Looking for Someone to Blame: Delegation, Cognitive Dissonance, and the Disposition Effect*

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Abstract

We analyze brokerage data and an experiment to test a cognitive-dissonance based theory of trading: investors avoid realizing losses because they dislike admitting that past purchases were mistakes, but delegation reverses this effect by allowing the investor to blame the manager instead. Using individual trading data, we show that the disposition effect – the propensity to realize past gains more than past losses – applies only to non-delegated assets like individual stocks; delegated assets, like mutual funds, exhibit a robust reverse-disposition effect. In an experiment, we show increasing investors' cognitive dissonance results in both a larger disposition effect in stocks and also a larger reverse-disposition effect in funds. Additionally, increasing the salience of delegation increases the reverse-disposition effect in funds. Cognitive dissonance provides a unified explanation for apparently contradictory investor behavior across asset classes and has implications for personal investment decisions, mutual-fund management, and intermediation.

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1 Introduction

In recent years, economists have come to appreciate the importance of household investment decisions for understanding both decision making under risk and the impact of financial markets on real decisions (e.g. Campbell (2006)). One of the most robust facts describing individual trading behavior is the disposition effect: investors have a greater propensity to sell assets when they are at a gain than when they are at a loss.[1] Despite the near-ubiquity of the disposition effect, the underlying mechanism is not well understood. Empirical work has been much more successful in identifying problems with various proposed explanations than in finding positive evidence that points directly to a particular theory to the exclusion of all others.[2]

In an apparently puzzling contrast, the disposition effect is *reversed* in mutual funds, where investors have a greater propensity to sell losing funds compared to winning funds. This fact has been known at least since Friend et al. (1970), but it has primarily been discussed in the context of the positive performance/flow relationship (e.g. Chevalier and Ellison (1997)): funds that exhibit high returns receive greater inflows, while those with low returns receive outflows. Importantly, the finding holds for flows from existing investors as well as new investors (Ivković and Weisbenner (2009) and Calvet et al. (2009)). With a few exceptions (e.g. Kaustia (2010a)), the positive performance/flow relationship has not been thought of as equivalent to a reverse disposition effect, and it has received little discussion in the literature that seeks to understand what causes the disposition effect.

[1] Across asset markets, the disposition effect has been documented in stocks (Odean (1998)), executive stock options (Heath et al. (1999)), real estate (Genesove and Mayer (2001)), and on-line betting (Hartzmark and Solomon (2012)). Across investor types it has been found in futures traders (Locke and Mann (2005)), mutual fund managers (Frazzini (2006)), and individual investors (for the US Odean (1998), for Finland Grinblatt and Keloharju (2001), and for China Feng and Seasholes (2005)).

[2] See the discussion in Sections 5 and 6. One class of explanations has involved investors having non-traditional preferences over returns, such as prospect theory (Kahneman and Tversky (1979)) or realization utility (Barberis and Xiong (2009, 2012)). Other explanations have included a non-rational belief in mean reversion (Odean (1998)), and cognitive dissonance (Zuchel (2001)).

In this paper, we examine cognitive dissonance as a parsimonious model for understanding variation in the disposition effect both within and across asset classes. We analyze data from individual trading accounts and an experiment in order to provide positive evidence in favor of cognitive dissonance as a driver of the disposition effect. We also show that several broad classes of existing theories – such as rational and semi-rational learning models, purely returns-based preferences, and variation in risk attitudes – are insufficient to explain our results.

Cognitive dissonance is defined as the discomfort that arises when a person recognizes that he or she makes choices and/or holds beliefs that are inconsistent with each other (Festinger (1957)). In the current context, we argue that the disposition effect arises as a result of investors trying to rationalize their past trading choices with the fact that they have lost money on an asset they purchased. For most assets, traders will avoid realizing losses because doing so would force them to admit that their decision to invest in the asset was a mistake. In contrast, traders desire to sell losing funds because delegated portfolios (i.e. the ceding of decision-making authority to an outside agent) provide an alternative way to resolve the cognitive dissonance: traders can blame the manager, instead of themselves, for poor performance. Simply put, investors do not like to admit that they were wrong, and will blame someone else if they can.[3]

Our first main contribution is to document the scope of the puzzle: how much does the disposition effect vary across asset classes? In individual trading data (the dataset used in Barber and Odean (2000)), we show that the disposition effect in stocks and the reverse-disposition effect in actively managed funds holds for *the same investors at the same time.* In contrast, investors in *passively* managed funds (e.g. index funds), where the role of the

[3]See Barberis (2011) for a discussion of cognitive dissonance in the context of bank losses during the financial crisis. The idea that delegation is useful because it provides someone to blame for poor performance similar in spirit an idea in Lakonishok et al. (1992). In their analysis of delegated portfolio management of tax-exempt funds, the authors state that part of the appeal of external management of pension funds is the result of a desire by the treasurer's office "to delegate money management in order to reduce its responsibility for potentially poor performance of the plan's assets".

portfolio manager is minimal, exhibit a small but directionally positive disposition effect that is significantly different from actively managed funds but not from stocks. Looking across a broad range of asset classes (including options, warrants, bond funds, real estate trusts, etc.), we find the level of the disposition effect is almost rank-ordered with delegation, and the effect of delegation survives controlling for other asset class characteristics such as volatility, holding period, and position size. In addition, the variation across asset classes is largely driven by differences in the propensity to sell losses, which is consistent with the effects of cognitive dissonance because it is primarily a theory about how investors react in the loss domain.

The existing literature focuses on understanding the disposition effect in general, but it does not provide a ready explanation for the variation across asset classes. Because the variation in trading behavior across asset classes exists even within investors that hold both assets, the variation is unlikely to be due to clientele-based explanations, such as investors in each asset class having different preferences over returns or risk. If the disposition effect is driven purely by preferences over returns (e.g. prospect theory, loss aversion, realization utility), some other factor must be invoked to explain its nonexistence in funds. Finally, our trading-data results motivate a direct experimental test of the role of delegation where we can exogenously increase the psychological impact of delegation and cognitive dissonance on an individual's choices, while holding fixed the economic differences in the underlying assets and managerial skill.

Our second main contribution is to provide direct, positive evidence of the role of cognitive dissonance in generating the disposition effect. We run an online trading experiment in which undergraduate students trade a preselected group of actual stocks or funds at daily market closing prices over a period of 12 weeks. Participants were subjected to two different randomized treatments. All students had to give a reason for purchasing an asset (stock or fund), and the first treatment, which we call the "Story" treatment, reminds students of their stated reason when they move to sell the asset. By emphasizing their previous choice and its reasons, this treatment is designed to increase the cognitive dissonance discomfort that students experience when facing a loss, and therefore to increase the actions that individuals will take in response to the cognitive dissonance.

As predicted, we find that this treatment generates an increase in the magnitude of the disposition effect for stocks *and also* the reverse-disposition effect for funds. The fact that the same treatment has opposite effects for stocks and funds is consistent with the effect of cognitive dissonance (as both actions are hypothesized to be responses to the same underlying cognitive dissonance discomfort). It is, however, difficult to reconcile with competing explanations, particularly since students are not provided with any information other than their own previously stated reasons for their purchases.

The second treatment, which we call the "Fire" treatment, is designed to increase the salience of the intermediary (i.e. the fund manager) while preserving all the underlying economic differences that may be associated with delegation. Students in the Fire treatment have the words "Buy", "Sell", and "Portfolio performance/gain/loss" replaced with the words "Hire", "Fire", and "Fund Manager's performance/gain/loss" throughout the website. In addition, students in the Fire treatment are provided with links to fund managers' biographies. As predicted, when the role of the manager is made more salient to investors, they display a larger reverse-disposition effect.

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. One potential concern is that increasing the salience of fund managers increases learning with regards to fund manager skill. We use the survey results to test this possibility directly. In addition, cognitive dissonance predicts that learning should be asymmetric in gains and losses, as shown in other settings (e.g. Kuhnen (2013) and Mobius et al. (2012)). The asymmetry arises from the fact that individuals are more likely to discount new information that suggests that the decision to purchase the asset was a bad one. 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 more learning conditional on having an aggregate gain than an aggregate loss.

Our results suggest that cognitive dissonance is an important driver of the disposition effect, and that the psychological effects of portfolio delegation help explain the apparently contradictory household behavior across different asset classes. These conclusions suggest a reinterpretation of some of the existing theories of the disposition effect. Models of loss aversion have primarily contemplated investors as having preferences over the returns themselves. Instead, our findings suggest that at least part of the carrier of utility when evaluating portfolio gains and losses is the psychological costs of admitting mistakes and resolving cognitive dissonance. How exactly to theoretically model such behavior is a question deserving of further research.[4]

In addition, our results have implications for mutual fund management and intermediation. Because the disposition effect measures households' propensity to withdraw funds after a gain relative to a loss, it also measures the financial slack available to intermediaries from the household sector after price declines. Instruments that are passive or that give households a greater sense of "ownership" in investment decisions may have less fragility in their funding during crises. We discuss these implications in section 7 and point to areas of potential future research.

[4]One intriguing possibility is to recast cognitive dissonance as a psychological foundation for a form of realization utility (Barberis and Xiong (2012)). Specifically cognitive dissonance causes investors to experience negative utility when selling a stock at a loss (i.e. realizing a loss). But in the case of delegated assets, this effect can be offset by placing the blame for the assets poor performance on the manager.

2 Hypotheses

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 that one will go to great lengths to alleviate. Individuals 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. Bayesian updating of one's priors). For example, if I believe that I am a skilled investor and receive information that my portfolio has declined in value, I can reduce the dissonance between these two contradictory cognitions by updating my belief about my skill level and reducing my estimate of my ability, such as in Seru et al. (2009).

While economists have traditionally focused on this mechanism – assuming individuals dispassionately incorporate new information to update their beliefs about the world – the psychological evidence is that new information contradicting one's priors is often met with a combination of defense mechanisms and mental tricks. One of the key findings in this literature is the important role of actions in shaping beliefs. Once an action is undertaken, individuals believe that the decision was made for a good reason, and then the decision-identity cognition becomes primary. When faced with a subsequent dissonant cognition, individuals will use various psychological means to reduce dissonance-related discomfort *without* relinquishing the original decision-identity cognition.[5]

There is a direct map between the three methods for reducing dissonance and whether or not investors will display a disposition effect. The two relevant cognitions after an asset has declined in value are:

1. The original decision-identity cognition: "I bought this stock/fund for a good reason."

2. The new information that the stock or fund went down in value.

Notice that there is no dissonance when the stock or fund increases in value. Nonetheless, since the disposition effect only describes the *difference* between the willingness to sell at a gain versus a loss, an effect that operates only in the loss domain is sufficient to generate the observed patterns.

The first way of dealing with cognitive dissonance is to change one or both cognitions so they are congruent. Given that the new information (i.e. the asset has decreased in value) is generally hard to interpret in a positive fashion, this would entail changing the original decision-identity cognition – that is, relinquishing the notion that buying the asset was a good idea. Traders resist this path because, as documented extensively in the psychology literature, the decision-identity cognition is extremely stable and difficult to change.

The second way of dealing with dissonance is to alter the importance of one of the cognitions. Because actions create particularly strong links between cognition and identity, it is difficult to reduce the perceived importance of the initial purchase decision. Instead, it is easier to convince oneself that the new information in the price decline is unimportant or irrelevant. For example, investors may prefer to rationalize their poor performance as a temporary setback due to bad luck or noise in stock returns.

[5] Once a decision has been made, individuals will tend to change their future actions and beliefs to justify the decision, rather than question the rationale behind the initial decision. Examples include induced compliance (e.g. Festinger and Carlsmith (1959) and Aronson and Carlsmith (1963) among many others), the free choice paradigm (e.g. Brehm (1963) and Egan et al. (2010)), effort-justification (Aronson and Mills (1959)), belief disconfirmation (Festinger et al. (1956)), and the Benjamin Franklin effect (Jecker and Landy (1969)).

Furthermore, selling after a price decline would potentially lead to additional cognitive dissonance discomfort. That is, it is difficult to rationalize to oneself why it was a good decision to buy the stock *and* a good decision to sell it at a loss.[6]

The third way of dealing with dissonance is to add a third, ameliorating cognition. When the asset is a delegated portfolio, such a cognition is readily available: the decline is the manager's fault. In particular, if an investor buys a stock directly there is, roughly speaking, a single choice that drives returns: 'my decision to buy this stock'. In a delegated portfolio, however, there are two choices driving returns: 'my decision to hire this fund manager' and 'the fund manager's decision to purchase the stocks in the fund'. As such, the presence of a fund manager gives investors an alternative actor to blame as a way of excusing their poor returns.

By blaming the manager, investors have a way of relieving the cognitive dissonance that does not require them to refrain from selling losing funds. Investors could still choose to blame themselves for their role in the returns if they wished – nonetheless, the point of cognitive dissonance theory is that they are looking for a reason to excuse their own behavior, so having such a reason at hand makes it likely that investors will choose that course instead.

Significantly, once the blame has been attributed to the fund manager, investors may *actively desire* to sell losing funds, rather than simply being indifferent between holding or not. This is because continuing to hold the fund would expose them to another source of dissonance: why do I continue to invest with a fund manager who generates low returns? Similarly, selling the fund becomes a concrete action taken to punish the manager for the poor performance, consistent with the evidence on scapegoating and responsibility

[6]While not a direct prediction of cognitive dissonance, there are other reasons to suspect that investors in stocks may actively *desire* to sell at a gain, rather than simply refraining from selling at a loss. The confirmation bias (Nickerson (1998)) suggests that investors will prefer, and even seek out, information that confirms their beliefs. While selling does not actually generate new information, it may make the status of the existing gain 'permanent' and confirm that this particular narrative episode (e.g. I bought share X at \$5 and sold it at \$10) was a good decision (Barberis and Xiong (2012)).

attribution (Bartling and Fischbacher (2012)).[7]

Our hypothesis is that when a manager is available, the third method is the easiest way to resolve cognitive dissonance, and therefore investors will sell actively managed funds after losses more than after gains. When a manager is not available, the second method is easiest and investors will sell stocks after gains more than after losses. Hence we predict that:

1. Assets that are delegated portfolios will display a reverse-disposition effect, while those that are not delegated will display a disposition effect. This difference should be due to the fact of delegation itself.

2. If investors have a higher level of cognitive dissonance, they will display a larger disposition effect in non-delegated assets like stocks and a larger reverse-disposition effect in delegated assets like funds.

3. If investors focus more on the role of the fund manager instead of their own role, they will display a larger reverse-disposition effect.

3 Evidence from Small Investor Trading Data

We begin by examining the extent to which real world trading data are consistent with cognitive dissonance and other explanations of the disposition effect. Data from individual trading is most suited to testing the first of the predictions above, namely whether delegated

[7] It is possible that investors may blame the Chief Executive Officer (CEO) of the company for the poor stock returns, rather than themselves, but this seems unlikely. First, the CEO's task in managing the company is fundamentally different to the investor's choice of picking financial assets. The fund manager, by contrast, is choosing between assets in a way similar to the investor. Hence, fund managers are more credible as a substitute figure to excuse the investor's own choices. Second, the existence of the fund manager as a person to blame operates in addition to the CEO in the case of equity funds. In other words, if investors were inclined to blame company management for bad stock returns, they could still do this for equity mutual funds. As a result, the fund manager is always an additional potential avenue of blame. This idea is similar to the one proposed in Lakonishok et al. (1992). There, pension fund managers delegate the task of portfolio management in order to have someone credible to blame in case of poor fund performance.

assets have more of a reverse-disposition effect than non-delegated assets. We document three new stylized facts based on the Barber and Odean (2000) small-investor trading data:

- The disposition effect in stocks and the reverse-disposition effect in funds occur 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, even after controlling for asset volatility, holding period, and position size (Tables 3 and 10).

- Within equity mutual funds, index funds (which have a fund manager, but one who plays a less important role in terms of delegated management) display a small positive and statistically insignificant disposition effect. This effect is significantly different from other mutual funds but not from stocks (Table 4).

3.1 Data

The individual trader data used are the same as in Barber and Odean (2000). 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 November 1996. The data comprise 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 at an 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 the end of each month using the positions file. To obtain a snapshot of securities prices at each point in time from which to calculate gains and losses, we rely on the prices and holdings in the monthly position files.[8] Using the portfolio snapshot each month, we match each security in the portfolio with the most recent purchase price. By comparing the price with the purchase price, we define the variable *Gain* to be 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. 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. In periods where there is no sale at all, it is difficult to tell if this is a deliberate choice by the investor or simple inattention. By comparing only months with sales, we ensure that the investor is actually paying attention to their portfolio during that period. Table 1 presents summary statistics for the individual trader data.

3.2 The Disposition and Reverse-Disposition Effects

In the main analysis, we wish to test whether individuals exhibit a higher tendency to sell those securities that are at a gain than those that are at a loss. To do this, we use the following as our basic regression specifications:

$$Sale_{ijt} = \alpha + \beta Gain_{ijt} + \epsilon_{ijt}, \tag{1}$$

$$Sale_{ijt} = \alpha + \beta Gain_{ijt} + \gamma Gain_{ijt} \times Fund_j + \delta Fund_j + \epsilon_{ijt}, \tag{2}$$

[8] We do this to ensure that all assets are using comparable price information at the same point in time. Daily price information is not available during the sample period for many of the asset classes that we are interested in (e.g. mutual funds, preferred stocks, options).

where (1) is estimated separately on stocks and funds and (2) is run on the combined data. Observations are at the account (i), asset (j), and date (t) level, and they are included for all stocks or funds (according to the specification) on months where the investor sold some position in their overall portfolio. In addition, as described above, *Sale* is a dummy variable equal to one if the individual reduced their position in the asset in that month and zero otherwise, and *Gain* is a dummy variable that equals one if the asset was at a gain at the start of the month and zero otherwise. *Fund* is a dummy variable equal to 0 for stocks and 1 for funds. In all our regressions, standard errors are two-way clustered at the account and date levels.

Because the dependent variable is a dummy variable equal to one if the asset was sold, the mean of the dependent variable is the probability of selling a particular position given that the investor sold something that day. By regressing this variable on *Gain*, the constant in the regression measures the probability of selling a position that is at a loss (i.e. *Gain*=0). The coefficient on *Gain* measures the increase in the probability of selling a position if that position is at a gain, and this coefficient is the measure of the disposition effect – the increased propensity to sell gains relative to losses.[9] A negative coefficient indicates a reverse-disposition effect.

The purpose in running the two regression specifications is to separately test whether the disposition effect in stocks and funds are different from zero and from each other. The coefficient on $Fund \times Gain$ in (2) measures the difference in the disposition effect for stocks and funds. Here, β represents the disposition effect (i.e. the difference between the propensity to sell gains vs. losses) for stocks, and the sum of the two coefficients β and γ provides a measure of the disposition effect for funds.

[9]The regression specification in (1) is also analogous to the method used in Odean (1998), who calculates the disposition effect as the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR). In the regression above, the probabilities will be the same as the proportions, and the coefficient on *Gain* is the difference between PGR and PLR. The main advantage of using a regression specification is that additional controls can be added in later tables, and the standard errors can be clustered properly to avoid assuming that every sale choice is entirely independent.

To determine if the difference in the level of the disposition effect in stocks and funds is driven by a clientele effect – selection of different investor types into each asset class – we test the disposition effect across various subsets of investors and assets. We examine: 1) all investors in each asset class; 2) investors who held both stocks and funds at some point in their trading history, considering all observations from both asset classes; 3) investors who held both stocks and funds at the same time, considering only observations in the months where they hold both assets simultaneously. Group 3 is the most stringent test since this involves a single investor reacting to the returns of stocks and funds at the same time, allowing us to measure an individual's concurrent disposition effect across the two asset classes.

The results of these regressions are presented in Table 2. We observe the presence of a significant disposition effect in stocks and a significant reverse-disposition effect in funds, even within the set of investors who simultaneously hold both assets. For all investor subsets, the coefficient for *Gain* is positive for stocks and negative for funds (with all coefficients being significant at the 5% level or greater).

The *Gain* coefficient for the stock-only sample ranges from 0.0391 for the all-investor sample to 0.0157 for the investors who simultaneously hold both stock and funds. The interpretation of this coefficient is that on months when an investor sells some asset, they are between 3.91% and 1.57% more likely to sell a stock if it is at a gain. This is compared with the base probability of selling any stock (from the constant in the regression), which is 21.7% for all investors and 18.9% for those simultaneously holding both stocks and equity mutual funds.

For equity mutual funds, the coefficient for *Gain* ranges from -0.0656 for the all-investor sample to -0.0485 for investors who simultaneously hold both stocks and equity mutual funds, again significant at the 5% level or greater. Investors are between 6.56% and 4.85% less likely to sell a fund if it is at a gain, compared with the base probability of selling any fund (on months with the sale of some asset) of 32.5% and 23.2%. In addition, the *Fund*$\times$*Gain* coefficient is negative and significant at the 1% level in all cases.

Note also that the difference in the disposition effect between stocks and funds is driven by differences in investor propensity to sell losses (i.e. the coefficient for *Fund* is large and significant while the sum of the coefficients for *Fund* and *Fund*$\times$*Gain* is small and statistically insignificant in all three investor groups).

The fact that the *Gain* coefficient (for both stocks and funds) gets somewhat closer to zero as the sample gets more restricted suggests that there are some differences between stock and fund investors that affect the level of the disposition effect being displayed. Nonetheless, the fact that the difference between stocks and funds holds for the same set of investors at the same time means that differences between investors, such as preferences or information, cannot explain all of the difference in investor behavior.

These results are difficult to reconcile with theories that posit that the disposition effect is purely the result of selection into assets according to differences in investor preferences over returns. Instead, it appears as though there is something about the asset classes themselves that is driving the difference in the sign of the disposition effect between stocks and funds.

3.3 Delegation and the Disposition Effect Across Asset Classes

One key feature of our cognitive dissonance-based predictions is the important role intermediaries can play in resolving cognitive dissonance. If delegation is the relevant asset class characteristic, then delegation 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 a reverse-disposition effect, and if it does not, it ought to have a disposition effect. In contrast, if the reverse-disposition effect is limited to mutual funds, this would suggest that the distinction may be more likely due to some other institutional features of mutual funds.

We test whether delegation is the relevant characteristic by re-running the regression (1) 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 trading firm. These classifications include warrants, options, convertible preferred stock, bond mutual funds, and others. The only asset class we exclude is money market funds; many of these have a price that is fixed at some value such as one dollar per share, and hence there are very few observable gains and losses.[10]

Table 3 lists the different fund asset classes, an indicator for whether or not they are delegated, and the coefficient on *Gain* from (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 delegation: while investors usually exhibit a positive disposition effect for un-managed assets like stocks, actively managed asset classes usually exhibit a reverse-disposition effect. Of the 24 different asset classes reported by the trading firm, all 4 asset classes with statistically significant positive disposition effects are not delegated portfolios. Of the 7 assets with statistically significant reverse-disposition effects, 5 are actively managed, with the two exceptions (preferred stock and options equity) accounting for the two smallest (in magnitude) coefficients.

[10] For each asset class, we also attempt to classify them according to whether the asset involves delegation to a portfolio manager. There are some cases where this distinction is not entirely clear. In the case of a Real Estate Trust, where the assets are fixed over long periods, it is not easy to say whether the manager has more in common with the CEO of a regular industrial company or a portfolio manager of a fund. We classify Real Estate Trusts as delegated, interpreting the ambiguity conservatively in the way that will work against the main relationship. A similar question arises for Master Limited Partnerships; we classify these as being non-delegated, although the estimated disposition effect is close to zero and also close to the middle of the asset class range, and hence changing the classification does not significantly affect the results.

3.4 Index Funds

In examining the role of delegation, index funds are a useful test case because while they have many of the same institutional details as actively managed mutual funds, the fund manager does not actively trade the underlying securities. It seems likely that investors do *not* think that index funds will generate abnormal returns; indeed, the whole rationale for passive investing is that it is pointless to attempt to generate abnormal returns and beat the market. Thus, the fund manager of an index fund is a less credible target to blame for the poor performance of the fund, and we expect that – despite all the institutional and return-moment-based similarity with mutual funds – index funds will *not* exhibit a reverse-disposition effect. In addition, since an investment in index funds is often in support of a passive strategy, we expect that index funds will display less of a positive disposition than stocks.

To test this prediction, we take the names of mutual funds from the CRSP Mutual Funds database and classify funds as an index fund if their name contains any of 'Index', 'S&P 500', 'Russell 2000', 'Dow 30', or variations thereof. We match these classifications with the trader database using the CUSIP of the funds. The CUSIP data for the CRSP database only become available starting in 1996. We use CUSIPs between 1996 and 2001 and merge these with CRSP data from earlier years. In addition to the basic regression of *Sale* on *Gain* for index funds, we also run the following regression:

$$Sale_{ijt} = \alpha + \beta Gain_{ijt} + \gamma Gain_{ijt} \times Index_j + \delta Index_j + \epsilon_{ijt}, \tag{3}$$

We run the regression first on the sample of index funds only, then for the sample of all equity mutual funds (both actively and passively managed), and finally for the combination of index funds and stocks. The results are reported in Table 4.

The base level of the disposition effect for index funds, as given by the coefficient on *Gain*, is 0.0035. This coefficient is both statistically and economically insignificant and is only about 9% as large as the coefficient on *Gain* for stocks in Table 2. In column 2, the sample is all equity mutual funds. The coefficient on *Gain*$\times$*Index* is 0.0587 and significant at the 10% level, suggesting that index funds have less of a reverse-disposition effect than other funds. Indeed, the index fund interaction offsets nearly all of the base reverse-disposition effect for equity funds in general, as measured by the base coefficient of -0.0662. The small number of index funds observations contributes to the marginal significance of the coefficient.

The matching procedure of using CUSIPs that are dated from 1996 to 2001 contains a potential lookahead bias because any fund classified as an index fund needs to be matched on CUSIP, which requires it to exist at least in 1996. To ensure that this potential bias is not driving the results, in column 3 we include an additional specification with a dummy variable *Alive* that equals one for any fund that existed between 1996 and 2001 and zero otherwise, and interact this with the *Gain* variable. Including this variable makes the difference between index funds and other mutual funds stronger, with the *Gain*$\times$*Index* coefficient increasing to 0.0672, significant at the 5% level.

Finally, in column 4 we examine whether index funds display a significantly lower disposition effect than stocks by running a regression with index funds and stocks. The coefficient on *Gain*$\times$*Index* is -0.0357, indicating that the disposition effect in index funds is directionally lower than for stocks, although the difference is not significant.

3.5 Summary

The results from the individual trader data demonstrate two important facts. The first is that the different levels of the disposition effect between stocks and funds do not appear to be driven by differences in the preferences of investors in these two asset classes. The second is that across a variety of assets, the level of delegation in the asset is related to the level of the disposition effect that investors display. Actively managed assets (including, but not limited to, equity mutual funds) tend to display a reverse-disposition effect, while non-delegated assets tend to display a disposition effect. We also show (in Section 5.2) that this relationship holds even when controlling for asset volatility, holding period, and position size.

The variation in disposition effects across asset classes is not captured in most explanations of the disposition effect (see Sections 5 and 6), but it is consistent with the trading behavior of an investor facing cognitive dissonance. Or to paraphrase Langer and Roth (1975), "Heads I win, tails it's the manager's fault." The next step is to provide direct, positive evidence for cognitive dissonance, and for that we turn to an experimental setting.

4 The Experiment

4.1 Goals

To provide direct evidence of cognitive dissonance as a cause of the disposition effect, we ran an experiment on 520 undergraduate students over 12 weeks. In the experiment, we directly test for positive evidence of the role of cognitive dissonance in the disposition effect by manipulating the level of cognitive dissonance that investors experience. We find that increasing the level of cognitive dissonance investors experience causes an increase in the disposition effect in stocks and an increase in the reverse-disposition effect in funds.

Second, we show that delegation has a psychological effect on investors' trading behavior. While the previous section provides evidence that delegation matters for the disposition effect, there are numerous uncontrolled for economic differences between delegated and non-delegated portfolios, such as learning about managerial skill, moral hazard, other agency problems, etc. To ensure that these other differences are not driving the relationship, we vary the *salience* of the intermediary, while keeping asset composition constant (and with it any economic differences in the underlying assets). We find that increasing the salience of the delegation aspect of mutual funds increases the reverse-disposition effect.

Finally, we test whether the differences in investor behavior between stocks and funds are driven by learning about managerial skill. We test the learning hypothesis directly, using survey evidence from students taken after the conclusion of the experiment on how much they learned about the skill of fund managers, and we find results that are consistent with cognitive dissonance but not with several "learning stories", loosely defined.

4.2 Experimental Setting

Our experiment involved 520 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 prerequisite. 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. The game started on January 23, 2012 and ended on April 16, 2012 (12 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, the students 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 orders 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 satisfy their budget constraint. Trades were executed without transaction costs. After the last trading day, students were given a closing survey. The list of mutual funds, the opening and closing surveys, and screen-shots from the game are all presented in the appendix.

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 in their portfolio page and on the sell screen. If they had made multiple previous purchases, the portfolio page contained the most recent reason given, while in the sell screen 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 when they face a loss on an asset, regardless of whether they are trading stocks or funds. By prominently displaying their earlier reasoning, now shown to be faulty by the drop in price, it is harder for the student to avoid or ignore the fact that they may have made a mistake. Therefore the theory predicts that the Story treatment should have different effects for stocks and funds: it should lead to an *increase* in the propensity of individuals to sell winners relative to losers for stocks and a *decrease* in the propensity of individuals to sell winners relative to losers for funds. This is because both actions are viewed as being responses to the underlying discomfort of cognitive dissonance.

The second treatment, "Fire", was applied randomly to students in the mutual fund group. Students in the Fire treatment have the words "Buy", "Sell", and "Portfolio performance/gain/loss" replaced with the words "Hire", "Fire", and "Fund Manager's performance/gain/loss" throughout the website. In addition, the buy and sell screens included a link to the mutual fund manager's online biography. Screen-shots with and without the Fire treatment are in the appendix. This treatment was designed to increase the salience of the intermediary (i.e. the fund manager). If intermediation causes traders to alleviate cognitive dissonance by blaming the manager for the poor performance, then increasing the salience of the manager's role should lead to an increase in the magnitude of the reverse-disposition effect.

Population summary statistics across the treatment arms are given in Table 5. Observable characteristics are quite similar across the different treatment arms, and in regressions (not shown) we found that no observable characteristic was statistically different across any combination of treatment groups.

The nature of this experimental design may cause our analysis to *understate* the true impact of the treatments. The experiment took place over 12 weeks, and some of the students may have talked to each other about the trading game, despite being requested not to do so. Since treatments were randomized at the student level, it seems unlikely that class social networks would be correlated with treatments assignment. Thus, to the extent that student communications created a correlation in the trading behavior of traders, it would constitute a cross contamination of our treatment cells and bias our measured treatment effects toward zero.[11]

At the conclusion of the experiment, students were given a closing survey asking about what they had learned during the experiment, described in Section 5.

4.3 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 because 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 monthly. We consider all securities held in the investor's portfolio each day, and for each security we calculate the volume-weighted average purchase price ("purchase price"). As before, *Gain* is a dummy variable that equals one if the price that

[11]For example, consider a case in which two students work together, one of whom is in the Fire treatment and one not. Both students are then likely to exhibit behavior somewhere between the behavior of a pure Fire treated student and a pure control student, driving the apparent effect of the treatment toward zero. As a result, our point estimates should be interpreted as lower bounds of the true treatment effects.

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 we estimate

$$\begin{aligned} \text{Funds}: \quad Sale_{ijt} &= \alpha + \beta Gain_{ijt} + \gamma Gain_{ijt} \times Story_i + \delta Story_i \\ &\quad + \eta Gain_{ijt} \times Fire_i + \theta Fire_i + \epsilon_{ijt} \end{aligned} \tag{4}$$

$$\text{Stocks}: \quad Sale_{ijt} = \alpha + \beta Gain_{ijt} + \gamma Gain_{ijt} \times Story_i + \delta Story_i + \epsilon_{ijt}, \tag{5}$$

where *Fire* and *Story* are indicator variables for whether an individual i is in the Fire and Story treatments respectively. Since students are randomly assigned into treatment groups, η and γ are interpretable as causal impact of the treatments on the disposition effect.

Observations are at the individual (i), asset (j), and date (t) levels, and they include only days on which an investor sells an asset. This choice was to help ensure that observations were created only for those days the student was actually examining his or her portfolio. Treating each trading day as an observation regardless of whether a trade takes place generates qualitatively similar results. As before, all standard errors are two-way clustered at the individual-date level.

Table 6 reports the result of equation 4 for the mutual funds group. These results demonstrate an unconditional reverse-disposition effect across all students (column 1), as in the individual trading data. On days with a sale, students are 14.1% less likely to sell a fund that is at a gain (with the base probability of selling any given fund, conditional on a sale, being 52.7%). This is seen in the coefficient of -0.141 on the *Gain* variable and is significant at the 5% level.

In terms of the treatments, column 2 shows that students in the Fire treatment displayed a significantly larger reverse-disposition effect, consistent with the cognitive dissonance hypothesis. This is seen in the coefficient on $Gain \times Fire$, which is -0.211 and significant at the 5% level. Adding this to the base coefficient on *Gain* means that students not in the Fire treatment were 5.9% less likely to sell funds when they were at a gain (statistically insignificant), while students in the Fire treatment were 27.0% less likely to sell funds when they were at a gain.

Column 3 indicates that students in the Story treatment also displayed a significantly greater reverse-disposition effect when trading mutual funds. The coefficient on $Gain \times Story$ is also -0.211 and significant at the 5% level. Adding this to the base coefficient on *Gain* means that students not in the Story treatment were 4.8% less likely to sell funds when they were at a gain (statistically insignificant), while students in the Story treatment were 25.9% less likely to sell funds when they were at a gain.

Column 4 shows that both the Fire and Story treatments increase the reverse-disposition effect when examined together.

Table 7 reports the effect of the Story treatment for stocks. For the stock group, we see that students as a whole exhibit a directionally positive (but not statistically significant) disposition effect for stocks in aggregate (column 1), being on average 3.38% more likely to sell stocks when they are at a gain, conditional on some sale of a stock that day. The point estimate of the stock disposition effect (0.0338) is quite close to the estimated stock disposition effect in the individual trader data for all traders (0.0391, in Table II, column 1), suggesting that the lack of significance may be more due to a lack of statistical power from the smaller number of observations, rather than an unusually weak base effect in the experiment.

Across treatment conditions, we find that the Story treatment increases the magnitude of the disposition effect – the coefficient on $Gain \times Story$ is 0.157, significant at the 5% level. Combining this with the base coefficient on *Gain* means that students who did not have their explanations repeated back to them were 3.51% less likely to sell stocks when they were at a gain relative to a loss, while students who had their explanations repeated back to them were 12.2% more likely to sell stocks when they were at a gain relative to a loss.

Overall, the results shown in Tables 6 and 7 are consistent with the predictions of cognitive dissonance. Increasing the level of dissonance investors feel (by repeating back their earlier reasoning for making a purchase decision) causes an increase in the disposition effect for stocks and an increase in the reverse-disposition effect for funds. When cognitive dissonance discomfort is greater, investors in a stock are more likely to dismiss or disregard any new information contained in the price decline, while investors in a fund are more likely to blame the fund manager. In addition, increasing the salience of the fund manager increases the reverse-disposition effect for funds.

5 Alternative Hypotheses

5.1 Learning

Perhaps the most attractive alternate explanation for some of our experimental results (and the fact that delegation seems a key characteristic in determining the sign of the disposition effect in the Odean trading data) is that they are the result of learning. In this view, the difference in investor behavior towards delegated and non-delegated assets is due to investors learning about the skill of fund managers for delegated assets. If investors also have a desire to allocate more funds to managers with high skill (as measured by returns), such learning could lead to a positive fund performance-flow relationship (i.e. the reverse-disposition effect).

We do not argue that learning is not occurring. Instead, we seek to show that 1) learning about skill is not *necessary* to explain the reverse-disposition effect for actively managed funds, and 2) experimentally, there is a substantial effect of delegation that can be shown *not* to be driven by learning about manager skill. To that end, we first characterize what form learning must take in order to explain the results of our experiment, and second, we directly measure the effect of our treatments on learning in the experiment through a closing survey.

First, neither of our treatments provide any new information, so they should have no effect under standard learning models. For learning to be driving the effect of the treatments, it must be that reminding participants of the existence of fund managers or reminding them of their stated reasons for purchasing a fund somehow causes significant changes in their beliefs.

In addition, since the time-frame of the experiment is fairly short (12 weeks) and most mutual fund managers in our sample typically have a tenure measured in multiple years, such learning must be either have a recency bias (e.g. overweighting recent information) or be very localized (e.g. highly dependent on local market conditions). That is, the most recent few weeks of returns must significantly alter beliefs about the skill of fund managers, even though several years of past returns are available.

Moreover, given the fact that the Story treatment increases the disposition effect in stocks while increasing the reverse-disposition effect in funds, reminding traders about their stated reasons for purchasing an asset must somehow either engender opposite learning effects for stocks and funds, or learning must lead to opposite effects with respect to trading behavior.

Second, notwithstanding that such learning would clearly be inconsistent with many models, we directly test whether the treatments are correlated with different rates of learning of any kind through a series of questions in the exit survey. In it we asked participants to rate how much they learned about the skill of the managers of the funds they owned (if in the fund group) during the course of the trading game. Students who traded funds were asked the following five questions, with answers to be given on a scale from 1 to 10:

1. Based on your performance in this assignment, how would you rate your skill as an

investor, from 1 to 10 (with 10 being 'highly skilled' and 1 being 'very unskilled')?

2. Through the trading game, how much did you learn about your own skill as an investor?

3. Through the trading game, how much did you learn about the skill of the available mutual fund managers?

4. Going forward, how willing are you to invest your own money in mutual funds as a whole?

5. Going forward, how willing are you to invest your own money in the mutual funds you traded?

For students who traded stocks, in question 3 the phrase "skill of the available mutual fund managers" is replaced by "value of the available companies", and in questions 4 and 5, the phrase "mutual funds" is replaced by "stocks".

The results of this survey for fund traders are given in Table 8. Column 3 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 the two treatments did not increase learning about fund manager skill.

Panel B in Table 8 shows the exit survey results with the full set of interactions between whether or not the portfolio experienced a net gain ("Profit") and the experimental treatments. Here we find that learning about both one's own skill and the fund manager's skill was reduced when a subject's portfolio experienced a profit. Given the fact that students could have chosen not to trade at all (i.e. maintain a cash only position), we interpret the negative coefficient on *Profit* as indicative of an ex-ante expectation that they would earn a positive return on their purchases.

More importantly, under the Story treatment (when cognitive dissonance was increased), there was a strong asymmetry in learning between portfolio profits and losses. Subjects in the Story treatment who traded funds reported learning substantially less at a loss than at a profit (see also Kuhnen (2013) and Mobius et al. (2012)). The results for stock traders (presented in Table 9) are qualitatively similar, though not statistically significant at conventional levels. The asymmetric learning in the Story treatment indicates that increasing the cognitive dissonance that traders experience causes them to learn substantially less when the results are negative than positive. This result is consistent with cognitive dissonance in general and the literature on the attribution bias in particular. That is, when the results are congruent with the idea that the purchase decision was a good one, individuals update their beliefs, while dissonant information is disregarded or downgraded in importance.

5.2 Volatility, Horizon, and Position Size Effects

While our focus has been on delegation, one might be concerned that there are other differences between mutual funds and stocks that drive the levels of the disposition effect.

The first possibility is the effect of return volatility. Both Ben-David and Hirshleifer (2012) and Kaustia (2010b) report that the propensity to sell is not flat across the domain of gains and losses, while Linnainmaa (2010) points out that sell limit orders can mechanically generate "a trading pattern that is observationally equivalent to the disposition effect." In such a case, assets with high volatility are likely to have returns which place them in regions with different propensities to sell, and this may drive the measured disposition effect even if the overall relationship between returns and selling propensity is the same for both assets.

Second, there may be differences in the investing horizon between investors in delegated and non-delegated assets. Within equities, Ben-David and Hirshleifer (2012) report that the length of the holding period affects the level of the disposition effect, and it may be that differences in the holding periods for delegated and non-delegated assets are driving the apparent difference in the disposition effect.

Finally, there may be differences in the overall portfolio importance of delegated and non-delegated assets. Investors may hold a larger or smaller amount of their money in different asset classes, and this may drive their level of attention to the asset or level of risk displayed (particularly if the investor uses mental accounting to treat each asset separately).

In Table 10, we test whether the effect of delegation survives after controlling for asset volatility, holding period, and position size. The regressions are similar to those in Table 2 but include observations of all assets from Table 3 (i.e. all assets other than money market funds), rather than just stocks and equity mutual funds. The regressions are:

$$\begin{aligned} Sale_{ijt} = \alpha &+ \beta Gain_{ijt} + \gamma Gain_{ijt} \times Delegated_j + \delta Delegated_j \\ &+ \zeta Gain_{ijt} \times Controls_{ijt} + \eta Controls_{ijt} + \epsilon_{ijt}, \end{aligned} \tag{6}$$

where i is an account, j is an asset, and t is the time period. Observations are included for all assets on days where the investor sold a position in some asset. *Delegated* is a dummy variable that equals one if the asset class involves delegated portfolio management, according to the classifications in Table 3.

The vector *Controls* includes *Volatility*, *Holding Period (Account)*, *Holding Period*, *Log Dollar Value (Position)*, and *Portfolio Weight (Position)*. *Volatility* is the average volatility of returns for that asset class, computed by taking the standard deviation of returns for each individual security, then averaging for all securities in the particular asset class. *Holding Period (Account)* is the average holding period for that account, computed as the total length of time between the first observation for the security and the last observation for the security, averaged across all securities in the account. *Holding Period* is the same holding period but taking the average for all securities in the asset class. *Log Dollar Value (Position)* is the dollar value of the position in that asset at the start of the month, while *Portfolio Weight (Position)* is the weight in that security in the investor's portfolio at the start of the month. Interactions with the *Gain* variable capture whether these variables are associated with different levels of the disposition effect.

The results are reported in Table 10. They indicate that delegated assets have a significantly lower disposition effect than other assets, over and above the effects of volatility, holding period, and position size. The base effect of the *Gain* variable in column 2 is 0.0341, with the interaction of $Gain \times Delegated$ having a coefficient of -0.0802, meaning that the overall *Gain* coefficient for delegated assets is $0.0341 - 0.0802 = -0.0461$.

The interpretation of the coefficients is that non-delegated assets are 3.41% more likely to be sold if they are at a gain, compared with a base probability of 22.1%. For non-delegated assets, they are 4.61% less likely to be sold if they are at a gain, compared with a base probability of being sold of 21.5%. This difference between delegated and non-delegated assets remains significant after controlling for the asset-level volatility (column 3), asset-level average holding period (column 4), and account-level average holding-period (column 5), log dollar value of the position (column 6), portfolio weight (column 7), as well as all of these variables in combination (column 8).

5.3 Heterogeneous Effects: Experience and Gender

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.[12] In this context, we examined whether students who have more experience display lower or higher levels of the disposition effect in stocks and the reverse-disposition effect in funds.

We use three proxies for experience: self-reported skill, enrollment in an upper level investments class, and ownership of stocks or funds in real life. In regressions not shown, we

[12]For example, List (2003) and List (2011) find that experienced sports card traders exhibit far less of an endowment effect than inexperienced traders, while Haigh and List (2005) find that experienced futures and options traders exhibit greater myopic loss aversion than student subjects. 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.

test whether experience reduces the level of bias by running our basic regression (Equation 1) with a each measure of experience and an interaction term between *Gain* and that measure. For mutual fund traders, we find evidence that more experienced traders exhibit a lower level of the reverse-disposition effect, with the effects being statistically significant for self-reported experience and ownership experience, and marginally significant for students in the Investments class. For stocks, the results are inconsistent across the measures of experience, with students who own stocks displaying a significantly lower disposition effect, but Investments students displaying a weakly greater disposition effect. This last result does not seem to admit a clear interpretation.[13]

Similar to experience, a literature on gender-based differences in preferences suggests that we might observe differences in the reaction to the treatments from men and women.[14] In regressions not shown, we repeated our standard regression (Equation 1) with a dummy for female and an interaction term between *Gain* and the female dummy. Consistent with Ben-David and Hirshleifer (2012), we do not find significant differences between men and women in terms of their level of the disposition effect,[15] but we do not have enough statistical power to rule out substantial differences between genders.

6 Discussion

6.1 Cognitive Dissonance

Our results contribute to the literature that argues in favor of a cognitive dissonance explanation of the disposition effect. This explanation was first advanced by Zuchel (2001),

[13] Actual ownership of stocks and funds may be a better measure of experience than self-reported measures or having taken more classes. This last measure may be problematic if the composition of students in the Investments class is systematically different in ways beyond trading experience.

[14] See Croson and Gneezy (2009) for a recent review of the literature.

[15] Women display a larger disposition effect in stocks and a larger reverse-disposition effect in funds, but neither difference is significant at conventional levels. Similarly, women display a smaller response to all of the treatments, but the differential is not statistically significant at conventional levels.

and a similar argument was put forward in Kaustia (2010b) based on self-justification and regret avoidance. While cognitive dissonance is plausible as an explanation of the disposition effect, the previous literature has provided little positive evidence that points directly to it as the cause.[16] We present direct evidence in favor of cognitive dissonance as a driver of the disposition effect.

Cognitive dissonance also provides a potential explanation for a puzzling contrast in the mutual fund literature. Mutual fund *managers* who inherit an existing portfolio tend to sell off the losing stocks and hold the winners (Jin and Scherbina (2011)), but fund managers trading their own stock choices do the opposite (Frazzini (2006)).[17] Jin and Scherbina (2011) argue that new managers have incentives to trade in a way that distinguishes them from their predecessor, which is likely part of the explanation. Nonetheless, cognitive dissonance provides another way to understand the divergent behavior: since the new manager did not make the choice to buy the stocks, the fact that some are at a loss does not cause him any cognitive dissonance, and hence there is no bias away from selling the losers.

A second set of results that is consistent with cognitive dissonance is the finding in Shapira and Venezia (2001) that investors who trade independently display a larger disposition effect than those who trade with the assistance of a broker. In this case, broker advice can be thought of as being partway between full delegation to a fund manager and trading entirely on one's own account, and the reduced disposition effect is consistent with this.

Cognitive dissonance also provides an alternative explanation for the experimental result in Weber and Camerer (1998) that the disposition effect is significantly reduced when traders have their shares automatically sold for them (with the option of costlessly repur-

[16] Zuchel (2001) and Hartzmark and Solomon (2012) mainly argue for cognitive dissonance by noting problems with competing explanations, while Kaustia (2010b) argues for the cognitive dissonance approach based on the discontinuity in the probability of selling at a gain, which is also consistent with other explanations.

[17] Weber and Zuchel (2005) and Pedace and Smith (2013) document similar behavior among experimental subjects in a trading game and managers of Major League baseball teams, respectively.

chasing them), rather than having to choose to sell shares deliberately. Weber and Camerer (1998) argue that this result is part of a general desire to not realize losses, as in prospect theory. Cognitive dissonance predicts the same result through a different mechanism: by automatically selling all assets at the start of each period, investors no longer need to actively admit they were wrong in order realize losses.

Finally, cognitive dissonance provides a potential explanation for the result in Strahilevitz et al. (2011) that investors are reluctant to *re*-purchase stocks that have risen in price since the previous sale. Strahilevitz et al. (2011) argue that this is due to investor regret over the previous decision to sell, and an avoidance of assets that generated previous negative emotions. Cognitive dissonance provides a related explanation, whereby investors dislike repurchasing assets that have risen in price because this would force them to admit that the previous decision to sell was a mistake. Interestingly, Frydman et al. (2013) study the repurchase effect and find a very strong relation across investors between the level of the disposition effect and the level of the repurchase effect (correlation = 0.71, p-value$<$0.001). This is consistent with the possibility that both effects are driven by the level of cognitive dissonance that investors experience when analyzing the negative consequences of past investment decisions.

6.2 Private Information, Portfolio Re-balancing, and Mean-Reversion

Two potential explanations for the disposition effect that are close to standard portfolio choice models are private information or portfolio diversification (re-balancing). Odean (1998) argues against private information driving the effect in stocks, noting that disposition effect trading in stocks reduces returns. Separately, Frazzini (2006) and Wermers (2003) show that increased disposition-effect behavior is associated with lower performance for mutual fund managers. These findings are consistent with the momentum effect in stock prices (Jegadeesh and Titman (1993)) whereby stocks with high past returns (which investors tend to sell) have higher future returns, while stocks with low past returns (which investors tend to hold) have lower future returns. The fact that investors have a reverse-disposition effect in equity mutual funds, even though these do not show such return persistence (Carhart (1997)), means that a reverse-disposition effect is unlikely to increase investor returns in funds.

Traders may also sell winning stocks to avoid having those stocks over-weighted in their portfolio, but Odean (1998) also casts doubt on this explanation by showing that the disposition effect also holds for sales of the individual's entire holding of a stock. Our results reinforce this conclusion, as it is not clear why portfolio re-balancing should cause investors to trade differently in stocks versus funds in either our small investor trading data or our experiment.

An alternative explanation (from Odean (1998)) is based on an unjustified belief in mean-reversion of stock prices. In this view, disposition-related trading is due to mistaken estimates of future price movements. Odean (1998) argues in favor of this by casting doubt on a host of alternative rational explanations, although a direct test of an irrational belief in mean-reversion has proven difficult to devise. If belief in mean-reversion is driving our results, then traders must believe simultaneously in mean-reversion in returns across a wide variety of non-delegated assets (as in Table 3 and the papers listed in footnote 1), and also believe in return persistence for delegated assets.

Cognitive dissonance gives a different perspective on the possibility of a mistaken belief in mean-reversion. In particular, investors may indeed convince themselves that a stock that they have bought which has fallen in price is likely to experience a subsequent price increase. The difference, however, is that the change in beliefs is the *result* of responding to the underlying cognitive dissonance, rather than the direct cause. More importantly, under a cognitive dissonance view, investors do not have a belief in mean reversion for stocks in general. They do not even have an ex-ante believe in mean reversion for the stocks they buy. Instead, they only believe in mean reversion once they face a loss in a particular asset, as a way to rationalize current poor performance.

6.3 Returns-Based Preferences

An important class of explanations for the disposition effect assumes that traders have non-standard preferences over returns. Initial behavioral explanations focused on prospect theory (Kahneman and Tversky (1979)) and mental accounting (Thaler (1980)). Under these theories, 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)). Given the problems of simple prospect theory explanations,[18] richer models based on preferences over gains and losses have been proposed. Barberis (2012) models casino gambling with time-inconsistent, prospect-theory preferences, and demonstrates a disposition effect. Another proposed explanation has been realization utility (Barberis and Xiong (2009, 2012), Ingersoll and Jin (2013)), where traders gain utility from the act of selling at a gain, rather than from receiving information about the gain. Frydman et al. (2012) have provided neurological evidence from fMRI imaging that the disposition effect is associated with enjoyment at the point that gains 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.

Our results present a challenge for explanations based purely on preferences over returns.

[18] Barberis and Xiong (2009) and Hens and Vlcek (2011) show theoretically that prospect theory may not produce a disposition effect after accounting for the investor's decision to enter the market in the first place. Empirically, Hartzmark and Solomon (2012) document the existence of the disposition effect in negative expected return gambling markets, which standard prospect theory investors seem unlikely to enter. Kaustia (2010b) and Ben-David and Hirshleifer (2012) both examine the predictions of prospect theory and realization utility for the *shape* of the relationship between the propensity to sell and the level of gains and losses. Kaustia (2010b) finds a discontinuity in the probability of selling at zero and a steepening response in the gain region but little response in the loss region, which he argues is inconsistent with prospect theory. By contrast, Ben-David and Hirshleifer (2012) find a V-shape that is steeper in the gain region and argue that this is inconsistent with realization utility but is consistent with belief revision.

In particular, the results in Table 2 show that different disposition-effect behavior is observed for the same investor across different asset classes. Since that investor presumably has the same preferences over returns from different asset classes, some other explanation must be invoked for why investors display a reverse-disposition effect in delegated assets. However, this does imply that preferences over returns do not play any role in the disposition effect. Instead, cognitive dissonance provides a new perspective on the evidence that investors have realization preferences over gains and losses, such as in Frydman et al. (2012). The difference is that, unlike in Barberis and Xiong (2012), the utility derived is not due to the returns themselves, but rather to the uncomfortable feelings generated by having to face up to poor decisions. Our findings are thus consistent with the evidence on realization utility but suggest that the carrier of utility may not just be wealth, but also the psychological costs of admitting to mistakes.

7 Conclusion

In this paper, we examine how the propensity of traders to sell assets at a gain varies across asset classes, and we provide an explanation as to the underlying cause of this variation. Investors display a disposition effect in stocks, being more likely to sell when at a gain, but a reverse-disposition effect in funds, being more likely to be sell at a loss. Using both individual trading data and experimental data, we argue that both effects can be understood as a response by investors to feelings of cognitive dissonance when they face a loss.

The results in this paper have implications for intermediation in financial decision-making. Our results suggest that programs designed to promote active individual investor involvement may have the unintended consequence of exacerbating the disposition effect. In some cases, such as investors trading stocks, this may by costly for investors by decreasing returns to investing.

In other contexts, however, a greater level of disposition behavior may actually be desirable. For many managed funds, the tendency of investors to withdraw money in response to poor fund returns is directly costly because of the increased trading expenses and the possibility of inefficient forced liquidation. From a market behavior perspective, withdrawals from funds after losses are a key part of the mechanism underlying the difficulty arbitrageurs face in correcting mispricing (e.g. the "Limits to Arbitrage" literature, such as Shleifer and Vishny (1997)).

Our findings suggest that whether or not investors react to poor fund performance by withdrawing money depends on whether they view their own choices or the fund manager's choices as being more responsible for the investor's performance. The base tendency is to blame the fund manager, but our experimental treatments indicate that this tendency can be increased or decreased according to whether the investor is encouraged to focus on the role of the manager. This suggests that funds may be able to decrease the likelihood of receiving outflows in bad times by encouraging investors to feel more ownership of the fund's investment decisions. For agency theory more generally, our results show that a principal may not treat returns generated by an agent the same way as returns they generate themselves.

Cognitive dissonance presents a departure even from many other theories in behavioral finance, in that investors' actions are ultimately driven by *psychological* costs, rather than financial ones. In other words, part of the pain associated with negative returns is not just the foregone wealth and consumption (although this obviously plays a considerable role), but also the discomfort from having to face up to the foolishness of one's earlier decisions. The idea that investors may change their beliefs or take costly actions to preserve their sense of self-identity may seem odd in a financial setting, but would not be surprising to many social psychologists. The question of what other effects cognitive dissonance may have on market behavior and agency relationships is one worthy of future study.

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Table I
Individual Trader Summary Statistics [a]

	Mean	Std	25th Pct	50th Pct	75th Pct	N
Panel A				*Stocks*		
Assets Per Account (Total)	7.850	12.766	2	4	9	104,752
Assets Per Account/Month Observation	3.689	4.976	1	2	4	4,141,661
Stock/Month Observations at a Gain (By Account)	0.485	0.413	0	0.5	1	2,149,216
Stock/Month Observations Involving a Sale (By Account)	0.064	0.207	0	0	0	4,016,449
Stock/Month Observations at a Gain (Total)	0.504					5,846,197
Stock/Month Observations Involving a Sale (Total)	0.064					14,448,908
Number of Accounts						104,752
Number of Account/Month Observations						15,277,062
Panel B				*Equity Funds*		
Assets Per Account (Total)	3.928	5.202	1	2	4	40,320
Assets Per Account/Month Observation	2.402	2.317	1	2	3	1,250,467
Stock/Month Observations at a Gain (By Account)	0.717	0.391	0.5	1	1	757,853
Stock/Month Observations Involving a Sale (By Account)	0.045	0.190	0	0	0	1,205,419
Stock/Month Observations at a Gain (Total)	0.719					1,770,721
Stock/Month Observations Involving a Sale (Total)	0.050					2,843,772
Number of Accounts						40,320
Number of Account/Month Observations						3,004,133
Panel C				*All Assets*		
Assets Per Account (Total)	9.984	17.414	2	5	11	128,707
Assets Per Account/Month Observation	4.286	5.776	1	3	5	5,292,574
Stock/Month Observations at a Gain (By Account)	0.547	0.405	0	0.5	1	2,889,879
Stock/Month Observations Involving a Sale (By Account)	0.060	0.197	0	0	0	5,140,275
Stock/Month Observations at a Gain (Total)	0.556					8,742,490
Stock/Month Observations Involving a Sale (Total)	0.062					21,384,909
Number of Accounts						128,707
Number of Account/Month Observations						22,681,469

[a] This table presents summary statistics for the individual trading data (from Barber and Odean (2000), a sample of 128,809 accounts from a discount brokerage house between January 1991 and November 1996), described in Section 3. Gains are measured by comparing the price in that month with the volume-weighted average purchase price, calculated from the actual purchase prices. Measures listed as 'By Account' are describing the distribution of account-level averages, while measures listed as 'Total' are describing the distribution of asset-account-month observations. Panel A presents information for stocks (US equities, foreign equities, and ADRs). Panel B presents information for equity mutual funds. Panel C presents information for all assets.

Table II
The Disposition Effect: Individual Trader Data [a]

	All Investors			*Hold Stocks & Funds*			*Simultaneously Hold Stocks & Funds*		
	Stocks	*Funds*	*Both*	*Stocks*	*Funds*	*Both*	*Stocks*	*Funds*	*Both*
Gain	0.0391***	-0.0656***	0.0391***	0.0254***	-0.0543**	0.0254***	0.0157**	-0.0485**	0.0157**
	(0.0066)	(0.0260)	(0.0066)	(0.0060)	(0.0222)	(0.0060)	(0.0064)	(0.0225)	(0.0064)
Fund			0.1079***			0.0746***			0.0428**
			(0.0222)			(0.0194)			(0.0175)
Fund*Gain			-0.1047***			-0.0797***			-0.0642***
			(0.0235)			(0.0201)			(0.0199)
Constant	0.2170***	0.3249***	0.2170***	0.1952***	0.2698***	0.1952***	0.1888***	0.2316***	0.1888***
	(0.0188)	(0.0356)	(0.0188)	(0.0140)	(0.0303)	(0.0140)	(0.0173)	(0.0308)	(0.0173
Adj. R-Squared	0.002	0.004	0.004	0.001	0.003	0.002	0.0002	0.003	0.001
Observations	1,811,176	354,125	2,165,301	639,229	252,704	891,933	411,728	206,152	619,528

[a]This table examines the variation in the disposition effect between stocks and equity mutual funds for different subsets of investors. The data are individual trading records for a sample of 128,809 accounts from a discount brokerage house between January 1991 and November 1996, described in Section 3. Observations are taken monthly for assets in the particular class, during months where at least one asset of any type was sold. The dependent variable is *Sale*, a dummy variable that equals one if the investor reduced his position over the month and zero otherwise. *Gain* is a dummy variable that equals one if the price at the end of the previous month is greater than the volume-weighted average purchase price and zero otherwise. *Fund* is a dummy variable that equals one for equity mutual funds, and zero otherwise. The sample of assets includes either stocks (US equities, foreign equities and ADRs), equity mutual funds, or both, as labeled. The sample of investors includes either all investors, investors who held both stocks and equity mutual funds at some point in the sample, or investors who held both stocks and equity mutual funds in that particular month, as labeled. Standard errors are clustered by account and month, and *, **, and, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table III
The Disposition Effect by Asset Type [19]

	Delegated?	Coefficient on *Gain*	σ	*Obs.*
Warrants	No	0.1414***	(0.0219)	5,066
Foreign (Canadian)	No	0.0570***	(0.0098)	55,446
US Company Shares	No	0.0388***	(0.0071)	1,665,017
Real Estate Trust	Yes	0.0348	(0.0512)	730
Foreign (Ordinaries)	No	0.0344*	(0.0200)	15,901
Units	No	0.0276	(0.0429)	783
ADR	No	0.0235	(0.0200)	74,812
Convertible Preferred	No	0.0060	(0.0151)	11,703
Closed-End Mutual Funds	Yes	0.0026	(0.0141)	120,099
Master Limited Partnership	No	-0.0012	(0.0103)	21,310
Mutual Funds (In-House)	Yes	-0.0263	(0.0332)	41,046
Option Equity	No	-0.0285*	(0.0162)	21,642
Options Index	No	-0.0312	(0.0562)	1,647
Preferred Stock	No	-0.0351**	(0.0145)	15,979
Marketplace Load Equity Funds	Yes	-0.0366	(0.0316)	4,518
Marketplace Load Bond Funds	Yes	-0.0486	(0.0572)	480
Bond Mutual Funds	Yes	-0.0492*	(0.0265)	16,314
One Source Bond Funds	Yes	-0.0525**	(0.0222)	34,621
One Source Equity Funds	Yes	-0.0614**	(0.0283)	246,927
Ex One Source Bond Funds	Yes	-0.0749	(0.0474)	2,185
Equity Mutual Funds	Yes	-0.0806***	(0.0214)	85,846
Ex One Source Equity Funds	Yes	-0.0844***	(0.0295)	16,834

Table IV
The Disposition Effect in Index Funds and Other Equity Mutual Funds [a]

	Index Funds Only	*All Equity Funds*	*All Equity Funds*	*Index Funds & Stocks*
Gain	0.0035	-0.0662***	-0.0433	0.0391***
	(0.0369)	(0.0261)	(0.0263)*	(0.0066)
Index		-0.0515**	-0.0388	0.0036
		(0.0234)	(0.0240)	(0.0327)
Index*Gain		0.0587*	0.0672**	-0.0357
		(0.0300)	(0.0301)	(0.0361)
Alive			-0.0328***	
			(0.0081)	
Alive*Gain			-0.0315***	
			(0.0087)	
Constant	0.2206***	0.3253***	0.3454***	0.2170***
	(0.0425)	(0.0357)	(0.0354)	(0.0188)
Adj. R-Squared	0.0000	0.0044	0.0080	0.0021
Observations	13,218	354,125	354,125	1,824,394

[a]This table examines how the disposition effect varies between index funds, actively managed mutual funds and stocks. The data are individual trading records for a sample of 128,809 accounts from a discount brokerage house between January 1991 and November 1996, described in Section 3. Observations are taken monthly for the asset classes listed, during months where at least one asset of any type was sold. The dependent variable is *Sale*, a dummy variable that equals one if the investor reduced his position over the month and zero otherwise. *Gain* is a dummy variable that equals one if the price at the end of the previous month is greater than the volume-weighted average purchase price and zero otherwise. *Index* is a dummy variable that equals one if the mutual fund is an index fund and zero otherwise. *Alive* is a dummy variable that equals one if the fund was still in existence between 1996 and 2001 (when the CUSIPs that match up the index fund data first became available). Standard errors are clustered by account and month, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table V
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
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
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
N	-	141	-	122

[a] This table presents summary statistics for an experiment where 514 undergraduate students traded either 30 mutual funds or 30 stocks at daily closing prices over a period of 12 weeks, as described in Section 4. *Fire* and *Story* are the two randomized treatment conditions, described in section Section 4. 'Class Level' is the year of the student in their degree. 'Owns Stocks' and 'Owns Funds' refer to whether the student owns either stocks or mutual funds in real life. 'Investing Experience' is the student's self-rated score of their investing experience. In all cases, baseline characteristics are not statistically distinguishable across any treatment arms. 19 students had class year variables of "other" and were not included in the Class Year summary statistic.

Table VI
The Experimental Disposition Effect For Funds [a]

Gain	-0.141**	-0.0594	-0.048	-0.000771
	(0.0553)	(0.067)	(0.061)	(0.0655)
Fire		0.116		0.106
		(0.0987)		(0.0957)
Gain*Fire		-0.211**		-0.174*
		(0.103)		(0.104)
Story			0.0655	0.0396
			(0.0895)	(0.0832)
Gain*Story			-0.211**	-0.173**
			(0.0883)	(0.0877)
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]This table presents the results of regressions examining how the disposition effect in mutual funds varies with two randomized treatments affecting delegation and cognitive dissonance. An experiment was conducted in which 257 undergraduate students traded 30 mutual funds at daily closing prices over a period of 12 weeks, as described in Section 4. Observations are taken daily for all funds in the student's portfolio, on days where the student sold at least one fund. The dependent variable is *Sale*, a dummy variable that equals one if the student reduced his position in the fund that day and zero otherwise. *Gain* is a dummy variable that equals one if the price on the previous day is greater than the volume-weighted average purchase price and zero otherwise. *Fire* is a dummy variable for the Fire treatment. This is designed to increase the salience of the fund manager, by replacing "Buy", "Sell", and "Portfolio performance/gain/loss" replaced with the words "Hire", "Fire", and "Fund Manager's performance/gain/loss" throughout the website. *Story* is a dummy variable for the Story treatment. This is designed to increase the cognitive dissonance that participants feel when they face a loss. All subjects must list a reason for purchasing each asset, and treated subjects are reminded of their previously stated reasons on the portfolio screen and the sell screen. Both treatments are described in more detail in Section 4. Standard errors are clustered by student and day, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table VII
The Experimental Disposition Effect For 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]This table presents the results of regressions examining how the disposition effect in stocks varies with a randomized treatment affecting cognitive dissonance. An experiment was conducted in which 263 undergraduate students traded 30 Dow Jones stocks at daily closing prices over a period of 12 weeks, as described in Section 4. Observations are taken daily for all funds in the student's portfolio, on days where the student sold at least one fund. The dependent variable is *Sale*, a dummy variable that equals one if the student reduced his position in the fund that day and zero otherwise. *Gain* is a dummy variable that equals one if the price on the previous day is greater than the volume-weighted average purchase price and zero otherwise. *Story* is a dummy variable for the Story treatment. This is designed to increase the cognitive dissonance that participants feel when they face a loss. All subjects must list a reason for purchasing each asset, and treated subjects are reminded of their previously stated reasons on the portfolio screen and the sell screen. The treatment is described in more detail in Section 4. Standard errors are clustered by student and day, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table VIII
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
Profit	-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*Profit	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*Profit	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] This table examines how self-reported learning about trading mutual funds varies with the two treatments in the trading experiment, as described in Section 4. At the conclusion of the experiment, students evaluated, on a 1-10 scale, their own skill, how much they learned about their own skill and the skill of the managers of the funds they purchased, and their willingness to invest in funds in general and the actual funds they purchased. In Panel A, these survey responses are regressed on the treatment condition the student was assigned. *Fire* is a dummy variable for the Fire treatment. *Story* is a dummy variable for the Story treatment. In Panel B, the *Story* and *Fire* variables are interacted with *Profit*, a dummy variable that equals one if the student finished the experiment with a total portfolio gain and zero otherwise. Standard errors are clustered by student and day, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table IX
Exit Questionnaire: Stocks [a]

	Panel A				
	Own Skill	*Learning*		*Willingness to Invest*	
		Self	Firm Value	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	Firm Value	Any	Owned
Profit	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*Profit	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]This table examines how self-reported learning about trading stocks varies with the treatment in the trading experiment, as described in Section 4. At the conclusion of the experiment, students evaluated, on a 1-10 scale, their own skill, how much they learned about their own skill and the value of the companies they purchased, and their willingness to invest in stocks in general and the actual stocks they purchased. In Panel A, these survey responses are regressed on the treatment condition the student was assigned. *Story* is a dummy variable for the Story treatment. In Panel B, the *Story* variable is interacted with *Profit*, a dummy variable that equals one if the student finished the experiment with a total portfolio gain and zero otherwise. Standard errors are clustered by student and day, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table X
The Impact of Delegation, Volatility and Holding Period on the Disposition Effect [a]

Gain	0.0188	0.0341	-0.0123	0.0564	-0.1253	-0.0025	0.0035	-0.1000
	(0.0081)**	(0.0063)***	(0.0141)	(0.0082)***	(0.0190)***	(0.0195)	(0.0055)	(0.0296)***
Delegated		0.0675	0.0818	0.0736	0.0776	0.0662	0.0463	0.1110
		(0.0149)***	(0.0176)***	(0.0145)***	(0.0145)***	(0.0155)***	(0.0136)***	(0.0138)***
Delegated*Gain		-0.0802	-0.0351	-0.0843	-0.0850	-0.0795	-0.0655	-0.0687
		(0.0185)***	(0.0156)**	(0.0182)***	(0.0184)***	(0.0187)***	(0.0169)***	(0.0125)***
Volatility			0.0098					0.0275
			(0.0069)					(0.0052)***
Volatility*Gain			0.0302					0.0093
			(0.0098)***					(0.0082)
Holding Period (Account)				-0.0861				-0.0658
				(0.0100)***				(0.0095)***
Holding Period (Account)*Gain				-0.0110				-0.0140
				(0.0039)***				(0.0032)***
Holding Period					-0.2267			-0.1857
					(0.0158)***			(0.0157)***
Holding Period*Gain					0.1074			0.0856
					(0.0119)***			(0.0115)***
Log Dollar Value (Position)						0.0043		-0.0170
						(0.0016)***		(0.0020)***
Log Dollar Value (Position)*Gain						0.0040		0.0002
						(0.0023)*		(0.0016)
Portfolio Weight (Position)							0.6266	0.6314
							(0.0115)***	(0.0134)***
Portfolio Weight (Position)*Gain							0.0935	0.0794
							(0.0079)***	(0.0083)***
Constant	0.2328	0.2212	0.2064	0.3383	0.5620	0.1856	0.1470	0.6098
	(0.0200)***	(0.0185)***	(0.0156)***	(0.0258)***	(0.0203)***	(0.0286)***	(0.0160)***	(0.0253)***
Adj. R-Squared	0.0005	0.0022	0.0029	0.0235	0.0077	0.0027	0.0917	0.1133
Observations	2,468,473	2,468,346	2,468,346	2,468,346	2,468,346	2,468,346	2,468,346	2,468,346

[a] This table examines how the level of the disposition effect varies with delegation, asset volatility and holding period. The data are individual trading records for a sample of 128,809 accounts from a discount brokerage house between January 1991 and November 1996, described in Section 3. Observations are taken monthly for assets in all asset classes except money market funds, during months where at least one asset of any type was sold. The dependent variable is *Sale*, a dummy variable that equals one if the investor reduced his position over the month and zero otherwise. *Gain* is a dummy variable that equals one if the price at the end of the previous month is greater than the volume-weighted average purchase price and zero otherwise. *Delegated* is a dummy variable that equals one if the asset class involves delegation to a portfolio manager and zero otherwise. *Volatility* is the volatility of returns for that asset class, calculated by first estimating the standard deviation of returns for each asset individually, then averaging across the asset class. *Holding Period* is the average holding period by asset class. *Holding Period (Account)* is the average holding period for all assets in an individual account. *Log Dollar Value (Position)* is the log of the dollar value of a given position. *Portfolio Weight (Position)* is the account level portfolio weight of a given position. Standard errors are clustered by account and month, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Appendix: Mutual Funds and Figures

The funds included in the experiment were the following:

#	Fund Name	Ticker
1.	Fidelity Contrafund	FCNTX
2.	Fidelity Advisor New Insights I	FINSX
3.	ING Value Choice Fund	PAVAX
4.	Franklin Growth Adv.	FCGAX
5.	Franklin Rising Dividends Fund	FRDAX
6.	Janus Aspen Perkins Mid Cap Value	JAMVX
7.	Janus Triton Fund Class A	JGMAX
8.	American Century Equity Income A	TWEAX
9.	American Century Mid Cap Value Inv	ACMVX
10.	American Century Small Cap Value Inv	ASVIX
11.	Vanguard Dividend Appreciation	VDAIX
12.	Vanguard Dividend Growth	VDIGX
13.	Vanguard PRIMECAP Admiral Shares	VPMAX
14.	Dreyfus Research Growth Z	DREQX
15.	Dreyfus Tax-Managed Growth I	DPTRX
16.	Invesco Van Kampen SmallCapValue Y	VSMIX
17.	Invesco Charter R	CHRRX
18.	Invesco Diversified Dividend Investor	LCEIX
19.	Invesco Mid Cap Core Equity I	GTAVX
20.	JPMorgan Investor Growth Select	ONIFX
21.	JPMorgan Small Cap Equity A	VSEAX
22.	JPMorgan US Equity Select	JUESX
23.	Prudential Jennison Equity Income A	SPQAX
24.	Prudential Jennison Mid Cap Growth R	JDERX
25.	Schroder US Opportunities Inv	SCUIX
26.	Schroder US Small & Mid Cap Opportunities	SMDIX
27.	ING Mid Cap Opportunities Fund	NMCIX
28.	Wells Fargo Advantage Growth C	WGFCX
29.	Wells Fargo Advantage Omega Growth R	EKORX
30.	Wells Fargo Advantage Premier Large Companies	EKJYX

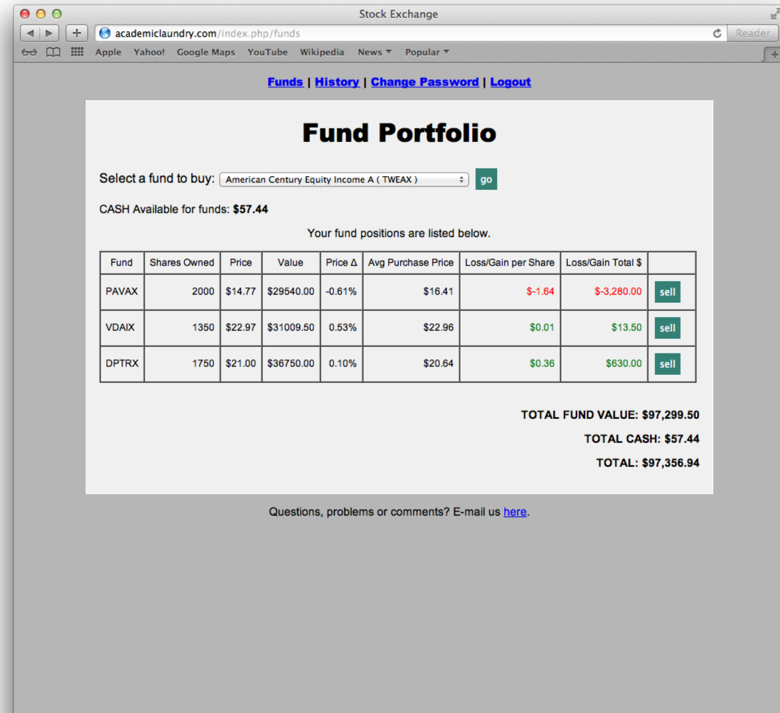

Figure 1: Main portfolio screen, no treatments.

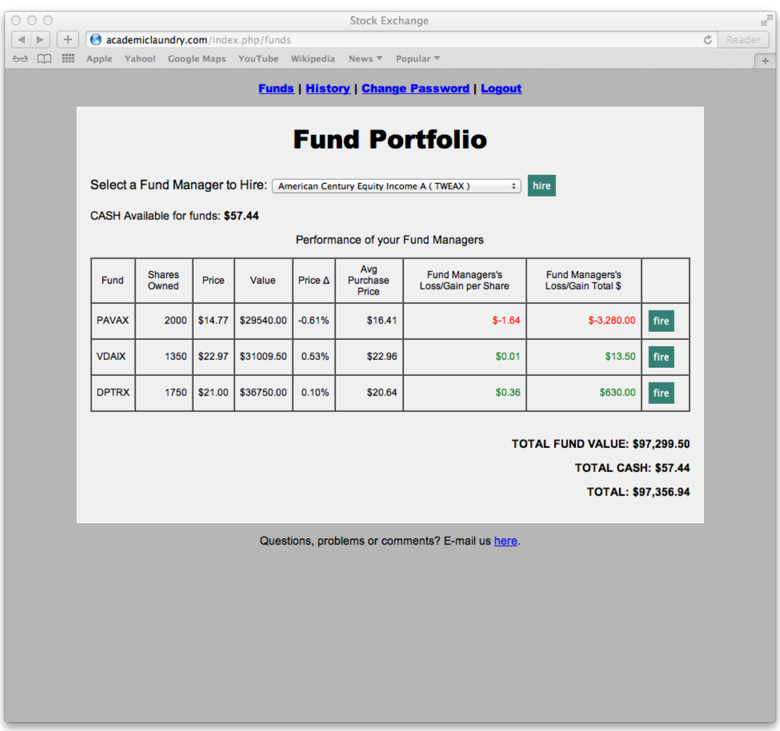

Figure 2: Main portfolio screen, Fire treatment.

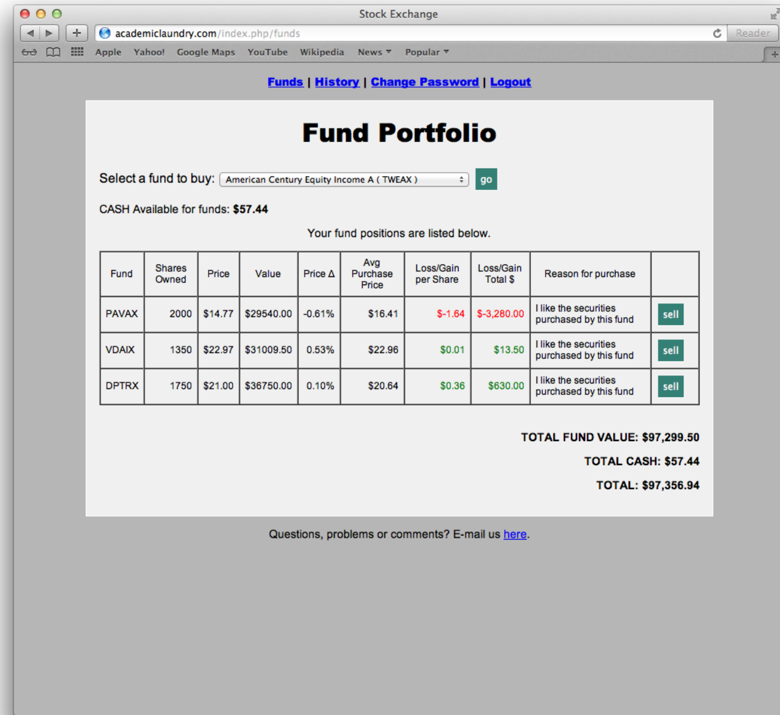

Figure 3: Main portfolio screen, Story treatment.

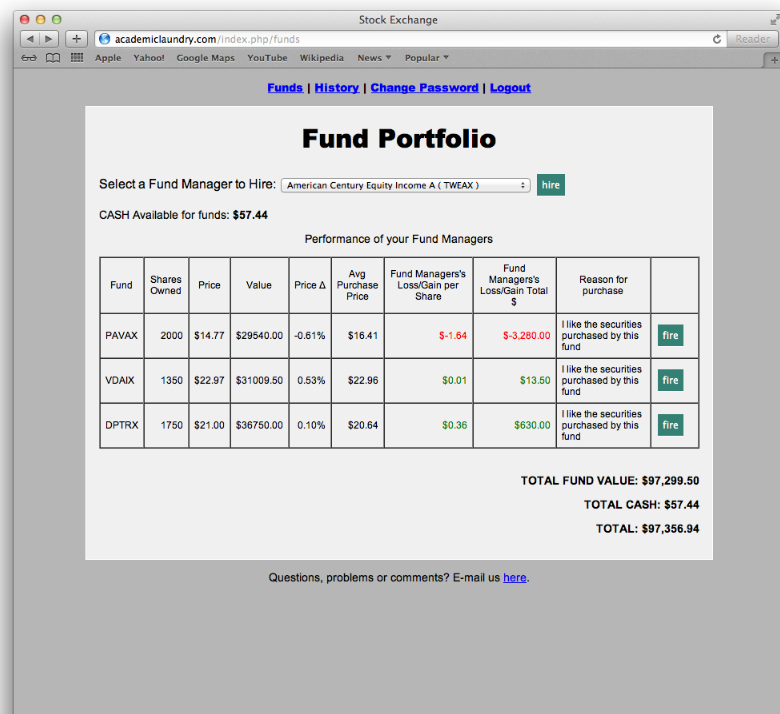

Figure 4: Main portfolio screen, both treatments.

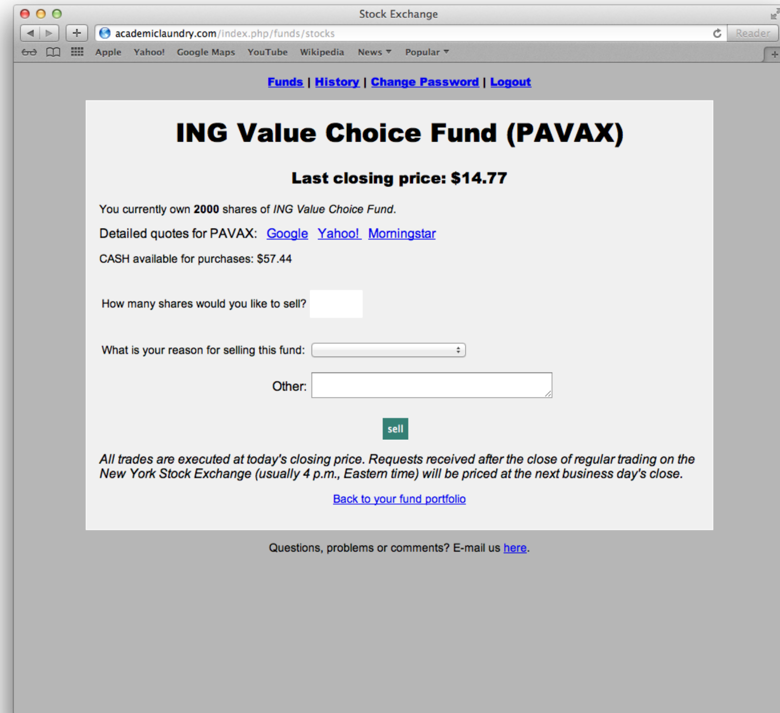

Figure 5: Sell screen, no treatments.

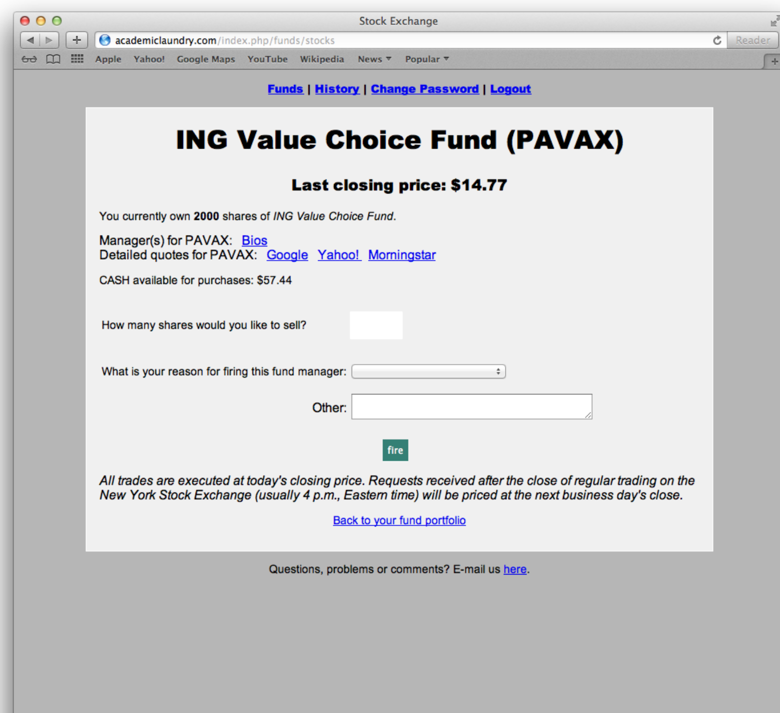

Figure 6: Sell screen, Fire treatment.

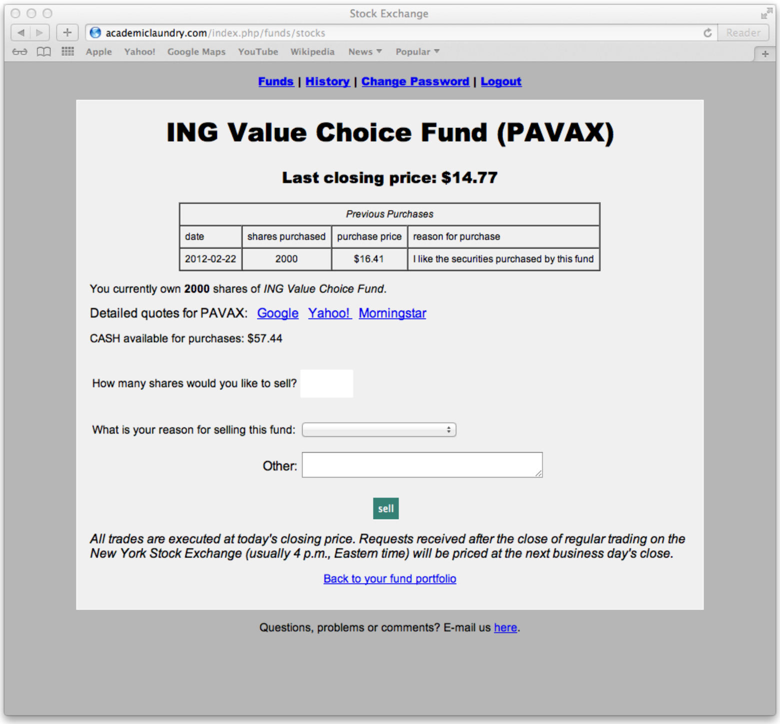

Figure 7: Sell screen, Story treatment.

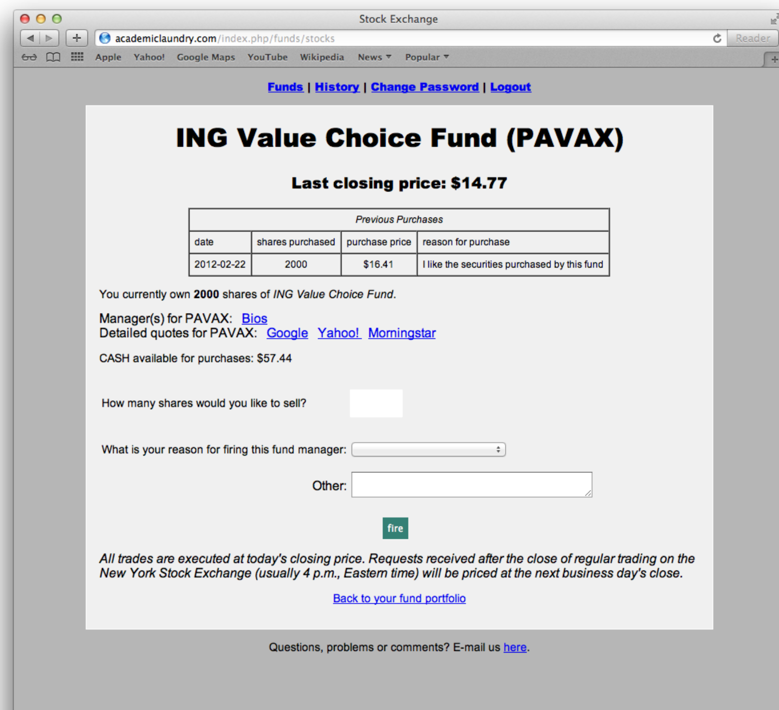

Figure 8: Sell screen, both treatments.