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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 nondelegated assets like individual stocks; delegated assets, like mutual funds, exhibit a robust reverse-disposition effect. In an experiment, we show that increasing investors' cognitive dissonance results in both a larger disposition effect in stocks and 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.

IN RECENT YEARS, ECONOMISTS have come to appreciate the importance of household investment decisions for understanding both decision-making under risk and the behavior of investors in financial markets (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 (Shefrin and Statman (1985)).[1] Despite the near-ubiquity of the disposition effect, however, the underlying mechanism is not

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

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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, as investors have a greater propensity to sell losing funds compared to winning funds. This fact has been known at least since Friend, Blume, and Crockett (1970), but has been discussed primarily 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 greater outflows. Importantly, this finding holds for flows from existing investors as well as new investors (Ivković and Weisbenner (2009) and Calvet, Campbell, and Sodini (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 has received little discussion in the literature that seeks to understand what drives the disposition effect.

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 begin by describing the psychological theory of cognitive dissonance—formalized by a three-period trading model in the Internet Appendix[3]—demonstrating how cognitive dissonance can generate a disposition effect in nondelegated assets like stocks but a reverse-disposition effect in delegated assets like mutual funds. We then analyze data from individual trading accounts and an experiment, and 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 semirational learning models, purely returns-based preferences, and variation in risk attitudes—are insufficient to explain our results. Finally, we provide direct empirical evidence of the role of cognitive dissonance in generating a disposition (and reverse-disposition) effect from an online trading experiment.

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)). This discomfort is particularly acute when one of the beliefs in question relates to the individual's self-concept (e.g., Gecas (1982)). We argue that investors feel a cognitive dissonance discomfort when faced with losses—there is a disconnect between the belief that the investor makes good decisions and the fact that the investor has now lost money on the position. While all losses cause such dissonance, realized losses create a greater level of discomfort than paper losses: when the loss exists only on paper the investor is able to partly resolve the dissonance by convincing themselves that the loss is only a temporary setback. This reduces the blow to their self-image of being someone who makes good decisions. When the loss is realized, it becomes permanent, which makes it harder for the investor to

[2] See the discussion in Sections III.D and IV.

[3] The Internet Appendix is available in the online version of the article on the *Journal of Finance* website.

avoid the view that buying the share may have been a mistake. Cognitive dissonance provides the basis for an overall reluctance to realize losses, and thus generates a wedge relative to the investor's propensity to realize gains (where no such dissonance discomfort exists).

An important difference arises in the case of delegated assets, where decision-making authority has been ceded to an outside agent. For these assets, investors can instead resolve the disutility of realized losses by scapegoating and blaming the manager. Specifically, if the asset is delegated, then the investor can blame the fund manager for the poor performance and sell the asset without admitting to his or her own mistakes. At its simplest level, the model captures the intuition that investors do not like to admit that they were wrong, and will blame someone else to avoid admitting a mistake if they can.[4]

Our first contribution is to empirically document the scope of the puzzle: how much does the disposition effect vary across asset classes? In individual trading data (the data set 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 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 that 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 driven by differences in the propensity to sell losses. This is consistent with the predictions of cognitive dissonance, since it is only in the loss domain that there is a dissonance to be resolved.

Existing literature focuses on understanding the disposition effect in general, but does not provide a ready explanation for the variation across asset classes. Because the variation in trading behavior across asset classes exists even among investors that hold multiple asset classes, 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, realization utility), some other factor must be invoked to explain its nonexistence in funds.

Our second contribution is to provide direct, positive evidence of the role of cognitive dissonance in generating the disposition effect. In particular, we

[4] The experimental literature on delegation and blame documents that principals blame agents for bad outcomes (see, for example, Hamman, Loewenstein, and Weber (2010) and Bartling and Fischbacher (2012), and the discussion in Section I). The idea that delegation is useful because it provides someone to blame for poor performance is similar in spirit to the idea in Lakonishok, Shleifer, and Vishny (1992, p. 342) 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." See Barberis (2011) for a discussion of cognitive dissonance in the context of bank losses during the financial crisis.

exogenously increase cognitive dissonance and the psychological impact of delegation on an individual's choices while holding fixed the economic differences in the underlying assets and managerial skill. 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 are subjected to two different randomized treatments. The first treatment effect, which we call the "Story" treatment, is designed to increase cognitive dissonance. All students have to give a reason for purchasing an asset (stock or fund), and students in the Story treatment are reminded 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 increase the actions that individuals take in response to the cognitive dissonance.

As predicted by our model, we find that this treatment generates an increase in both the magnitude of the disposition effect for stocks *and also* the magnitude of 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 difficult to reconcile with competing explanations, however, particularly since students are not provided 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. For students in the Fire treatment, the words "Buy," "Sell," and "Portfolio performance/gain/loss" are 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 links to fund managers' biographies. As predicted, when the role of the manager is made more salient to investors, they display a more pronounced reverse-disposition effect.

Finally, we report 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 about fund manager skill. We use the survey results to test this possibility directly. We find that, while the treatments themselves have no impact on self-reported measures of learning, the mean effect masks an effect consistent with our theory: increasing cognitive dissonance reduces the amount that individuals claim to learn when they are at a loss, which is when the new information conflicts with their priors.[5]

[5] Cognitive dissonance predicts that learning should be asymmetric in gains and losses, as shown in other settings (e.g., Mobius et al. (2012) and Kuhnen (2015)). The asymmetry arises from the fact that individuals are more likely to discount new information if it suggests that the decision to purchase the asset was a bad one.

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 existing theories of the disposition effect. Models based on prospect theory or realization utility primarily consider investors as having preferences over the returns themselves. Instead, our findings suggest that at least part of the source of utility when evaluating portfolio gains and losses is the psychological cost of admitting mistakes.

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 V.

I. The Intuition behind Cognitive Dissonance

In this section, we introduce cognitive dissonance intuitively. The theory is formalized in a simple trading model in the Internet Appendix.

Social psychology defines a "cognition" as a mental process or thought 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 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 as in Seru, Shumway, and Stoffman (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 importance of actions in shaping beliefs, particularly beliefs relating to positive self-concept.

Once an action is undertaken in support of a belief, this belief becomes extremely strong. As Festinger (1957, p. 1) describes, such action-supported beliefs are often so strong that if "he is presented with unequivocal and undeniable evidence that his belief is wrong . . . [t]he individual will frequently emerge, not only unshaken, but even more convinced of the truth of his beliefs than ever before." In other words, when individuals are faced with a subsequent cognition that is dissonant with the original decision-consistent one, they will use various psychological means to reduce dissonance-related discomfort *without* relinquishing the original cognition.[6] These defense mechanisms are particularly powerful when the original cognition relates to positive self-image.[7] In particular, people are particularly reluctant to change their beliefs in ways that would cause them to have a more negative view of themselves. More generally, the key finding in the literature on self-concept or self-identity is that facts and preferences are molded to fit one's identity, as opposed to the other way around (see, for example, Gecas (1982)).

There is a direct map between the three methods for reducing dissonance and whether investors will display a disposition effect. The two relevant cognitions after an asset has declined in value are:

1. The original decision-consistent cognition: "I am a clever investor that bought this asset for a good reason."
2. The new information that the asset 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 means changing the original, decision-consistent cognition—that is, relinquishing the notion that buying the asset was a good idea. Traders resist this path because, as described above, admitting that they made a poor investment choice would negatively impact their self-image, and the action of having purchased the asset strengthens their belief in the soundness of their decisions.

[6] 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, Bloom, and Santos (2010)), effort justification (Aronson and Mills (1959)), belief disconfirmation (Festinger, Reckon, and Schacterl (1956)), and the Benjamin Franklin effect (Jecker and Landy (1969)).

[7] For example, Greenwald and Ronis (1978, p. 54) state that "the motivational force in present versions of dissonance theory has much more of an ego-defensive character . . . The theory seems now to be focused on cognitive changes occurring in the service of ego defense, or self-esteem maintenance."

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.

The third way of dealing with dissonance is to introduce an ameliorating cognition. When the asset is a delegated portfolio, such a cognition is readily available: the decline can be blamed on the portfolio manager. In this case investors in mutual funds will blame the fund manager for poor returns, rather than themselves. Importantly, this blame is tied to an action: selling fund shares. If the investor thinks the fund manager is at fault for a loss (or has downgraded his assessment of the manager's quality), then a minimum consistency requirement of blaming the fund manager is that the investor is more likely to sell the fund's shares.

The essential question the investor faces when deciding whom to blame is how to assign overall culpability for the bad outcomes. Because investors will seek to preserve their self-image, it is easier for them to decide that the actions of the manager contributed more to the bad outcome rather than the investor's own actions. As a result, blaming the manager allows them to excuse their own role in the process and preserve their self-image that they make sound decisions. Logically, investors could (and maybe should) still choose to blame themselves for their role in the returns if they wished, for instance, for their choice of fund manager. Nonetheless, the point of cognitive dissonance theory, particularly as it relates to the preservation of self-conception, is that investors are actively 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.

Assessing the relevance of the portfolio manager for blame requires addressing two questions: first, "Do principals blame delegates?", and second, "Is the fund manager an important target for blame in this case?". To answer the first question, we draw on an extensive experimental literature describing the relationship between delegation and blame: "principals acting through agents do not feel responsible for outcomes, even though their actions played a central role in producing [the] outcomes" (Hamman, Loewenstein, and Weber (2010, p. 1827)) and "responsibility can be effectively shifted [to the delegate] and . . . this can constitute a strong motive for the delegation of a decision right" (Bartling and Fischbacher (2012, p. 67)).[8]

Experimental evidence on how to choose between potential scapegoats is more scarce, but we believe the fund manager is particularly salient. This is as opposed to, for example, the CEO of a company, an index fund manager, or other potential targets for blame. First, the task of the active portfolio manager (picking assets with high returns) is similar to the task of the investor (picking a good fund, or picking a good fund manager) in a way that the task of the CEO

[8] See also, for example, Coffman (2011), Fershtman and Gneezy (2001), and Paharia et al. (2009).

(running a public company) or index fund manager (matching an index) is not. This makes the active fund manager's actions a good psychological substitute for the investor's actions. Second, the active fund manager is performing a task (picking assets) that the investor could conceivably do well himself and may have some experience with, which makes negative assessment easier ("I could have done a better job"). Third, the active fund manager has a clear impact on returns, which has been experimentally linked to the tendency to shift blame (e.g., Bartling and Fischbacher (2012)). Finally, we do not require that the active fund manager be the unique recipient of blame, but only that *adding* such a manager between the investor and the asset makes the delegate a target for blame.

In sum, the fact of a loss creates a psychological pain that the investor seeks to resolve. Regardless of what path the trader takes to resolve cognitive dissonance, realizing losses has an impact above and beyond the financial consequences, as with Barberis and Xiong (2009, 2012). While selling itself does not generate new information, it makes the status of the existing gain/loss "permanent" and confirms a particular narrative episode (e.g., I bought share X at $10 and sold it at $5). One method of resolving cognitive dissonance is to downplay the information, and take the appropriate inaction. This effect generates an overall reluctance to realize losses relative to gains, thereby creating a positive disposition effect. For delegated assets, a second method is to blame a scapegoat (the fund manager). Since blaming the manager and selling the related asset reduces the pain associated with losses under cognitive dissonance, delegated assets will display a smaller disposition effect (at a minimum) or a negative or reverse-disposition effect if the effect of delegation is large enough.

We formalize this logic in a three-period model (with an extension to learning from prices) in the Internet Appendix. We predict that:

1. Assets that are not delegated will display a disposition effect, while those that are delegated will display a lesser disposition effect or a reverse-disposition effect. This difference is due to the psychological effects of delegation rather than the economic effects.
2. If investors experience a high level of cognitive dissonance, they will display a larger disposition effect in nondelegated assets like stocks and a larger reverse-disposition effect in delegated assets like funds. Similarly, if investors experience a low level of cognitive dissonance, they will display little to no disposition effect.
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.

II. Evidence from Individual 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 are most suited to testing the first of the predictions above, namely, whether delegated assets have more of a reverse-disposition effect than nondelegated assets. We document three new stylized facts based on the Barber and Odean (2000) Individual-investor trading data:

1. The disposition effect in stocks and the reverse-disposition effect in funds are exhibited by the same investors at the same time (Table II).
2. Across asset classes, investor-chosen assets are associated with a positive disposition effect and delegated-portfolio assets are associated with a reverse-disposition effect (Table III).
3. 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 IV).

Our results are robust to several additional tests and extensions, including alternate controls, samples, weighting schemes, and combinations of fixed effects, as described in Section II.E and detailed in the Internet Appendix.

A. 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 that 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.[9] 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*

[9] 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).

equals one if the individual reduced the size of their position between the current month and the next month, and zero otherwise. Similarly 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 his account. In periods when 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 his portfolio during that period. We discuss the effects of this assumption in both Section II.E and in the Internet Appendix, and show that it does not drive the results. Table I presents summary statistics for the individual trader data.

B. The Disposition and Reverse-Disposition Effects

In the main analysis, we 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 so, we use the following specifications as our base models:

$$Sale_{ijt} = b_0 + b_1 Gain_{ijt} + \epsilon_{ijt}, \tag{1}$$

$$Sale_{ijt} = b_0 + b_1 Gain_{ijt} + b_2 Gain_{ijt} \times Fund_j + b_3 Fund_j + \epsilon_{ijt}, \tag{2}$$

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 are included for all stocks or funds (according to the specification) in months in which 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 his 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. The dummy variable *Fund* is equal to zero for stocks and one 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 the investor sold something that month. 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.[10] A negative coefficient indicates a reverse-disposition effect.

[10] 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 to avoid assuming that every sale choice is independent.

Table I

Individual Trader Summary Statistics

This table presents summary statistics for the individual trading data (from Barber and Odean (2000), a sample of 128,707 accounts from a discount brokerage house between January 1991 and November 1996), described in Section II. 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 account-month averages ("AMA") mean that first the average is computed for each account-month combination, and then the distribution of the account-month averages is reported. Measures listed as asset-account-month ("AAM") consider the pooled distribution of all asset-account-month observations together. Panel A presents information for stocks (U.S. equities, foreign equities, and ADRs). Panel B presents information for equity mutual funds. Panel C presents information for all assets.

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

The purpose in running the two regression specifications is to separately test whether the disposition effect in stocks and funds is 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, b_1 represents the disposition effect (i.e., the difference between the propensity to sell gains versus losses) for stocks, and the sum of the two coefficients b_1 and b_2 provides a measure of the disposition effect for funds.

To determine if the difference in the level of the disposition effect in stocks and funds is driven by a clientele effect (i.e., selection of different investor types into each asset class), we test the disposition effect across various subsets of investors and assets. In particular 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; and (3) investors who held both stocks and funds at the same time, considering only observations in the months in which they hold both assets simultaneously. Group 3 represents the most stringent test since it involves a single investor reacting to the returns of stocks and funds at the same time, which allows us to measure an individual's concurrent disposition effect across the two asset classes.

We present the results in Table II. We observe 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 on *Gain* is positive for stocks and negative for funds (with all coefficients significant at the 5% level or better).

For the stock group, the coefficient on *Gain* ranges from 0.0391 for the all-investor sample to 0.0157 for the investors who simultaneously hold both stocks and funds. The interpretation of this coefficient is that, in months when an investor sells some asset, the investor is between 3.91% and 1.57% more likely to sell a stock if it is at a gain. This is compared to 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 who simultaneously hold both stocks and equity mutual funds.

For equity mutual funds, the coefficient on *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 better. Investors are between 6.56% and 4.85% less likely to sell a fund if it is at a gain, compared to the base probability of selling any fund (in months with the sale of some asset) of 32.5% and 23.2%. In addition, the coefficient on *Fund*×*Gain* is negative and significant at the 1% level in all cases.

Note that the difference in the disposition effect between stocks and funds is driven by differences in investor propensity to sell losses. The coefficient on *Fund*, which measures the differential propensity to sell funds at a loss compared to stocks at a loss, is large and significant. By contrast, the sum of the coefficients on *Fund* and *Fund*×*Gain*, which measures the propensity to sell funds at a gain versus stocks at a gain, is small and statistically insignificant for all three investor groups.

The fact that the coefficient on *Gain* (for both stocks and funds) moves toward zero as the sample becomes more restricted suggests that there are some differences between stock and fund investors that affect the level of the disposition effect. Nonetheless, the fact that the difference between stocks and funds holds for the same set of investors at the same time means that differences

Table II

The Disposition Effect: Individual Trader Data

This table examines the variation in the disposition effect between stocks and equity mutual funds for different subsets of investors. Observations are taken monthly for stocks and equity mutual funds in months when at least one asset was sold, from 128,809 accounts from a discount brokerage house between January 1991 and November 1996. The dependent variable is *Sale*, a dummy variable for whether the investor reduced his position over the month. *Gain* is a dummy variable for whether the price at the end of the previous month is greater than the volume-weighted average purchase price. *Fund* is a dummy variable that equals one for equity mutual funds, and zero otherwise. The sample of assets includes stocks (U.S. equities, foreign equities and ADRs) and equity mutual funds. The sample of investors includes either all investors (Panel A), investors who held both stocks and equity mutual funds at some point in the sample (Panel B), or investors who held both stocks and equity mutual funds in that particular month (Panel C). Standard errors (in parentheses) are clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

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 that something about the asset classes themselves is driving the difference in the sign of the disposition effect between stocks and funds.

C. 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 should have a reverse-disposition effect, and, if it does not, it should have a disposition effect. By contrast, if the reverse-disposition effect is limited to equity mutual funds, this would suggest that the distinction may be more likely due to some other institutional features of such funds.

We test whether delegation is the relevant characteristic by rerunning 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.[11]

Table III lists the different fund asset classes, an indicator for whether 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 nondelegated assets such as stocks, delegated asset classes usually exhibit a reverse-disposition effect. Of the 22 different asset classes reported by the trading firm, all four asset classes with statistically significant positive disposition effects are nondelegated portfolios. Of the seven assets with statistically significant

[11] For each asset class, we also attempt to classify them according to whether the asset involves delegation to a portfolio manager. For some cases 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 nondelegated, although the estimated disposition effect is close to zero. Since it is close to the middle of the asset class range, changing the classification does not significantly affect the results.

Table III

The Disposition Effect by Asset Type

This table examines how the level of the disposition effect varies across asset classes according to whether the asset involves delegation to a portfolio manager. The data are individual trading records for a sample of 128,707 accounts from a discount brokerage house between January 1991 and November 1996, described in Section II. Observations are taken monthly for assets in the particular class, during months when at least one asset of any type was sold. Regressions are run separately for each asset class listed. 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* describes whether the asset class involves delegation to a portfolio manager. σ is the standard error on the *Gain* coefficient, and Obs. is the number of observations in the regression. Standard errors are clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	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

reverse-disposition effects, five are delegated, with the two exceptions (preferred stock and options equity) accounting for the two smallest (in magnitude) coefficients.

D. 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 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. Accordingly, 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 fund CUSIPs. The CUSIP data 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 base regression of *Sale* on *Gain* for index funds, we also run the following regression:

$$Sale_{ijt} = b_0 + b_1 Gain_{ijt} + b_2 Gain_{ijt} \times Index_j + b_3 Index_j + \epsilon_{ijt}. \tag{3}$$

We run (3) first for the sample of index funds only, then the sample of all equity mutual funds (both actively and passively managed), and finally the combination of index funds and stocks. We report the results in Table IV.

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 II. In column 2, the sample is all equity mutual funds. The coefficient on *Gain*× *Index* is 0.0697, significant at the 1% level, indicating that index funds have less of a reverse-disposition effect than other funds. Indeed, the index fund interaction offsets all of the base reverse-disposition effect for equity funds in general, as measured by the base coefficient of −0.0662.

The matching procedure of using CUSIPs that are dated from 1996 to 2001 contains a potential look ahead bias because any fund classified as an index fund needs to be matched on CUSIP, which requires that it 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 slightly stronger, with the coefficient on *Gain*×*Index* increasing to 0.0782, significant at the 1% 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*×*Index* is −0.0357, indicating that the disposition effect in index funds is directionally lower than for stocks, although the difference is not statistically significant.

Table IV

The Disposition Effect in Index Funds and Other Equity Funds

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 128,707 accounts from a discount brokerage house between January 1991 and November 1996, described in Section II. Observations are taken monthly for the asset classes listed, during months in which 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 (in parentheses) are clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Index Funds	Equity Funds		Index Funds & Stocks
Gain	0.0035	−0.0662***	−0.0433*	0.0391***
	(0.0369)	(0.0261)	(0.0263)	(0.0066)
Index		−0.1048***	−0.0920***	0.0036
		(0.0197)	(0.0196)	(0.0327)
Index*Gain		0.0697***	0.0782***	−0.0357
		(0.0254)	(0.0248)	(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^2	0.0000	0.0048	0.0080	0.0021
Observations	13,218	354,125	354,125	1,824,394

E. Extensions and Robustness

We conduct several extensions and robustness checks that we summarize here and discuss in detail in the Internet Appendix:

1. Volatility, Investment Horizon, and Position Size Effects: One might be concerned that any of these could impact the disposition effect and thus might drive differences in levels of the disposition (and reverse-disposition) effect. In the Internet Appendix we test whether the effect of delegation survives after controlling for asset volatility, holding period, and position size, and we find that it does: delegated assets have a significantly lower disposition effect than other assets.
2. Effects of Nontrading Days and Weighting by Account Size: One might also be concerned that the set of months when a sale is reported is a selected sample, or that large accounts are overcounted because they have more sales. In the Internet Appendix, we re-estimate the results of Table II using alternative specifications designed to address these

concerns. We show that the difference in the disposition effect between stocks and funds is not driven by nontrade months, and that the disposition effect in stocks and the reverse-disposition effect in funds are both larger in magnitude for traders with fewer assets.

3. Stock and Fund Difference Using Fixed Effects: We can use fixed effects to control for account-level variation in trading. In the Internet Appendix we show that successive addition of various fixed effects does not eliminate the significance of the $Gain \times Fund$ interaction.

F. Summary

The results from the individual trader data reveal two important observations. The first is that the different levels of the disposition effect between stocks and funds do not appear to be driven by the fact that investors in these two asset classes have different preferences or skill. 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 nondelegated assets tend to display a disposition effect.

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

III. The Experiment

A. Goals

To provide direct evidence of cognitive dissonance as a driver of the disposition effect, we run 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 causes an increase in the disposition effect in stocks and an increase in the reverse-disposition effect in funds.

We also show that delegation has a psychological effect on investors' trading behavior. While the previous section suggests that delegation matters for the disposition effect, various other economic differences between delegated and nondelegated portfolios, such as learning about managerial skill, moral hazard, other agency problems, etc., are not controlled for. To ensure that these other differences are not driving the relation between delegation and the disposition effect, 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 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. The results are consistent with cognitive dissonance but not with several "learning explanations," loosely defined.

B. Experimental Setting

Our experiment involved 520 undergraduate students participating in a stock and mutual fund trading game over the course of a semester.[12] The students were enrolled in one of seven undergraduate finance sections in the Marshall School of Business at the University of Southern California: 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 nonmajors. 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 multifactor 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. 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 buy 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

[12] USC University Park Institutional Review Board Project # UP-10-00452, approved December 3, 2010.

is its net asset value per share. If a student's order exceeded their budget, the order was filled proportionately so as to satisfy his budget constraint. Trades were executed without transaction costs. After the last trading day, students were given a closing survey. The list of mutual funds and screen-shots from the game are all presented in the Internet 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 one- to two-page write-up due on April 23, 2012. Performance was based on the overall portfolio return relative to that of 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 had been, 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 (1) come up with both their own investment plan (although we said we hoped they would use class information) and (2) 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.

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, which is now less credible, it is harder for the student to avoid or ignore the fact that he 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 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 had 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. This treatment was designed to increase the salience of the intermediary (i.e., the fund manager). If delegation 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 groups are given in Table V. Observable characteristics are quite similar across the different

Table V

Trader Characteristics by Treatment

This table presents summary statistics for an experiment where 520 undergraduate students traded either 30 mutual funds or 30 stocks at daily closing prices over a period of 12 weeks, as described in Section III. Fire and Story are the two randomized treatment conditions, described in Section III. 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 investing experience. In all cases, baseline characteristics are not statistically distinguishable across any treatment arms. Nineteen students had class year variables of "other" and were not included in the Class Level summary statistic.

Panel A: Stocks and Funds		
	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

	Fire	Story	Both	None
Panel B: Funds				
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				
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

treatment groups, and we find 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 treatment assignments. However, to the extent that student communications created a correlation in the trading behavior of traders, this would constitute a cross contamination of our treatment cells and bias our measured treatment effects toward zero.[13]

At the conclusion of the experiment, students were given a closing survey asking about what they had learned during the experiment. We discuss results of this survey in Section III.D below.

C. 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 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 of equation (1) that includes dummies for our treatments. Specifically, we estimate

$$\begin{aligned} \text{Funds:} \quad Sale_{ijt} &= b_0 + b_1 Gain_{ijt} + b_2 Gain_{ijt} \times Story_i + b_3 Story_i \\ &\quad + b_4 Gain_{ijt} \times Fire_i + b_5 Fire_i + \epsilon_{ijt} \end{aligned} \tag{4}$$

$$\text{Stocks:} \quad Sale_{ijt} = b_0 + b_1 Gain_{ijt} + b_2 Gain_{ijt} \times Story_i + b_3 Story_i + \epsilon_{ijt}, \tag{5}$$

where *Fire* and *Story* are dummy variables for whether an individual i is in the Fire or the Story treatment, respectively. Since students are randomly assigned into treatment groups, b_2 and b_4 can be interpreted as the 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 VI reports results 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,

[13] For example, consider a case in which two students work together, one of whom is in the Fire treatment and one is 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.

Table VI

The Experimental Disposition Effect for Funds

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 III. Observations are taken daily for all funds in the student's portfolio, on days when 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 treatment is designed to increase the salience of the fund manager, by replacing "Buy," "Sell," and "Portfolio performance/gain/loss" 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 treatment 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 III. Standard errors (in parentheses) are clustered by student and day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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^2	0.012	0.02	0.029	0.034
Observations	2,011	1,957	1,957	1,957

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 on the *Gain* variable, which is −0.141 and 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*×*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*×*Story* is also −0.211 and significant at the 5% level. Adding

Table VII

The Experimental Disposition Effect for Stocks

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 III. Observations are taken daily for all funds in the student's portfolio, on days when 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 III. Standard errors (in parentheses) are clustered by student and day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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^2	0.001	0.010
Observations	4,106	4,026

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 VII 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*×*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 in Tables VI and VII 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. This is consistent with the hypothesis that, 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.

D. Alternative Hypothesis: Learning

Perhaps the most appealing alternative 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 Barber and Odean (2000) trading data) is that the effect of delegation is related to learning. In this view, the difference in investor behavior toward delegated and nondelegated assets is due to investors learning about the skill of fund managers. If investors also have a desire to allocate more money 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 to explain the results of our experiment. We then 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 the case 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 either have a recency bias (e.g., overweight 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 engender opposite learning effects for stocks and funds, or learning must lead to opposite effects with respect to trading behavior.

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 particular, 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 VIII. 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 VIII shows the exit survey results with the full set of interactions between whether 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 lower 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), individuals reported learning less when they were at a loss than at a profit, significantly different from subjects in the base condition who learned more when at a loss (see Kuhnen (2015) and Mobius et al. (2012)). For instance, in the "Learning about self" category, the negative coefficient on *Profit* of −1.011 indicates that subjects in the control condition on average learn less when at a profit (7.612–1.011= 6.601) than when at a loss (7.612), whereas under the Story treatment subjects learn more when at a profit (7.612–1.011–1.276 + 1.622=6.947) than when at a loss (7.612–1.503=6.109). Consistent with the

Table VIII
Exit Questionnaire: Funds

This table examines how self-reported learning about trading mutual funds varies with the two treatments in the trading experiment, as described in Section III. 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 both funds in general and 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 (in parentheses) are clustered by student and day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Baseline Effect				
		Learning		Willingness to Invest	
	Own Skill	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^2	0.008	0.006	0.006	0.002	0.000
Observations	242	243	243	242	240
	Panel B: Interacted with Profit				
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^2	0.08	0.06	0.04	0.01	0.08
Observations	242	243	243	242	240

predictions of cognitive dissonance, the difference in effect is driven mostly by the loss domain (7.612 control versus 6.109 story) rather than the profit domain (6.601 control versus 6.947 story). The results for stock traders (presented in Table IX) 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

Table IX

Exit Questionnaire: Stocks

This table examines how self-reported learning about trading stocks varies with the treatment in the trading experiment, as described in Section III. 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 both stocks in general and 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 (in parentheses) are clustered by student and day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Baseline Effect				
		Learning		Willingness to Invest	
	Own Skill	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^2	0.008	0.006	0.006	0.002	0.000
Observations	242	243	243	242	240
	Panel B: Interacted with Profit				
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^2	0.04	0.01	0.01	0.05	0.04
Observations	246	246	246	247	246

to learn substantially less when the results are negative than when they are positive. This result is consistent with cognitive dissonance in general and the literature on the attribution bias in particular.[14] 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.

[14] A somewhat puzzling result is that learning about managerial skill follows the same pattern as own learning. If assigning blame means learning about the manager, individuals facing a loss should learn more about managerial skill under the Story treatment. One interpretation of our results is that assigning blame while preserving one's self-image has a more complicated mapping to learning about third parties.

IV. Discussion

Our results contribute to the literature that argues in favor of a cognitive dissonance–based explanation of the disposition effect. This explanation was first advanced by Zuchel (2001), and a similar argument was put forward in Kaustia (2010b) based on self-justification and regret avoidance. In this section, we collect other documented behavioral puzzles that cognitive dissonance helps resolve or that are consistent with a cognitive dissonance based explanation. We then discuss the empirical evidence relating to other existing explanations of the disposition effect.

A. Cognitive Dissonance

Cognitive dissonance 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)).[15] 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 such an effect.

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 (with the option of costlessly repurchasing 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 that they were wrong in order realize losses.

Finally, cognitive dissonance provides a potential explanation for the result in Strahilevitz, Odean, and Barber (2011) that investors are reluctant to *re*purchase stocks that have risen in price since the previous sale. Strahilevitz, Odean, and Barber (2011) argue that this is due to investor regret over

[15] 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.

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, Camerer, and Rangel (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.

It is worth noting, however, that cognitive dissonance does not provide a universal explanation for all known facts about the disposition effect. In particular, our model of cognitive dissonance does not help explain the result in Frydman et al. (2014) that investors appear to experience direct positive utility when gains are realized. Since cognitive dissonance does not speak to the question of utility for gains, such a result is more consistent with explanations such as realization utility (discussed below).

B. Private Information, Portfolio Rebalancing, and Mean-Reversion

Two potential explanations for the disposition effect that are close to standard portfolio choice models are private information or portfolio diversification (rebalancing). 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 overweighted in their portfolio, but Odean (1998) 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 rebalancing should cause investors to trade differently in stocks versus funds in either our individual investor trading data or our experiment.

An alternative explanation (from Odean (1998)) is based on an unjustified belief in mean reversion of stock prices. Under 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 a belief in mean reversion is driving our results, then traders must believe simultaneously in mean reversion in returns across a wide variety of nondelegated assets (as in Table III and the papers listed in footnote 1) and also in return persistence for delegated assets.

Cognitive dissonance gives a different perspective on the possibility of a mistaken belief in mean reversion. In particular, while investors may indeed convince themselves that a stock they have bought that has fallen in price is likely to experience a subsequent price increase, under cognitive dissonance the change in beliefs is the *result* of responding to the underlying cognitive dissonance, rather than the direct cause. More importantly, under cognitive dissonance investors do not have a belief in mean reversion for stocks in general. They do not even have an ex ante belief 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.

C. Returns-Based Preferences

An important class of explanations for the disposition effect assumes that traders have nonstandard preferences over returns. Early behavioral explanations focused on prospect theory (Kahneman and Tversky (1979)) and mental accounting (Thaler (1980)). Under these theories, an investor facing a loss becomes risk-seeking in order to avoid the loss now, whereas the same investor facing 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,[16] 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 is realization utility (Barberis and Xiong (2009, 2012) and Ingersoll and Jin (2013)), whereby traders gain utility from the act of selling at a gain, rather than from receiving information about the gain. Frydman et al. (2014) provide neurological evidence from fMRI imaging that the disposition effect is associated with enjoyment when the gains are realized, rather than only when information about the gain is first disclosed. This supports the interpretation that realization utility is a component of traders' disposition effect behavior (as our version of cognitive dissonance has no action in the gain region).

[16] Barberis and Xiong (2009) and Hens and Vlcek (2011) show theoretically that prospect theory may not result in 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 consistent with belief revision.

Our results present a challenge for explanations based purely on preferences over returns. In particular, the results in Table II 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 not imply that preferences over returns play no role in the disposition effect.

Instead, cognitive dissonance provides a new perspective on the evidence that investors have realization preferences over gains and losses (e.g., Frydman et al. (2014)). In one sense, cognitive dissonance can be thought of as a microfoundation for realization utility, particularly in the loss domain. Realization utility as a theory (as in, for instance, Barberis and Xiong (2012)) does not specify exactly *why* investors feel discomfort from realizing losses. The uncomfortable feelings investors experience when facing a past poor decision are a potential basis for thinking about realization utility in the loss domain. Realization utility may also be driven by overall heuristics that selling at a gain is beneficial and wealth increasing, while selling at a loss is harmful and costly. Such alternative foundations are particularly likely for the gains domain, where cognitive dissonance cannot provide an explanation. There is no particular reason to suppose that all realization utility shares a single common source.

Indeed, one way to interpret the results of the current paper is that the mapping between a given level of realized losses and the realization disutility may vary according to the situation. Cognitive dissonance provides a number of distinct predictions relative to existing models of realization utility about when the disutility from a given realized loss will be larger or smaller according to the amount of dissonance discomfort that the scenario is likely to generate. 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.

V. 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 sell at a loss. Using individual trading data as well as 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 be costly for investors by decreasing returns to investing. In other contexts, however, greater 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 (see the limits to arbitrage literature, such as Shleifer and Vishny (1997)).

Our findings suggest that whether investors react to poor fund performance by withdrawing money depends on whether they view their own choices or the fund manager's choices as 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.

Cognitive dissonance represents a departure 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 forgone wealth and consumption (although this obviously plays a considerable role), but also the discomfort from having to face 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 worthy of future study.

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REFERENCES

Aronson, Elliot, 1997, The theory of cognitive dissonance: The evolution and vicissitudes of an idea, in Craig McGarty and Alexander Haslam, eds.: *The Message of Social Psychology: Perspectives on Mind and Society* (Blackwell Publishing, Oxford, UK).

Aronson, Elliot, and J. Merrill Carlsmith, 1963, Effect of the severity of threat on the devaluation of forbidden behavior, *Journal of Abnormal and Social Psychology* 66, 584–588.

Aronson, Elliot, and Judson Mills, 1959, The effect of severity of initiation on liking for a group, *Journal of Abnormal and Social Psychology* 59, 177–181.

Barber, Brad, and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 116, 261–292.

Barberis, Nicholas, 2011, Psychology and the financial crisis of 2007–2008, Working paper, Yale School of Management.

Barberis, Nicholas, 2012, A model of casino gambling, *Management Science* 58, 35–51.

Bartling, Björn, and Urs Fischbacher, 2012, Shifting the blame: On delegation and responsibility, *Review of Economic Studies* 79, 67–87.

Ben-David, Itzhak, and David Hirshleifer, 2012, Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect, *Review of Financial Studies* 25, 2485–2532.

Brehm, Jack, 1963, Postdecision changes in the desirability of alternatives, *Journal of Abnormal and Social Psychology* 52, 384–389.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, 2009, Fight or flight? Portfolio rebalancing by individual investors, *Quarterly Journal of Economics* 124, 301–348.

Campbell, John Y., 2006, Household finance, *Journal of Finance* 61, 1553–1604.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Coffman, Lucas C., 2011, Intermediation reduces punishment (and reward), *American Economic Journal: Microeconomics* 3, 1–30.

Egan, Louisa C., Paul Bloom, and Laurie R. Santos, 2010, Choice-induced preferences in the absence of choice: Evidence from a blind two choice paradigm with young children and capuchin monkeys, *Journal of Experimental Social Psychology* 46, 204–207.

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

Fershtman, Chaim, and Uri Gneezy, 2001, Strategic delegation: An experiment, *The RAND Journal of Economics* 32, 352–368.

Festinger, Leon, 1957, *A Theory of Cognitive Dissonance* (Stanford University Press, Sanford, CA).

Festinger, Leon, and James M. Carlsmith, 1959, Cognitive consequences of forced compliance, *Journal of Abnormal and Social Psychology* 58, 203–210.

Festinger, Leon, Henry W. Reicken, and Stanley Schacterl, 1956, *When Prophecy Fails: A Social and Psychological Study of a Modern Group that Predicted the Destruction of the World* (Harper Torchbooks, New York, NY).

Frazzini, Andrea, 2006, The disposition effect and under-reaction to news, *Journal of Finance* 61, 2017–2046.

Friend, Irwim, Marshall Blume, and Jean Crockett, 1970, *Mutual Funds and Other Institutional Investors: A New Perspective* (McGraw-Hill, New York, NY).

Frydman, Cary, Nicholas Barberis, Colin Camerer, Peter Bossaerts, and Antonio Rangel, 2014, Testing theories of investor behavior using neural data, *Journal of Finance* 69, 907–946.

Frydman, Cary, Colin Camerer, and Antoinio Rangel, 2013, Neural measures of regret and stock repurchases, Working paper, USC Marshall School of Business.

Gecas, Viktor, 1982, The self-concept, *Annual Review of Sociology* 8, 1–33.

Genesove, David, and Christopher Mayer, 2001, Loss aversion and seller behavior: Evidence from the housing market, *Quarterly Journal of Economics* 116, 1233–1260.

Greenwald, Anthony G., and David L. Ronis, 1978, Twenty years of cognitive dissonance: Case study of the evolution of a theory, *Psychological Review* 85, 53–57.

Grinblatt, Mark, and Bing Han, 2005, Prospect theory, mental accounting and momentum, *Journal of Financial Economics* 78, 167–184.

Grinblatt, Mark, and Matti Keloharju, 2001, What makes investors trade?, *Journal of Finance* 56, 589–616.

Hamman, John R., George Loewenstein, and Roberto A. Weber, 2010, Self-interest through delegation: An additional rationale for the principal-agent relationship, *American Economic Review* 100, 1826–1846.

Hartzmark, Samuel M., and David H. Solomon, 2012, Efficiency and the disposition effect in NFL prediction markets, *Quarterly Journal of Finance* 2, 1–42.

Heath, Chip, Steven Huddart, and Mark Lang, 1999, Psychological factors and stock option exercise, *Quarterly Journal of Economics* 114, 601–627.

Hens, Thorsten, and Martin Vlcek, 2011, Does prospect theory explain the disposition effect?, *Journal of Behavioral Finance* 12, 141–157.

Ingersoll, Jonathan E., and Lawrence J. Jin, 2013, Realization utility with reference-dependent preferences, *Review of Financial Studies* 26, 723–767.

Ivkovic, Zoran, and Scott Weisbenner, 2009, Individual investor mutual fund flows, *Journal of Financial Economics* 92, 223–237.

Jecker, Jon, and David Landy, 1969, Liking a person as a function of doing him a favor, *Human Relations* 22, 371–378.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jin, Li, and Anna Scherbina, 2011, Inheriting losers, *Review of Financial Studies* 24, 786–820.

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–291.

Kaustia, Markku, 2010a, Disposition effect, in *Behavioral Finance, Robert W. Kolb Series in Finance* (John Wiley & Sons, Inc., Hoboken, NJ).

Kaustia, Markku, 2010b, Prospect theory and the disposition effect, *Journal of Financial and Quantitative Analysis* 45, 791–812.

Kuhnen, Camelia M., 2014, Asymmetric learning from financial information, *Journal of Finance*, 70, 2029–2062.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1992, The structure and performance of the money management industry, *Brookings Papers: Microeconomics* 339–391.

Langer, Ellen J., and Jane Roth, 1975, Heads I win, tails it's chance: The illusion of control as a function of the sequence of outcomes in a purely chance task, *Journal of Personality and Social Psychology* 32, 951–955.

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

Mobius, Mark M., Muriel Niederle, Paul Niehaus, and Tanya S. Rosenblat, 2012, Managing self-confidence: Theory and experimental evidence, Working paper, NBER.

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

Paharia, Neeru, Karim S. Kassam, Joshua D. Greene, and Max H. Bazerman, 2009, Dirty work, clean hands: The moral psychology of indirect agency, *Organizational Behavior and Human Decision Processes* 109, 134–141.

Pedace, Roberto, and Janet K. Smith, 2013, Loss aversion and seller behavior: Evidence from major league baseball, *Economic Inquiry* 51, 1475–1488.

Seru, Amit, Tyler Shumway, and Noah Stoffman, 2009, Learning by trading, *Review of Financial Studies* 23, 705–739.

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

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777–790.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Strahilevitz, Michal A., Terrance Odean, and Brad M. Barber, 2011, Once burned, twice shy: How naive learning, counterfactuals, and regret affect the repurchase of stocks previously sold, *Journal of Marketing Research* 48, 102–120.

Thaler, Richard H., 1980, Towards a positive theory of consumer choice, *Journal of Economic Behavior and Organizations* 1, 39–60.

Weber, Martin, and Colin F. Camerer, 1998, The disposition effect in securities trading: An experimental analysis, *Journal of Economic Behavior and Organization* 33, 167–184.

Weber, Martin, and Heiko Zuchel, 2005, How do prior outcomes affect risk attitude? Comparing escalation of commitment and the house money effect, *Decision Analysis* 2, 30–43.

Wermers, Russ, 2003, Is money really "smart"? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence, Working paper, Robert H. Smith School of Business.

Zuchel, Heiko, 2001, What drives the disposition effect?, Working paper, Universitat Mannheim.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.