What Drives the Disposition Effect? A Cognitive Dissonance-Based Explanation[1]

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[1] Thanks...

Abstract

Traders in most asset classes exhibit the disposition effect, closing out winning positions more than losing positions. Mutual fund investors, however, tend to exhibit the opposite behavior. Using individual trader data, we show that both these effects exist for the same investors at the same time. The tendency to realize losers more than winners holds for a wide range of delegated portfolios. These facts are consistent with the disposition effect being caused by cognitive dissonance: investors are reluctant to realize losses as this would mean admitting that their initial investment was a mistake. Delegating to a manager allows the investor to blame somebody else and close out the position. Using an experimental setting, we document that i) both the disposition effect in stocks and the anti-disposition effect in funds are stronger if the level of cognitive dissonance is increased, and ii) the anti-disposition effect in funds is stronger if participants are primed to focus on the role of the fund manager.

JEL Classification:

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1 Introduction

The disposition effect is the empirical regularity that investors are more likely to sell assets after they have risen in price than after they have fallen in price. This was originally described by Shefrin and Statman (1985), and has proven to be one of the most robust findings in behavioral finance.The effect has been documented in markets as varied as stocks, executive stock options (CITE), real estate (Genesove and Mayer (2001)), and on-line betting (Hartzmark and Solomon (2012)), and has been linked to several pricing phenomena including post-earnings announcements drift and stock-price momentum. The tendency to sell winners and hold on to losers exists even though such actions often prove costly.[1]

While the existence of the disposition effect is widely documented, the underlying cause is much less clear. The originally cited explanation was a combination of prospect theory (Kahneman and Tversky (1979)) and mental accounting (Thaler (1980)). Recent papers have proposed richer preference-based explanations, including prospect theory with time inconsistent preferences (Barberis and Xiong (2009, 2012)) and realization utility (Barberis and Xiong (2012), Frydman et al. (2012)). Other explanations have centered on a non-rational belief in mean reversion (Odean (1998)), and cognitive dissonance (Kaustia (2010), Zuchel (2001), Hartzmark and Solomon (2012)).

In addition, little attention has been paid to the fact that the disposition effect varies across asset classes. One notable asset class that does not exhibit a disposition effect (and in fact displays an anti-disposition effect) is that of managed funds. This is observable from the positive slope of the performance-flow relationship: funds that exhibit high returns receive greater inflows, while those with low returns receive outflows (see e.g. Chevalier and Ellison (1997)). This effect holds not just for new investors in the funds, but existing investors as well (Ivković and Weisbenner (2009)), meaning that investors are, in aggregate, selling losing funds and holding winning funds. While this fact (at least in terms of aggregate fund flows) has been known for a long time in the mutual funds literature, it has received curiously little discussion in the literature on the disposition effect. And the question of why some assets (e.g. stocks) exhibit strong disposition effects, while other assets (e.g. stock funds) exhibit a strong anti-disposition effect remains one of the major challenges facing any theory of the disposition effect.

In this paper, we examine cognitive dissonance as a lens to understanding both the disposition effect within an asset class, and the variation of this effect across asset classes. Drawing on evidence from both individual trading account data and experiments, we present

[1] For stocks, these trades tend to reduce returns due to the existence of return continuation in winning and losing stocks (see e.g. Jegadeesh and Titman (1993) for general momentum and Odean (1998) for individual portfolios), and go against optimal tax-loss selling.

evidence that cognitive dissonance would explain the variation in the magnitude of the disposition effect both across and within asset classes.

Cognitive dissonance[2] is one of the most studied and robust findings from clinical psychology in the past 50 years. It is defined as the discomfort that arises when a person recognizes that he or she makes choices and/or holds beliefs that are dissonant with each other – actions and/or beliefs that do not fit together. For example, an investor who buys an asset which later declines in price may believe both "I am financially skilled" and "My stock choice had a bad outcome". Or, they may realize a conflict between beliefs and actions: "I am good at choosing investments" and "the investment I chose performed poorly".

There are several ways a person may try to respond to the discomfort, or cognitive dissonance, caused by the conflict. First, the person may change their beliefs. For example, an investor may decide they are not as skilled as the previously believed. While this response is perhaps most in line with standard economic theory, it is considered the least likely outcome by social psychologists. Psychology research tells us that beliefs about oneself are extremely stable and not easily changed. As such individuals experiencing cognitive dissonance will resolve such conflicts in some other way. For example, an investor may find a rationalization to explain why a financially skilled person like himself would experience bad outcomes (e.g. they may find a third-party scapegoat, may blame bad luck, or may explain the bad performance as a temporary setback that will soon be reversed).

Our first finding, which we obtain from analyzing a dataset of individual trader accounts used in **?**, is that the disposition effect in stocks and the anti-disposition effect in mutual funds exists for the *same investors at the same time*. The difference between investor behavior when trading stocks and funds is not selection: investors who buy only stocks, investors who buy both stocks and funds, and investors who only buy funds all exhibit the same asset-class specific level of the disposition effect (positive for stocks, negative for funds).

Our second finding from the same data is that if we look across a broad range of asset classes (including options, warrants, bond funds, real estate trusts etc.), those assets that are delegated portfolios are associated with lower or negative disposition effects by their investors. The relationship between delegation and the disposition effect is quite strong with the size of the disposition effect almost rank-ordered with delegation. These results means that any explanation for the disposition effect must account for the effect of asset-class characteristics without relying on differences in investor preferences. Explanations for the disposition effect that rely on market segmentation (i.e. clientele effects), preferences over returns, such as prospect theory, loss aversion, or time-inconsistent behaviors, struggle to explain why investors react differently to returns in different asset classes, unless other

[2] As first described by Festinger (1957) and summarized in (XXX Psychology World XXX).

factors specific to funds are added to these models. We continue by experimentally testing an alternative hypothesis, cognitive dissonance.

Next we report the results of an online trading game experiment in which undergraduate students trade a preselected group of real-world stocks or funds at daily market closing prices over a period of 14 weeks. Participants were subject to two different randomized treatments. The first treatment, which we call the story treatment, reminds students of their stated reason for purchasing a stock. By emphasizing their previous choice and its reasons, this treatment is designed to increase the cognitive dissonance discomfort. We therefore expect that this treatment will increase the magnitude of the bias. That is the treatment should generate an increase in the disposition effect for stocks and an increase in the anti-disposition effect for funds.

The second treatment, which we call the hire/fire treatment, is designed to explore the role of delegation in the disposition effect. Students in the hire/fire treatment have the words "buy", "sell" and "Portfolio performance" replaced with the words "hire", "fire" and "Fund Manager's performance" throughout the website. In addition students in the fire treatment are provided with links to fund manager's bios. This treatment is designed to increase the salience of the intermediary (i.e. the fund manager). If intermediation is indeed a channel for relieving cognitive dissonance, increasing the salience of that channel should increase the size of the anti-disposition effect in funds.

Our results are consistent with all three of these predictions. Students who had their explanations repeated back to them displayed an economically and statistically significant increase in the disposition effect if they were trading stocks, but a significantly larger anti-disposition effect if they were trading funds. Meanwhile, students assigned to the hire/fire treatment displayed a significantly larger anti-disposition effect in their trading of funds.

Finally, we report the results of a survey conducted at the conclusion of the experiment to examine the impact of our treatments on investor learning. While a learning model would predict that our treatments would be correlated with an increase in learning, cognitive dissonance would predict that learning would be dependent on gains and losses (i.e. learning is asymmetric in gains).[3] We find that while the treatments themselves have no impact on self-reported measures of learning, the mean effect masks an asymmetry as predicted by cognitive dissonance: individuals report learning more conditional on having an aggregate gain than an aggregate loss.

Overall, our results suggest that cognitive dissonance is a key component of the disposition effect, and that the psychological effects of portfolio delegation explain the different

[3]The asymmetry arises from the fact that individuals are more likely to discount or disregard information that runs contrary to idea that the decision to purchase the asset was a good one - i.e. confirmation bias.

levels of the disposition effect between stocks and funds. These conclusions suggest a reinterpretation of some of the existing theories of the disposition effect. Models of loss aversion or realization utility have primarily contemplated investors as having preferences over the returns themselves. Instead, our findings suggest that at least part of the aversion and utility (realized, expected, prospect or otherwise) is better thought of as being over the psychological costs of admitting mistakes and resolving cognitive dissonance. How exactly to theoretically model such behavior is a question deserving of further research.

2 Cognitive Dissonance

Social psychology defines a "cognition as a piece of knowledge, and "dissonance as the conflict created when an individual simultaneously holds two contrary or dissonant cognitions. Cognitive dissonance theory, which has been characterized as the most important development in social psychology (Aronson 1997) holds that when one experiences such dissonance, it creates an unpleasant feeling which one will go to lengths to alleviate. Individuals experiencing such discomfort can then reduce the dissonance in one of three ways:

1) Changing one or both cognitions so they are congruent.
2) Altering the importance of one of the cognitions.
3) Adding a third, ameliorating cognition.

The first mechanism is the one most familiar to economists and is utilized in rational learning models (e.g. Baysian updating of ones priors). For example if I purchase an asset because I think its undervalued, but subsequently received information that contradicts this belief, I can reduce the dissonance between these two contradictory cognitions by updating my belief about the asset being undervalued.

While economists have focused almost exclusively on the first mechanism, social psychologist tend to emphasize the importance of the second and third methods of dissonance reduction. That is while economists generally assume individuals dispassionately incorporate new information to update their beliefs about the world, social psychologies generally assume individuals respond in anything but a neutral way to new information. And that new information that contradicts ones priors may be met with a combination of defense mechanisms and mental tricks.

One of the key finding in this literature is the key role of actions (i.e. decisions making) in shaping beliefs. That once an action is undertaken, individuals believe that that decision was made for a good reason, and that this cognition (which we will refer to as the decision-identity cognition) becomes primary. Then when faced with a subsequent dissonant cognition, individuals will tend to use a host of psychological means to reduce dissonance related discomfort without relinquishing the original decision-identity cognition.

Induced compliance (Festinger and Carlsmith 1959, Aronson and Carlsmith 1963 among many others), the free choice paradigm (Brehm 1956, Egan et al 2010), effort-justification (Aronson and Mills 1956), belief disconfirmation (Festinger et al 1956), and the Benjamin Franklin effect (Jecker and Landy 1969) are all examples of this phenomena; that once a decision has been made, individuals will change their future actions and beliefs to justify that decision, rather than question the rationale behind the initial decision. In terms asset markets, once an individual has purchased an asset, subsequent information that indicates that the decision was a bad one may be distorted, discounted or simply ignored in order to preserve the idea that the decision to purchase was a sound one. For example if receive information that contradicts my belief that the asset I purchased is undervalued, instead of updating my beliefs about the true value of the assets, I may respond by simply reducing the importance of the new cognition and treat the new information as being unreliable, mistaken or biased. This type of behavior can generate confirmation bias effects like the disposition effect and momentum trading (CITE).

Research has also shown that the presence of a decision making intermediary may provide individuals with another channel to reduce dissonance related discomfort through responsibility attribution a.k.a. scapegoating (Bartling and Fischbacher 2012). For example if a trader receives information that a purchasing an asset may not have been a good decision, they may relieve the dissonance discomfort by shifting responsibility for the assets poor performance on a decision making intermediary. This type of dissonance reducing behavior could generate an anti-disposition effect. If so this would suggest that the disposition effect will have a negative relationship with the level of responsibility attribution.

2.1 Predictions

1. The presence of a decions making intermediary will predict the sign of the disposition effect in asset classes.
2. Increasing the salience of the original purchase decision will lead to an increase in the magnitude of the disposition and anti-disposition effects.
3. Increasing the salience of the intermediary will increase the magnitude of the anti-disposition effect.
4. Whether an asset posts a gain or a loss will affect the trader "learning".

3 Literature Review

While evidence for the existence of the disposition effect is strong, the underlying cause for it remains unclear. Explanations based on standard economic models of rationality have found limited empirical support. Private information seems unlikely, as Odean (1998) shows the winning stocks sold early have higher returns over the subsequent year than losing stocks that are retained. Another possibility is portfolio rebalancing, where traders sell winning stocks to avoid being overweighted in their portfolio. Odean (1998) also casts doubt on this, as traders also exhibit the disposition effect when considering sales of the individuals entire holding of a stock. More common explanations have focused on behavioral models. Initial explanations focused on prospect theory and mental accounting (Kahneman and Tversky (1979) and Thaler (1985)). Under this theory, an investor at a loss becomes risk-seeking in order to avoid the loss now, whereas the same investor at a gain becomes risk-averse in order to preserve the gain (Weber and Camerer (1998), Grinblatt and Han (2005), Frazzini (2006)). The other leading explanation (from Odean (1998)) is based on an unjustified belief in mean-reversion of stock prices, so disposition-related trading is due to mistaken estimates of future price movements.

Recently, Barberis and Xiong (2009) and Hens and Vlcek (2011) have questioned whether prospect theory preferences alone can produce a disposition effect. Barberis and Xiong (2009) argue that the disposition effect in stock markets is more consistent with prospect theory preferences based on realized losses rather than annual (paper) losses. In order for propsect theory to explain the disposition effect, the expected returns on the asset must be sufficiently high for a prospect theory investor to enter the market in the first place. Nonetheless, the disposition effect has also been documented in negative expected return gambling markets (Hartzmark and Solomon (2012)), which require more complicated versions of propsect theory including investors with time-inconsitent preferences, such as in the Barberis (2012) model of casino gambling.

Recently, Frydman et al. (2012) have provided evidence that the disposition effect is best explained by realization utility. Using neurological data from fMRI imaging, they document that traders displaying the disposition effect show enjoyment at the point that gains and losses are realized, rather than when information about the gain and loss is first disclosed. This supports the interpretation that the realization utility is a component of traders' disposition effect behavior.

An alternative explanation for the disposition effect based on cognitive dissonance was advanced by Zuchel (2001). As described earlier, the idea is that individuals face cognitive dissonance when trying to reconcile their self-perception as a clever investor with the fact that the stock that they bought has lost money. They may adjust their beliefs about the stock in order to avoid selling it, thereby not realizing the loss. A similar argument was put forward in Kaustia (2010), based on self-justification and regret avoidance. In both cases, when faced with a paper loss, investors may be reluctant to realize the loss as this means admitting to the mistake of investing in the first place.

4 Evidence from On-line Trading

We establish two stylized facts based on the **?** small-investor trading data (Table 1):

- The disposition effect in stocks and the anti-disposition effect in funds occurs in the same investors at the same time (Table 2).
- Across asset classes, investor-chosen assets are associated with a positive disposition effect and delegated-portfolio assets are associated with negative disposition effects (Table 3).

The individual trader data come from **?**. The data come from a large discount brokerage, and include 128,829 accounts with monthly position information, comprising 73,558 households (out of 78,000 initially sampled), from January 1991 to November1996. The data comprises a file of monthly position information, and a file of trades. For each position in an individual's portfolio, we use the information on purchases in the trades file to calculate the volume-weighted average purchase price (”purchase price”) for each point in time. If a position is eliminated entirely and later repurchased, the purchase price is reset to zero upon the sale of the entire position. Assets are excluded from the analysis if they were held during the first month of the sample, since this implies they were purchased an at unknown price before the start of the sample.

Once the purchase price is known for each security, we compare the gains and losses investors face on each security at each point in time. Other papers (e.g. Odean (1998), **?**) combine the trades file with daily securities prices to calculate the investor's portfolio of gains and losses each day. In the current setting, our interest includes assets for which daily price data is not as easy to obtain (e.g. preferred stocks, options). As a result, to obtain a snapshot of securities prices at each point in time from which to calculate gains and losses, we use the prices and holdings in the monthly position files. This gives us a portfolio snapshot each month, and we match each security in the portfolio with the most recent purchase price. By comparing the price with the purchase price, we classify the variable 'Gain' as being equal to one if the price is greater than the purchase price, and zero otherwise.

We then classify each position according to the change in the individual's position between the current month and the next month. The variable 'Sale' equals one if the individual reduced the size of their position between the current month and the next month, and zero otherwise. [4]. Similar to Odean (1998), we examine the portfolio of gains and losses on all dates when an individual investor conducted a sale of any security in their account. By comparing days with some sale, this ensures that the investor was actually paying attention to their portfolio on that day (rather than assuming that the investor deliberately chose not to sell on a particualr day, when they may have simply not being paying attention to their portfolio). The interpretation of the disposition effect is thus a measure of the choice of which securities to sell, given that a sale occurs.

In the main analysis, we wish to test whether individuals are more likely to sell those securities that are at a gain than those that are at a loss. To do this, we use a standard regression specification on a sequence of different investor. Specifically we estimate

$$sale_{ijt} = \alpha + \beta Gain_{ijt} + \gamma Gain_{ijt} \times Fund_j + \delta Fund_j + \epsilon_{ijt}, \tag{1}$$

where observations are at the account (i), asset (j), date (t) level. *Sold* is a dummy variable that equals 1 if the transaction was a sale, and *Gain* is a dummy variable that equals 1 if the price of the asset is above an individual's average purchase price, and *Fund* is a dummy variable equal to 0 for stocks and 1 for funds. In all our regressions, standard errors are then two-way clustered at the account (i) date (t) level.

In the first set of tests, the assets being examined are limited to stocks and mutual funds. We seek to examine whether the presence of the disposition effect in stock investors and the anti-disposition effect in mutual fund investors is driven by the different characteristics of the investors in each asset class. To test this, we examine the disposition effect in stocks and funds for different groups of investors: 1. All investors in each asset class 2. Investors who held both stocks and funds at some point in their trading history 3. Investors who held both stocks and funds at the same time, in those months where they hold both assets simultaneously

Moving from group 1 to group 3 helps eliminate the possible explanation that the different levels of the disposition effect between stocks and funds are driven by different investor attributes. Group 3 is the most stringent test, since this involves the same investors reacting to the returns of stocks and funds at the same time, allowing us to measure an individuals

[4] As a result, we consider whether the security was at a gain or a loss at the end of the month before the change in position, rather than considering the price on the day of the sale itself. This loses some precision in terms of classifying gains and losses, but has the advantage that the prices of all securities in the portfolio are compared on the same day

disposition effect across the two asset classes for the same points in time.

The results of these regressions are presented in Table 2. For all investor subsets, the coefficient for *Gain* is positive for stocks and negative for funds. That we observe a significant disposition effect in stocks and an anti-disposition effect in funds. While these results do not rule out the importance of clientele effects it does show that it cannot be the only explanation. Rather most of the difference between the levels of the disposition effect in stocks and funds appears not to be driven by the selection is that causes some investors to buy stocks or funds or both. Instead, it appears as though there is something about the asset classes themselves which is driving the difference in the sign of the disposition effect between stocks and funds.

While there are a number of differences between stocks and funds that may be driving the variation in the level of the disposition effect, one key difference from a cognitive dissonance point of view is the presence of an intermediary, or fund manager. Under a cognitive dissonance explanation, delegating the choice of assets to a separate manager gives the investor an alternative person to blame in the event of poor performance, thus insulating themselves from the need to hang on to losing assets in order to justify their earlier beliefs.

If delegation is the relevant asset class characteristic, then this provides a testable prediction across a range of asset classes other than equities and equity mutual funds - if the asset involves delegated portfolio management, it ought to have an anti-disposition effect, and if it does not, it ought to have a disposition effect. We test this prediction by re-running the regressions separately for each asset class label reported in the data. While some of the labels describe similar types of assets (e.g. various types of equity mutual funds), for transparency we report separately each of the classifications listed by the firm. These include warrants, options, convertible preferred stock, bond mutual funds, money market funds, and others.

Table 3 lists the different fund asset classes, an indicator for whether or not they are actively managed, and the coefficient on *Gain* in equation 1 estimated using only that asset class. These asset classes, ordered in terms of their disposition effect, show a striking relationship between the level of the disposition effect and active management. Specifically we find that while investors exhibit a positive disposition effect for unmanaged assets like stocks, actively managed asset classes all exhibit an anti-disposition effect.

More specifically of the 24 different asset classes reported by the trading firm, all 5 asset classes with statistically significant positive disposition effects are not actively managed. Of the 8 assets with statistically significant anti-disposition effects, 6 are actively managed, with the two exceptions (preferred stock and options equity) accounting for the two smallest (in magnitude) coefficients.

The results from the individual trader data demonstrate two important facts. The first is that we demonstrate that the different levels of the disposition effect between stocks and funds is not driven by differences in the attributes of investors in these two asset classes. The second fact is that across a variety of assets, the level of delegation in the asset is related to level of the disposition effect that investors display. Actively managed assets (including, but not limited to, equity mutual funds) tend to display an anti-disposition effect, while non-delegated assets tend to display a disposition effect.

While these two features of the data are not captured in most potential explanations of the disposition effect, they are both consistent with the trading behavior of investors facing cognitive dissonance. Specifically in the absence of an intermediary, an investors prefers to hang on to a losing asset as an alternative to acknowledging their earlier poor choice. But when the asset involves delegating to a manager, the presence of an intermediary provides an additional channel through which an investors can relieve their cognitive dissonance. That is an intermediary serves as an easy scapegoat, serving as a way for investors justify selling an poorly performing asset without acknowledging any mistake on their part. Or to paraphrase Langer and Roth (1975), "Heads I win, tails it's the manager's fault."

5 The Experiment

5.1 Goals

To further test the idea that cognitive dissonance is a major source of the disposition effect, we ran an experiment on 514 undergraduate students designed to directly test a number of predictions about the relationship between cognitive dissonance, delegation and the disposition effect.

5.2 Experimental Setting

Our experiment involved 514 undergraduate students participating in a stock and mutual fund trading game over the course of a semester. The students were enrolled in one of seven undergraduate finance sections in the Marshall School of Business at the University of Southern California. There were three sections of "Introduction to Business Finance" taught by Mark Westerfield, two sections of "Introduction to Business Finance" taught by Tom Chang, and two sections of "Investments" taught by David Solomon. Each section had between 45 and 75 students. "Introduction to Business Finance" is a core undergraduate finance class that is required for all undergraduate business majors and is optional for non-majors; the course material contains basic accounting, the time value of money and applications, capital markets up to the CAPM and options, and firm valuation and investment up to Modigliani-Miller. "Investments" is an elective undergraduate class with "Introduction to Business Finance" as a pre-requisite; the course material covers portfolio theory, the CAPM and multi-factor models of stock returns, behavioral finance, mutual funds, and bond pricing. The trading game was part of the course material for each class and students were told that the results would also be used for research purposes. The students were given the choice to opt out of the research but not the assignment. The game started on Janaury 23, 2012 and ended on April 16, 2012 @@@@ (13 weeks duration).

Students were randomly assigned to trade either stocks or mutual funds when they enrolled in the class. If they were assigned to the stock group, they would make investment choices over the 30 Dow Jones Industrial Average stocks; if they were assigned to the fund group, they would make investment choices over 30 actively managed mutual funds. These funds were chosen among the set of four- and five-star rated equity funds on Morningstar before the start of the experiment, and the list of funds is included in the appendix. Before the game began, they were given a survey that assessed their attitude toward risk and their experience trading stocks and funds. Students started with an initial endowment of an imaginary \$100,000 .

The assignment itself was conducted through a website. Students could log in to the website at any time and place buy or sell orders for stocks or funds. Students chose the amount to purchase or sell, and order were queued and executed just after the close of the trading day on the NYSE. Students were required to give a reason for each trade. Orders were filled at the closing NYSE price using data obtained from Yahoo Finance; orders were only filled on days in which the NYSE had been open (not holidays or weekends). A mutual fund's share price is its net asset value per share. If a student's order exceeded their budget, the order was filled proportionately so as to equal their budget. Trades were executed without transaction costs. After the last trading day, students were given a closing survey.

Students' activities in the trading game constituted 10% of their overall class grade; 5% was based on their performance and 5% was based on a 1-2 page write-up due on April 23, 2012. Performance was based on overall portfolio return relative to the other students with the same investment opportunities (stocks or funds). The write-up was a retrospective description of how they had analyzed their opportunities, what their strategy was, and how they evaluated their own investment performance. The assignment was pitched to the students as an open ended experience: they were told that they needed to both 1) come up with their own investment plan (although we said we hoped they would use class information) and 2) come up with the specific trades that would execute their plan.

There were two treatments. The first was the "Story" treatment, which was applied randomly to both the stock and fund groups. If a student was in the Story treatment, they were reminded of the reason they gave for buying a stock or fund when they decided to sell that stock or fund. If they had made multiple previous purchases, they were reminded of all the reasons given in reverse chronological order. Screen-shots with and without the Story treatment are in the appendix. According to cognitive dissonance theory, showing individuals their stated reason(s) for a purchase decision should increase the level of cognitive dissonance. Therefore a very interesting prediction for the *Story* treatment then is that it should increase the absolute value of the disposition effect in both stocks and funds. That is the Story treatment should opposite effects on stocks and funds, leading to an *increase* in the propensity of individuals to sell winners relative to losers for stocks, and a *decrease* in the propensity of of individuals to sell winners relative to losers for funds.

The second treatment was the "Fire" treatment, which was applied randomly to the mutual fund group. If a student was in the Fire treatment, the "Buy" and "Sell" buttons were re-labeled as "Hire" and "Fire" respectively and the label "Your Performance" on the portfolio page was replace with "Fund Manager's Performance". In addition the buy and sell included a link to the mutual fund manager's on-line bio. Screen-shots with and without the Fire treatment are in the appendix. This treatment was designed to increase the salience of the intermediary (manager). If intermediaries indeed act as a kind of cognitive dissonance release valve, then increasing their salience should lead to an increase in the magnitude of the anti-disposition effect.

Population summary statistics for across the treatment arms are given in Table 4. Observables characteristics are quites similar across the different treatment arms, and in regressions (not shown), it was found that no observable characteristic was statistically different across any combination of treatment groups.

6 Results

The data and methodology used in the trading game are in a similar format to the individual trader data from the previous section. The chief difference is that becuase we have fund and stock prices each day, we are able to consider the prices and trades of securities on a daily basis, rather than a monthly one. We consider all securities held in the investor's portfolio each day, and for each security in the student's portfolio we calculate the volume-weighted average purchase price ("purchase price"). As before, *Gain* is a dummy variable that equals one if the price that day is above the purchase price and zero otherwise, and *Sale* is a dummy variable that equals one if the student sold the security that day and zero otherwise.

To determine the impact of our treatments on the level of the disposition effect, we use a variant on equation 1 that includes dummies for our treatments. Specifically for stocks we estimate

$$Sale_{ijt} = \alpha + \beta D^g_{ijt} + \eta D^g_{ijt} * Story_i + \delta Story_i + \epsilon_{ijt}, \tag{2}$$

and for funds

$$Sale_{ijt} = \alpha + \beta D^g_{ijt} + \gamma D^g_{ijt} * Fire_i + \eta D^g_{ijt} * Story_i + \delta Fire_i + \delta' Story_i + \epsilon_{ijt}, \tag{3}$$

where D^g is dummy for whether an asset is above its mean dollar weighted purchase price, and $Fire$ and $Story$ are indicator variables for whether an individual i is in the Hire/Fire and Story treatments respectively. Since students are randomly assigned into treatment groups, γ and eta is interpretable as causal impact of the treatments on the disposition effect.

Observations are at the individual (i), asset (j), date (t) level, and include only days on which an investor sells an asset, again to ensure that the student was actually observing the portfolio on that particular day.[5] Standard errors are two-way clustered at the individual (i) date (t) level in all our regressions.

It should be noted that the estimation strategy we use make the implicit assumption that students do not work on the assignment together; something that is almost certainly untrue. This of course does not introduce a *bias* to our estimates since treatments are randomly assigned at the individual level. But it does create an interpretational issue. Specifically if students work together to jointly determing portfolio choices, the treatment coefficients we estimate will *understate* the true impact of the treatments.

Table 5 reports the result of equation 2. In the mutual funds group (Table 5), we first demonstrate an unconditional anti-disposition effect across all students (Column 1), as in the trading data. Columns 2 and 3 that the *Fire* and *Story* treatment both individually increase the magnitude of the anti-disposition effect, while column 4 shows that the both *Fire* and *Story* treatments increase the anti-disposition effect when examined together.

Table 6 reports the results of equation 3. For the stock group, we see that trades exhibit a small positive (but not statistically significant) disposition effect across all students (Column 1). Across treatment conditions, we find that the *Story* treatment increases the magnitude of the disposition effect.

[5] Treating each trading day as an observation regardless of whether a trade takes place or not results in coefficients that are qualitatively and statistically identical.

7 Heterogeneous Effects

7.1 Experience

Though not directly related to the main goal of understanding the disposition effect through the lens of cognitive dissonance theory, our data allows us to test the general idea that experience can reduce the magnitude of behavioral biases. For example List and Reiley (2000) finds that experienced sports card traders exhibit far less of an endowment effect than inexperienced traders. More directly related to our results, Shapira and Venezia (2001) find that brokerage professionals exhibit a smaller disposition effect than individual traders when trading stocks.

Tables 8 and 7 presents our main results with an additional interaction term for experience for stocks and funds respectively. We use three proxies for experience: self reported skill (columns 1 and 2), enrollment in an upper level investments class (columns 3 and 4), and a dummy for whether or not the individual currently owns stocks or mutual funds (columns 5 and 6). Consistent with Shapira and Venezia, we find suggestive evidence that experienced traders do indeed exhibit less of a disposition effect (marginally significant for two of our three experience measures). For mutual funds, we find strong evidence that experience reduces the magnitude of the anti-disposition effect across all three of our measures (significant for two measures, marginally significant for the third).

7.2 Gender

CITE literature on gender and congitive dissonance and other behavioral biases.

Table 9 present the impact of our treatment effects on asset sales with an interaction for gender. Consistent with this prior literature, we find evidence that our treatment effects have less of an effect on women than men. Specifically for all three cases, we find the coefficients for female*treatment is of the opposite sign of the effect on males (though not statistically significant at conventional levels). And while we find, in all three cases, that our treatments generate statistically meaningful increases in the disposition effect of stocks and the anti-disposition effect of funds, the effect of these treatments on females (gain*treatment + gain*treatment*female) is not statistically significant.

8 Alternative Explanations

Both the Odean data results and the experimental results described in the previous section are consistent with the predictions of cognitive dissonance theory. And while these results are clearly incompatible with strictly rational traders, they could still be consistent with either a behavioral or boundedly ratoinal models of trader behavior, or a combination of such models. In this section we examine some other models and discuss how these results pose a challenge to these alternative models.

8.1 Learning

Perhaps the most attractive alternate explanation is that our findings are the result of learning.[6] Specifically that investors may be learning about the skill of the fund managers, and that this learning leads to a positive fund performance flow relationship (i.e. the anti-disposition effect). This would explain both the cross sectional and individual level results in the Odean trading data. Furthermore, to the extent that the Story treatment and the Hire/Fire treatment as increase the rate of this learning, it would lead to an increase in magnitude of the anti-disposition effect.

Note that the long tenure of most fund managers means that traders must either be myopic or consider manager skill to be dependent on local market conditions. This is especially true in our experimental data as the timeframe of our experiment this would require learning to be localized at the level of weeks if not days. Furthermore, given the size of the treatment effects, both increasing the salience of the fund managers and reminding users of their purchase reason must significantly increase learning about fund manager skill.

The results of our exit survey provide at test of the localized learning hypothesis. This "closing survey" conducted at the at the end of the assignment[7] included a question asking participants to rate how much they *learned* about the skill of the managers of the funds they owned during the course of the trading game. The results of this survey for fund traders are given in Table 11. Column 2 in Panel A shows the impact of the *Story* and *Fire* treatments on learning about fund manager skill, and finds small, negative and statistically insignificant coefficients for both treatment dummies, indicating that is the two treatments did not increase learning about fund manager skill.

9 Conclusion

We use real world trading data to examine the differences in disposition effect across different asset classes. We find that individual traders exhibit a positive disposition effect when trading stocks and an anti-disposition effect when trading funds. This result is not due to a

[6] At least to our collegues and seminar participants.

[7] Included in the Appendix.

clientelle effect, but is present even for individuals who trade stocks and funds at the same time. In addition we find that intermediation is a key determinant in determining whether the sign of the disposition effect across asset classes. The latter result has important implications regarding the role of intermediation in financial decision making.

We then use a classroom experiment to directly test for the role of cognitive dissonance in determining the disposition effect. The first treatment (story) ramps up the cognitive dissonance associated with trading by reminding students of the stated reason for purchase in the sale screen. The story treatment significantly increased the size of the disposition effect among students who traded stocks. In sharp contrast the story treatment had the opposite effect among students who traded mutual funds, leading to a decrease in the size of the disposition effect (increases the size of the anti-disposition effect). The second treatment (hire/fire) was designed to increase the salience of the fund manager. This treatment lead to a substantial increase in the anti-disposition effect among our subjects.

Collectively our results strongly support the idea that cognitive dissonance is a driver of the disposition effect, and suggests that cognitive dissonance can serve as a parsimonious psychological foundation for a theory of trading that can explain both the disposition effect in general, and why it varies across asset classes.

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Table III
Disposition Effect by Asset Type [a]

	Managed?	*Disposition*	σ	*Obs.*
Marketplace Money Market Funds	No	0.3290	0.1213	2,873
Warrants	No	0.1474	0.0225	5,111
Foreign - Canadian	No	0.0531	0.0100	55,681
Foreign - Ordinaries	No	0.0361	0.0195	15,893
US Company Shares	No	0.0354	0.0070	1,664,671
Options Index	No	0.0342	0.0427	2,081
Real Estate Trust	Yes	0.0340	0.0560	708
Units	No	0.0324	0.0428	782
ADR	No	0.0290	0.0172	74,062
Convertible Preferred	No	0.0065	0.0152	11,668
Master Limited Partnership	No	-0.0008	0.0104	21,210
Closed-End Mutual Funds	Yes	-0.0032	0.0144	117,535
(In-House) Non-Sweep Money Market	Yes	-0.0140	0.1455	9,578
(In-House) Mutual Funds	Yes	-0.0261	0.0337	40,451
Marketplace Load Equity Funds	Yes	-0.0328	0.0316	4,528
Preferred Stock	No	-0.0357	0.0144	15,862
Option Equity	No	-0.0367	0.0151	22,692
Marketplace Load Bond Funds	Yes	-0.0488	0.0574	474
Bond Mutual Funds	Yes	-0.0501	0.0264	16,202
One Source Bond Funds	Yes	-0.0525	0.0221	34,501
One Source Equity Funds	Yes	-0.0610	0.0283	246,593
Equity Mutual Funds	Yes	-0.0798	0.0214	85,913
Ex One Source Bond Funds	Yes	-0.0808	0.0475	2,157
Ex One Source Equity Funds	Yes	-0.0846	0.0296	16,752

[a]Notes:

1. Asset types are ordered by the mean disposition involving trades of that asset type in the Odean data.

Table I
Odean Data Summary Statistics

	Mean	Std	25th Pctile	50th Pctile	75th Pctile	N
Panel A			*Stocks*			
Assets Per Account (Total)	7.849578051	12.76623972	2	4	9	104752
Assets Per Account/Month Observation	3.688631687	4.975679347	1	2	4	4141661
Stock/Month Observations at a Gain (By Account)	0.485366291	0.412532199	0	0.5	1	2149216
Stock/Month Observations Involving a Sale (By Account)	0.06419545	0.206482773	0	0	0	4016449
Stock/Month Observations at a Gain (Total)	0.50402578					5846197
Stock/Month Observations Involving a Sale (Total)	0.063747793					14448908
Number of Accounts						104752
Number of Account/Month Observations						15277062
Panel B			*Equity Funds*			
Assets Per Account (Total)	3.927579365	5.20253391	1	2	4	40320
Assets Per Account/Month Observation	2.40240886	2.316974165	1	2	3	1250467
Stock/Month Observations at a Gain (By Account)	0.716799445	0.391431857	0.5	1	1	757853
Stock/Month Observations Involving a Sale (By Account)	0.044751845	0.189518362	0	0	0	1205419
Stock/Month Observations at a Gain (Total)	0.71886819					1770721
Stock/Month Observations Involving a Sale (Total)	0.049486035					2843772
Number of Accounts						40320
Number of Account/Month Observations						3004133
Panel B			*All Assets*			
Assets Per Account (Total)	9.983753797	17.4139678	2	5	11	128707
Assets Per Account/Month Observation	4.285527042	5.776312363	1	3	5	5292574
Stock/Month Observations at a Gain (By Account)	0.546783445	0.405414477	0	0.5	1	2889879
Stock/Month Observations Involving a Sale (By Account)	0.060423469	0.196641308	0	0	0	5140275
Stock/Month Observations at a Gain (Total)	0.556407385					8742490
Stock/Month Observations Involving a Sale (Total)	0.061546159					21384909
Number of Accounts						128707
Number of Account/Month Observations						22681469

Table II
Disposition Effect: Odean Data [a]

	All Investors			*Hold Stocks & Funds*			*Simultaneously Hold Stocks & Funds*		
	Stocks	*Funds*	*Both*	*Stocks*	*Funds*	*Both*	*Stocks*	*Funds*	*Both*
Gain	0.0355***	-0.0650***	0.0355***	0.0222***	-0.0538**	0.0222***	0.0120*	-0.0481**	0.0120*
	(0.0065)	(0.0259)	(0.0065)	(0.0059)	(0.0221)	(0.0059)	(0.0062)	(0.0225)	(0.0062)
Fund			0.1053***			0.0739***			0.0420**
			(0.0220)			(0.0192)			(0.0174)
Fund*Gain			-0.1005***			-0.0760***			-0.0600***
			(0.0235)			(0.0201)			(0.0199)
Constant	0.2233***	0.3286***	0.2233***	0.2002***	0.2741***	0.2002***	0.1936***	0.2356***	0.1936***
	(0.02)	(0.04)	(0.02)	(0.01)	(0.03)	(0.01)	0.02	0.03	0.02
Adj. R-Squared	0.0017	0.0042	0.0033***	0.0007	0.0033	0.0022	0.0002	0.0030	0.0011
Observations	1,810,307	353,786	2,164,093	637,350	251,542	888,892	409,338	206,152	615,490

[a]Notes:

1. Panel A are all investors, Panel B contains the subset of investors that hold both stocks and funds at some point during the sample, and Panel C are the subset of investors that simultaneously hold both stocks and funds.
2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
3. QUESTION: Are the standard errors ROBUST or CLUSTERED?

Table IV
Trader Characteristics by Treatment [a]

Panel A	Funds	Stocks
Male	0.55	0.60
Class Level	3.37	3.48
Business Major	0.66	0.67
Owns Stocks	0.19	0.25
Owns Funds	0.11	0.12
Investing Experience	0.55	0.52
Risk Seeking	0.95	0.96
N	257	263

Panel B		Funds		
	Fire	*Story*	*Both*	*None*
Male	0.55	0.49	0.52	0.49
Class Level	3.35	3.38	3.32	3.34
Business Major	0.68	0.68	0.77	0.68
Owns Stocks	0.17	0.18	0.16	0.22
Owns Funds	0.09	0.10	0.07	0.11
Investing Experience	0.53	0.58	0.60	0.54
Risk Seeking	0.95	0.95	1.03	1.03
N	116	125	56	72

Panel C		Stocks		
	Fire	*Story*	*Both*	*None*
Male	-	0.60	-	0.59
Class Level	-	3.52	-	3.43
Business Major	-	0.66	-	0.67
Owns Stocks	-	0.21	-	0.30
Owns Funds	-	0.11	-	0.13
Investing Experience	-	0.49	-	0.56
Risk Seeking	-	0.92	-	1.01
N	-	141	-	122

[a]Notes:

1. In all cases baseline characteristics are not statistically distinguishable across any treatment arms.
2. 19 students had class year variables of "other" and were not included in the Class Year summary stat.

Table V

Sale of Funds [a]

Gain	-0.141**	-0.0594	-0.048	-0.000771
	(0.0553)	(0.067)	(0.061)	(0.0655)
Gain*Fire		-0.211**		-0.174*
		(0.103)		(0.104)
Gain*Story			-0.211**	-0.173**
			(0.0883)	(0.0877)
Fire		0.116		0.106
		(0.0987)		(0.0957)
Story			0.0655	0.0396
			(0.0895)	(0.0832)
Constant	0.527***	0.481***	0.497***	0.468***
	(0.0547)	(0.0674)	(0.0631)	(0.0742)
Adj. R-squared	0.012	0.02	0.029	0.034
Observations	2,011	1,957	1,957	1,957

[a]Notes:

1. Standard errors are two-way clustered at the individual day level.
2. Observations are taken only for days in which a transaction (buy or sell) occurred. Analysis with treating each trading day as the unit of observation produces qualitatively and statistically identical results.
3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table VI
Sale of Stocks [a]

Gain	0.0338	-0.0351
	(0.0339)	(0.0388)
Gain*Story		0.157**
		(0.0559)
Story		-0.133***
		(0.0434)
Constant	0.282***	0.358***
	(0.0262)	(0.0319)
Adj. R-squared	0.001	0.010
Observations	4,106	4,026

[a]Notes:

1. Standard errors are two-way clustered at the individual date level.
2. Observations are taken only for days in which a transaction (buy or sell) occurred. Analysis with treating each trading day as the unit of observation produces qualitatively and statistically identical results.
3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table VII
Experience and Funds [a]

	Self Rating		*Investment*		*Owns Funds*	
Gain	-0.256***	-0.0610	-0.187***	-0.0490	-0.155***	0.00909
	(0.0836)	(0.108)	(0.0597)	(0.0900)	(0.0573)	(0.0647)
Experience	-0.0579	-0.0486	-0.00791	0.0337	-0.475***	-0.584***
	(0.0371)	(0.0378)	(0.0812)	(0.105)	(0.0870)	(0.104)
Gain*Exper	0.0680**	0.0340	0.152*	0.104	0.338***	0.316**
	(0.0343)	(0.0357)	(0.0844)	(0.102)	(0.113)	(0.131)
Gain*Exper*Fire		-0.0515		-0.0313		0.148
		(0.0491)		(0.0938)		(0.119)
Gain*Exper*Story		0.0493		-0.171**		0.161*
		(0.0541)		(0.0705)		(0.0954)
Fire		0.0860		0.106		0.160*
		(0.0968)		(0.0953)		(0.0854)
Gain*Fire		-0.0851		-0.122		-0.231**
		(0.147)		(0.102)		(0.0941)
Story		0.0214		0.0537		0.0578
		(0.0799)		(0.103)		(0.0795)
Gain*Story		-0.240*		-0.152		-0.195**
		(0.132)		(0.105)		(0.0859)
Constant	0.527***	0.566***	0.529***	0.453***	0.546***	0.466***
	(0.0547)	(0.0977)	(0.0611)	(0.0999)	(0.0549)	(0.0736)
Adj R-squared	0.016	0.039	0.027	0.043	0.020	0.046
Observations	2,011	1,957	2,011	1,957	2,011	1,957

[a]Notes:

1. Experience self rating is from initial survey, Investment is a dummy for the upper level investment class, and Own Fund is a dummy for owing one or more funds.
2. Standard errors are two-way clustered at the individual day level.
3. Observations are taken only for days in which a transaction (buy or sell) occurred. Analysis with treating each trading day as the unit of observation produces qualitatively and statistically identical results.
4. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table VIII
Experience and Stocks [a]

	Self Rating		Investment		Owns Stock	
Gain	0.0737	-0.00663	0.00562	-0.0968**	0.0717**	-0.0194
	(0.0697)	(0.0892)	(0.0386)	(0.0398)	(0.0363)	(0.0443)
Experience	0.0388	0.0396	-0.00205	-0.0108	0.0872**	0.0702*
	(0.0258)	(0.0250)	(0.0470)	(0.0407)	(0.0443)	(0.0417)
Gain*Exper	-0.0256	-0.0331	0.128*	0.171**	-0.162**	-0.129*
	(0.0338)	(0.0461)	(0.0669)	(0.0735)	(0.0630)	(0.0752)
Gain*Exper*Story		0.00927		-0.0627		-0.0193
		(0.0638)		(0.0989)		(0.103)
Story		-0.137***		-0.133***		-0.124***
		(0.0413)		(0.0433)		(0.0424)
Gain*Story		0.146		0.175***		0.149***
		(0.120)		(0.0582)		(0.0556)
Constant	0.223***	0.299***	0.283***	0.361***	0.264***	0.339***
	(0.0531)	(0.0555)	(0.0276)	(0.0310)	(0.0281)	(0.0336)
Adj R-squared	0.003	0.012	0.009	0.019	4,100	4,020
Observations	4,100	4,020	4,106	4,026	0.007	0.014

[a]Notes:

1. Experience self rating is from initial survey, Investment is a dummy for the upper level investment class, Owns Stock is a dummy for owing one or more stocks.
2. Standard errors are two-way clustered at the individual day level.
3. Observations are taken only for days in which a transaction (buy or sell) occurred. Analysis with treating each trading day as the unit of observation produces qualitatively and statistically identical results.
4. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table IX
Gender and Treatment Effects [a]

gain	0.00272	-0.0894**
	(0.0283)	(-2.131)
gainfemale	-0.00843	0.112
	(-0.0592)	(1.215)
gainstory	-0.197*	0.159**
	(-1.729)	(2.093)
gainfemalestory	0.0474	-0.0445
	(0.247)	(-0.354)
gainfire	-0.298***	
	(-3.190)	
gainfemalefire	0.182	
	(1.028)	
femalestory	-0.176	-0.0293
	(-1.011)	(-0.317)
femalefire	-0.242	
	(-1.442)	
story	0.134	-0.112*
	(1.311)	(-1.650)
fire	0.262***	
	(2.863)	
female	0.0363	-0.0560
	(0.224)	(-1.074)
Constant	0.448***	0.375***
	(4.091)	(8.601)
R-squared	0.048	0.013
Observations	1,957	4,026

[a]Notes:

1. PLACEHOLDER TABLE - NEED TO REDO WITH STANDARD ERRORS AND ANY-SELL NOT ANYTRADE
2. Standard errors are two-way clustered at the individual date level.
3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table X
Trading Frequency [a]

	Funds		*Stocks*	
Gain	-0.165**	0.0361	0.0476	-0.0377
	(-2.299)	(0.443)	(0.831)	(-0.587)
FracTrade	0.519	0.631*	0.651***	0.356*
	(1.290)	(1.687)	(2.880)	(1.686)
Gain*FracTrade	0.104	-0.355	-0.126	-0.141
	(0.434)	(-1.430)	(0.221)	(-0.248)
Gain*FracTrade*Fire		0.981**		
		(2.400)		
Gain*FracTrade*Story		0.790**		1.369*
		(2.229)		(1.955)
Fire		0.126		
		(1.359)		
Gain*Fire		-0.242**		
		(-2.225)		
Story		0.0496		-0.120***
		(0.655)		(-2.706)
Gain*Story		-0.245***		0.0353
		(-2.648)		(0.406)
Constant	0.462***	0.376***	0.212***	0.313***
	(5.893)	(4.461)	(5.858)	(7.427)
Adj R-squared	0.042	0.067	0.010	0.022
N	2,011	1,957	4,106	4,026

[a]Notes:

1. FracTrade is a measure of the share of holdings an individual trades.
2. Standard errors are two-way clustered at the individual day level.
3. Observations are taken only for days in which a transaction (buy or sell) occurred. Analysis with treating each trading day as the unit of observation produces qualitatively and statistically identical results.
4. *** p¡0.01, ** p¡0.05, * p¡0.1

Table XI
Exit Questionnaire: Funds [a]

Panel A

	Own Skill	*Learning*		*Willingness to Invest*	
		Self	Manager	Any	Owned
Fire	-0.098	0.151	-0.181	0.330	-0.397
	(0.225)	(0.224)	(0.270)	(0.289)	(0.287)
Story	0.005	-0.389	-0.115	0.339	0.055
	(0.225)	(0.224)	(0.270)	(0.288)	(0.0287)
Constant	5.12***	6.87***	6.02***	5.89***	5.89***
	(0.186)	(0.186)	(0.223)	(0.238)	(0.237)
Adj. R-squared	0.008	0.006	0.006	0.002	0.000
Observations	242	243	243	242	240

Panel B

	Own Skill	*Learning*		*Willingness to Invest*	
		Self	Manager	Any	Owned
Gain	-0.131	-1.011	-1.338	0.048	0.518
	(0.405)	(0.413)**	(0.498)***	(0.541)	(0.520)
Fire	-0.167	0.186	-0.665	0.454	-1.101
	(0.408)	(0.417)	(0.503)	(0.546)	(0.524)**
Fire*Gain	0.159	-0.014	0.712	-0.162	1.025
	(0.482)	(0.491)	(0.593)	(0.645)	(0.620)*
Story	-1.116	-1.503	-1.276	0.125	-0.107
	(0.408)***	(0.416)***	(0.502)**	(0.545)	(0.523)
Story*Gain	1.632	1.531	1.622	0.305	0.347
	(0.482)***	(0.491)***	(0.593)***	(0.645)	(0.619)
Constant	5.197	7.612	6.999	5.854	5.470
	(0.346)***	(0.685)***	(0.426)***	(0.463)***	(0.444)***
Adj. R-squared	0.08	0.06	0.04	0.01	0.08
Observations	242	243	243	242	240

[a] Notes:

1. Answers can take values between 1 and 10.
2. All students completed the questionnaire. Missing observations are due to ambiguity in the answer due to illegible handwriting.
3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table XII
Exit Questionnaire: Stocks [a]

Panel A

	Own Skill	*Learning*		*Willingness to Invest*	
		Self	Management	Any	Owned
Story	-0.257	-0.141	-0.226	-0.221	-0.374
	(0.226)	(0.227)	(0.226)	(0.270)	(0.266)
Constant	5.29***	6.93***	6.78***	7.38***	6.57***
	(0.168)	(0.168)	(0.168)	(0.201)	(0.198)
Adj. R-squared	0.008	0.006	0.006	0.002	0.000
Observations	242	243	243	242	240

Panel B

	Own Skill	*Learning*		*Willingness to Invest*	
		Self	Management	Any	Owned
Gain	0.669	-0.575	-0.306	1.121	0.742
	(0.372)*	(0.378)	(0.376)	(0.441)**	(0.438)*
Story	-0.421	-0.394	-0.118	-0.184	-0.592
	(0.438)	(0.442)	(0.441)	(0.516)	(0.512)
Story*Gain	0.190	0.354	-0.135	-0.086	0.268
	(0.509)	(0.515)	(0.513)	(0.601)	(0.597)
Constant	4.800	7.350	7.000	6.567	6.033
	(0.317)***	(0.322)***	(0.321)***	(0.376)***	(0.373)***
Adj. R-squared	0.04	0.01	0.01	0.05	0.04
Observations	246	246	246	247	246

[a]Notes:

1. Answers can take values between 1 and 10.
2. All students completed the questionnaire. Missing observations are due to ambiguity in the answer due to illegible handwriting.
3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$