Do Losses Linger?

Evidence from proprietary stock traders.

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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]). Research has found strong support for the disposition effect among both retail and institutional market participants.[1]

We extend this research by examining how professional stock traders react to previous trading gains and losses; that is, 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 have an enhanced appetite for risk in the afternoon. This behavior is most likely brought on by their 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 that 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 least 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 that it is defined in terms of gains and losses rather than 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 facing possible 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.

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. Yet according to prospect theory, most people will opt for the more risky choice because they are reluctant to realize a loss, so they will gamble (hold the stock), hoping to break even. In the presence of gains, the opposite behavior will occur, and most people will opt for the more risk-averse choice (realize the gain).

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. These factors together help explain theoretically why people tend to hold on to their losses too long and sell their winners too soon.[2]

PRIOR LOSSES AND SUBSEQUENT RISKY BEHAVIOR

Our work differs from most studies of the disposition effect because we examine risky choices in a sequence of decisions, such as when a loss has already occurred. Suppose now the individual is a trader who has just lost $10,000, but then has the opportunity to participate in another trade with equal chances of winning $10,000 and losing $15,000. According to prospect theory, a trader who has not come to terms with the prior loss 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 Kahneman and Tversky note, "A person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise." [1979, 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] find evidence of a *break-even* effect. The break-even effect predicts that when individuals incur prior losses, they will be attracted to subsequent gambles that offer the opportunity to break even.[3]

More recently, Coval and Shumway [2005] and Locke and Mann [2004] examine how commodity traders at the Chicago Board of Trade and the Chicago Mercantile Exchange were influenced by their prior trading performance. Both studies find evidence of increased risk-taking following trading losses.

We examine the reaction of proprietary traders who work on an equity trading desk to earlier trading gains and losses. We also analyze the effect of this behavioral tendency on trading performance.

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 during the 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 in the overall strategies followed 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 involve 730,400 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 American Stock Exchange or New York Stock Exchange. This is one reason why over 99% of the shares traded are in Nasdaq-listed stocks.

The traders combined accounted for approximately 0.62% of Nasdaq share volume during the year, with trading concentrated in certain stocks on certain days, often generating a sizable 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 and JDS Uniphase, the only two stocks that 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, or 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 calculate gross and net round-trip trading profits. For every stock in a trader's account, we match opening trades with the subsequent closing trades on 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. 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 other study in behavioral finance that 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, one could easily question our assumptions and resulting findings. We know that the traders were strictly prohibited from holding positions overnight, however. 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 the 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 paid nearly $1.7 million in net trading costs during the course of the year, which had a significant impact on 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.[4]

The traders pay all 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 traders' take-home earnings are directly linked to their trading performance, our results are less susceptible to complications arising from agency costs.

Exhibit 1 presents some summary trading statistics for our traders. Overall, the traders almost broke even on a gross profit basis, losing only $45,000 or so during the course of the year. 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 of trading: an average of 5,244 trades per day with an average holding time of 13 minutes per round-trip and a 1 cent absolute price change. According to the firm they worked for, the major reason the traders were not profitable during this period was the then-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.

EXHIBIT 1
Trading Statistics

Trading	
Number of trades (000s)	1,316.3
Number of shares traded (millions)	2,534.5
Number of stocks traded	693
Performance	
Gross loss ($000s)	-$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

METHODOLOGY AND RESULTS

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

In order to examine the relation between prior performance and subsequent decision-making, we adopt an approach similar to that used by Coval and Shumway [2005], and split the trading day into two parts. We define a morning session of trading as from 9:30 am to 12:45 pm and an afternoon trading session as after 12:45 pm to 4:00 pm. Our main purpose in breaking 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 assimilate results of their performance going into the lunch period, so we can see how they react when they return in the afternoon.[5]

There is no set lunch period, but the data reveal that trading is lightest between 12 noon and 1 pm. Furthermore, from our discussions with members of the firm, we know the traders often stop 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 their positions in minutes, and it is rare for a trader to leave an open position unwatched for any period of time.

Measuring risk directly is difficult, so we look at a number of indirect measures, including four risk measures that are common among intraday traders. The first measure is the number of trades conducted. All else equal, trading more frequently can be construed as more risky trading behavior.

The second and third measures consist of the average dollar size per trade (price multiplied by quantity) and the aggregate or total dollar amount traded during the morning or afternoon trading session. All else equal, the average dollar size traded 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 follow 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. All else equal, if a trader deviates from his or her typical average absolute price change during a trading period, we infer that the trader is engaged in increased risk-taking.[6]

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 would mean a very different thing to a trader who never executes more than 50 trades a day and a trader whose daily trading activity averages 150 or more trades.[7]

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 traded. We use the trader-specific means to de-mean the trader's morning net profit figures. Then we divide the de-meaned 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 standardized separately.

Some summary statistics for the standardized risk measures are set out in Exhibit 2. The statistics are disaggregated by whether 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.[8]

The data suggest that the 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 higher), by trading in relatively larger trade sizes (0.070 SD higher), and by trading in relatively higher dollar amounts (0.074 SD higher). In the case of a morning net gain, the opposite is true—the standardized risk measures are below average in the afternoon.

EXHIBIT 2
Standardized Morning Net Profits and Afternoon Risk Measures

	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

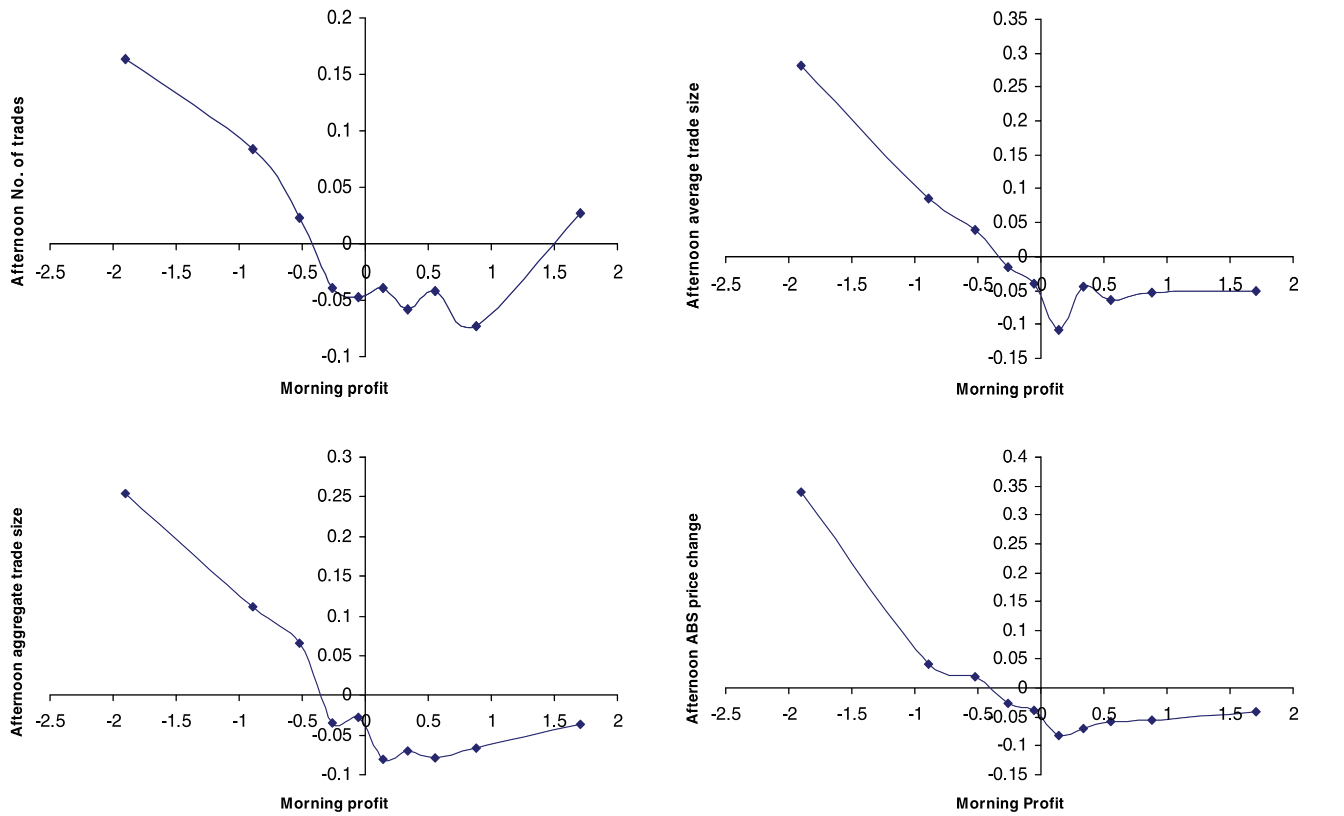
It appears that the traders' desire to recover from a morning loss is what leads them to trade more aggressively in the afternoon. For a visual examination of this behavior, we segregate the standardized morning net trading profits of trader-day observations into ten deciles. Exhibit 3 plots these against the average standardized afternoon risk measures for each decile group.

For each risk measure, we can see that as morning net profits decline, 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 that is not obvious from Exhibit 2.

The desire to break even after a loss, as well as the 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 theory decision rules. In our case, the focus is on a daily setting, 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 becoming conservative after morning losses. If the traders were to do this, it would send a signal that they had made poor decisions in the morning

EXHIBIT 3
Relation Between Morning Net Profit and Each Afternoon Risk Measure



trading session. Having to admit mistakes to colleagues or supervisors might intensify the emotional feeling of regret.

We note in Garvey and Murphy [2004] that, because professional traders often trade together, there can be a sense of competition on trading desks. Such rivalries amplify the tendency to maintain status and avoid regret. As we show below, this behavior hampers performance.

Regression Results

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

$$Risk^A_{i,t} = \alpha_i + \beta_\pi \pi^M_{i,t} + \beta_R Risk^M_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $Risk^A_{i,t}$ equals one of the four standardized afternoon risk measures for trader i at time t, $\pi^m_{i,t}$ is trader i's time t morning net profit, $Risk^M_{i,t}$ 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 the trader's morning net profits. The fixed-effects logit regression model takes the form:

$$P(Risk^A_{i,t} > 0) = \frac{e^{\alpha_i + \beta_\pi \pi^M_{i,t} + \beta_R Risk^M_{i,t}}}{1 + e^{\alpha_i + \beta_\pi \pi^M_{i,t} + \beta_R Risk^M_{i,t,i}}} \tag{2}$$

Finally, we estimate two Fama and MacBeth (FM) [1973] regression models that 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

Exhibit 4
Afternoon Trading Behavior and Morning Net Profits

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

t-statistics are in parentheses.

robustness of our findings. They suggest that our findings are driven by certain traders or days.[9]

Looking at the regression results in Exhibit 4, we can see strong evidence supporting our initial claim that traders are trying to recoup their morning losses, so that a mental account is not closed at a loss. All 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 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

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.

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 highest. 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 decline monotonically with the ranking of the losses. In the domain of morning gains, there is no obvious pattern.

Desire to Break Even and its Impact on Performance

Overall, our traders appear to exhibit a behavioral bias that is likely to have a great if 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 constant 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.[10]

At a more micro level, the behavioral bias we identify is likely to affect the firm's profits and the trader's net earnings. As Shefrin [2002] notes, recognizing behavioral biases in decision-making is important because knowledge like that can help market professionals improve their performance. 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. The dependent variable is the signed log of the absolute value of total net profits. The trader-specific behavioral bias measure is constructed in two steps. First, we run trader-by-trader regressions of Equation (1) for each of the four risk measures. Second, we average the four estimated morning profit coefficients (β_π) for each trader to obtain the 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 more poorly than other traders.

It is possible that only one of the four coefficients could dominate the others and drive the results. To address this concern, we examine the effect of each component 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.

EXHIBIT 5
Morning Net Gain/Loss and Subsequent Afternoon Trading Behavior

	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)

standard errors are in parentheses.

EXHIBIT 6
Overall Profitability and Measure of Behavioral Bias

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

t-statistics are in parentheses.

Assignment 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 of Exhibit 7 we segregate traders according to whether their behavioral bias coefficients are negative. In Panel B, we segregate traders according to 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 underperform those who do not. The average difference in the net profitability of the two groups ranges

Exhibit 7
The Performance of Traders and Their Behavioral Bias

Risk Measure	Average Net Profit: Behavioral Bias Traders	Average Net Profit: Other Traders	Difference	*t*-stat
	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

from –$1,400 to –$5,800. Of the four risk measures, only the difference using the absolute price change risk measure is statistically significant.

In Panel B of Exhibit 7 we focus on the traders who are most affected by their prior trading losses, i.e., traders with statistically significant negative morning profit coefficients. Now the difference in the net profitability of the behavioral bias and the other group of traders ranges from –$4,300 to –$14,400. Three 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 perform far below the overall average. 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 impairs their overall performance. Moreover, the more prone a trader is to this behavior, the more likely the trader is to lose money.

The practical implications of our results are unquestionably appealing from both an individual trader and a 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] use self-control in the disposition effect in order to explain the rationale for methods used to force people into realizing their losses (e.g., stop loss orders). 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 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 are realized, they may overlook aversion to sure loss tendencies. In order to prevent this sort of behavior on trading desks, firms could put automated controls in place to monitor prior trading profits and behavior and then alert traders by methods such as screen warnings or alarms when they diverge from their normal risk-taking tendencies. For example, if a trader has experienced a morning net loss and is trading 10% more than usual in the afternoon, an alert message appearing on the trading monitor could warn the trader (and the trading manager) at the time. Such control mechanisms might enhance a trader's performance.

CONCLUSION

Imagine that just after you enter a casino, you lose $500 on the roulette wheel. Will this $500 loss cause you to bet more conservatively with your future gambles, or will it increase your appetite for risk with ensuing gambles? We explore this question in a financial market setting by examining the sequential decision-making behavior of professional stock traders. How do a trader's morning gains or losses influence the afternoon trading decisions?

Our empirical results provide strong evidence that professional stock traders who experience morning losses take more risks in the afternoon. They probably do so in order to recover their losses and close out their daily accounts (mental accounts) in the black. Traders also appear to have asymmetric reactions to their morning gains and losses. Morning losses have a much more pronounced effect than morning gains.

Our findings are consistent with the behavioral theory underlying aversion to a sure loss and the disposition effect. They are also consistent 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 more poorly than other traders.

The fact that professional traders suffer from behavioral biases leads us to suspect that other stock market professionals could suffer from similar biases.

ENDNOTES

The authors thank Meir Statman for helpful comments and suggestions; seminar participants at the 2005 Financial Management Association Conference in Chicago for helpful comments and discussions; and executives at the securities firm for providing proprietary data.

[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.

[2]*Mental accounting* is the process of segregating gambles faced into separate accounts. Once this occurs, decision-makers apply prospect theory decision rules to each separate account. *Regret* is an emotional feeling, with the ex post knowledge that a different decision would have been better than the decision made. 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, but they often lack the willpower to change. This is why the disposition effect is often thought of as a *self-control* problem.

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

[4]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 (e.g., clearing fees, technology, administration). A trader who provides liquidity often receives a rebate from the exchange rather than paying a fee.

[5]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.

[6]We also include two other risk measures: share size and holding time per round-trip. While we do not report full results for these for space reasons, both of these risk measures provide results similar to the four risk measures selected.

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

[8]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.

[9]In addition to the two fixed-effect regressions, we also estimate pooled ordinary least squares and logit regressions. The results are the same as for the fixed-effects models, so we do not include the results in Exhibit 4.

[10]Confidentiality issues with proprietary datasets and differing time horizons across institutional investors are both likely to hinder further research efforts in this area. For instance, many portfolio managers display a valuation function consistent with the results for our intraday traders, but they are likely to use differing time horizons and reference points to evaluate their prior performance.

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