

## **Maximizing Wealth and Happiness: Improving Investor Decisions Through Improved Affective Forecasting**

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Given the economic crisis of the past few years and the plummeting value of individuals' retirement funds, the issue of consumer investment and savings has become crucial to consumer welfare. People have been forced to remain in jobs longer to attain their savings goals and seeing quarterly statements that show no growth has become the norm. With the economy finally showing signs of turning, it is important that consumers also make smart investment decisions that enable them to recover from this period of economic crisis and put them back on the path to attaining their savings goals.

A 2009 study concluded that average investors failed to achieve market index returns. From 1988-2008, the S&P 500 averaged an 8.4% return per year while the typical investor only achieved 1.9%, less than the inflation rate of 3% (Dalbar 2009). Why, if long term gains are the goal, do we see this 'irrational' behavior and what can be done to improve this circumstance?

We examine how experience and explicit feedback can reduce two of the main impediments to successful investor decision-making: loss aversion and myopia. Poor affective forecasting is believed to undermine investor decision making by fueling loss aversion which results in more myopic and suboptimal decision making. Improved affective forecasting frees investors to choose investments that are in their long-term best interest.

Using a simulated market environment, we are able to demonstrate that providing consistent outcome feedback that illustrates the gap between an individual's forecasted affective response to the outcome of an investment decision and the actual affective response reduces

affective forecasting errors. Once investors become better forecasters of their own reactions, they are less inclined to fear a temporary setback, thereby reducing their loss aversion. In other words, by improving affective forecasting, we can help consumers maximize both their wealth and their happiness.

After a brief review of the relevant literature and discussion of our model and predictions, we describe our experiment where a simulated investment market is used to enable both experienced and naive investors to make a series of investment decisions and receive explicit feedback regarding their affective forecasting errors over a relatively short time period. We then present the findings obtained from our model and end with a discussion of the implications of these results.

### *AFFECTIVE FORECASTING AND LOSS AVERSION*

Much research on investment decisions has shown that consumers tend to be both myopic and loss averse (Benartzi and Thaler 1995; Shiv et al. 2005; Thaler et al. 1997;). Two commonly observed and troubling findings support these shortcomings in investor behavior. The first of these being the well known “equity premium puzzle” which questions why, given the empirical fact that stocks have outperformed bonds over the last century by a surprisingly large margin, people are still willing to hold bonds. The second, referred to as “the disposition effect,” finds that investors are overly anxious to sell their winners and reluctant to sell their losers, resulting in reduced earnings (Shefrin and Statman, 1985). To a large extent, these shortcomings exist because of loss aversion.

The term loss aversion means that people are more sensitive in the region of losses than in the region of gains (i.e.  $\text{Value}(X) < |\text{Value}(-X)|$ ). For example, a loss of \$100 is evaluated more negatively (larger in magnitude) than a gain of \$100 is evaluated positively. In Kahneman and Tversky's (1979) words, "losses loom larger than gains." This implies that a loss of equal magnitude to a gain will have a larger magnitude of negative feeling than the positive feeling of the gain. Ariely, Huber, and Wertenbroch (2005) highlighted an important point about loss aversion; specifically, that it is reference dependent. In other words, losses and gains do not exist in a vacuum but rather only take on meaning in reference to some initial state. Imagine a child getting a piece of chocolate after dinner. The value of that chocolate would be much more the day before Halloween as compared to Halloween itself, when the child is already inundated with treats. To the extent that investors have goals, or expectations regarding expected earnings, these goals may serve as reference points for evaluating earning performance (Heath, Larrick, and Wu 1999). So, if two investors have different expectations for a stock's performance, one hoping to see a 12% return and the other expecting 8%, we would expect quite different reactions to a 10% earnings report.

In the context of affective forecasting, the loss aversion coefficient can be computed by calculating the ratio of the negative emotion realized by falling short of a goal by  $x$  to the positive emotion associated with exceeding the same goal by  $x$ . This is illustrated in equation (1) where  $V'_n(x)$  denotes the marginal decrease in the value function evaluated in the loss domain (i.e., where realized performance  $x$  is below the goal) and  $V'_p(x)$  is the marginal increase in the value function evaluated in the domain of gains. Ho, Lim and Camerer (2006) report loss aversion coefficients generally fall in the range of 1.3 – 2.7 and Heath, Larrick, and Wu (1999)

report the coefficient to be between two and four.

$$(1) \quad \left| \frac{V'_n(x)}{V'_p(x)} \right|$$

Kermer et al. (2006) note that loss aversion results from an affective forecasting error. Affective forecasting is what consumers engage in when they attempt to predict their affective responses to various outcomes. This is implicitly what individuals do when they face a decision, especially regarding something new. In other words, we only make decisions based on our forecast of what the experience will be. For example, before deciding whether to go on vacation to China or Italy, one may attempt to forecast which food would provide the most pleasure and then factor this into their decision. Kahneman and Snell (1992) were the first to make the distinction between decision utility, experienced utility, and predicted utility laying the groundwork for studying consumer's ability to forecast experienced utility. In their studies people were asked to make predictions of what it would be like to consume ice cream or yogurt and music every day for a week. While the modal prediction was decreased liking, their actual experience revealed the opposite.

The affective forecasting error (AFE) states that we are actually quite poor at forecasting how it will feel to experience an outcome. When asked to predict how they will feel if they lost a job or spouse, if they flunk an exam or if their team loses a game, people consistently overestimate the magnitude of their negative feelings and lottery winners often report levels of happiness identical to non-winners after just five years (Brickman, Coates, and Janoff-Bulman

1978; Gilbert, Driver-Linn, and Wilson 2002; Loewenstein, O'Donoghue and Rabin 2003; Mellers and McGraw 2001; Wilson and Gilbert 2003).

These examples illustrate poor affective forecasting in complex contexts but, Kermer et al. (2006) demonstrate how difficult we find forecasting even in the simplest of tasks. Their research studied peoples' response to the outcome of a coin flip. In one study, participants were given the following gamble. If the experimenter flipped heads, they would win \$5; if he flipped tails, they lost \$3. They were then asked to forecast their happiness after either outcome. The experimenter then flipped the coin, one outcome was realized and participants reported their affect. Even in this simple example, with only two outcomes, the same participant, and less than a few minutes separating the forecast from the actual affective response, participants showed poor calibration. They regularly overestimated the negative impact of losing \$3 with tails and, while less drastically, even overestimated the positive effect of winning with heads.

Kermer et al. (2006) point out that people show aversion to losses because they expect losses to have a larger magnitude of affective impact than equal sized gains. This suggests that, in fact, the asymmetry highlighted by the phrase "losses loom larger than gains" is not one of affective experience but of affective forecasting. Therefore, a more accurate statement might be that *forecasted* losses loom larger than *forecasted* gains, while actual losses are quickly and easily dealt with through psychological defense mechanisms.

Unfortunately, it is very difficult for people to correct their forecasting flaws without explicit education. Because many coping mechanisms occur automatically or nonconsciously, people often fail to anticipate how they are able to psychologically alter negative experiences (Gilbert et al. 1998). Furthermore, it is difficult to remember back to when a forecast was made and compare it to the actual affective response and, often, there is also no motivation to do so

(Einhorn and Hogarth 1982). Finally, there are often distorted memories of the forecasts. Upon meeting a colleague, one's first impression may be of distaste, but with more interaction, they end up being a close friend. Looking back, we may remember that we always liked him and knew he would be a great friend. With these psychological obstacles, people find it hard to learn that they are poor affective forecasters and, if we have no idea that we are poor forecasters, we have no reason or motivation to improve our forecasting skills.

But what if people did improve their affective forecasts? Could it change the manner in which they chased their goals? People invest conservatively because they are afraid of the affective cost of failure. By learning how to make better affective forecasts, they should find that failure is not as affectively costly as initially predicted and that the negative affect fades quickly, resulting in lowered loss aversion. Without this aversion to failure, people can make decisions that are less myopic and more wealth maximizing.

The issue, then, is what can be done to enable investors to improve their affective forecasts. In order for people to improve, they need specific, explicit feedback on their performance. Without explicit feedback, the learner will likely believe that their predictions were correct and affirm misconceptions about the quality of their prediction (Brosvic et al. 2005). Most forms of feedback are an effective tool to aid learning, continuous feedback is one of the most effective learning aids (Hembrooke et al. 2005). Most importantly to the current research, the most valuable feedback is on incorrect, rather than correct, answers (Pashler et al. 2005). Getting feedback about a correct answer (in our case, forecast) does not have a significant effect on retention. However, receiving feedback about an incorrect assessment significantly improves information retention, which should enable people to incorporate this newly learned knowledge into future tasks.

Specific feedback eliminates many of the causes for poor forecasting stated above. With feedback explicitly informing people that their forecasts are incorrect, we eliminate lack of motivation as a hindrance to learning. This also eliminates the possibility of misconstrual and motivated distortions. Feedback of the nature, “You predicted  $x$  but actually felt  $y$ ” is incontrovertible and confronts the person with undeniable evidence of their inaccurate forecasting.

To conclude, loss aversion is, in part, due to poor affective forecasting and leads us to maximize neither objective nor emotional outcomes. Our aim is to examine whether explicit individual feedback regarding the direction and size of affective forecasting error can improve calibration. We believe that if affective forecasting is improved, loss aversion will be reduced, enabling consumers to improve both their wealth and their happiness.

### *MODEL*

As discussed, theory suggests that people evaluate outcomes using their goals as a reference point that divides outcomes into successes and failures. These evaluations also exhibit properties of the prospect theory value function, most importantly, loss aversion. Therefore, using an appropriate model to estimate the value function should allow us to make inferences about loss aversion using parameter estimates from the model. We model the value function using the following form:

$$\begin{aligned}
(2) \quad & y_{it} - y_i^{ref} = c_i \left( \frac{2}{1 + \exp(-\beta |r_{it} - r^{ref}|)} - 1 \right) + \varepsilon_{it}, \quad \varepsilon_{it} \sim iid N(0, \sigma^2) \\
& \text{if } r_{it} \geq r^{ref}, \quad c_i = \max(y_{it}) - y_i^{ref}, \beta = \beta_p \\
& \text{if } r_{it} < r^{ref}, \quad c_i = -(y_i^{ref} - \min(y_{it})), \beta = \beta_n
\end{aligned}$$

In equation (2),  $y_{it}$  denotes either the affective forecast or actual response to a particular rate of return (ROR) denoted by  $r_{it}$  for individual  $i$  in investment scenario  $t$  and  $y_i^{ref}$  represents the affective forecast/response evaluated at the reference return,  $r^{ref}$ . The dependent variable in this analysis is operationalized as the difference between  $y_{it}$  and  $y_i^{ref}$ . Differencing  $y_{it}$  by  $y_i^{ref}$  centers each participant's affective forecasts/responses at 0. This eases the interpretation of estimated model parameters and allows us to control, in part, for individual differences in scale usage.

Individual differences in scale usage are also captured through the inclusion of  $c_i$ . The logistic form of the value function yields an s-shaped curve with individual-specific, asymptotic upper and lower boundaries,  $c_i$ . These upper and lower boundaries are computed, respectively, as a deterministic function of the maximum and minimum observed responses,  $y_{it}$ , and the reference response,  $y_i^{ref}$ .

The critical parameter of interest in this equation is  $\beta$  which controls the curvature of the value function. As  $\beta$  increases, the value function becomes increasingly steep (i.e., the affective response to slight departures from the reference point is more extreme). Like  $c_i$ , we allow  $\beta$  to assume different values above and below the reference point denoted by  $\beta_n$  in the loss domain and  $\beta_p$  in the gain domain. By allowing  $\beta$  to differ above and below the reference point, we



can capture the theoretical, asymmetric shape of the value function. If loss aversion exists, we would expect to see a value  $\beta_n$  that is larger than  $\beta_p$ . Note that the non-linear nature of the value function prohibits us from directly computing the loss aversion coefficient by examining the ratio of  $\beta_n$  to  $\beta_p$ , as presented in equation (1). We can, however, use evaluations of the value function to compute the implied loss aversion coefficient for each realized return,  $r_{it}$ . Consistent with prospect theory, non-linearity in the value function implies that the magnitude of loss aversion will decrease as realized returns,  $r_{it}$ , move further away from the reference point,  $r^{ref}$ .

The basic form of the value function in equation (2) can be modified to test for differences between experimental conditions of interest (i.e., feedback, experience, etc.). This is accomplished by re-expressing  $\beta$  as follows:

$$(3) \quad \begin{aligned} \beta_p &= \beta_{p,0} \times \left( 1 + \sum_k \delta_{p,k} z_k \right) \\ \beta_n &= \beta_{n,0} \times \left( 1 + \sum_k \delta_{n,k} z_k \right) \end{aligned}$$

where  $\beta_{p,0}$  and  $\beta_{n,0}$  denote the average curvature parameters across individuals in the study in the gain and loss domains, respectively. Equation (3) allows each given experimental condition,  $z_k$ , to alter these average curvature parameters through the estimated parameter,  $\delta_k$ . For example, if  $z_k=1$  (treated condition) and  $\delta_{p,k} > 0$  then the value function would become steeper in the domain of gains (i.e.,  $\beta_p$  would be larger). By examining the sign and statistical significance of  $\delta_k$ , we can determine the efficacy of our experimental manipulations and their

effect on the shape of the value function. These estimates, in addition to the estimates of  $\beta_{p,0}$  and  $\beta_{n,0}$ , provide a basis for testing the following predictions.

### *PREDICTIONS*

We expect that people learn from experience; in this case, learning would include both better affective forecasting and less myopic decision making. Therefore, more experienced investors are expected to be better calibrated in their affective forecasts given they have had numerous opportunities to make investment decisions and experience the outcomes of these decisions. For this reason, we believe that:

H1: Experienced investors will make smaller affective forecasting errors than naive investors.

Though experience provides an implicit opportunity to improve affective forecasting, it is not the most efficient manner in which to do so. Providing explicit individual feedback, regarding the direction and size of affective forecasting errors enables people to become better calibrated. They need not expend cognitive energy to pull together this comparison themselves, nor is there room for rationalizations or memory distortions that can hinder learning. To this end, we hypothesize that:

H2: Providing explicit feedback will improve investor calibration resulting in smaller affective forecasting errors

While feedback can be an effective learning tool, it need not be equally effective for all investors. Feedback should have its greatest impact on those who have learned the least to date. These people have the most room for improvement and, due to their lack of experience, a dearth of tools and knowledge to improve on their own. Therefore, explicit feedback about affective forecasting errors should be more effective for naive than for experienced investors.

H3: Providing explicit feedback will reduce the size of affective forecasting errors more for naive than for experienced investors

As discussed earlier, there is evidence to indicate that loss aversion is actually driven by the affective forecasting error (see Kermer et al. 2006). Therefore, we believe that improved affective forecasting will reduce loss aversion. In accordance, we hypothesize that:

H4: Providing explicit feedback will reduce the size of the loss aversion coefficient of the forecasting value function

Once again, the effect of feedback should be more pronounced on investors who have less experience. Therefore, these people should show the largest improvements in affective forecasting. If they improve their forecasts the most, they should reduce their loss aversion the most as well. Therefore:

H5: Providing explicit feedback will reduce the loss aversion coefficient of the forecasting value function more for naive than for experienced investors

The hypotheses presented so far claim that feedback and previous experience both will have an impact on the size of affective forecasting errors and, therefore, loss aversion coefficients. However, what is the value of reducing loss aversion? Consumer investment is plagued with myopia and fear of failure. Partly due to these two obstacles, armchair investors struggle to make the correct long-term investments. This aversion to short-term losses keeps people from making investments that would actually help them maximize their wealth in the long term. Providing feedback, by lowering loss aversion, should help investors make decision focusing on long-term returns. Therefore, we hypothesize that:

H6: Providing explicit feedback will lead to less myopic investment decisions that maximize long-term expected returns rather than short-term gains

## *INVESTMENT SIMULATION STUDY*

### *Method and Participants*

We developed a simulated investment environment in which we could test our hypotheses regarding feedback and experience. The only factor directly manipulated was the presence or absence of explicit feedback regarding the size of an individual's affective forecasting error. Level of investment experience is the second factor examined. This factor was measured rather than manipulated using self-report. In order to ensure that participants had a range of investment experience, both undergraduate business students ( $n = 213$ ) and MBA ( $n = 46$ ) students were recruited to participate. MBA students were included because of their likelihood of having more experience making investment decisions.

### *Procedure*

Participants entering the study were told they would spend approximately 45 minutes making investments in a simulated environment (see Figure 1). They were either given \$10 (MBA students) or class credit (undergraduate students) to participate. To ensure cognitive and affective involvement, participants were also told that the three people whose investments earned the most over the course of the experiment could be paid up to \$120 over and above their participation payment. Our interest is in participants' affective responses to investment earnings and not their investing prowess, therefore, the probabilistic incentive was provided so that participants would be involved in the study and experience strong emotions upon seeing the results of their investment decisions. The computer-based experiment was divided into two phases, referred to as the learning phase and application phase, respectively.

### *Learning Phase*

In the learning phase, all participants were told that the long term return on investment of mutual funds averaged 10% and, therefore, their goal was to make investment decisions that returned more than 10%. Participants in the “no feedback” condition were instructed to make investment decisions for 14 periods. In each period, these participants were given a set of nine possible funds in which to invest (see Appendix A) and asked to select one of the nine funds. Detailed information about each fund was provided and participants had an unlimited amount of time to study the information before making each investment decision. After selecting a fund, participants were presented with the fund’s performance in that period. The return rates ranged from 6% below the goal to 6% above the goal. This information was presented as both a percentage return and an absolute monetary return (i.e. your investment produced a 5% return that lead to a \$50 gain). Before continuing on to the next period, participants were asked to rate how they felt about the outcome of their investment decision on a scale ranging from 0-100.

While participants were told that their choice of fund mattered, in actuality, it had no bearing on their investment outcomes. Each participant experienced the same rates of return for their 14 periods of investment decisions. For each participant, the order of the return rates across the fourteen investment periods was randomly determined by the simulation to ensure that there was no confound between order and return rate.

Participants in the “explicit feedback” condition were first asked to make seven affective forecasts which were followed by seven investment decisions identical to the decisions made by participants in the “no feedback” condition. The seven affective forecasts were presented as hypothetical outcomes. During this affective forecasting task, individuals were not presented

with fund information, nor given the opportunity to select a fund. Instead, these participants were asked to imagine and report how they would feel if they had made an investment that received a specified rate of return. Consistent with the range of return rates used for the “no feedback” group, each participant in the “explicit feedback” condition was presented with the same return rates (6% below the goal to 6% above) about which they had to make their affective forecast. Again, the presentation order was randomly assigned by the computer. The same 0-100 scale that was described earlier was also used to assess participants’ affective forecasts.

After completing the series of seven affective forecasts, the “explicit feedback” condition participants engaged in seven actual investment decisions. The seven investment decisions were identical in nature to the ones made by the “no feedback” condition participants. Participants in the “explicit feedback” condition saw nine funds, chose one, saw the return on their investment, and evaluated it on the 1-100 affect scale. However, after making this evaluation, participants were presented with feedback comparing their affective forecast to their actual affective response. The rates of return of the actual investment decisions were matched with the returns imagined in the affective forecasting task to enable individualized feedback comparing predicted and actual affective responses at the same rate of return for each participant.

### *Application Phase*

Following the learning phase, participants were notified that a second round of the study was about to commence. In the application phase, participants from both the “no feedback” and “explicit feedback” conditions proceeded through the experimental procedure identically. Supposedly, five years had passed, and the participant had continued to invest on a regular basis; however, the market conditions had changed and the average long term return on the mutual

funds available to them was now 8%. Therefore, their goal was to make investment decisions that returned more than 8%. Each person was asked to make seven affective forecasts followed by seven investment decisions that were identical to the procedure in the learning phase for the “explicit feedback” condition. However, there were two critical changes: (1) the return rates were adjusted to reflect the change in the reference point (goal) which shifted from 10% to 8%, and (2) no feedback was provided following each investment decision. The data from the application phase allows for examination of affective forecasting errors, value functions, loss aversion and the degree of myopia in fund selection exhibited by each participant across feedback conditions and experience.

Finally, after completing the application phase, participants were asked questions to assess their level of investment experience, including a self-report measure, which is used in the following analyses as a measure of investment experience. They were also asked standard demographic questions such as gender, major, race and age.

## *RESULTS*

To test our hypotheses, we fit a variety of permutations of the value function presented in equation (2) using different operationalizations of the dependent variable (i.e., different subsets of respondents, different phases of the experiment, etc.) and different experimental conditions. To aid exposition, we present our results in both tabular and graphical form. Model parameters



for the value function are estimated using non-linear least squares. In the following sub-sections we describe each analysis and map its results back to our hypotheses.

### *Investment Experience and Affective Forecasting Errors*

Our objectives in this initial analysis are to first assess the degree to which affective forecasting errors are present in our sample. Second, if participants do make affective forecasting errors, we would like to determine if the magnitude of those errors differ for experienced investors vs. naive investors (hypothesis 1). Therefore, we specify equation (3) to be

$$\beta = \beta_0 (1 + \delta_1 \text{Actual} + \delta_2 \text{Experience} + \delta_3 \text{Actual} \times \text{Experience}).$$

Analysis proceeds by fitting the value function in equation (1) to the affective ratings data (both forecasted and actual) and evaluating the resulting parameter estimates. Conditions tested through the specification described in equations (3) include Actual vs. Forecast, Experience, and the interaction of the two. The first condition allows us to determine if the shape of the value function differs for ratings based upon actual vs. forecasted results. If the estimated parameters ( $\delta_1$  and  $\delta_3$ ) are equal to zero, this implies the two curves have identical slopes, indicating that participants do not make errors in their affective forecasts. The same logic holds for the Experience variable. If the estimated parameters ( $\delta_2$  and  $\delta_3$ ) are 0, all investors make the same degree of affective forecasting errors, irrespective of the level of experience.

In this first analysis we only use learning phase data from the “explicit feedback” condition. The “no feedback” participants made no forecasts; therefore, we can make no inferences about their forecasting errors. During this phase of the experiment, participants have not yet been influenced by explicit feedback on their affective forecasts. Therefore, we can

assess the impact of investor experience of forecasting errors, without worrying about the potential confounding influence of feedback.

Results of this analysis are presented in Table 1 and reveal a number of interesting findings. First, we observe that the baseline curvature parameters,  $\beta_{p,0}$  and  $\beta_{n,0}$ , are greater than zero. This implies that participant's affective ratings are increasing in the rate of return (i.e., higher returns make people happier). We also observe that the curvature parameter in the loss domain,  $\beta_{n,0}$ , is greater than the corresponding parameter in the gain domain,  $\beta_{p,0}$ . These estimates produce a curve that is consistent with the prospect theory value function. (i.e., the value function is steeper in the loss vs. gain domain with a kink at the reference point).

We also find that  $\delta_{n,1}$  is negative and statistically significant. This implies that the value function is flatter for actual ratings vs. forecasted ratings, indicating that participants overestimate the extremity of pain associated with losses. Interestingly,  $\delta_{p,1}$  is not statistically different from zero, suggesting that participants in our study make smaller affective forecasting errors in the domain of gains.

Finally, we observe that the estimated parameter for Experience,  $\delta_{n,2}$ , is negative and significant, indicating that experienced investors value curves are flatter than those of naive investors, and suggesting that experienced investors are better affective forecasters than naive investors. This result is presented graphically in Figures 2 and 3, where it is possible to view how the discrepancy between the actual and forecasted curves (and by extension, affective errors) differ across these two types of investors. This is direct support in favor of hypothesis 1.

[Insert Table 1 about here]

[Insert Figure 2 about here]

[Insert Figure 3 about here]

*Impact of Feedback and Experience on Affective Forecasting Errors (Between Subjects)*

In this second analysis, we attempt to determine if participants can learn to make better affective forecasts by receiving explicit feedback (hypothesis 2). Furthermore, we would like to determine if the benefit of feedback is attenuated by a respondent's degree of investment experience (hypothesis 3). We would also like to know how both feedback and experience influence the degree of loss aversion manifest in our participants (hypotheses 4 and 5).

Therefore, we specify equation (3) to be

$$\beta = \beta_0 (1 + \delta_1 \text{Feedback} + \delta_2 \text{Experience} + \delta_3 \text{Feedback} \times \text{Experience}).$$

We test these hypotheses by fitting the value function in equation (2) to both the forecast and actual rating data collected in the application phase (Phase 2) of the study. Conditions in this analysis that can influence the slope of the value function include whether or not participants received feedback in the learning phase of the study (Phase 1), their degree of investment experience, and the interaction of the two. Once again, we test the validity of our hypothesis by contrasting estimates of the  $\delta$  coefficients described in equation (3). If hypothesis 2 holds, we would expect  $\delta_1$  to be both negative and significant (i.e., respondents in the feedback condition are better calibrated as affective forecasters). If hypothesis 3 holds, we would also expect to observe a coefficient for the interaction of feedback and experience,  $\delta_3$ , that is positive and smaller than the estimated coefficient for feedback,  $\delta_1$ .

[Insert Table 2 about here]

[Insert Table 3 about here]

[Insert Figure 4 about here]

Results of this analysis are presented in Table 2. We do find that  $\delta_{n,1}$  is negative and significant, indicating that participants that received feedback in learning phase have a flatter value function in the domain of losses. Comparing Tables 2 and 3 allows us to claim that feedback leads to more accurate forecasts (see Figure 4). This is direct support for hypothesis 2 and suggests that it is possible for individuals to learn to be better affective forecasters. We also find that  $\delta_{p,2}$  and  $\delta_{n,2}$  are both significantly negative, indicating that experienced investors are better affective forecasters in both the loss and gain domains, providing further support for hypothesis 1. Finally, we find that  $\delta_{n,3}$  is significantly positive and is smaller than  $\delta_{n,1}$ . This implies that experienced investors learn less from feedback than naive investors. Naive investors that received feedback make smaller affective forecasting errors than naive investors that did not, especially in the domain of losses. Feedback for experienced investors has little, if any, impact on their affective forecasting ability.

We test the impact of feedback and experience on loss aversion by contrasting the estimated loss aversion function for each condition. As noted above, non-linearity in our value function precludes us from directly computing the loss aversion coefficient as the ratio of slope parameters in the loss and gain domains as presented in equation (1). Therefore, we compute the loss aversion coefficient (and by extension, function) according to equation (4), as the ratio of the value function in the negative domain relative to the positive domain evaluated for a particular rate of return.

$$(4) \quad \rho(|r - r^{ref}|) = \frac{c_n \left( \frac{2}{1 + \exp\left(-\beta_{n,0} \left(1 + \sum_k \delta_{n,k} z_k\right) |r - r^{ref}|\right)} - 1 \right)}{c_p \left( \frac{2}{1 + \exp\left(-\beta_{p,0} \left(1 + \sum_k \delta_{p,k} z_k\right) |r - r^{ref}|\right)} - 1 \right)}$$

Because our value function is non-linear, the loss aversion coefficient,  $\rho$ , differs as the rate of return,  $r$ , moves further away from the reference point. As such, we can compute  $\rho$  for a variety of values of  $r$  and plot the resulting loss aversion curve as a function of the rate of return. A plot of the loss aversion functions appears in Figure 5. We show in the Appendix B that statistical differences in these curves can be formally assessed by testing the significance of estimated values of  $\delta$ . If any of the estimated values of  $\delta$  are statistically different from zero, the loss aversion functions must also be statistically different. Since Figure 5 is constructed using only statistically significant coefficients, if the observed curves differ we can conclude that the loss aversion functions are also different.

As shown in Table 2, the estimated coefficient of  $\delta_{n,1}$  is statistically different from 0 indicating that feedback reduces loss aversion. This is support in favor of hypothesis 4. This same concept is presented graphically in Figure 5. Both naive and experienced investors who receive feedback are less loss averse than the counterparts that did not receive feedback. In Table 2, we also observe that  $\delta_{n,3}$  is significant indicating that feedback is more effective at reducing loss aversion for naive relative to experienced investors. This is also shown graphically in Figure

5. The magnitude of the decrease in loss aversion for individuals in the feedback condition is much larger for naive than experienced investors.

[Insert Table 3 about here]

[Insert Figure 5 about here]

### *Impact of Feedback and Experience on Affective Forecasting Errors (Within Subjects)*

Support for hypotheses 2 and 3 in the previous section is achieved through a between-subjects analysis. In this section we conduct a within-subjects analysis in order to further provide evidence that individuals can be taught to be better affective forecasters by using explicit feedback. To accomplish this, we fit the value function to data from the application phase (Phase 2) of the study for participants in the “explicit feedback” condition. Recall that we found evidence of affective forecasting errors in Phase 1 of the study for these same participants (see Table 1). By contrasting the estimated coefficients from these two models, we can determine if affective forecasting errors still exist after the learning phase of the study for participants in the feedback condition.

As shown in Table 4, we find that estimates of  $\delta_{p,1}$  and  $\delta_{n,1}$  are not statistically significant, indicating that the forecasting and actual curves are not different. On average, participants in the “explicit feedback” condition do not make affective forecasting errors in either the gain or loss domain. This result provides further support for hypothesis 2. Support for hypothesis 3 is shown in Figure 6 where we examine the value functions for naive and experienced investors in both the learning and application phases of the experiment. Affective forecasting errors for naive investors are substantially reduced as a result of feedback. Affective

forecasting errors are also reduced for experienced investors, but not to the extent of naive investors.

[Insert Figure 6 about here]

[Insert Table 4 about here]

### *Investment Myopia*

We test hypothesis 6 by observing how fund selection behavior differs for participants in the two feedback conditions. As described in the experimental procedure section, in each investment period, participants are asked to pick one of nine funds in which to invest. Basic information about each fund is provided, including the type of fund (i.e., Small Cap, Large Cap, etc.), a description of the funds basic investment strategy, and the average annualized returns reported for the past year, past three years, past five years, and since the fund's inception. Returns on these funds have been designed in such a way that the maximum historical annualized return occurs either in the previous 1-year period (short-term), or during the past 5 years (long-term). All funds exhibit substantial variability in returns over their lifetime, such that no single fund exists that would be the obvious choice for all investment scenarios.

By observing each respondent's investment behavior, we can infer the time frame (short or long) upon which they are basing their investment decisions. For example, if a participant selected a fund whose prior 1-year return was 10% and annualized 5-year return was 6% instead of a fund with a 1-year return of 5% and an annualized 5-year return of 12%, we can conclude that the fund was selected based upon the short-term criterion. We view this type of behavior as evidence of investment myopia: focusing on short term gains at the expense of long term gains.

We test the impact of feedback on investment myopia by first recoding our data set so that at each fund selection decision we can see if investors selected the fund that would maximize the short-term criterion (i.e., 1-year return) or the long-term criterion (i.e., annualized 5+ year return). We then compute the average number of times the long-term criterion was used in both learning and application phases. By taking the difference of these two we can examine how individual behavior evolves throughout the course of the experiment. If diminished loss aversion (through improved affective forecasting) leads investors to be less myopic in their investment decisions (hypothesis 6), we would expect this difference to be greater for individuals in the “explicit feedback” condition.

In a separate series of analyses, we recode the data so we can compute the expected short-term and long-term return. This is done by examining the fund that was selected and imputing the expected return for each decision criterion (short-term and long-term). For example, if an investor picked the fund described above with the 10% return in the past year and 6% annualized 5-year return, we would impute a value of 10% for the short-term expected gain and a value of 6% for the 5 year gain. This process is repeated for all funds and an average is computed for the learning and experience phases of the study (imputed separately for the 1 year and 5 year criterion). By differencing the expected returns across phases of the experiment we can observe how the expected returns change as a result of explicit feedback (or the lack thereof). If feedback reduces investment myopia, we would expect to see the change in expected short-term return to be less and the expected return for the long-term to be greater for respondents in the feedback condition.

In support of hypothesis 6, we find that respondents that receive feedback are approximately 5% more likely to select funds with a long-term maximal return ( $p < .05$ ) while



there was no significant change in investment behavior for individuals in the untreated group. Furthermore, the expected return based upon the short-term criterion decreases by -0.5% ( $p < .05$ ) for individuals in the feedback condition and does not change for the remainder of the sample. Likewise, the expected return based on the long-term criterion increases by 0.23% ( $p < .05$ ) for participants in the feedback group while the expected return remains unchanged for the untreated group. Neither experience nor the interaction of experience and feedback were statistically significant predictors of fund selection.

### *GENERAL DISCUSSION*

The results of our experiment and analysis support our general claim that improving affective forecasting can improve investment decisions by reducing loss aversion and myopia. We demonstrate that explicit feedback about affective forecasting errors significantly improve forecasting accuracy, especially for naive investors. We also provide evidence that this feedback reduces loss aversion and helps investors make investment decision that focus on long-term outcomes.

Hypothesis 6 predicted that explicit feedback, through reducing loss aversion, should reduce investment myopia. This hypothesis was supported by the data; however, a possible alternative explanation would be that multiple encounters with negative outcomes can sensitize people to losses and actually make them more loss averse (Thaler et al. 1997). Therefore, it could be that participants in the “no feedback” condition actually became more loss averse over the course of the experiment, due to the extra seven periods of investment in which they engaged. However, we see that loss aversion for these participants is actually reduced, rather than

increased, confirming that it is the reduction in loss aversion from feedback that drives the decrease in myopia.

Another interesting, and somewhat unexpected, result from our study is that experienced investors actually underpredicted (in magnitude) the size of the affective reactions. In other words, they did not think that a loss would be as bad as they actually felt. This finding is different from the finding for naive investors, who overpredicted, in magnitude, the size of their affective reactions to losses. Though this result is not focused on in this research, it is one of possible interest. Much literature has shown that experience and expertise often cause people to be overconfident. In this same vein, experienced investors may be overconfident in their ability to emotionally withstand losses. This may explain why they are able to remain active as investors even after making poor investment decisions. In the context of gambling, this might also explain why some people, even though they regularly lose money at the casinos, continue to return. When considering what to do with their weekend, for example, they underpredict the emotional toll that losing at the casino will take on their psyche. Therefore, they head to the casino, unafraid of the likely outcome of losing.

While our research has focused on how people react to investments that either surpass or fall short of their investment goals, all our rates of return remained in the domain of absolute gains. Of course, absolute gains and losses should lead to affective responses that also conform to prospect theory. In fact, zero is a very natural reference point and the pain of experiencing an absolute loss might be worse than just falling short of a goal, but still making an absolute gain. Therefore, it would be of value to also examine the role of feedback and experience on affective forecasting of real gains and real losses.

Finally, one very exciting implication of this work is that people are able to learn to make better investment decisions through explicit and continuous feedback about their poor affective forecasts. This would suggest that, simply by taking the time to explicitly record one's forecasted affective response to investment outcomes and then comparing them to their feelings upon seeing their real earnings could enable investors to make better decisions. This type of forecasting diary would be similar, in vein, to diet diaries that make people acutely aware of the discrepancy between what they should be eating and what they are eating. Given the success of diet diaries and the growth of websites such as [myfooddiary.com](http://myfooddiary.com) providing these diaries as a consumer service, it would be a very interesting business venture to develop similar affective diaries for investors. Companies like [etrade](http://etrade.com) could ask people to explicitly make affective forecasts before making real investments. They would then be able to provide, not just earning information, but forecasting information to their consumers. Over time, these forecasting diaries, by providing continuous and explicit feedback, could improve consumer ability to make their best investment decisions. If this were to happen, much the way diet diaries help people improve their health, the forecasting diary would help investors maximize both their wealth and happiness.

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**Table 1**  
**Learning Phase Forecasting and Actual Value Functions**  
**(Feedback Condition Only)**

		Gain		Loss	
		Estimate	Std Error	Estimate	Std Error
Baseline Curvature	$\beta_0$	0.444**	0.052	0.643**	0.048
Actual	$\delta_1$	-0.152	0.126	-0.556**	0.063
Experience	$\delta_2$	0.113	0.063	-0.056*	0.026
Actual*Experience	$\delta_3$	-0.136	0.072	0.171**	0.033

\*p<.05

\*\*p<.01

**Table 2****Impact of Feedback and Experience on the Forecasting Value Function**

		Gain		Loss	
		Estimate	Std Error	Estimate	Std Error
Baseline Curvature	$\beta_0$	0.633**	0.064	1.049**	0.059
Feedback	$\delta_1$	-0.100	0.120	-0.306**	0.057
InvExp	$\delta_2$	-0.067*	0.030	-0.112**	0.013
Feedback*InvExp	$\delta_3$	0.063	0.044	0.067**	0.021

\*p&lt;.05

\*\*p&lt;.01

**Table 3****Impact of Feedback and Experience on the Actual Value Function**

		Gain		Loss	
		Estimate	Std Error	Estimate	Std Error
Baseline Curvature	$\beta_0$	0.509**	0.053	0.881**	0.058
Feedback	$\delta_1$	-0.002	0.134	-0.165*	0.073
InvExp	$\delta_2$	0.002	0.038	-0.082**	0.018
Feedback*InvExp	$\delta_3$	0.009	0.050	0.025	0.027

\*p&lt;.05

\*\*p&lt;.01



**Table 4**  
**Application Phase Forecasting and Actual Value Functions**  
**(Feedback Condition Only)**

		Gain		Loss	
		Estimate	Std Error	Estimate	Std Error
Baseline Curvature	$\beta_0$	0.569**	0.052	0.727**	0.045
Actual	$\delta_1$	-0.155	0.110	-0.077	0.081
InvExp	$\delta_2$	-0.005	0.036	-0.064**	0.019
Actual*InvExp	$\delta_3$	0.003	0.047	0.003	0.030

\*\*p<.01

**Figure 1**  
**Experimental Procedure**

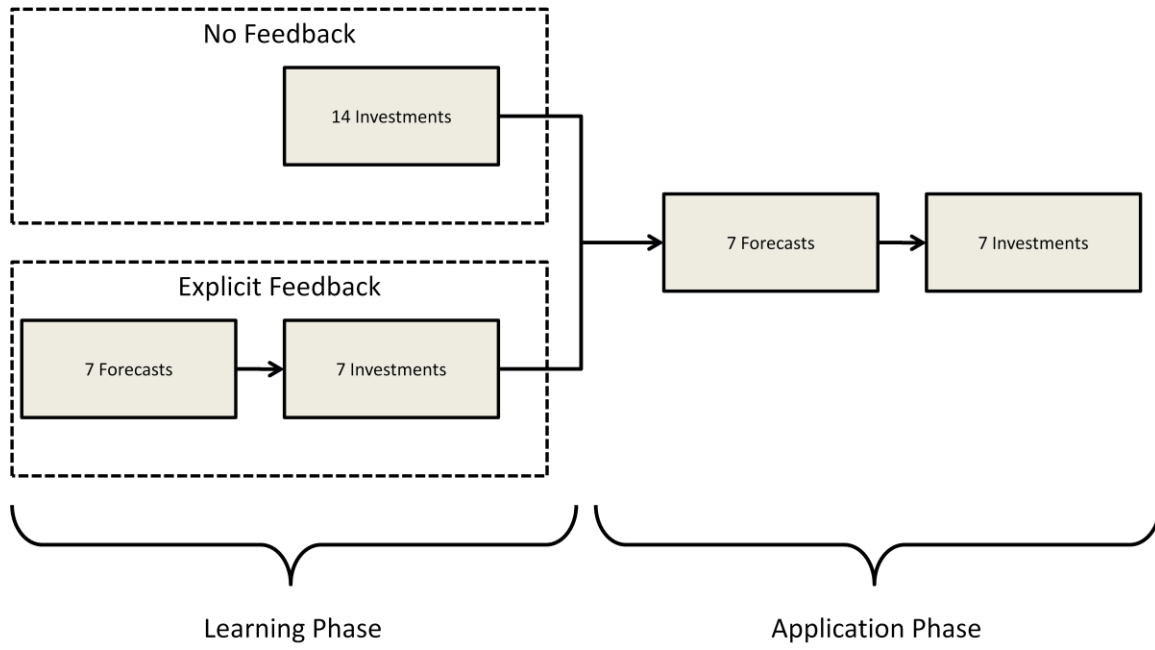
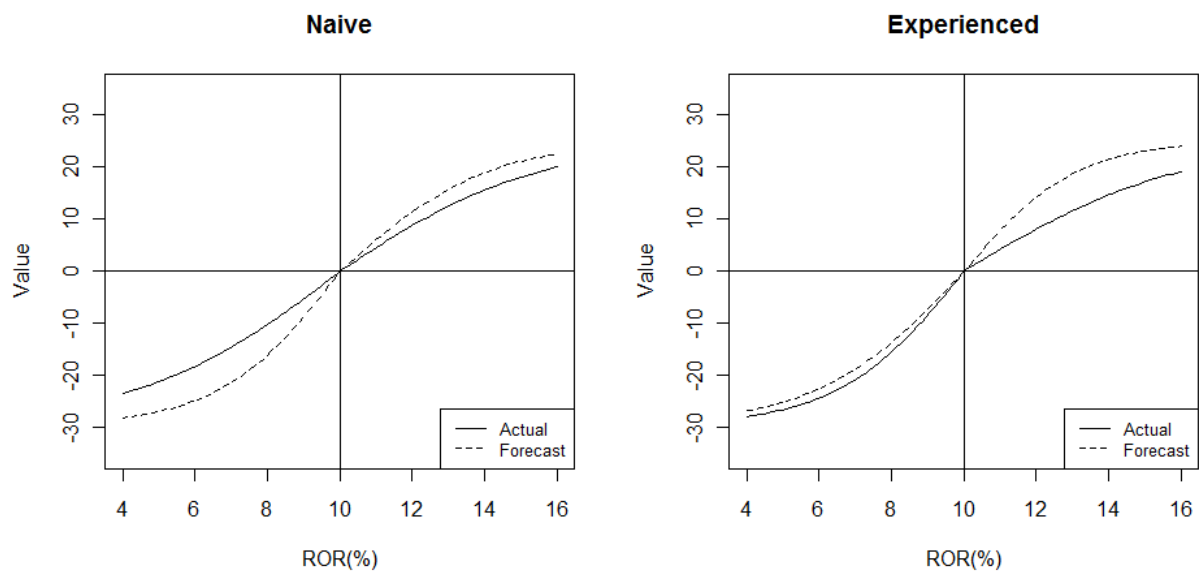


Figure 2

## Forecasting and Actual Value Functions

(Learning Phase, Explicit Feedback Condition)



**Figure 3**  
**Affective Forecasting Error**  
**(Learning Phase, Explicit Feedback Condition)**

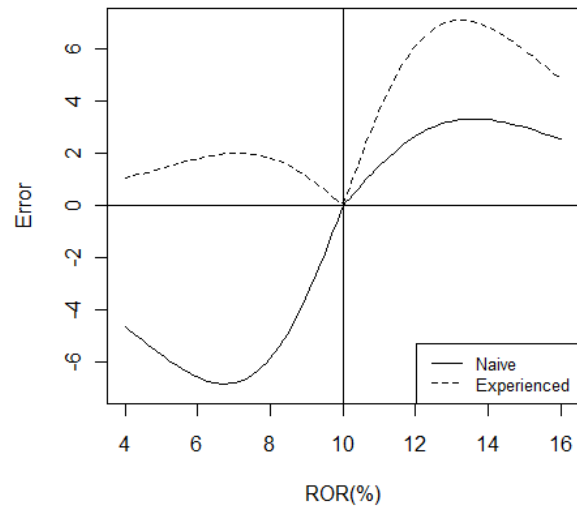


Figure 4

## Between Subjects AFE Comparison (Application Phase)

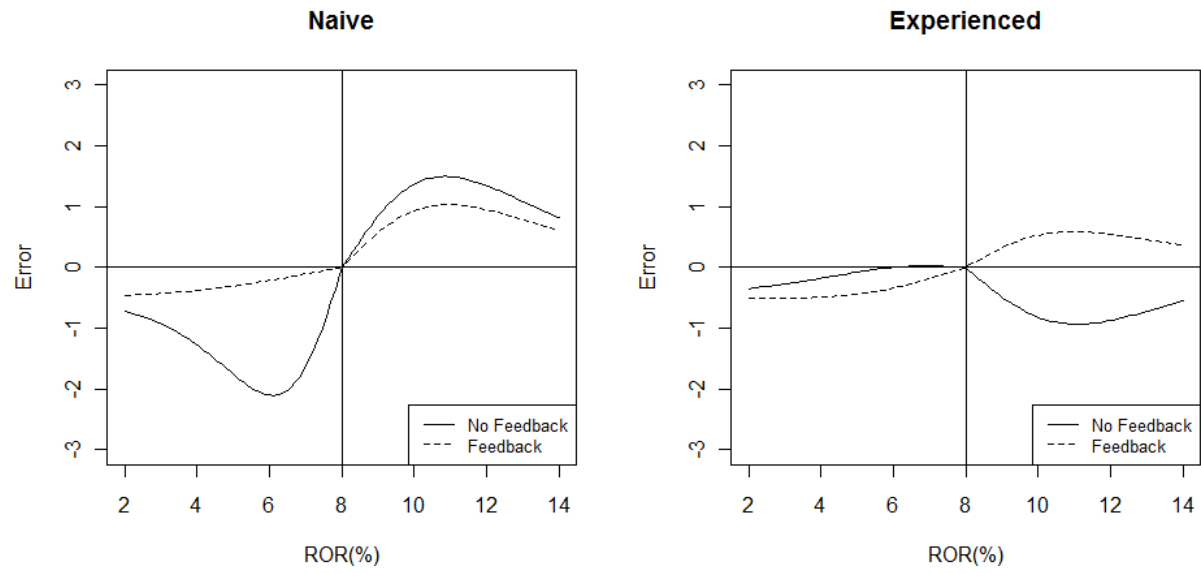


Figure 5

## Loss Aversion Coeff. (Application Phase)

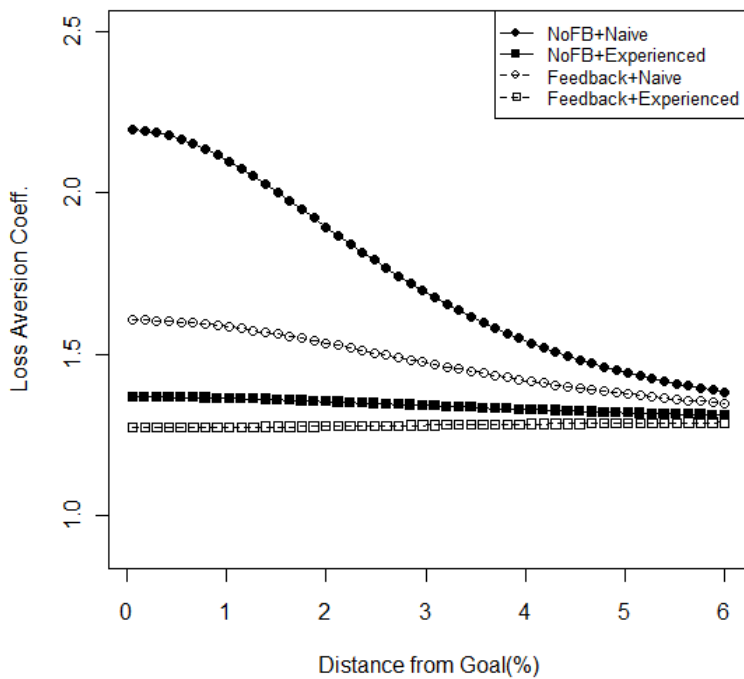
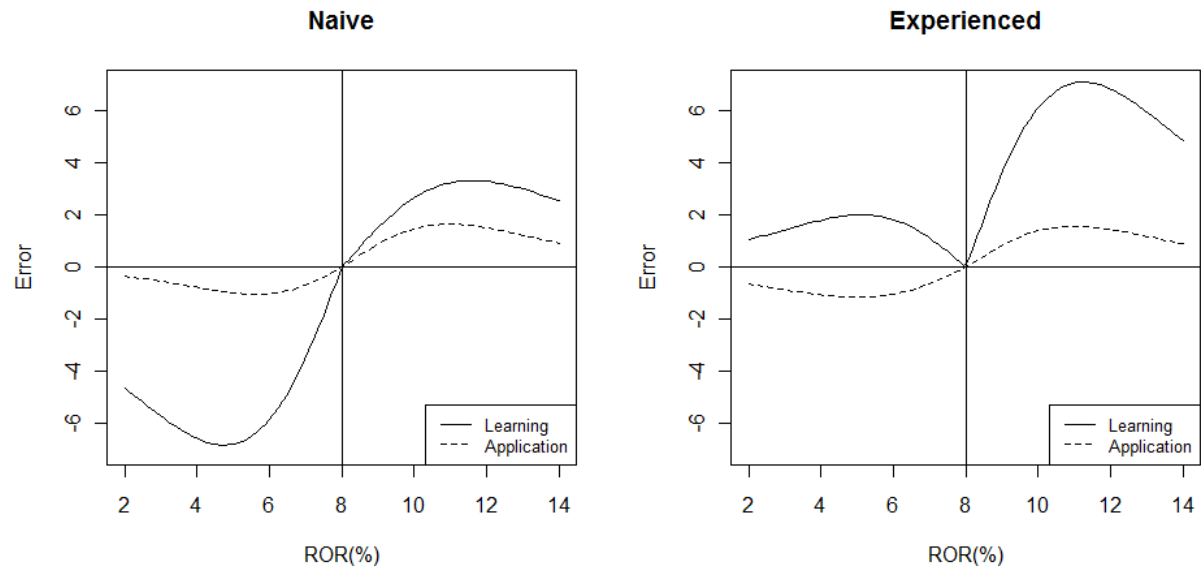


Figure 6

## Within Subjects AFE Comparison (Feedback Condition)



## Appendix A

### Sample Fund Information

#### AFEAX

**Category:** Large Growth

#### Fund Characteristic:

The investment seeks long-term capital growth. The fund normally invests at least 80% of assets in the common stocks of large capitalization companies excess \$5 billion.

#### Morningstar Rating:

★★★ Overall 440 Funds  
 ★★★★★ 3 Year 440 Funds  
 ★★★ 5 Year 394 Funds

#### Average Annual Returns:

1 Year	3 Year	5 Year	Inception
+13.12%	+4.41%	+7.58%	+10.81%

#### Fund Details:

Net Expense Ratio	1.53%	Availability	Open
Gross Expense Ratio	1.92%	Initial Investment	\$1,000
Total Net Assets	\$832.8 K	Transaction Fee	None
Fund Inception	9/24/01	Sales Charge	None

#### Top Holdings:



4.44%	International Business Machines
4.13%	Monsanto Company
4.10%	Catepillar Inc.
4.10%	Apple Inc.
3.57%	Gilead Sciences, Inc.

Top 5 holdings total 20.34% as of 5/31/2008



## Appendix B

### Statistical Testing of the Difference between Two Loss Aversion Curves

We model the value function using the following form:

$$y - y^{ref} = c \left( \frac{2}{1 + \exp(-\beta |r - r^{ref}|)} - 1 \right)$$

if  $r \geq r^{ref}$ ,  $c = c_p, \beta = \beta_{p,0} (1 + \delta_{p,1} z_1)$

if  $r < r^{ref}$ ,  $c = -c_n, \beta = \beta_{n,0} (1 + \delta_{n,1} z_1)$

Therefore, the loss aversion coefficient is

$$\rho(|r - r^{ref}|) = \frac{c_n \left( \frac{2}{1 + \exp(-\beta_{n,0} (1 + \delta_{n,1} z_1) |r - r^{ref}|)} - 1 \right)}{c_p \left( \frac{2}{1 + \exp(-\beta_{p,0} (1 + \delta_{p,1} z_1) |r - r^{ref}|)} - 1 \right)}$$

To test if  $z_1$  significantly changes the loss aversion coefficient, we must reject the null

hypothesis that the two loss aversion curves ( $z_1 = 0$  vs.  $z_1 = 1$ ) are identical:

$$H_0 : \rho(|r - r^{ref}|)_{\text{when } z_1=0} = \rho(|r - r^{ref}|)_{\text{when } z_1=1}, \forall |r - r^{ref}|$$

This null hypothesis can be restated as follows:

$$\begin{aligned}
\rho(|r-r^{ref}|)_{\text{when } z_1=0} &= \rho(|r-r^{ref}|)_{\text{when } z_1=1}, \forall |r-r^{ref}| \\
\Leftrightarrow \frac{c_n \left( \frac{2}{1+\exp(-\beta_{n,0}|r-r^{ref}|)} - 1 \right)}{c_p \left( \frac{2}{1+\exp(-\beta_{p,0}|r-r^{ref}|)} - 1 \right)} &= \frac{c_n \left( \frac{2}{1+\exp(-\beta_{n,0}(1+\delta_{n,1})|r-r^{ref}|)} - 1 \right)}{c_p \left( \frac{2}{1+\exp(-\beta_{p,0}(1+\delta_{p,1})|r-r^{ref}|)} - 1 \right)}, \forall |r-r^{ref}| \\
\Leftrightarrow \beta_{n,0} &= \beta_{n,0}(1+\delta_{p,1}) \& \beta_{p,0} = \beta_{p,0}(1+\delta_{p,1}) \\
\Leftrightarrow \delta_{p,1} &= \delta_{n,1} = 0
\end{aligned}$$

Consequently, if either  $\delta_{p,1}, \delta_{n,1}$  is significantly different from 0, the two loss aversion curves are also significantly different from each other. In other words, testing for a significant difference between the two loss aversion curves is equivalent to the significance of the parameters that differentiate the two curves.