Do Losses Linger? Evidence from Proprietary Stock Traders

Ryan Garvey, Anthony Murphy, and Fei Wu*,**

Revised – November 2005

* Ryan Garvey is assistant professor of finance at the A.J. Palumbo School of Business Administration and the John F. Donahue Graduate School of Business, Duquesne University, Pittsburgh, PA. 15282. Telephone number is 412-396-4003. Fax number is 412-396-4764. Email is Garvey@duq.edu. Anthony Murphy is a Research Fellow at Nuffield College, Oxford OX1 1NF, UK. Telephone number is 44-1865-278526. Fax number is 44-1865-278621. Email is Anthony.Murphy@nuf.ox.ac.uk. Fei Wu is senior lecturer in finance at Massey University, Massey, New Zealand. Telephone number is 64-6-350-5799. Email is F.Wu@massey.ac.nz. Fax number is 64-6-350-5651.

** We would like to thank the editor, Frank Fabozzi, and the referee, Meir Statman, for their helpful comments and suggestions. We are grateful to seminar participants at the 2005 Financial Management Association Conference (Chicago) for helpful comments and discussions. We thank the executives at the securities firm for providing their proprietary data. All errors and omissions are our responsibility.

Abstract

We examine how professional stock traders, working for a Nasdaq market maker, are influenced by their recent trading performance. Our results show that, in aggregate, when the traders incur morning losses, their desire to recoup these losses before the close of trading leads them to trade more aggressively in the afternoon. This behavior is consistent with the behavior underlying the disposition effect. An analysis of individual trading performance shows that traders who are more influenced by their prior trading losses perform far worse than those who are less influenced.

The general tendency to hold losing trades too long, and sell winning trades too soon is referred to as the disposition effect [Shefrin and Statman, 1985]. Existing research has found strong support for the disposition effect among both retail and institutional market participants.[1] In this paper, we extend this research by examining how professional stock traders react to prior trading gains and losses. Specifically, we examine the effect of trading losses in the morning on trading decisions in the afternoon. We find that professional stock traders have a tendency to engage in risky behavior after prior losses. Traders who experienced trading losses in the morning tend to increase their subsequent appetite for risk in the afternoon. This behavior is most likely brought on by the traders desire to recover from their morning losses before the close of trading.

The desire to recover from a loss, and the ensuing risky behavior that follows, is consistent with the behavioral tendencies which underlie prospect theory and the disposition effect. For example, people who hold losing trades longer than winning ones tend to continue gambling hoping to, at a minimum, break even rather than realize a loss. What we find is that the traders who are more influenced by their morning losses perform far worse than traders who are less affected.

The Disposition Effect

The disposition effect is an extension of Kahneman and Tversky’s [1979] prospect theory model of decision making under risk. Under prospect theory, individuals maximize the expected value of an S-shaped valuation function when confronted with risky choices. The value function differs from the standard utility function since it is defined in terms of gains and losses rather than the level of wealth. It is also concave in the domain of gains and convex in the domain of losses, which implies that people exhibit risk averse behavior when facing possible gains and risk-seeking behavior when confronted with potential losses. A central feature of prospect theory is that losses have a much greater impact than gains of the same absolute magnitude. This is why individual decision-makers are considered loss-averse.

For example, suppose an individual is faced with a choice between selling a stock for a capital loss of $10,000, or holding the stock when there is a 50% chance of losing $20,000 and a 50% chance of breaking even. The expected loss in both choices is $10,000. However, according to prospect theory, most people will opt for the more risky choice because they are reluctant to realize a loss and so they will gamble (i.e. hold the stock) hoping to break-even. In the presence of gains, the reverse behavior will occur and most people will opt for the more risk-averse choice (i.e. realize the gain).[2]

Shefrin and Statman [1985] apply prospect theory to a financial market setting and also place it in a wider theoretical framework, which includes mental accounting, regret aversion, and self-control.[3] These four factors help explain theoretically why people tend to hold on to their losses too long and sell their winners too soon.

Prior Losses and Subsequent Risky Behavior

Our paper differs from most studies of the disposition effect since we examine risky choices in a sequential decision-making framework when, for example, a loss has already occurred. For example, consider a variant of the example at the end of the last Section but now suppose the individual is a trader who has just lost $10,000. Suppose the trader has the opportunity to participate in another trade with equal chances of winning

$10,000 and losing $15,000. According to prospect theory, if the trader has not come to terms with the prior loss, he or she is more likely to engage in the second trade despite its unfavorable terms. This psychological tendency is referred to as aversion to a sure loss. As noted by Kahneman and Tversky [1979], "A person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise" (p. 287).

A small body of research has examined the link between prior outcomes and subsequent decision-making in a number of different settings. In an experimental setting, Thaler and Johnson [1990] found evidence of the "break-even effect". The break-even effect predicts that, when individuals incur prior losses, they will be attracted to subsequent gambles which offer the opportunity to break-even.[4] More recently, Coval and Shumway [2005] and Locke and Mann [2004] examine how commodity traders, working at the Chicago Board of Trade (CBOT) and Chicago Mercantile Exchange (CME), were influenced by their prior trading performance. Both studies found evidence of increased risk-taking following trading losses. In our paper, we examine the reaction of proprietary traders, who work on an equity trading desk, to their prior trading gains and losses. In addition, we analyze the effect this behavioral tendency has on trading performance. Our dataset has two important advantages for examining behavioral tendencies and trading performance, which we discuss in the next Section

Data

The data for our study are the trading records of 150 professional stock traders who worked on behalf of a National Securities Dealer. The traders were the only ones employed on the proprietary trading desk over our sample period. The traders were located at five different branch offices in the U.S.. Although we find differences in skill levels among the traders, there are few differences between the overall strategies employed in the various branches.

The data cover the period June 3, 2002 through May 30, 2003. During this period, the U.S. stock markets were open for 251 days. In total, the data consist of over 1.3 million executed trades, which involved 730.4 thousand intraday round trips and 2.5 billion shares. The firm encourages the traders to trade Nasdaq listed stocks. In fact, only 31 traders were allowed to trade stocks listed on the AMEX or NYSE. This is one reason why over 99% of the shares traded occurred in Nasdaq listed stocks. The traders combined to account for approximately 0.62% of Nasdaq share volume during the year. However, they concentrated their trading in certain stocks on certain days, often generating a sizeable percentage of the overall daily stock volume. For example, the traders accounted for 1.5% and 3.3% of the annual share volume of Sun Microsystems (SUNW) and JDS Uniphase (JDSU), the only two stocks which they traded every day.

The data are in the form of a transaction database. For every trade, we know the identity of the trader, the time the trade was sent and filled, the type of trade (marketable versus limit order), the charge for taking liquidity, the rebate for providing liquidity, the fixed charge levied by the firm, the action taken (buy, sell, short, and cover), the volume, the price, the market where the order was sent, the contra party on the trade (if given), and the location of the trader. Using this information, we calculated gross and net round-trip trading profits. For every stock in a trader's account, we matched opening trades with the subsequent closing trade(s) in the same day. The traders did not always open and close positions with two trades. Traders often laid off part of an open position or combined a closing transaction with an opening transaction. Regardless of whether the traders opened, closed, or simultaneously opened and closed a position, we searched forward in time each day until the opening position was closed out, keeping track of accumulated inventory, the corresponding prices paid or received, and the cost or rebate associated with each trade.

Our data have two important advantages. First, we know the exact time horizon of our traders. To our knowledge, this is not the case with any previous study in behavioral finance which uses individual trader data. We assume that the reference point for gains and losses is the opening position of the day and that each day represents a separate mental account. If traders were allowed to hold positions overnight, then one could easily question our assumptions and resulting findings. However, we know that the traders were strictly prohibited from holding positions overnight. We also know that they did not actually hold any positions overnight since we were able to match all 1.3 million trades during the intraday.

The second advantageous feature of our data is that we have the exact costs involved with trading. Again, this is fairly rare but it is critical in behavioral studies measuring trader performance. Our traders pay nearly $1.7 million in net trading costs during the course of the year, which has a significant impact on their overall performance. On each trade, the traders pay a fixed charge and either pay a variable cost or receive a variable rebate, depending on the exchange used and whether the trader takes or provides liquidity.[5] The traders pay all of their net trading losses and keep a percentage of their net profits. This take-home percentage is negotiable, but it typically ranges from 70% to 80%. Because the traders take home earnings are directly linked to their trading performance, our results are less susceptible to complications arising from agency costs.

Exhibit 1 sets out some summary trading statistics for our traders. Overall, the traders almost broke even on a gross profit basis. They only lost $45,000 or so during the course of the year. However, when trading costs are considered, the traders lost over $1.7 million, with an average daily loss of $6,792. Looking at some other trading measures, we can see the intensity in which these traders trade. They conducted an average of 5,244 trades per day with an average holding time of 13 minutes per round trip, with a 1 cent absolute price change. According to the firm they worked for, the major reason why the traders were not profitable during this period was the recent switch to decimal pricing**.** The fact that the traders lost money overall does not hamper our analysis because the traders experienced many profitable periods.

Empirical Results

Methodology and Summary Statistics

The proprietary stock traders are pure day traders, who never hold positions overnight. At the end of each day, the traders receive a printout from the firm showing their daily trading performance. The continual daily focus of these traders strongly leads us to believe that a one-day trading period is most appropriate for examining their trading behavior.

In order to examine the relationship between prior performance and subsequent decision-making, we adopt a similar approach to that used by Coval and Shumway [2005] and split the trading day into two parts. We define a morning session of trading from 9:30 am to 12:45 pm and an afternoon trading session from 12:45 pm to 4:00 pm. Our main purpose in breaking up the trading day into two halves, rather than examining trading behavior and profitability on a trade-by-trade basis, is to allow traders time to digest their performance going into the lunch period and then see how they react when they return in the afternoon.[6] There is no set lunch period but, in our data, trading is lightest between 12 noon and 1 pm. Furthermore, from our discussions with members of the firm, we know that the traders often break for lunch around then. There is little concern with open positions carrying over from the morning to the afternoon period. The traders rapidly close out of their positions in minutes and it is rare for a trader to leave an open position unwatched for any lengthy period of time.

Measuring risk directly is difficult so we look at a number of indirect measures. For our study, we select four potential risk measures, which are common among intraday traders.[7] The first measure is the number of trades conducted. Other things being equal, trading more frequently can certainly be construed as a more risky trading behavior. Our second and third measures consist of the average dollar size (price multiplied by quantity) per trade and the aggregated or total dollar amount traded during the morning or afternoon trading session. Other things being equal, the average dollar size traded etc. is positively correlated with risk, a view held by most traders. Finally, we use the average absolute price change per round-trip as a potential measure of risk. Most proprietary traders attempt to adhere to a disciplined approach to their potential round trip gains and losses. Our traders primarily seek to capture the bid-ask spread, since over 80% of their round-trips involve an absolute price change of 1 cent or less. Other things being equal, if a trader deviates from their usual average absolute price change during a trading period, we infer that they are engaged in increased risk-taking.[8]

Because the traders are likely to differ in terms of their trading behavior and performance, we look at standardized morning and afternoon net profits and risk measures for each trader. This approach allows us to better interpret the data across traders. For example, executing 100 trades in the afternoon means very different things to a trader who never executes more than 50 trades a day than to one whose daily trading activity averages 150 or more trades.[9]

In order to standardize the morning net profit data, we calculate the mean and standard deviation of morning net profits for every trader, using data for every day they traded. We use the trader specific means to demean the trader's morning net profit figures. Then we divide the demeaned data by the trader specific standard deviation of each trader. This same standardization procedure is used to standardize the other variables we use. Note that the morning and afternoon data are separately standardized.

Some summary statistics for the standardized risk measures are set out in Exhibit 2. The statistics are disaggregated by whether or not the traders made a net gain or loss in the morning period. Of the 16,260 observations across traders and days, a little under 40% involve a morning net gain.[10]

The data suggest that morning net profits and the afternoon risk measures are negatively related. When the traders realized a morning net loss, they followed this by placing relatively more afternoon trades (0.045 standard deviations, SD, higher than average), by realizing relatively larger price changes (0.067 SD's higher), by trading relatively larger trade sizes (0.070 SD's higher) and by trading relatively larger dollar amounts (0.074 SD's higher). In the case of morning a net gain, the opposite is true – the standardized risk measures are below average in the afternoon.

It appears that the traders desire to recover from a morning loss is what leads them to trade more aggressively in the afternoon. In order to visually examine this behavior, we segregate the standardized morning net trading profits of trader-day observations into ten deciles. Exhibit 3 plots these against the average standardized afternoon risk measures for each decile group. For each risk-measure, we can see that as morning net profits decrease, afternoon risk-taking increases. The desire to get-even is especially evident when traders lose a lot. The lowest net profit decile is associated with the highest level of afternoon risk-taking. Exhibit 3 also shows that the response to morning net profits and losses is quite asymmetric, an effect which is not obvious from Exhibit 2.

The desire to break-even after a loss, as well as the near asymmetric response following prior net gains and losses, is consistent with prospect theory. Other behavioral tendencies also help explain the behavior in Exhibit 3. For example, mental accounting helps clarify the conditions for applying prospect theoretic decision rules. In our case, the focus is on a daily setting and so each trading day represents a separate mental account. Regret aversion explains why the traders are unlikely to close their daily account at a loss by being conservative after morning losses. If the traders were to do this, it would send a signal that they had made had poor decisions in the morning trading session. Having to admit such mistakes to other colleagues or supervisors might intensify the emotional feeling of regret. Garvey and Murphy [2004] note that, because professional traders often trade together, a sense of competition can exist on trading desks. Such rivalries increase the tendency to maintain status and avoid regret. As we subsequently show, this behavior lowers performance.

Regression Results

In order to examine the robustness of the preliminary results set forth in Exhibits 2 and 3, we estimate a series of regression models, the results of which are displayed in Exhibit 4. Our first model is a trader-specific, fixed effects regression with robust standard errors that takes the form:

$$Risk_{i,t}^{A} = \alpha_i + \beta_\pi \pi_{i,t}^{M} + \beta_R Risk_{i,t}^{M} + \varepsilon_{i,t} \qquad (1)$$

where $Risk_{i,t}^{A}$ equals one of the four standardized afternoon risk measures for trader *i* at time *t*, $\pi_{i,t}^{m}$ is trader *i*'s time *t* morning net profit, $Risk_{i,t}^{M}$ is trader *i*'s morning risk measure at time *t*, and $\varepsilon_{i,t}$ is a random error term.

We then estimate a fixed effects logit regression model in order to determine the probability that a trader's above average afternoon risk-taking is dependent on their morning net profits. The fixed effects logit regression model takes the form:

$$P(Risk_{i,t}^{A} > 0) = \frac{e^{\alpha_i + \beta_\pi \pi_{i,t}^{M} + \beta_R Risk_{i,t}^{M}}}{1 + e^{\alpha_i + \beta_\pi \pi_{i,t}^{M} + \beta_R Risk_{i,t\,i}^{M}}} \qquad (2)$$

Finally, we estimate two Fama and MacBeth [FM, 1973] type regression models where we average our behavioral bias coefficients. First, we conduct trader-by-trader regressions and then average the coefficients across traders. Then, we conduct day-by-day regressions and average the coefficients across days. The FM regression results are a good test of the robustness of our findings. They suggest that our findings are driven by certain traders or days.[11]

Looking at the regression results in Exhibit 4, we can see strong evidence supporting our initial claim that the traders are trying to recoup their morning losses, so that a mental account is not closed at a loss. All of the morning net profit coefficients are negative, indicating that as morning net profits declined, the traders engaged in above average afternoon risk-taking. The coefficients are statistically significant at the conventional 5% level in 14 out of the 16 regressions. Also evident in the data is a strong positive correlation between morning and afternoon risk-taking, which suggests that above average morning risk is often followed by above average afternoon risk-taking. The risk-taking tendencies exhibited by the professional stock traders are consistent with the results for commodity traders in Coval and Shumway [2005] and Locke and Mann [2004].

Trading Behavior in the Domains of Gains and Losses

Our previous analysis investigated the correlation between a trader's afternoon risk-taking and their morning net profitability. In prospect theory, individuals display value functions that are convex in the domain of losses and concave in the domain of gains so the impact of a loss is much greater than the impact of a gain. For example, Kahneman and Tversky [1979] find that a loss has approximately 2.25 times the impact of a gain of the same magnitude, which is why individual decision makers are considered loss-averse.

In order to examine the asymmetry in the behavior of traders with morning gains and losses in more detail, we segregate morning net profit observations into gains and losses. We then sort the gains and losses into five bins ranging from lowest to largest. The average afternoon risk measures associated with each bin are shown in Exhibit 5.

We can clearly see the asymmetric response to prior gains and losses. Moreover, in the domain of morning losses, all afternoon risk-taking measures monotonically decrease in step with the ranking of the losses. In the domain of morning gains, there is no obvious pattern.

The Desire to Break Even and its Impact on Performance

Overall, our traders appear to exhibit a behavioral bias which is likely to have a large, albeit transitory, impact on market prices. More than 70% of the traders 2.5 billion executed shares provide rather than take liquidity, which indicates the traders are very active in setting market prices. Furthermore, our proprietary stock traders are licensed traders who receive continuous training on various trading strategies and techniques from the firm's management. The financial sophistication of these traders leads us to believe that other stock market professionals, such as portfolio managers, could also suffer from the same behavioral tendency.[12]

At a more micro level, the behavioral bias we identified is likely to effect the firms profits and the trader's net earnings. As Shefrin [2003] notes, recognizing behavioral biases in decision-making is important because it can help market professionals improve their performance. In order to examine this issue, we regress a trader's overall profitability on a trader-specific behavioral bias measure.

Our overall performance measure consists of total net profits of each trader over the one-year sample period. In practice, we used the signed log of the absolute value of total net profits as our dependent variable. Our trader specific behavioral bias measure is constructed in two steps. First, we run trader-by-trader regressions of equation (1) for each of our four risk measures. Second, we average the four estimated morning profit coefficients (β_π) for each trader to obtain our trader specific behavioral bias measure.

The regression results are reported in Exhibit 6. The estimated coefficient on the trader specific behavioral bias measure is positive and statistically significant at the 1% level, which implies that traders who are more influenced by their morning trading losses perform worse than other traders.

Our regression approach uses the average of four estimated morning profit coefficients as our trader-specific behavioral bias measure. However, it is possible that only one of the four coefficients could dominate the others and be driving the results. In order to address this concern, we examined the effect of each of the components of our behavioral risk measure. In Exhibit 7 we compare the net profitability over the entire sample period of traders who had a tendency to exhibit increased risk-taking following morning losses (behavioral bias traders) and traders who did not. The allocation of traders to the two groups is determined by the sign and statistical significance of the estimated coefficients on morning profitability in separate trader by trader regressions of equation (1) using the four risk measures. In Panel A, we segregate traders based on whether their behavioral bias coefficients are negative or not. In Panel B, we segregate traders based on whether their behavioral bias coefficients are negative and statistically significant at the 10% level.

The results in Panel A of Exhibit 7 show that traders who engage in increased risk-taking following morning losses (i.e. traders with negative β_π coefficients) generally under perform those who do not. The average difference in the net profitability of the two groups ranges from -$1,400 to -$5,800. However, out of the four risk measures, only the difference using the absolute price change risk measure is statistically significant.

In Panel B we focus on the traders who are most affected by their prior trading losses i.e. those with statistically significant negative morning profit coefficients. Now the difference in the net profitability of the “behavioral bias” and other group of traders ranges from -$4,300 to -$14,400. Three out of four of the differences in net profitability are now significant at the 10% level or higher. Although the average trader lost $11,400, traders who engaged in increased risk-taking following morning net losses is far below the overall average. On the other hand, traders who did not suffer from this behavioral tendency outperformed the average.

The results in Exhibits 6 and 7 imply that the traders desire to get even, so that their daily account (mental account) is not closed at a loss, subsequently lowers their overall performance. Moreover, the more prone a trader is to this behavior, the more likely they are to lose money. The practical implications of our results are unquestionably appealing from both an individual trader and firm perspective. Institutions could put control measures in place to prevent or educate traders so as to limit this behavioral tendency. Shefrin and Statman [1985] employ self-control in the disposition effect in order to explain the rationale for methods (e.g., stop loss orders) used to force people into realizing their losses. In our case, the firm has some organizational control measures in place to force loss realization when trader self-control fails. For example, the traders are required to close out of their open positions by the end of the trading day, a trading manager monitors every trade entered into during the trading day, and the traders are trained to use trailing stop orders after entering a position. While these measures help ensure losses get realized, they may overlook aversion to sure loss tendencies. In order to prevent the latter behavior on trading desks, firms could put automated controls in place to monitor prior trading profits and behavior and then alert (e.g., screen warnings, alarms, etc.) traders when they deviate from their normal risk-taking tendencies. For example, if a trader has experienced a morning net loss and they are trading 10% more than they usually do in the afternoon, an alert message appearing on their trading monitor could notify them (and the trading manager) of this situation. Such control mechanisms could likely enhance a trader's performance.

Conclusion

Imagine that shortly after entering a casino, you lose $500 on the roulette wheel. Will this $500 loss cause you to bet more conservatively with your future gambles or increase your appetite for risk with ensuing gambles? Our paper examines these issues in a financial market setting by examining the sequential decision-making behavior of professional stock traders. Specifically, we analyze how the trader's morning gains or losses influence their afternoon trading decisions.

Our empirical results provide strong evidence that, when our professional stock traders experience morning losses, they take more risks in the afternoon. They probably do so in order to recover their losses and close their daily account (mental account) in the black. The proprietary traders also appear to exhibit an asymmetric reaction to their morning gains and losses. Morning losses have a much more pronounced effect than morning gains. Our findings are consistent with the behavioral tendencies underlying aversion to a sure loss and the disposition effect. In addition, our results are inline with other research on commodity traders (Coval and Shumway, [2005]; and Locke and Mann, [2004]) and the break even effect in Thaler and Johnson [1990].

At the individual trader level, we find that the break even or behavioral bias effect tends to reduce net profits. Traders who were most affected by their prior / morning losses performed far worse than other traders.

We examined the behavior of professional traders working on the proprietary trading desk of a Nasdaq market maker whose earnings are closely related to their net profits. The fact that many of these traders suffered from behavioral biases leads us to suspect that other stock market professionals could also suffer from similar biases.

References

Coval, Joshua D., and Tyler Shumway. "Do Behavioral Biases Affect Prices?" *Journal of Finance*, February 2005, pp. 1-34.

Fama, Eugene F., and James D. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, May/June 1973, pp. 607-636.

Garvey, Ryan, and Anthony Murphy. "Are Professional Traders Too Slow to Realize Their Losses?" *Financial Analysts Journal*, July/August 2004, pp. 35-43.

Kahneman, Daniel and Amos Tversky. "Prospect Theory: An Analysis of Decisions under Risk." *Econometrica*, March 1979, pp. 236-291.

Locke, Peter R., and Steven C. Mann. "Prior Outcomes and Risky Choices by Professional Traders." *Working Paper*, 2004, Texas Christian University.

Odean, Terrance. "Are Investors Reluctant to Realize Their Losses?" *Journal of Finance*, October 1998, pp. 1775-1798.

Shefrin, Hersh. "Beyond Greed and Fear." 2002 Oxford University Press, New York, New York.

Shefrin, Hersh, and Meir Statman. "The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence." *Journal of Finance*, July 1985, pp. 777-790.

Thaler, Richard H., and Eric Johnson. "Gambling With The House Money And Trying To Break Even: The Effects Of Prior Outcomes On Risky Choice." *Management Science*, June 1990, pp. 643-660.

Scherbina, Anna, and Li Jin. "Change is Good or The Disposition Effect Among Mutual Fund Managers." *Working Paper*, 2005, Harvard Business School.

Endnotes

[1] In U.S. equity markets, Shefrin and Statman [1985] and Odean [1998] find evidence of the disposition effect among retail investors. Garvey and Murphy [2004] and Scherbina and Jin [2005] find evidence of the disposition effect among professional traders and mutual fund managers respectively.

[2] For example, suppose an individual is faced with a choice between (1) selling a stock for a capital gain of $10,000, or (2) holding the stock when there is a 50% chance of gaining $20,000 and a 50% chance of gaining nothing. The expected gain in both choices is $10,000. However, according to prospect theory, most people will realize the gain.

[3] *Mental accounting* is the process of segregating gambles faced into separate accounts. Once this occurs, decision makers apply prospect theoretic decision rules to each separate account. *Regret* is an emotional feeling with the ex post knowledge that a different past decision would have fared better than the one chosen. The desire for pride, and the fear of regret, leads people to hold losers too long and sell winners too soon. Shefrin and Statman [1985] show that people are generally aware of the dangers of holding on to losers. However, they often lack the willpower to stop it. This is why the disposition effect is often thought of as a *self-control* problem.

[4] The break-even effect suggests that people are averse to closing a mental account for a loss. When a loss occurs, and a subsequent gamble offers the opportunity to break-even, people will engage in a form of hedonic editing in which they will integrate the prior loss with the future prospect of breaking even. This integration process will induce a risk-seeking behavior.

[5] The variable charge covers trade execution (what it costs the firm to trade) and the fixed charge covers the costs involved with running a trading desk (clearing fees, technology, administration, etc.). If a trader provides liquidity they will often receive a rebate from the exchange rather than pay a fee.

[6] We know that the traders were aware of their performance at all times throughout the day. A box in the corner of their trading terminal keeps track of their trading profits in real time.

[7] We also measure two other risk measures: share size and holding time per round-trip. We exclude these for space considerations. However, both of these risk measures provide similar results to the four risk measures selected.

[8] In order to learn more about the environment we were studying, we spent time at the firm talking with traders and observing them trade.

[9] Our results are robust with respect to the standardization procedure used. When we ran more sophisticated panel data regressions with two-way (trader and day) fixed effects and other predetermined controls, we obtained very similar results.

[10] Of the 16,260 observations, morning net gains were made in 6,279 cases, net losses in 9,973 cases and zero net profits in 8 cases.

[11] In addition to the two fixed effect regressions, we also estimate pooled-OLS and logit regressions. However, the results are qualitatively the same as the fixed effects models and therefore we do not include the results in Exhibit 4 for brevity purposes.

[12] Confidentiality issues with proprietary datasets and differing time horizons among institutional investors are both likely to hinder further research efforts in this area. For instance, many portfolio managers display a valuation function consistent with our intraday traders. However, they are likely to use differing time horizons (e.g., quarter, year, etc.) and reference points to evaluate their prior performance.

Exhibit 1: Trading Statistics

This exhibit sets out some summary trading statistics for the 150 professional stock traders who traded the capital of the National Securities Dealer from May 2002 to June 2003.

Trading	
Number of trades (000's)	1,316.3
Number of shares traded (millions)	2,534.5
Number of stocks traded	693
Performance	
Gross loss ($000's)	-$44,791
Trading costs	-$1,659,948
Net loss	-$1,704,739
Daily Averages (251 days)	
Average number of trades	5,244
Average number of shares per trade	1,925
Average daily net profit	-$6,792
Round-trip Averages (730,417)	
Average net profit	-$2.33
Average holding time	13 minutes
Average absolute price change	$0.01

Exhibit 2: Standardized Morning Net Profits and Afternoon Risk Measures

This exhibit provides summary statistics for the morning net profits and the afternoon risk measures. The data are standardized by trader and shown separately for observations involving a net morning gain and loss. The morning period is 9:30 am to 12:45 pm and the afternoon period is 12:45 pm to 4:00 pm.

	Trader/Days with a morning net gain – (6,279 observations)		
	Mean	Median	Std. Dev.
Morning net gains	0.694	0.531	0.620
Afternoon Risk Measures			
Number of trades	-0.041	-0.188	0.960
Absolute price change	-0.061	-0.246	0.889
Average trade size	-0.064	-0.311	0.977
Aggregate trade size	-0.067	-0.344	0.945
	Trader/Days with a morning net loss – (9,973 observations)		
Morning net losses	-0.761	-0.550	0.741
Afternoon Risk Measures			
Number of trades	0.045	-0.114	1.031
Absolute price change	0.067	-0.181	1.096
Average trade size	0.070	-0.173	1.011
Aggregate trade size	0.074	-0.231	1.044

Exhibit 3: This exhibit displays the relationship between morning net profit and each afternoon risk measure. Both morning net profit and afternoon risk are standardized by trader. Morning net profits are segregated into ten deciles and plotted against the relevant afternoon risk measures.

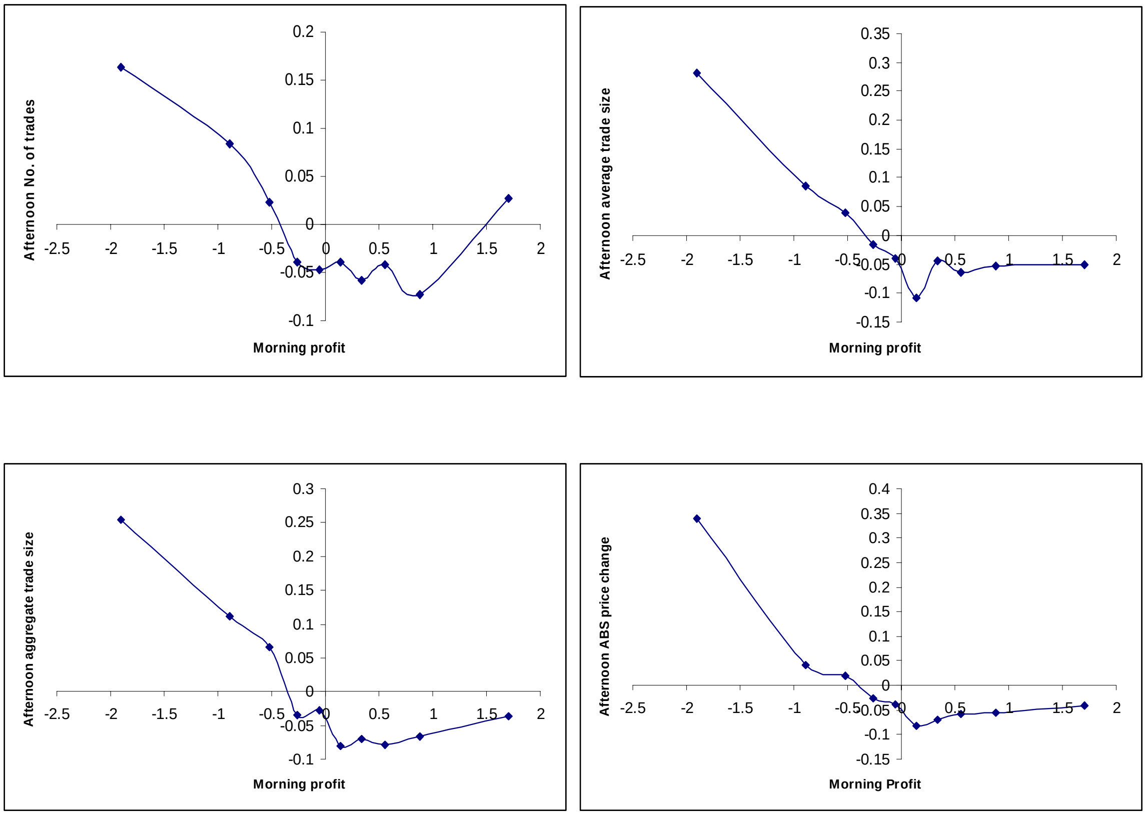

Exhibit 4: Afternoon Trading Behavior and Morning Net Profits

This exhibit reports various regression results relating trader's morning net profits to their subsequent afternoon trading behavior. The four dependent variables (afternoon risk-taking measures) used are number of trades, average dollar trade size, aggregate dollar trade size, and absolute price change. The independent variables used are the morning net profit (at 12:45 pm) and the morning lagged risk measure. Both morning profit and afternoon risk are standardized by trader. The *t*-statistics are in parentheses.

Regression Method	Constant	Morning Net Profit Coefficient	Morning Risk Coefficient	R^2 or Pseudo R^2
Dependent Variable: Number of Trades				
Fixed Effects	-	-0.038 (-5.15)	0.358 (48.86)	13.04%
Fixed Effects Logit	-	-0.0457 (-2.72)	0.6651 (36.10)	7.28%
FM by Date	-0.001 (-0.044)	-0.040 (-3.75)	0.354 (32.25)	-
FM by Trader	-0.000 (-0.577)	-0.017 (-0.72)	0.298 (12.99)	-
Dependent Variable: Average Dollar Trade Size				
Fixed Effects	-	-0.037 (-5.85)	0.582 (91.28)	34.35%
Fixed Effects Logit	-	-0.131 (-7.00)	1.354 (51.28)	20.42%
FM by Date	0.021 (1.55)	-0.034 (-4.23)	0.547 (48.95)	-
FM by Trader	0.000 (1.89)	-0.037 (-2.56)	0.546 (28.12)	-
Dependent Variable: Aggregate Dollar Trade Size				
Fixed Effects	-	-0.025 (-3.71)	0.519 (77.25)	27.28%
Fixed Effects Logit	-	-0.050 (-2.72)	1.145 (45.82)	15.73%
FM by Date	0.017 (0.98)	-0.022 (-2.21)	0.497 (41.29)	-
FM by Trader	0.000 (0.27)	-0.001 (-0.49)	0.467 (21.62)	-
Dependent Variable: Absolute Price Change				
Fixed Effects	-	-0.064 (-8.32)	0.249 (32.42)	7.20%
Fixed Effects Logit	-	-0.040 (-2.33)	0.523 (27.65)	6.24%
FM by Date	-0.017 (-1.24)	-0.069 (-5.26)	0.240 (20.22)	-
FM by Trader	0.000 (0.73)	-0.059 (-3.13)	0.247 (14.81)	-

Exhibit 5: Morning Net Gain/Loss and Subsequent Afternoon Trading Behavior

We segregate the observations of morning net profits into two domains of gains and losses, and then within each domain into five bins from lowest to largest. The results below report the average corresponding afternoon risk measures. Both the morning net profit and afternoon risk variables are standardized by trader. Standard errors are in parentheses.

	Number of Trades	Average Dollar Trade Size	Aggregate Dollar Trade Size	Absolute Price Change
Morning Losses				
1 (Low)	0.160	0.281	0.255	0.340
	(0.031)	(0.028)	(0.031)	(0.039)
2	0.095	0.086	0.112	0.042
	(0.026)	(0.025)	(0.026)	(0.024)
3	0.031	0.039	0.065	0.019
	(0.025)	(0.026)	(0.026)	(0.023)
4	-0.035	-0.015	-0.035	-0.026
	(0.024)	(0.024)	(0.023)	(0.023)
5 (High)	-0.028	-0.041	-0.028	-0.039
	(0.025)	(0.025)	(0.025)	(0.025)
Morning Gains				
1 (Low)	-0.050	-0.108	-0.081	-0.083
	(0.023)	(0.022)	(0.022)	(0.021)
2	-0.070	-0.044	-0.071	-0.070
	(0.022)	(0.024)	(0.023)	(0.023)
3	-0.051	-0.064	-0.079	-0.057
	(0.024)	(0.024)	(0.022)	(0.023)
4	-0.053	-0.052	-0.067	-0.056
	(0.023)	(0.04)	(0.023)	(0.020)
5 (High)	0.020	-0.051	-0.036	-0.040
	(0.025)	(0.025)	(0.024)	(0.021)

Exhibit 6: Overall Profitability and a Measure of Behavioral Bias

This exhibit presents the results of regressing each trader's overall log net profitability (using the signed log absolute value) on a constructed measure of their behavioral bias. See text for details. The *t*-statistics are in parentheses.

Constant	Behavioral Bias Coefficient (10^4)	R^2	No of Observations
-1.057	2.625	6.96%	150
(-9.18)	(3.33)		

Exhibit 7: The Performance of Traders and Their Behavioral Bias

This exhibit compares the net profitability over the entire sample period of traders who had a tendency to exhibit increased risk-taking following morning losses (behavioral bias traders) and traders who did not. The allocation of traders to the two groups is determined by the sign and statistical significance of the estimated coefficients on morning profitability in separate trader by trader regressions of equation (1) using the four risk measures shown in the table. In Panel A, we segregate traders based on whether their behavioral bias coefficients are negative or not. In Panel B, we segregate traders based on whether their behavioral bias coefficients are negative and statistically significant at the 10% level.

Risk Measures	Average net profit		Difference	*t*-stat
	Behavioral bias traders	Other traders		
	Panel A. Behavioral Bias = Negative Coefficient			
Number of Trades	-$12,876	-$9,160	-$3,716	-1.58
Absolute Price Change	-$13,913	-$8,122	-$5,791	-2.52
Average Trade Size	-$12,057	-$10,267	-$1,790	-0.75
Aggregate Trade Size	-$12,013	-$10,605	-$1,408	-0.60
	Panel B. Behavior Bias = Statistically Significant Negative Coefficients at 10% Level			
Number of Trades	-$21,248	-$8,685	-$12,563	-4.74
Absolute Price Change	-$22,241	-$7,804	-$14,437	-5.94
Average Trade Size	-$15,041	-$10,766	-$4,275	-1.28
Aggregate Trade Size	-$16,473	-$10,533	-$5,940	-1.79