Odean (1998) shows that PGR is approximately 50% higher than PLR, except for tax-motivated selling in December. Odean (1998) rules out alternative explanations such as portfolio rebalancing or transaction costs. Based on individual data from an Israeli brokerage during 1994, Shapira and Venezia (2001) examine the behaver of both independent investors and clients with accounts managed by brokerage specialists. They show that both trader types exhibit the disposition effect, although the effect is significantly weaker among the professional investors.

Dhar and Zhu (2006) provide additional evidence that sophisticated investors are less prone to the disposition effect. They use a large data of discount brokerage containing accounts of more than 50,000 personal investors between 1991 and 1996 and test demographic and socioeconomic variables as possible explanatory variables. They conclude that households with higher self-reported income and those working in a professional occupation are less disposed to the disposition effect. They also report that higher trading frequency is associated with a lower disposition effect. We are not aware of other studies linking frequency to the disposition effect.

Chen et al. (2007) study investment decisions in emerging markets by analyzing data from a Chinese brokerage containing almost 50,000 Chinese traders between 1998 and 2002. Almost 87% of the investors in their sample are either overconfident (i.e., they under-diversify and trade too often), form momentum expectations (i.e., buying recent short-term winners), or prone to the disposition effect. Using methods similar to Odean (1998), Chen et al. (2007) also report that the difference between PGR and PLR is significantly higher for Chinese investors compared to US investors. Their findings also show that 67% of Chinese investors are prone to the disposition effect.

According to Frino et al. (2015), culture plays a role in investment behavior in general and in the disposition effect in particular, using 46,289 accounts from a leading Australian retail brokerage house between October 2010 and August 2012. Frino et al. (2015) split the traders into two groups: Chinese and non-Chinese investors. They conclude that the disposition effect is much more widespread among Chinese investors compared with non-Chinese investors. They also find that while the disposition effect exists in all groups, it is more prevalent among women, older investors, people who do not trade often, people with relatively small portfolios, and people who tend to invest in low-priced stocks.

2.3. Experimental

Weber and Camerer (1998) are probably the first to conduct an experimental analysis on the disposition effect and provide experimental evidence confirming the empirical findings. In their experiments, subjects observed random price values of six different shares over 14 periods. Subjects knew the possible distributions in general but had no information about the specific probability distribution used for each share. In Weber and Camerer (1998), subjects sold winners at a 50% higher rate than losers.

Chui (2001) examine experimentally the disposition effect in Macau showing a stronger effect compared to Weber and Camerer (1998). Chui (2001) also examines whether the disposition effect relates to the “locus of control” of Rotter (1966). Accordingly, individuals with an internal locus of control believe that they have control over the outcome of situations in their lives, whereas individuals with an external locus of control do not feel responsible for their results. Chui (2001) show that investors with internal locus of control exhibit a higher degree of the disposition effect.

Weber and Welfens (2007) study experimentally how the disposition effect is affected by tasks and time. They find that the disposition effect decreases over time, and show no significant gender difference.

In contrast, Da Costa et al. (2008) show experimentally that the disposition effect may be affected by gender. On average, men are more prone to the disposition effect than women. Contrary to this finding, Rau (2014) finds a significant disposition effect among females and none among males. Finally, Da Costa et al. (2013) find that experienced investors (with more than five years of practice in the stock market) are less affected by the disposition effect.

3. Experimental Design

In this paper, we use experimental data gathered by Hoshihata et al. (2018) in six laboratory sessions of experimental asset markets based on Lahav (2011). The experiments were conducted at the University of Tsukuba in Ibaraki, Japan. 12 subjects participated in each session and traded shares of an experimental asset. At the beginning of each session, each subject was endowed with six asset shares and 7,500 experimental currency units (ECUs). At the end of each period, each share paid its owner a stochastic dividend of either 0 or 30 ECUs with equal probability, adding to the subject's cash balance. During a session, asset and cash were carried over from one period to the next. Each session included 100 periods.

The experimental markets were computerized, using CM trading rules. Traders were not authorized to submit a buy price higher than their sell price at the same period, so self-trade was impossible. Furthermore, the buy orders could not exceed the cash balance and the sell orders could not exceed the number of shares that the trader was holding. When submitting their orders, subjects could not observe other traders' orders. After all traders have submitted their orders, a single market price was computed for all assets in the period using the intersection of the market demand and supply curves generated from the traders' orders. At the end of each period, subjects were notified on the market price, the number of shares that they have exchanged, periodic dividend value and their cash balance. If all selling orders were higher than all buying orders, no market price was determined, and traders were informed that no trade was fulfilled.

Prior to the trade phase of the experiment, subjects passed a CRT test based on three questions, and completed a demographic questionnaire that included information about their gender, age, major study, etc.

4. Research Hypotheses

Although many laboratory experiments have confirmed the existence of the disposition effect in a controlled environment, only a few use experimental asset markets where market prices are determined endogenously based on traders' decisions. Additionally, to the best of our knowledge, none of the prior experimental work uses sessions with a long-horizon. As mentioned above, and in accordance with the findings of Lahav (2011), we believe that unlike sessions with a relatively short number of periods, in sessions with many periods, decisions in most periods are not affected by the end-game effect.[4] Using existing data from experimental asset markets with long-horizon, we investigate whether the disposition effect is present in an experimental setup with 100 periods and study its characteristics. An additional research concern is the potential difference between traders' observed actions (transactions) and often hidden intentions. Since our data was gathered using CM trading rules, we treat selling orders as willingness to sell. Another study angle is traders' personal characteristics. The data we use contain information on traders' gender and their level of intelligence based on a CRT test. We use this information in our analysis to test their linkage to the disposition effect. We now formalize our arguments in a series of hypotheses.

First, to our knowledge, we are the first to study the disposition effect on intentions rather than actions. When measuring the disposition effect, a reference value must be used to determine whether the offered stock is a losing or winning stock. In the data we use the market price is revealed to the subjects only after they submit their orders and cannot update them. Furthermore, while equilibrium price represents the market value of the asset on an aggregate level, it might not well represent the asset value perceived by each subject. For example, a subject may be willing to sell for a price lower than the purchase price, but market demand generates a higher price for the transaction. We therefore consider selling prices submitted by subjects as their "willingness to sell" and argue that this submitted price should be the relevant value when measuring the disposition effect. This way, we define here the disposition effect using intentions instead of actions: the disposition effect is the willingness (or intention) to sell winners and ride losers. Our hypotheses use this definition.

Hypothesis 1: Subjects tend to offer to sell more shares when the sale price is above the asset value than when the sale price is below the asset cost.

Dhar and Zhu (2006) find a negative relationship between trading frequency and the disposition effect. In our next hypothesis we test this issue using experimental data. We believe that subjects who trade frequently are more willing to "accept their losses" and by that, reducing the disposition effect.

Accordingly, we formulate the following hypothesis:

Hypothesis 2: Subjects that trade less frequently tend to exhibit a higher disposition effect.

Most of the existing literature on the disposition effect concentrates on the effect itself rather than on how traders' characteristics influence the disposition effect. Some exceptions show ethnic effects (Chen et al., 2017 and Frino et al., 2015), professionality and income characteristics (Dhar and Zhu, 2006). Gender effects are studied in some other experimental research with mixed results. Weber and Welfens (2007) find no gender effect,

[4] Lahav (2011) tests the possibility that the bubble and crash phenomenon in experimental asset market occur due to the end-game effect. Lahav (2011) show significantly different price patterns in long horizon, including multiple bubbles and crashes.

while Da Costa et al. (2008) and Rau (2014) find opposite results. The experimental data we use contain 50 male subjects and 22 female subjects. In our next hypothesis we use this information to test for gender differences in the disposition effect.

Hypothesis 3: the disposition effect does not depend on gender.

The effect of cognitive ability (or cognitive sophistication) on decisions is documented in many papers and attracts a growing interest among researchers. Some of these findings are relevant to experimental asset markets in general, and in particular to our study. Bosch-Rosa et al. (2018) show that markets populated with traders with higher cognitive ability do not exhibit bubbles. Corgnet et al. (2014) and Breaban and Noussair (2015) report a positive correlation between subject's scores on cognitive ability tests and their earnings in assent market experiments. It is likely that subjects who score high on their cognitive ability tests are also less prone to behavioral biases. The data we use include the subject's CRT score. The CRT measures a person's tendency to overcome heuristics, or behavioral shortcuts, in decisions and problem-solving mechanism and is shown to have some correlation with measures of intelligence. We assume that subjects with higher CRT scores are less prone to the disposition effect.

Hypothesis 4: Disposition effect is negatively correlated with the individual CRT.

5. Results

5.1. Measuring the disposition effect

When measuring the disposition effect, by definition, selling price should be compared to the purchase price. However, it is possible (in actual as well as in experimental markets) that different units of the same asset are purchased at different times with different prices. Since all units of the same asset are identical, a value of the asset should be calculated and used as a reference, substituting the purchase price. Odean (1998), for instance, use the average value approach to approximate purchase price. Weber and Camerer (1998), on the other hand, use the FIFO, LIFO, and average methods.

Similarly, the experimental design generating our data requires the calculation of a reference value. We follow Odean (1998) and use the average value approach to calculate the "inventory value" of a share, which is the weighted average of all purchase prices of the shares held by individual *i*, net of periodic dividends and prior sold units.

Odean (1998) calculates *Proportion of gains realized (PGR)* and *Proportion of Losses realized (PLR)* on an aggregate level to measure sales in gain and loss relative to the full potential of sales. Dhar and Zhu (2006) argue that these measures should be calculated for each trader separately, because the disposition effect is not the same across traders. The result is a calculated $PGR_{i,t}$ and $PLR_{i,t}$ for each subject *i* in each period *t* as follows:

If in period *t*, $Price_{i,t} > Inventory\ Value_{i,t}$, then:

1. $PGR_{i,t} = \frac{Realized\ Gain}{\#shares\ at\ the\ beginning\ of\ period\ t}$

If in period *t*, *Price* $_{i,t}$ < *Inventory Value* $_{i,t}$:

2. $PLR_{i,t} = \frac{Realized\ Loss}{\#\ shares\ at\ the\ beginning\ of\ period\ t}$

where “Realized Gain/Loss” is the number of winner/loser stocks sold by individual *i* at time *t* and winner/loser state is defined by the relation between price and inventory value in equations (1) and (2) respectively.[5]

For prices, in our calculations, we use subjects’ offering quotes, expressing their intentions (their willingness to sell). Consequently, we replace the realized gains and losses of Odean (1998) with offers. We use our data to calculate the variables *Proportion of Gains Offered* (*PGO*) and *Proportion of Losses Offered* (*PLO*) for each individual (*i*) in each period (*t*):

If in period *t*, *Offer Price*$_{i,t}$ > *Inventory Value*$_{i,t}$, then:

3. $PGO_{i,t} = \frac{\#\ offered\ shares_{t,i}}{\#shares\ at\ the\ beginning\ of\ period\ t}$

If in period *t*, *Offer Price*$_{i,t}$ < *Inventory Value*$_{i,t}$:

4. $PLO_{i,t} = \frac{\#\ offered\ shares_{t,i}}{\#\ shares\ at\ the\ beginning\ of\ period\ t}$

For each subject (*i*), in each session, we calculate the average *PGO* and *PLO* as follows:

5. $APGO_i = \frac{\sum_{t=2}^{100} PGO_{t,i}}{N_{G_i}}$

6. $APLO_i = \frac{\sum_{t=2}^{100} PLO_{t,i}}{N_{L_i}}$

where N_{G_i} and N_{L_i} represent the number of periods where $PGO_{i,t}$ and $PLO_{i,t}$ are observed, respectively. Because each trader starts the session with an initial endowment of six shares with undetermined inventory value for the first period, we calculate *PGO* and *PLO* starting at $t = 2$, using the market price of $t = 1$ as the initial inventory value for all subjects. At the end of each period we update the inventory amount and (average) value and then, when a dividend is paid, we subtract the value of the dividend from the inventory value.

In some periods, subjects offer to sell their shares at a rather high price, most likely assuming that probably the offer will not be realized. We refer to these offers as ‘*unrealistic*’ (or rather opportunistic) and assume that they might not correctly represent willingness to sell. We therefore filter out those offers generating a subsample of ‘*realistic*’ proposals, which we define as offers to sell with prices that do not exceed 150% of the

[5] Prior literature, such as Dhar and Zhu (2006), write in the denominator of PGR/PLR the sum of Realized Gain/Loss and Paper Gain/Loss, which equals the number of shares at the beginning of the period when using the weighted average price for the inventory.

previous equilibrium price. Accordingly, we also calculate their proportions using equations (3) and (4) and their respective averages using equations (5) and (6).

In addition, and aiming to provide findings comparable to previous research, we calculate '*actual sales*' proportions using equations (3) and (4) with only offers that turned into sales, and their individual averages using equations (5) and (6). By ignoring unrealized offers, we capture actual "Realized Gain/Loss" and compare our results to prior studies.

Following Odean (1998), we calculate the Disposition Effect measure (*DE*) using equation (7) as the difference between the average proportions of gains and losses for each subject. If a trader has no losing offers during the session, we set $PLO_i = 0$.

7. $DE_i = APGO_i - APLO_i$

DE_i varies between –1 and 1. A positive DE_i indicates that the majority of shares are offered as winners. Investors with $DE_i = 1$ ($DE_i = -1$) are willing to sell all their shares as winners (losers).

Results are summarized in *Table 1*, partitioned into the three sample categories: (i) All offers; (ii) Realistic offers, and (iii) Actual sales. Panel 1 presents means and panel 2 medians of $APGO_i$, $APLO_i$ and DE_i for all participants in each subsample. The *p-value* for one-tailed *t-test* is shown in parentheses where a mean *DE* is reported and a Wilcoxon rank-sum test where a median *DE* is reported.

Table 1 provides a strong support for our first hypothesis. All samples yield similar results and confirm positive values for the mean and median DE as shown in panels 1 and 2 of *Table 1*. We reject the null hypothesis of no disposition effect based on both parametric and nonparametric tests at a high statistical significance (zero p-value). Therefore, we cannot reject *Hypothesis 1*.

[Table 1 around here]

A positive median *DE* in Table 1 indicates that the majority of the investors are affected by the disposition effect. Panel 2 of *Table 1* shows that the majority of traders are prone to the disposition effect in all subsamples.

While the purpose of our study is to measure and characterize the disposition effect, clearly some traders are not prone to it. Our next step is to separately report, in *Table 2*, the results for individuals that are prone to the disposition effect (positive DE_i) and those who are not prone to it (negative DE_i). The majority of traders (72 percent) exhibit a positive DE_i. Such a majority is an unlikely event (p-value much lower than 1%) under a null hypothesis of equal group size. This again supports Hypothesis 1.

To test *Hypothesis 2*, we calculate the average trading frequency for each subject by dividing the number of active periods of that subject by the total number of periods in each session. An active period is one in which a subject places a buy and/or sale order.

8. $$Frequency_i = \frac{\sum_{t=1}^{100} N_{i,t}}{100}$$

where $N_{i,t}$ equals 1 if subject *i* submitted a trading offer in period *t* and zero otherwise. The denominator represents the total number of periods in each session. Again, unlike prior literature where only actual trades are counted, in this paper, *frequency* is a measure of active participation in the market, whether it results in an actual trade or not.

Table 2 shows that traders that are prone to the disposition effect trade less compared to those who are not prone to it. This result is valid for all sub-samples and is consistent with *Hypothesis 2*. We formally test *Hypothesis 2* using regressions in a subsequent section.

[Table 2 around here]

To test *Hypothesis 3* we divide our data into two groups by gender and test whether the mean DE_i of the two groups differ significantly. In our sample of 72 subjects 50 are males and 22 are female, of which 37 and 17 respectively exhibit significant disposition effect, evidenced by their significantly positive DE_i (with a p-value of 0.05 or lower). The proportions of subjects with a significantly positive DE_i of the entire group in each gender seem similar: 74 and 77.3 percent for the male and female subgroups respectively. The null hypothesis of equal proportions cannot be rejected (two-sided p-value = 0.77 using equality of proportion test). Hence, we conclude that there are no gender differences regarding the disposition effect in our sample.

5.2. Regression analysis

In this section we explore the relations between the disposition effect and potential explanatory variables, including trading, personal, and market characteristics, using the following OLS regression:

9. $$DE_i = \alpha + \beta_1 \cdot CRT_i + \beta_2 \cdot Gender_i + \beta_3 \cdot ln(Money\ Earned_i) + \beta_4 \cdot (Normalized\ Dispersion_i) + \beta_5 \cdot Turnover_i + \beta_6 \cdot Frequency_i + \beta_7 \cdot Feedback_i + \beta_8 \cdot Passive_i + \varepsilon_i$$

The dependent variable, DE_i, is calculated for each subject using equation (7). CRT_i is the CRT score of subject *i* (ranges from the lowest score 0 to the highest score 3). $Gender_i$ is a dummy variable, assigning "1" to a male trader and "0" to a female, $ln(Money\ Earned_i)$ is the natural logarithm of the total amount of money subject *i* has earned by the end of the session. The other variables are presented below.

Normalized Dispersion and *Turnover*[6] are two measures of market condition. We include them in our regression under the assumption that a booming market may affect the behavior of traders differently compared to a contracting market. The *Normalized Dispersion* is the sum of all periodic relative deviations of prices from fundamental values. A high (low) value indicate large (small) differences and measures the extent to which market prices and fundamental values resemble each other over all periods.

10. $$Normalized\ Dispersion = \sum_{t=1}^{100} \frac{|P_t - f_t|}{f_t}$$

where t is the period number, P_t is the period price and f_t is the period fundamental value.

Turnover is a normalized measure of the amount of trading volume over the entire time horizon. It is the total trading volume in the market divided by the number of shares outstanding. A high (low) value indicate high (low) trading activity. A high *Turnover* is often associated with mispricing and large bubbles (Noussair and Tucker, 2016; Smith et al., 2000).

11. $$Turnover = \frac{\sum_{t=1}^{100} q_t}{TSU}$$

where q_t is the number of assets transacted in period t, and *TSU* (Total Stock of Units) is the total number of shares issued.

Frequency is a measure of each individual trade activity and is defined above in equation (8).

Feedback and *Passive* are two types of investors presented in a three-period assent market model developed by DeLong et al. (1990). *Feedback* subjects trade based on momentum. They buy shares after an increasing price trend and sell following a decreasing trend. *Passive* investors trade is based on fundamental values. They buy when market prices are below the fundamentals and sell when prices are above fundamental. To classify each trader by their types, we apply the following calculation based on Haruvy and Noussair (2006).[7] We create two scores for each trader, one for each type. A score increases by 1 in period t if the behavior of the trader in this period is consistent with the specific type. A subject is classified as *feedback* in period t if the equilibrium price in period $t-1$ is higher (lower) than in period $t-2$ and the subject submits a buy (sell) order. A subject is classified as *passive* in period t if the fundamental value in period t is higher (lower) than

[6] These two bubble measures are widely used to measure bubbles in experimental asset markets. See Haruvy et al. (2007) for a short review.

[7] DeLong et al. (1990) present three types: *frequency, feedback* and *speculators. Speculators* trade based on their belief that after an increasing price trend, prices should fall eventually. Haruvy and Noussair (2006) use of CDA trading rules enables classification to the *speculator* type. Our data, on the other hand, is of experimental asset markets using CM trading rules, which are not suitable to characterized traders as *speculator*, thus our regression analysis does not include this type.

his bid (ask) price in period *t*, thus adapting the *passive* investor definition to our *intention* related data and research theme.

Scores are calculated based on periods 3 to 100. At the end of period 100, we sum up each score for each trader and label him as *Categorical Feedback* or *Categorical Passive* according to the highest score and assign 1 and 0 to the appropriate type dummy variables of the subjects. Following Haruvy and Noussair (2006), when scores are equal for both types, we assign 0 to the two categorical dummy variables. Table 3 presents the descriptive statistics of the regression variables.

[Tables 3 & 4 around here]

Regression results are reported in *Table 4* for each sub-sample. In line with earlier studies, the coefficient of *Frequency* is negative and highly significant. This finding supports our *Hypothesis 2* which states that subjects who trade more frequently are less prone to the disposition effect. Dhar and zhu (2006) document this negative relationship and explain it using the findings of List (2003, 2004). Accordingly, there is a disparity between the willingness to offer and pay among traders. This disparity (known as the endowment effect) is relatively large among inexperienced traders and gradually diminishes with experience. One missing element to this explanation is the relation between the willingness to offer and the asset value. Even if the endowment effect is decreasing with experience, it must be linked to the asset value, which can be higher or lower than the willingness to offer (using List terminology).

An alternative explanation for the negative effect of frequency on the disposition effect is a positive correlation between frequency and the wish to sell. It is possible that traders who submit more sell orders simply have higher desire to sell their shares and therefore gradually more willing to accept lower prices. This in turn generate sales in losses, which reduce the disposition effect. Testing these explanations is beyond the scope of this paper and we leave it for future work.

The results in *Table 4* are consistent with the equality of proportion test presented in section 5.1, showing that *Gender* coefficient is insignificant, supporting *Hypothesis 3* that the disposition effect is not affected by gender. The results also address our *Hypotheses 4*, which states that intelligence level, represented by *CRT* scores, is a significant predictor of *DE*. The statistically significant positive coefficient of *CRT* implies that subjects with higher intelligence level are more prone to the disposition effect.

We find both variables *Normalized Dispersion* and *Turnover* to be generally insignificant in our regressions, implying that the disposition effect is a behavioral bias that is not materially affected by market condition. Lastly, the results also show that the disposition effect is not related to the strategic types included in the regression, as evident from the insignificant coefficients of both types (*feedback* and *passive*). The same applies to money earned.

To further investigate the impact of trading strategies on the disposition effect, we use equation (12). Here, we use the *feedback* and *passive* scores variables instead of their categorical values. Since these two scores are correlated, we calculate this regression twice, each time with one of the scores only.

12. $$DE_i = \alpha + \beta_1 \cdot CRT_i + \beta_2 * Gender_i + \beta_3 \cdot ln(Money\ Earned)_i + \beta_4 \cdot Normalized\ Dispersion_i + \beta_5 \cdot Turnover_i + \beta_6 \cdot Score_i + \varepsilon_i$$

Table 5 presents regression 12 results. In the "Feedback only" regression, we notice a negative coefficient for the *Feedback Score* variable. This coefficient is significant at 5% level for all subsamples. The negative coefficient sign shows that a momentum trader is less prone to the disposition effect. The "Passive only" regression reveals a small coefficient, negative and significant only in the "actual sales" subsample. This shows that an investor whose trading decision depends mainly on rational decisions such as stock price relative to its fundamental value, would generally remain prone to the disposition effect. We find this result very interesting. First, in general, momentum traders tend to sell when prices decrease and buy when they increase, which by definition lowers (if not entirely offsets) the disposition effect. In fundamental trading, on the other hand, reaction to increasing and decreasing price trends, depends on whether prices are above or below fundamental values. Second, pure momentum traders, by definition, submit transaction orders "dictated" only by external data (past equilibrium market prices), without personal processing and biases. This neutralizes individual disposition effects and thus the coefficients of *Feedback Score* are all negative and statistically significant. In contrast, in our calculations, using bid and ask prices, passive traders rely on their personal analysis and processing and thus remain exposed to the disposition effect.

[Table 5 around here]

6. Conclusions

One of the main purposes of experimental economics is to provide researchers with information that they cannot obtain in the field. In finance, the experimental approach has been extensively used, mainly to design markets with specific trade methods that allow researchers to observe traders' behavior and performance, and also to generate unique data that cannot be gathered in the field, such as beliefs and intentions.

The disposition effect has been extensively documented both in the field and in the laboratory. It is virtually undisputed that the disposition effect is a behavioral outcome.

Thus, using experimental methods to understand its origin is a natural choice. However, while prior experimental studies on the disposition effect exist already, there are still unanswered questions that warrant additional studies.

Shefrin and Statman (1995) define the disposition effect as "*the disposition to sell winners and ride losers*." In other words, selling winners and riding losers is a matter of active choice, not a consequence. Accordingly, we believe that the disposition effect should also be studied using traders' intentions. Currently, most (if not all) studies (including experimental) measure the disposition effect using actual prices.

We therefore believe that our main contribution in this experimental work is to measure the disposition effect using subjects' willingness to sell and their offered prices instead of using only their actual trades and market equilibrium prices. The experimental design used to generate the data precludes us from comparing disposition effect measures based on actions and intentions because period prices in the data we use are revealed only after sell orders are submitted. However, we show that most of the subjects are prone to the disposition effect. Additionally, and consistent with prior literature, we find that those who trade more frequently are less prone to the disposition effect and hence more willing to accept losses.

Most experimental asset markets include about 15 trading periods. It has been shown that such relatively short markets generate 'the end-game' effect, in which traders begin to realize the need to get rid of the shares a few periods before the end of the market. Therefore, it is possible that subjects in experimental asset markets with short horizon base their trade decision also on the structure of the experiment rather than merely on their perceived (or expected) value of the asset. The data we use is taken from experimental asset markets with a long horizon, which diminishes the 'end-game' effect, at least during most periods. We are not aware of a prior research of the disposition effect in a long horizon experimental asset market.

Our data also allow us to provide more information on the effects of personal characteristics like Gender and *CRT*, and trade characteristics scores on the disposition effect. Starting with personal characteristics, consistent with some previous studies, we find no gender effect. However, the positive correlation between *CRT* scores and the disposition effect is somehow surprising. Intuitively (and consistent with prior literature), one might expect an opposite correlation, because higher *CRT* scores indicate a higher cognitive sophistication which one would expect would lead to a more rational trading, thus subjects with higher *CRT* scores are expected to have lower measures of the disposition effect. One possible explanation to this surprising result could be that these subjects are more reluctant to realize losses, which they perceive as inconsistent with their capabilities.

To test the effect of trade characteristics, each trader is characterized by his decisions as either *feedback* or *passive*. The first type appears to believe in momentum strategy and the second in fundamental values. We show that higher scores on *feedback* are associated with subjects that are less prone to the disposition effect whereas *passive* trading net effect on disposition is small and mostly statistically insignificant.

We believe that more research on the disposition effect is needed. While the effect is found empirically in several markets and among the majority of traders, we think that further research should focus on the origins of the effect, and its possible influence on market outcomes.

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Table 1: The Disposition Effect – statistical significance

	All offers	Realistic offers	Actual sales
Panel 1:			
Mean ($APGO_i$)	0.18	0.18	0.20
Mean ($APLO_i$)	0.10	0.10	0.10
Mean (DE_i)*	0.08	0.08	0.10
	(0.00)	(0.00)	(0.00)
Panel 2:			
Median ($APGO_i$)	0.14	0.13	0.14
Median ($APLO_i$)	0.00	0.00	0.00
Median (DE_i)**	0.09	0.09	0.10
	(0.00)	(0.00)	(0.00)
Number of observations	3,895	3,443	913

Notes. * Ho: Mean DE ≤ 0, ** Ho: Median DE ≤ 0

Table 2: The Difference Between subjects with Positive DE and Negative DE

	Positive DE Traders	Negative DE Traders
All offers		
Number of traders	52	20
Number of trades	2557	1338
Average trading frequency	49.17	66.9
Mean (DE_i)	0.16	-0.11
Median (DE_i)	0.09	-0.06
Realistic offers		
Number of traders	51	21
Number of trades	2281	1162
Average trading frequency	44.73	55.33
Mean (DE_i)	0.16	-0.11
Median (DE_i)	0.11	-0.06
Actual sales		
Number of traders	52	20
Number of trades	600	313
Average trading frequency	11.54	15.65
Mean (DE_i)	0.18	-0.10
Median (DE_i)	0.13	-0.05

Table 3: Descriptive statistics of the entire sample

	Mean	Median	S.D.	Min	Max
DE	.0838	.0867	.1704	-.4049	.4923
Frequency	.5410	.5650	.2580	.0400	.9500
Feedback Score	31.92	34	11.85	7	52
Passive Score	40.96	42.5	15.70	7	94
CRT	1.78	2.00	1.08	0	3
Money Earned	3776	3524	1738	883	8734
Normalized Dispersion	53.43	45.75	40.32	6.24	108.3
Turnover	4.26	4.17	.614	3.31	5.36

Notes. 50 of the 72 participants are male. 15 subjects count as *categorical feedback* and 55 as *categorical passive*.

Table 4: Regression Results

	All offers	Realistic offers	Actual sales
Constant	.312 (.402)	.323 (.431)	.268 (.438)
CRT	.046*** (.007)	.052*** (.005)	.039** (.026)
Gender	.019 (.636)	.027 (.542)	.031 (.447)
ln(Money Earned)	.012 (.783)	.011 (.797)	.017 (.675)
Normalized Dispersion	-.191E-3 (.727)	-.349E-3 (.573)	.001 (.292)
Turnover	-.070* (.059)	-.061 (.155)	-.081** (.033)
Frequency	-.311*** (.000)	-.309*** (.001)	-1.309*** (.000)
Categorical Feedback	.073 (.517)	-.013 (.934)	.082 (.149)
Categorical Passive	.056 (.594)	-.011 (.945)	.119** (.032)
R Square	.408	.376	.478
Adjusted R Square	.333	.297	.412

Notes. The regression is specified in Eq. (6). The dependent variable is the disposition effect (DE). *P-value* for *t*-statistics are provided in parenthesis. *, **, ***, Means significant at 10%, 5% and 1% levels, respectively.

Table 5: Regression Results

	Regression results – Feedback only			Regression Results – Passive only		
	All offers	Realistic offers	Actual sales	All offers	Realistic offers	Actual sales
Constant	.206 (.579)	.152 (.689)	.018 (.960)	-.165 (.629)	-.191 (.591)	-.239 (.499)
CRT	.045** (.012)	.046** (.013)	.043** (.027)	.052*** (.005)	.049** (.011)	.051*** (.008)
Gender	.047 (.270)	.051 (.255)	.058 (.220)	.041 (.357)	.039 (.395)	.037 (.419)
ln(Money Earned)	.027 (.528)	.033 (.448)	.053 (.214)	.067* (.098)	.067 (.114)	.080* (.058)
Turnover	-.077** (.012)	-.082** (.010)	-.093*** (.005)	-.082*** (.009)	-.095*** (.005)	-.084** (.010)
Feedback Score	-.004** (.018)	-.003** (.040)	-.008** (.041)			
Passive Score				-.002 (.153)	.001 (.506)	-.007** (.021)
R Square	.297	.280	.282	.258	.237	.294
Adjusted R Square	.244	.225	.227	.202	.179	.240

Notes. The regressions is specified in Eq. (10) and (11). The dependent variable is the disposition effect (DE). *P-value* for *t*-statistics are provided in parenthesis. *, **, ***, Means significant at 10%, 5% and 1% levels, respectively.