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Why Do Investors Sell Losers? How Adaptation to Losses Affects Future Capitulation Decisions*

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Abstract
According to disposition effect theory, people hold losing investments too long. However, many investors eventually sell at a loss, and little is known about which psychological factors contribute to these capitulation decisions. This study integrates prospect theory, utility maximization theory, and theory on reference point adaptation to argue that the combination of a negative expectation about an investment's future performance and a low level of adaptation to previous losses leads to a greater capitulation probability. The test of this hypothesis in a dynamic experimental setting reveals that a larger total loss and longer time spent in a losing position lead to downward adaptations of the reference point. Negative expectations about future investment performance lead to a greater capitulation probability. Consistent with the theoretical framework, empirical evidence supports the relevance of the interaction between adaptation and expectation as a determinant of capitulation decisions.

JEL Classification: C91, D03, D81

Keywords: Investments, Adaptation, Reference Point, Capitulation, Selling Decisions, Disposition Effect, Financial Markets

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One of the most intriguing phenomena related to decision making under uncertainty, particularly in financial markets, is the disposition effect. Shefrin and Statman (1985) propose that investors tend to hold their losing investments too long and sell their winning investments too early. This claim received empirical support in a laboratory setting (Weber & Camerer, 1998), an online setting (Lee, Park, Lee, & Wyer, 2008), in the stock market (Odean, 1998), and in property markets (Genesove & Mayer, 2001). The widespread attention to the disposition effect reflects its potentially harmful effect on current and future wealth through suboptimal financial decision making. A timely sale of losing investments can substantially improve a household's financial position (Dhar & Zhu, 2006; Odean, 1998). Therefore, it is important to answer the key remaining question: Why do many investors eventually capitulate to their losing investment? Current theory only provides insight into why investors hold on to losers too long. Current theory does not explain why investors eventually do sell losers. Next to theoretical relevance, our study has societal implications. Determining the factors that stimulate or impede a timely capitulation is important from a welfare perspective and may be useful for financial advisory work and the enhancement of financial literacy.

Empirical results reported by Lee et al. (2008) attribute the disposition effect to differences in the values that investors attach to possible gains and losses, rather than to any differences in their perceived likelihood of occurrence. This reasoning is also reflected in prospect theory (Kahneman & Tversky, 1979). Prospect theory claims that investors do not perceive a gain or a loss in absolute terms. Instead, investors measure the perceived value of each outcome according to its distance from the investor's reference point. Any value above (below) that reference point is perceived as a gain (loss) by the investor. However, asymmetry in the value function causes losses to exert approximately twice the psychological effect of equally sized gains.

Although prospect theory attempts to explain investors' overall tendency to sell winning investments too soon and hold losing investments too long, it cannot explain how investors eventually reach their capitulation decisions. Prospect theory usually assumes the reference point is static and equal to the initial value of the investment. Yet investors might engage in reference point adaptations, adjusting their reference point in the direction of a prior outcome: upward for gains and downward for losses (Arkes, Hirshleifer, Jiang, & Lim, 2008). In the domain of losses, which is the topic of interest for this study, a downward adjustment of the reference point implies a smaller perceived loss. Arkes et al. (2008) do not study the antecedents of reference point adaptation, but we argue that both the size of the loss and the time spent in a losing position might affect the extent of this adaptation.

For this study, we therefore combine reference point adaptation with prospect theory and the expected utility model to pose an explanation of why many investors eventually capitulate to their losing investments. Standard expected utility theory implies that investors' expected utility of an outcome is a function of (1) their subjective expectation of the (objective) future value changes of the investment, and (2) the subjective values they attach to the objective value changes (Lee et al., 2008). Although the expected utility of an outcome clearly depends on many factors, studies of the disposition effect generally focus on these two (e.g., Lee et al. 2008). Because the investor's objective in the expected utility model is determined by the interaction of his or her subjective expectations and subjective values attached to the possible outcomes, we hypothesize that their interaction also affects decisions to hold or sell a losing investment. Investors with negative expectations about the investment's future performance should be more likely to capitulate to a losing investment if they have adapted less to previous losses. With this hypothesis, we depart from prior research by Weber and Camerer (1998), who assume that investors hold on to losers if they have barely adapted. In addition to developing and testing our alternative hypotheses, we apply the expected utility model with reference point adaptation in a dynamic rather than a static

setting. Therefore, unlike prior research, we test how dynamically changing expectations and reference point adaptation levels affect financial decision-making.

Accordingly, our empirical analysis relies on this conceptual framework and the results of two recently published empirical papers. Lee et al. (2008) show that the disposition effect is mostly due to the different subjective values that investors attach to gains and losses. However, they compare subjective values in the gain and loss domains only in a single-decision setting. Arkes et al. (2008) also show that an investor's reference point shifts after a change in the value of an investment. By focusing on a single value change, these authors do not link the adaptation of reference point levels directly to financial decision-making. In contrast, we conduct a dynamic experiment to determine how reference point adaptation occurs in a dynamic setting with multiple decision moments, as well as how it influences the decision to hold or sell losing investments. Our experiment thus provides insight into the antecedents of reference point adaptation. Furthermore, by allowing for multiple decision moments, we can observe the variation in expectations and reference point adaptations over time, which we exploit in turn to study their interaction. Our combination of adaptation-level theory and the expected utility model provides insight into why investors eventually sell losing investments. Our experimental approach also approximates real-life investment decision-making better than static experimental procedures. In reality, investors operate in a dynamic, multiperiod setting. Therefore, the experimental framework we use to study multiple consecutive investor decisions offers better external validity.

Theoretical Framework

The expected utility model predicts that the expected utility of each possible outcome affects choice behavior. For example, if the expected utility of holding on to a losing investment is low, we should observe fewer investors holding on to a losing stock. The expected utility of an outcome is the product of (1) its subjective probability of occurrence and (2) its subjectively perceived value. Thus, both a higher perceived likelihood of negative

outcomes and lower subjective values attached to those outcomes produce lower expected utilities, which in turn lead to higher capitulation probabilities.

Lee et al. (2008) suggest that subjective probabilities and values have interactive effects on investors' decisions, though without formally testing this prediction. We provide a test of these interaction effects and study their impact on the decision to capitulate to a losing investment. Accordingly, we discuss the notions of expectations and probabilities, the concept of subjective value as determined by adaptation levels, and our hypothesis regarding how the interaction between probabilities and perceived values might be linked to the capitulation decision.

Expectation and Capitulation

According to the expected utility framework, decision makers determine the value of an outcome by multiplying its subjective probabilities and their subjectively perceived values. Probabilities thus have linear effects. Prospect theory (Kahneman & Tversky, 1979) instead suggests nonlinear influences, such that people overweight low probability events and underweight medium and high probability events. We adopt a standard finance perspective: It is rational for an investor to sell a losing investment only if he or she does not expect its price to increase sufficiently to offset its risk. We do not demand a clear choice between linear versus nonlinear probability weighting functions, because we are only interested in the interaction between the subjective value and subjective expectation. Therefore, in our experimental setting, participants formulate subjective expectations of whether the investment will increase or decrease. This requires less cognitive effort than formulating a subjective probability (and weighting) of each individual possible outcome (Lee et al., 2008). The expectation of the direction of future performance may be the only cognitive statement the decision maker can formulate, or it may be a summary statement of a more fine-grained set of beliefs. Either way, we expect this expectation to affect the investor's decision to sell a losing investment, either due to changes in perceived probabilities or to changes in

probability weights. In particular, negative expectations about future price development should lead to a greater tendency to capitulate.

Lee et al. (2008) test the relation between past performance and expected future performance. They find that on average, people believe that the future price of a current loser is more likely to increase, whereas the price of a currently held winner is more likely to decrease. Our approach differs from Lee et al.'s (2008) in two main ways. First, we focus on the effect of subjective beliefs about the likelihood of future price increases or decreases on actual financial decision-making, not the link between past performance and future expectations. Second, we concentrate solely on the loss domain, which provides a clearer, more direct view of the capitulation phenomenon.

Investors may have positive expectations of stocks that previously incurred losses, especially if they think the losing stock has bottomed out and will regain some of its losses in future investment periods (Andreassen, 1988). This negative recency effect (i.e., tendency to predict the opposite of the last event) is known as the gambler's fallacy (Ayton & Fischer, 2004). In contrast, when investors adopt the hot hand fallacy, they expect a positive recency effect and the recurrence of an event (Ayton & Fischer, 2004). Concretely, they develop negative expectations about future performance after a loss. Both phenomena appear in actual investment strategies, referred to as momentum (positive recency) and contrarian (negative recency) strategies, respectively (Morrin, Jacoby, Johar, He, Kuss, & Mazursky, 2002). Therefore, we do not predict that either of these two single fallacies is dominant in our framework. Rather, we only infer that subjective negative expectations should relate to a greater probability to capitulate.

Prospect Theory and Reference Point Adaptation

Prospect theory postulates that investors evaluate outcomes according to a reference point. If the outcome is above (below) this point, it represents a gain (loss) (Kahneman & Tversky, 1979). Moreover, investors experience loss aversion, in that the concavity of the

value function above the reference point and its convexity below this point (see Figure 1) causes investors to be risk averse in the gain domain and risk seeking in the loss domain. Although selling a losing investment can prevent additional losses, actually realizing the loss has more value only if the perceived probability of incurring additional losses is very high. Consider for example an investment that has dropped from its initial neutral value, as represented by the reference point R0 in Figure 1, to the low value L1. The perceived value of the investment now equals V1. A subsequent drop in the price of the asset to L2 implies a smaller change in perceived value compared with the first drop, because of the convexity of the value function in the loss domain (Weber & Camerer, 1998). Conversely, an increase from L1 implies a comparatively larger difference in perceived value. Therefore, investors tend to favor the risky option (holding on to the losing investment and incurring only a "paper loss") over the safe option (realizing the loss and avoiding further pain).

INSERT FIGURE 1 HERE

Determining the appropriate reference point is a fundamental issue. Kahneman and Tversky (1979) suggest it might be the status quo or the expectation or aspiration level. It is unclear though where the reference point actually lies. In financial decision-making, there is no consensus about which price determines the reference point: the initial purchase price (Odean, 1998; Weber & Camerer, 1998), the historical peak of a stock price (Gneezy, 2005), or the expected value of future outcomes (Köszegi & Rabin, 2006; Yogo, 2008).

This controversy is further complicated if we consider that the reference point may be dynamic. Kahneman and Tversky (1979) propose that the current level of perceived wealth depends on a person's adaptation to past and present stimuli, just as the adaptation level is affected by prior stimuli (Helson, 1964). Reference point adaptation, also referred to as a shift of the reference point or an updated reference point, implies that in a dynamic setting, the reference point adapts upward (downward) as gains (losses) accumulate. Subsequent prices then get evaluated relative to the adapted reference point. The adaptation process also may be

asymmetric, such that people adapt more to gains than to losses of the same magnitude (see Arkes et al., 2008; Chen & Rao, 2002).

Although adaptation to economic gains and losses is demonstrated by prior literature, the extent of adaptation over time has not been analyzed. Adaptation-level theory suggests that the perceived magnitude of a stimulus depends on its relation to an adapted level or reference point, determined by preceding stimuli. According to Helson's (1964) formula, the reference point (R_t) is the average of past stimuli levels,

$$R_t = t^{-1} \cdot \sum_{\tau=0}^{t} X_\tau \,, \tag{1}$$

where X_t represents the current stimulus level, and t represents time. It is unlikely that investors adapt to losses exactly as suggested in Equation (1) though, and Helson's theory has been criticized on several grounds. Sarris (1967) argues that extreme stimuli do not affect the adaptation level as much as Helson (1964) claims, and Parducci (1968) suggests that the effect of a stimulus is influenced by the rank of the stimulus in a group of other stimuli. Moreover, Equation (1) cannot differentiate how a loss experienced, say two years ago, and a recent one, experienced two days ago, affect adaptation levels differently. To account for this temporal component, Hardie, Johnson, and Fader (1993) propose modeling the adaptation level as

$$R_t = \alpha X_{t-1} + (1-\alpha) R_{t-1}, \tag{2}$$

for a scalar $0 \leq \alpha \leq 1$. Although the parameter α grants recent stimuli more weight than past stimuli, it still cannot provide for a full separation of time and stimuli levels.

To achieve more flexibility in capturing reference point adaptation, we propose examining the unique effects of time and past stimuli on the adaptation level separately. Equation (1) implies that the adapted reference point emerges as a recursive average of all preceding stimuli. Therefore, in a loss domain, we expect the adapted reference point to relate positively to the sum of all previous losses (i.e., size of total loss), but negatively to the number of time points elapsed. The sum of past stimuli in our setting thus collapses to the

size of the total loss since $t = 0$, or $(p_0 - p_t)$. As the stock price continues to decline, the total loss increases, and we expect the adapted reference point to decrease. A lower adapted reference point actually indicates a greater extent of reference point adaptation if the investment is in a losing position. We do not expect the adaptation process to follow the precise dynamics of Equation (1), but we anticipate a significant relationship of both the total sum of past stimuli and the elapsed time to the final adapted reference point. We thus hypothesize that in a loss domain:

H1a: A larger total loss leads to a lower adapted reference point (R_t) and a higher adaptation level $(AL_t = p_t - R_t)$.

H1b: A longer time spent in a losing position leads a lower adapted reference point (R_t) and a higher adaptation level $(AL_t = p_t - R_t)$.

We model the effect of total loss and time on the adaptation level as

$$AL_t = p_t - R_t = \alpha + \beta_1 \cdot t + \beta_2 \cdot TL_t + \beta_{int} \cdot t \cdot TL_t + \varepsilon_t \,, \tag{3}$$

where AL_t denotes the adapted reference point, p_t is the current price of an investment, t is time in a losing position, and TL_t is the size of the total loss. Because it takes time for a loss to accumulate, there must be some correlation between time spent in a losing position and size of total loss; therefore, we also include an interaction term. As seen in hypotheses H1a and H1b, we define the "adaptation level" as the extent to which one has adapted to prior losses. The adaptation level has a negative relation to the adapted reference point and also directly relates to the current price level p_t. In our experimental design, the current definition of the adaptation level is important because different subjects are exposed to different price shocks at different stages of the experiment. The inclusion of the current price level in the measure for the adaptation level corrects for this. For example, consider subjects A and B who both start at a price $p_0 = 100$, but are hit by different losses and end up at $p_t^A = 80$ and $p_t^B = 50$, respectively. If both subjects have an adapted reference point level of $R_t^A = R_t^B = 80$, it is clear that subject A has fully adapted, whereas subject B has not. This corresponds

with the value of the adaptation level, which is 0 for subject A and –30 for subject B. Full adaptation is achieved if the adaptation level is 0.

We integrate our use of adaptation-level theory with prospect theory in a dynamic context. When an investor experiences a loss, the reference point in the prospect theory framework adapts downward, which influences his or her subsequent capitulation decisions. The use of adaptation theory is thus indispensible for a realistic understanding of the capitulation decision in a dynamic investment experiment.

Value Function for Multistage Decisions

According to the S-shaped value function from prospect theory, if the reference price equals the current price (full adaptation), no disposition effect occurs (Dhar & Zhu, 2006; Weber & Camerer, 1998). In the absence of adaptation though, the S-shaped value function implies a maximum disposition effect (Weber & Camerer, 1998). The convexity of the value function in the loss domain implies that further losses have a smaller impact on value if the reference point does not change (see Figure 1). The comparison of the extremes of full versus no adaptation implies that more adaptation leads to a relatively smaller tendency to hold on to losing investments. Thus, more adaptation should partly offset the disposition effect. Holding expectations constant, investors who have adapted more to their losses should be more likely to capitulate.

This proposition differs from Weber and Camerer's (1998) claims. We argue that in a dynamic setting, an alternative value function is more applicable than the original S-shaped value function from prospect theory. Thaler and Johnson (1990) consider the S-shaped value function useful for describing risk aversion in a gain domain and loss aversion in a loss domain for *one-stage decisions* without prior outcomes. Examples of such decisions include decisions about which university to attend or which particular house to buy. However, other decisions involve repeated choices, which requires a dynamic, multistage perspective. Examples include consumers who decide, for example, whether to repurchase a product, or

investors who decide whether to hold or to sell investments at different points in time. Previous literature provides many examples of how prior outcomes and sunk costs affect subsequent investment decisions (e.g., Arkes & Blumer, 1985; Laughhunn & Payne, 1984). However, Weber and Camerer (1998) assume that prior gains or losses do not influence subsequent decisions, beyond the magnitude effects that occur for larger single-stage gains or losses. For example, after incurring a $30 loss, an additional $10 loss has the same negative utility as a $40 single-stage loss (Weber & Camerer, 1998). Our experimental design allows for an ongoing effect of prior losses on subsequent decisions.

Thaler and Johnson (1990) report empirical evidence that prior gains induce risk-seeking behavior in subsequent choices and thus propose a quasi-hedonic editing rule: in a two-stage gamble with a prior loss, a subsequent loss is not automatically integrated with the initial loss. Their findings suggest people may be risk averse if they have experienced a prior loss, such that the value function in a loss domain may contain a concave region, in addition to a convex region. Several other studies confirm that the value function in the loss domain is not always convex but rather is convexo-concave for increasing absolute loss sizes. Markowitz (1952) was the first to propose a utility function with convex and concave regions in both the gain and loss domains. Kahneman and Tversky (1979) have been cited mainly for their S-shaped value function, but they also consider special circumstances and alternative specifications. For example, they suggest that because large losses often lead to lifestyle changes, concave regions are likely in the value function for losses. Using horse race betting data, Jullien and Salanié (2000) find that bettors appear risk averse for large losses.

Moreover, several experimental studies reveal evidence of concave utility functions for losses when respondents must choose among options with different risk levels, such as a lottery choice between a low payoff/low-risk versus a large payoff/high-risk profile (Abdellaoui, Bleichrodt, & L'Haridon, 2008; Laughhunn, Payne, & Crum, 1980; Laury & Holt, 2008; Loehman, 1998; Sullivan & Kida, 1995; Zeelenberg & van Dijk, 1997). Outside

the laboratory setting, analyses based on health insurance plans further suggest the utility function for losses is convex at first but becomes concave for large losses (Marquis & Holmer, 1996). Using this evidence, De Giorgi, Hens, and Post (2005) propose a formal modification of the S-shaped value function, namely, a piecewise exponential value function, which contains a concave region of the value function in the loss domain. Finally, explicitly allowing for different behaviors in the value function for small versus larger losses is particularly important in our case, because we study dynamic capitulation decisions when losses accumulate over time. Despite the growing evidence of a concave region in the value function for large losses, prior studies consider only stand-alone decisions that do not relate dynamically, unlike the multistage decision setting we employ here.

In Figure 1, we illustrate the value function that we use in our theoretical framework for investors who do not adapt to losses. The function is based on the piecewise exponential value function (De Giorgi et al., 2005) and is consistent with the quasi-hedonic editing rule (Thaler & Johnson, 1990). Close to the reference point R0, the value function is kinked and convexo-concave in the realized value, as proposed by Kahneman and Tversky (1979). But for large losses, the piecewise exponential value function is concave in the loss domain and discourages extreme risk taking. For example, consider a stock price decline from its initial price R0 to L1 at time 1, and then a further decline to L2 at time 2. According to this value function with a second kink in the loss domain, the perceived value would be V3 rather than V2.

Reference Point Adaptation and the Capitulation Decision

We expect investors who have adapted to prior losses to be less likely to sell losing investments. Consider the example in Figure 2, in which we illustrate the reference points of both investors in a horizontal manner. Investor A and investor B both start investing in a stock at t_0. They buy the stock at the same initial price of $100, which we assume is equal to their initial reference point. For the sake of simplicity, we also assume that the value

functions of investors A and B are exactly the same. However, the extent to which each investor adapts to gains or losses differs. At t_1, the stock price drops from \$100 to \$50, after which investor A's reference point (R_A) decreases to \$90, whereas that of investor B (R_B) shifts to \$70. Thus, investor B adapts more to the loss than investor A. We further assume that the stock price at t_2 is equally likely to drop further to \$40 or bounce back to \$60.

INSERT FIGURE 2 HERE

For simplicity, we assume that the shape of the value function remains the same and only its horizontal position changes. As Figure 2 shows, the less adapted investor A is in the concavo-convex area of the value function, whereas investor B is clearly in the convex region for the two possible outcomes. Investor A thus is more likely to sell the asset, but investor B is more likely to hold it. If both investors predict negative future performance, the effect gets reinforced, such that investor A's expected value function decreases much faster than that of investor B, due to the concavity for large losses. We then would expect more pronounced differences in capitulation decisions between less adapted and more adapted investors who hold similar negative views on the stock's future performance. This interaction between adaptation and expectation represents an innovative feature in our model. We summarize our complete dynamic model of an investor's financial decision-making in Figure 3, with the following expectations:

H2: A negative expectation about an investment's future performance combined with a low adaptation level ($AL_t = p_t - R_t$) leads to a larger capitulation probability.

INSERT FIGURE 3 HERE

Methodology

Participants and Procedure

Respondents considered a single stock, about which they had to make multiple decisions to hold or sell. The amounts and timing of losses varied across respondents. In our experiment, 111 students at a Dutch university (72 male, 39 female) participated, with a

chance to win a €100 prize by enrolling in a lottery. Better performance in the investment experiment resulted in a higher probability of winning the prize.

Participants arrived at the lab and were assigned to individual cubicles. They reviewed a scenario in which they recently started investing in a single stock, stock X. The amount invested in stock X was predetermined and equal for every participant. We specified up to 10 investment periods for the experiment. After each period, participants received information on the stock's performance and were asked whether they wanted to hold or sell the stock. They could only choose to sell or hold the entire invested amount. Before each decision, respondents answered a short questionnaire that elicited their expectation of the stock's future performance and their reference point adaptation level.

Previous studies of the disposition effect have employed a limited number of predetermined price patterns (Lee et al., 2008; Weber & Camerer, 1998). To increase the generalizability of our findings though, we generated a wide range of intermediate price dynamics over the ten investment periods. All participants incurred losses in their investment, but to make the price patterns realistic and avoid long runs of losses, we included some mild upward movements in the intermediate stages. To avoid overly frequent upward movements, we divided the (up to) ten investment periods into three unequally sized blocks. Participants were randomly assigned a first loss of 5%, 10%, 20%, or 40%, roughly evenly spread out over the initial 1, 3, or 5 periods in block 1. Then in block 2, prices stayed relatively stable (upward or downward stock price movements of around 1%) for either 2 or 4 periods. A second major loss of 5%, 10%, or 15% took place in block 3 within 1 period. Then the experiment ended. Therefore, participants considered various combinations of price patterns, based on randomly assigned sizes and durations of losses (see Table 1). A visualization of the different price paths is given in Figure 4.

INSERT FIGURE 4 HERE

INSERT TABLE 1 HERE

Investment Goals as Measures of Adaptation

Several measures of adaptation levels have been proposed in previous studies. For example, Baucells, Weber, and Welfens (2007) ask subjects to report the selling price at which they would feel "neither happy nor unhappy." However, these participants must understand the concept of indifference and be able to express that psychological state in terms of stock prices. Another limitation of former studies (Baucells et al., 2007; Chen & Rao, 2002) stems from their presentation of a series of outcomes, after which participants report their reference point. This type of retrospective evaluation can be highly biased (Freedman, Thorton, Camburn, Alwin, & Young-DeMarco, 1988). Moreover, this methodological approach does not allow researchers to observe how reference points change over the course of the study.

Arkes et al. (2008) instead ask participants to report how much an investment must appreciate (depreciate) further to make them feel as happy (sad) as they were when they learned about a previous gain (loss). However, people may have difficulty imagining how they would feel about future gains and losses, and comparing these imagined feelings with recollections of recently experienced feelings. Affective forecasting studies demonstrate that people's predictions of their own hedonic reactions to future events are susceptible to errors and biases (Wilson & Gilbert, 2005). Although people often predict the valence of their emotional reaction (good vs. bad) or even specific emotions (e.g. joy, sadness) correctly, they also overestimate the intensity and duration of their emotional reactions. Wilson and Gilbert (2005) suggest that in the case of negative events, people underestimate how quickly they will cope with the pain or loss.

If the prospect value function in Figures 1 and 2 is constant over time, it does not matter which measure of reference prices we use. Most reference points generally refer to current wealth, though aspiration levels also can serve as anchoring values (Kahneman & Tversky, 1979). Heath, Larrick, and Wu (1999) further argue that goals can serve as reference

points, such that outcomes have a smaller marginal impact when they are more distant from a postulated goal, and failing to reach the goal is more psychologically harmful than overshooting it (i.e., loss aversion). Their findings also suggest that goals influence people's performance, effort, and persistence in non-risky situations, as well as their choices in risky settings. When presented with a single decision task, people are more risk seeking when they have not attained their goal, consistent with the S-shaped value function in prospect theory. Therefore, we use investors' goals as an indicator of an adapted reference point. This choice receives support from the psychological notion that goals energize and direct human behavior (Austin & Vancouver, 1996; Elliott & Dweck, 1988). Moreover, previous management studies show that the aspiration level is adaptive and affected by performance feedback (Lant, 1992; Mezias, Chen, & Murphy, 2002). Rasmussen, Wrosch, Scheier, and Carver (2006) also find that goals serve as reference values for feedback. If a goal is perceived as unattainable, people disengage from this goal and then reengage with new goals which benefit their well-being (Wrosch, Miller, Scheier, & Brun de Pontet, 2007). Accordingly, we consider goals an appropriate measure of reference point adaptations in our setting.

Specifically, when investors adapt their reference points, the adaptation is reflected in their goals. To measure investors' goals, we asked the participants, after each new price realization, to report at what price level they would feel satisfied and at what price level they would be willing to sell their invested security. We use these selling prices as measures of reference point adaptation, similar to Arkes et al. (2008), though we do not adopt their use of the BDM procedure (Becker, DeGroot, & Marschak, 1964). The BDM procedure, which specifies two future prices with equal probabilities, cannot distinguish the reference point from the selling decision. That is, participants in a BDM study indicate a minimum selling price prior to the random selection of one of the two future prices. They must sell at the random price if it equals or is higher than their minimum selling price. Therefore, the decision is inherently determined by the minimum selling price. In our experiment,

investment goals did not lead to any hold/sell obligation; rather, participants could hold or capitulate, regardless of their previously postulated investment goals. Our measure of reference point adaptation also is more intuitive and requires less cognitive effort than measures used in previous studies (e.g., Baucells et al., 2007), so participants can manage to provide answers about their adapted reference points for multiple points in time.

However, our calculation of the adapted reference point requires some additional discussion. We use the investment goal measures to estimate the adapted reference points, as in Arkes et al. (2008). If the adapted reference point at time t_0 is R_0 and the satisfactory price is S_0, the difference between R_0 and S_0 should be the same as the difference between R_1 and S_1 at t_1, with the assumption that the shape of the prospect theory value function remains unchanged:

$$S_0 - R_0 = S_1 - R_1 \rightarrow \Delta R_t = R_t - R_{t-1} = S_t - S_{t-1} \text{ . (4)}$$

If one participant reports a satisfactory price of \$37 at t_0 and \$35 at t_1, the adapted reference point has adjusted \$2 downward. Although neither the satisfactory price nor the selling price is the reference point per se, by holding the prospect theory value function constant, we can determine any reference point adaptation over time according to the adaptations in the satisfactory price and selling price over time. By tracking the differences in the satisfactory and selling prices over the course of the experiment, we also capture the movement of the adapted reference point. The adaptation level is then defined by the difference between the current price the computed reference point, $AL_t = p_t - R_t$.

Investors who set high investment goals also may have a more optimistic expectation of the investment's performance, which would imply a positive correlation between the reference point and expected performance. Nonetheless Heath et al. (1999) find that the effect of goals on persistence, effort, and task performance is independent of expectations or likelihood. To account for any potential correlation between expectation and goal, in our analysis we made use of partial least squares regression, which supposes that all the variables

in the model are correlated. Thus any possible statistical correlation between goals (adapted reference point) and expectation is controlled for in our analysis.

Questionnaire

We borrowed four measures from Arkes et al. (2008) and Ayton and Fischer (2004). For the investment goal, we use two items, pertaining to the satisfactory price of investors—"In the next period, what is the price of stock X that would make you feel satisfied?" (M= \$32.75, SD = \$5.35)—and estimates of the selling price—"In the next period, if the stock price increases, what is the price you would sell at?" (M = \$35.64, SD = \$6.26). The initial price of the stock was \$33.61. We also measure expectations of the rational system by asking, "How do you think the price of stock X will change in the next period?" The responses used a nine-point scale (1 = "surely decrease," 9 = "surely increase," M = 5.68, SD = 1.66). We only asked participants to report their subjective expectation for the near future (next period). We did not administer measures of their expectations about the more distant future. Therefore, our expectation measure is myopic and could prompt myopic decision-making. Finally, we measure whether participants chose to hold on to or capitulate their losing investment by asking: "Do you want to hold or sell stock X now?"

We also administered several control questions to assess individual differences related to age, gender, risk aversion, motivation to perform well, perception of the riskiness of the stock, and investment experience in any kind of financial products and in equity. Risk aversion was measured through asset allocation tasks. Participants' motivation to perform well and their perception of the riskiness of the stock were measured on nine-point scales on which larger numbers indicated higher motivation and risk perceptions.

We prefer to test all hypothesized relations simultaneously, to control for the correlation among the variables. Structural equation modeling (SEM) seems appropriate in this situation, but covariance-based techniques do not allow for dichotomous dependent variables, such as the hold/sell decision in our framework. We therefore apply partial least

squares (PLS) regression analysis, which is a distribution-free technique with fewer constraints. In particular, it allows for the simultaneous testing of hypotheses, single- and multi-item measurement, the use of both reflective and formative scales, and the use of dichotomous dependent variables. Our use of PLS thus is not related to measuring latent variables but rather reflects our goal to analyze the complete model at once. We tested our three hypotheses using SmartPLS 2.0 (Ringle, Wende, & Will, 2005). The adapted reference point has two measures. The remaining variables all have one measure each, which means reliability and validity tests are not applicable for these single-measure variables. We pooled a total of 552 decisions for analysis. A limitation of PLS due to its complexity and iterative nature of the estimation process is that no exact statistical theory is available for inference. Standard errors for the PLS parameter estimates are usually computed based on the bootstrap, see Ringle, Wende & Will (2005). We follow this line and use a bootstrap procedure with 500 replications to assess parameter significance.

Results

Preliminary Results

Before we estimate our structural model, we present some descriptive statistics in Figure 5. The left-hand panel in Figure 5 plots the empirical capitulation frequencies of the 111 participants over the (maximum) 10 stages of the experiment, disaggregated over the size of the loss in the first stage of the experiment. The frequencies are computed per first-stage loss size by dividing the number of capitulators over the period by the number of subjects that still participated at the start of the period. The frequencies can thus be interpreted as discrete time hazard rates. The figure shows that the participants with the 5% loss size only left the experiment early, or not at all. This is probably due to the small size of the loss, which remains comparable to the small up and down random price movement during the second stage of the experiment. The 40% loss subjects show less systematic behavior. A few capitulate in the first 5 periods, but most subjects participate till the end. The subjects with

the 10% and particularly the 20% loss rates show more variation over time. The 20% loss subjects appear to capitulate somewhat later in the experiment, suggesting that the loss size influences the capitulation decision. Note, however, that these descriptive statistics do not control for all the other hypothesized effects.

The right-hand panel in Figure 5 shows the capitulation frequencies disaggregated over the duration of the first-stage loss. The pattern there is much clearer. A number of individuals cannot suffer the first-stage loss and capitulate early on. Subsequently, there are flatter segments where most subjects remain in the experiment and do not capitulate. Finally, a second big shock is administered and many subjects leave the experiment directly. Interestingly, the subjects whose first-stage loss was spread out over 5 periods do not react as fiercely as the other groups to the final (third-stage) large loss. We now turn from the descriptive statistics to the actual model estimation.

INSERT FIGURE 5 HERE

Before testing the full model, we estimated a preliminary model with time spent in a losing position, total price change since the initial period (such that a more negative price change indicated a larger total loss), and the most recent price change since the previous period (such that a more negative price change indicated a larger recent loss). These explanatory variables refer to the expectation and probability of capitulation (see Figure 6). The results show that the size of the total price change relates negatively to expectations (β = -.196, t = 4.447, $p < .001$), such that participants expect a bounce back (negative recency) in prices as losses accumulate. However, the size of the most recent price change relates positively to expectations (β = .203, t = 4.226, $p < .001$), so participants expect a momentum (positive recency) effect and positively correlated price movements in the short run. These results are consistent with our expectation that both positive and negative recency effects occur simultaneously. We also find a positive relation between the size of the total price change and the capitulation probability (β = .076, t = 2.387, p = .017). This finding indicates

that a larger loss relates to a larger probability to hold on to the losing investment, consistent with the notion that people avoid realizing losses. As the total price change becomes more negative, the probability to capitulate decreases, and a negative expectation relates to a greater probability of capitulation. This effect is significant (β = –.275, t = 6.808, p < .001). However, the size of recent losses and time spent in a losing position do not significantly influence the capitulation probability (β = –.036, t = 1.088, p = .277; β = .053, t = 1.128, p = .260), nor does time spent in a losing position affect expectations (β = –.073, t = 1.356, p = .176). The explanatory power of this preliminary model is limited (R^2 = .086), because we excluded some important interaction terms. Our complete model addresses this gap.

INSERT FIGURE 6 HERE

Complete Model Results

We provide the results for the complete model in Figure 7, which shows that the findings are consistent with the preliminary model, in that more negative expectations about the stock's future performance predict a stronger likelihood to capitulate (β = -.230, t = 7.202, p < .001). Higher values for our expectations measure imply more positive expectations about the investment's future values. Thus, a negative effect implies that people with lower expectations are more likely to sell.

INSERT FIGURE 7 HERE

The time spent in a losing position (measured by the time index of the hold/sell decision, Time = 1,…,10) and the size of the total loss have a significant impact on reference point adaptation. Participants are more adapted if the total loss they experienced (i.e., their negative total price change) is larger (β = .517, t = 14.761, p < .001) and if the time spent in the losing position is longer (β = .096, t = 2.554, p = .011). In our experimental setting, it generally takes time for losses to accumulate, so losses correlate with longer times in a losing position. To ensure that the effects of the size of the total price change and time are unique, and to disentangle their effects on the adaptation level, we include an interaction term

between time and the total price change. This interaction term significantly affects the adaptation level (β = .114, t = 2.465, p = .014). We conclude that there is strong empirical support for Hypotheses 1a and 1b. Larger total losses and a longer time spent in a losing position induce greater adaptation level. We find no direct effect of the adaptation level on capitulation (β = -.037, t = 1.034, p = .302).

Finally, we test whether the interaction between the adaptation level and expectations affects the tendency to capitulate. We find a significant interaction effect (β = .543, t = 9.320, p < .001). We examine the interaction effect more closely by splitting the sample. On the nine-point measurement scale for expectations, we designate those equal to 6 or greater as positive expectations, and the rest as negative. In Table 2, we provide the means of the capitulation probability for positive versus negative expectations and high versus low adaptation level. For positive expectations, the capitulation probability is small for both high and low adaptation level groups. However when the expectation is negative, the capitulation probability is greater for the low than for the high adaptation level group, which is in line with the proposition as in Hypothesis 2.

INSERT TABLE 2 HERE

Our findings in Figure 7 indicate that the effect of the total price change on the selling decision becomes insignificant (β = .052, t = 1.264, p = .207) when we include the adaptation level and its interaction term with expectation in the model. Thus, when we control for the extent to which subjects have adapted, the relation between the size of the total loss and the capitulation probability becomes irrelevant. To predict investors' capitulation decisions, the actual size of the total loss is not an important factor, because investors adapt to losses. Instead, it is more important to know how much the investors have adapted to the loss.

To mitigate concerns about the robustness of the results, we incorporate the individual characteristics of respondents as controls in our analysis for the expectation, the adaptation level, and the capitulate decision. The results remain robust. Investment experience has no

direct effect on expectation, adaptation level, or capitulation. Higher risk aversion induces more positive expectations (β = .218, t = 4.061, p < .001). Also, if the stock is perceived as riskier (β = .068, t = 1.997, p = .046) or the subject reports a higher motivation to perform well in the experiment (β = .093, t = 2.211, p = .028), the capitulation probability is significantly higher.

In summary, we find (empirical) support for Hypotheses 1a, 1b, and 2. Furthermore, the variance in the capitulation probability can be substantially better explained by the complete model (R^2 = .379) than by the preliminary model (R^2 = .086). The interaction between expectation and adaptation thus offers a powerful explanation of investors' capitulation decisions in a dynamic setting: pessimistic expectations about future stock performance matter most if one has not adapted to prior losses. We confirm this claim with a simple exercise: dropping only the interaction term from the full model in Figure 7 reduces the R^2 to a meager .086 again.

General Discussion

We investigate how investors eventually come to the decision to sell their losing investments. Our conceptual model integrates prospect theory and adaptation-level theory, and we test that model with a laboratory experiment. Previous literature has tested subjective expectations and subjective value as two separate determinants of investors' hold/sell decisions. To the best of our knowledge, this study is the first investigation of their interaction effect on capitulation probability. In addition, we have proposed a novel way to model investors' subjective values of losses by measuring their adaptation to losses.

Our study confirms previously reported empirical findings and adds to existing knowledge about reference point adaptation. In particular, our finding that negative expectations lead to larger selling probabilities is consistent with standard economic theories, such as Lee et al.'s (2008) finding that a participant's subjective expectation cannot explain the disposition effect. Our empirical results also are consistent with Arkes et al.'s (2008)

claim that investors adapt to losses. We provide additional insight into the separate effects of time spent in a losing position and the size of losses, because we disentangle their unique influences. In line with Hardie et al. (1993), we find that the temporal component plays a critical role in (financial) decision-making, but we also note that the adaptation level depends on the time spent in a losing position. That is, it takes time for investors to adapt to a financial loss. Lee et al. (2008) also find that investors' subjective values attached to gains and losses affect their hold/sell decisions. We extend these findings by proposing a dynamic model for predicting subjective value, based on investors' expectations and adaptation to prior losses.

The opposite effects of the size of a recent loss and total losses on expectations warrant some attention as well. When the size of total losses increases, participants report significantly more optimistic expectations (β = -.196, t = 4.395, p < .001), a reflection of the bounce-back effect, according to which participants expect a depreciated stock to appreciate again in the future. When the recent loss is larger though, participants report negative expectations (β = .203, t = 4.214, p < .001), implying that they expect momentum in future stock market prices. These results simultaneously support both the gambler's fallacy and the hot hand fallacy. They also highlight the importance of studying the role of time and the differential impact of recent and total losses on investors' expectations and decision-making. Through this link, we can explain why many investors eventually capitulate to their losing investments.

Furthermore, unlike Weber and Camerer (1998), we aim to determine how reference points adapt in a multiple-period setting and its relation to decision-making. As our main contribution, we bring several concepts together in a dynamic model to predict investors' decisions. The concept of reference point adaptation is relatively recent (Arkes et al. 2008) and has not been linked clearly to investment decisions. Therefore, we exploited Kahneman and Tversky's (1979) prospect theory to discuss the concept of reference point adaptation but also needed to take into account the quasi-hedonic editing rule (e.g., Thaler & Johnson,

1990). Prospect theory, the quasi-hedonic editing hypothesis, as well as the piecewise quadratic utility function all suggest a "tipping point" in the loss domain, after which concavity (and thus risk aversion) sets in for large or subsequent losses. The importance of this point for our experimental setting and empirical model design is evident. As losses accumulate over time, the values of future prospects by an individual investor depend on his or her level of adaptation.

We provide key insights into reference point adaptation in a dynamic context. Over time, both the size of the loss and the time spent in a losing position lead to more downward adjustments of the reference point and increases in the level of adaptation. Moreover, we find that individuals' adaptation level to prior losses interacts with expectations to affect capitulation. If expectations are negative, ill-adapted subjects (i.e., with lower adaptation levels) have on average a higher tendency to capitulate. These findings imply a link between reference point adaptation and (financial) decision–making, and are particularly relevant to decision-making research in a multi-period or longitudinal setting. Such a dynamic setting closely resembles decision-making in reality, because people face repeated decisions daily. Our findings are also relevant for investment markets such as pension funds, which are designed to be held over prolonged periods. The related buying and selling decisions are less frequent, and the role of time may be even more important. Our model may also apply to other situations that involve price changes and continuous decision-making. For example, Lewis (2006) attempts to explain the negative effect of promotions on brand equity using adaptation theory (Blattberg, Briesch, & Fox, 1995; Neslin, 2002), such that deeply discounted prices lead to the formation of lower reference prices. Adaptation also might be relevant for nonfinancial consumer behavior elements, such as when consumers stay with service providers that offer declining levels of service quality. If the decline is gradual, adaptation may explain inertia, together with an avoidance of switching costs (De Ruyter,

Wetzels, & Bloemer, 1998). Further research should adjust our dynamic experiment to test the relevance of adaptation in such non-financial settings.

In addition, several limitations in our study suggest further directions for research. We acknowledge that an investor's adapted reference point (inferred from the investment goal) and expectation about the stock's future performance may be correlated. Lant (1992) shows that models applied to expectation formation are useful for describing aspiration formation. Thus, adaptation to losses could induce more negative expectations about future price performance. A more negative forecast about stock prices also may increase willingness to sell the stock at a lower price, in line with models proposed by Köszegi and Rabin (2006) and Yogo (2008) who define the reference point as an expectation about future outcomes. To estimate the expected value of the future outcome, individuals must be aware of their own perceived current state (i.e., adapted reference point), so it should not be surprising that investors' expectations about the stock's future performance relates to their adapted reference point. However, we measured both variables, instead of manipulating them in our experimental setting and thus cannot conclude any causal relationship. Additional research should investigate these possible relations.

In addition, we conducted this experiment within a short time frame, whereas in reality, investors have more time between various decision moments. Future studies should try to replicate our findings using larger samples in more natural settings. Another potential follow-up study could test if our model also works in the domain of gains. Our participants were undergraduates, and many of them lacked any actual investment experience, which may raise questions about the generalizability of our results. However, we do not find a significant difference in the capitulation tendency between those who have and do not have prior investment experience.

The dynamic methodology we used is novel; therefore, the results should be validated in follow-up experiments. For example, additional experiments might provide money to

participants to invest prior to the start of the investment task, which would increase realism and force participants to invest their own money. To minimize the "house money" effect, the prior task for which participants get paid should appear unrelated to the investment study. Other studies could make use of other price patterns, such as periods of insignificant price changes prior to a shock of loss. Finally, further research might administer additional measures of expectations in the long term.

Conclusion

Prospect theory (Kahneman & Tversky, 1979) proposes that values of financial gains or losses are not perceived in absolute terms but rather depend on a comparison against a reference point. Arkes et al. (2008) find that such a reference point is not static, and people adapt to gains and losses. The value of a second gain or loss partly depends on the adaptation of reference points to the first gain or loss. We therefore investigate the antecedents of reference point adaptation and the role that it plays in the decision to capitulate to a losing investment.

By using a dynamic experiment, we can conclude that a larger prior loss and a longer time spent in a losing position predict greater reference point adaptation. Consistent with standard finance theory, negative expectations lead to a stronger tendency to capitulate. Moreover, the effect of negative expectations is stronger when investors have adapted less to their prior loss. Thus, in the presence of negative expectations, investors who adapted more to prior losses are less likely to capitulate to their losing investment, compared with those who have adapted little.

We relate our finding to the disposition effect (Shefrin & Statman, 1985) and suggest that the adaptation of reference points influences investors' probability to capitulate to their losing investment. Our findings may also apply in other multistage decision-making settings, such as those related to consumers' repurchase or switching choices for product or service suppliers.

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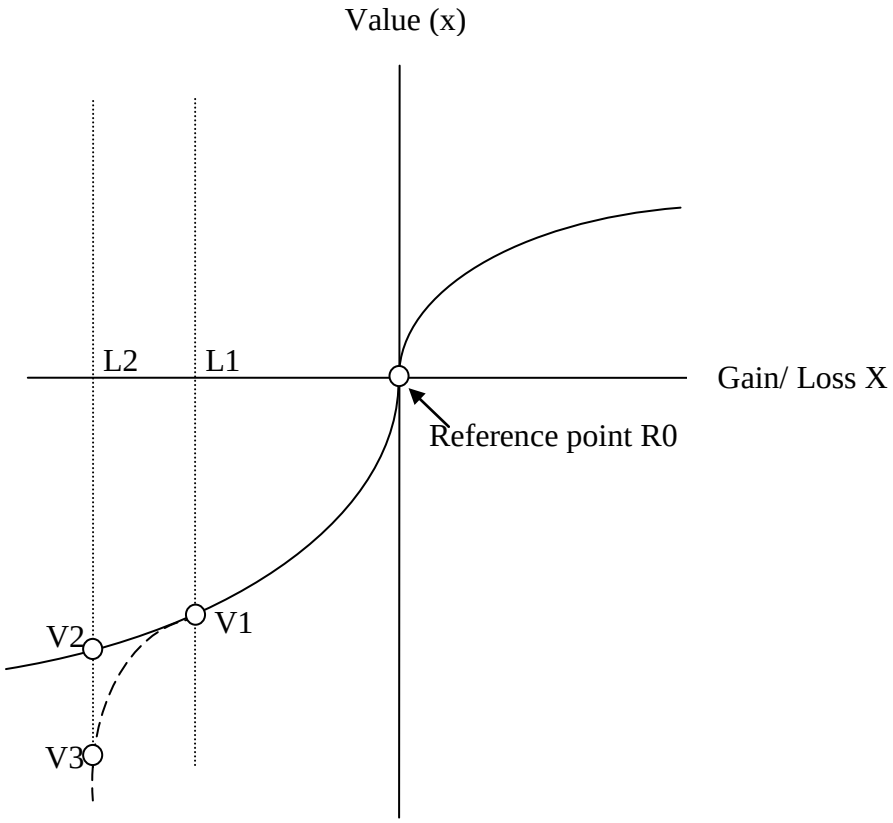
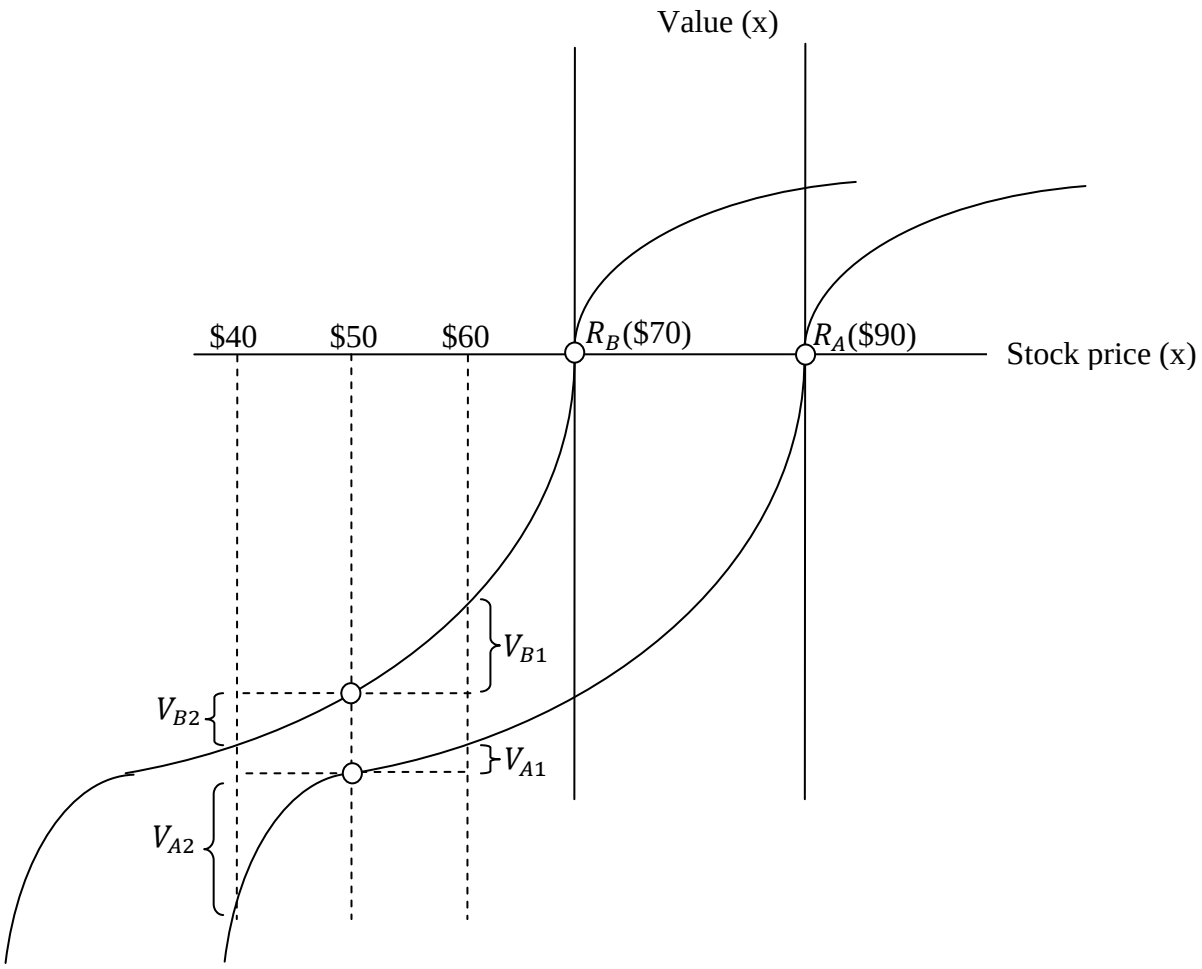
Figure 1. S-shaped value functions and the disposition effect



Notes: The solid line represents the S-shaped value function proposed by Kahneman and Tversky (1979) in a one-stage setting. For larger losses in a two-stage setting, the quasi-hedonic editing rule (Thaler & Johnson 1990) suggests a concave region (dashed line) in the value function of the loss domain.

Figure 2. Interaction between expectation and reference point adaptation



Notes: Investor A and investor B both start investing in stock X at t_0 with \$100 per share. At t_1, the stock price drops from \$100 to \$50. Investor A's reference point (R_A) moves to \$90, while that of investor B (R_B) moves to \$70. Assume at t_2 there is an equal chance that the price drops further to \$40 or bounces back to \$60. If the stock price decreases to \$40, it results in a more negative value for investor A than for investor B ($V_{A2} > V_{B2}$). If the stock price increases to \$60, it leads to a more positive value V_{B1} for investor B than for investor A ($V_{B1} > V_{A1}$). Using the expected value function, investor A sells the stock, but investor B holds it. This effect is strengthened if both investors hold similarly negative views on the future performance of the stock due to concavity of the value function of the non-adapted investor A for stock prices below the current price.

Figure 3. Proposed model of decision-making for a losing investment.

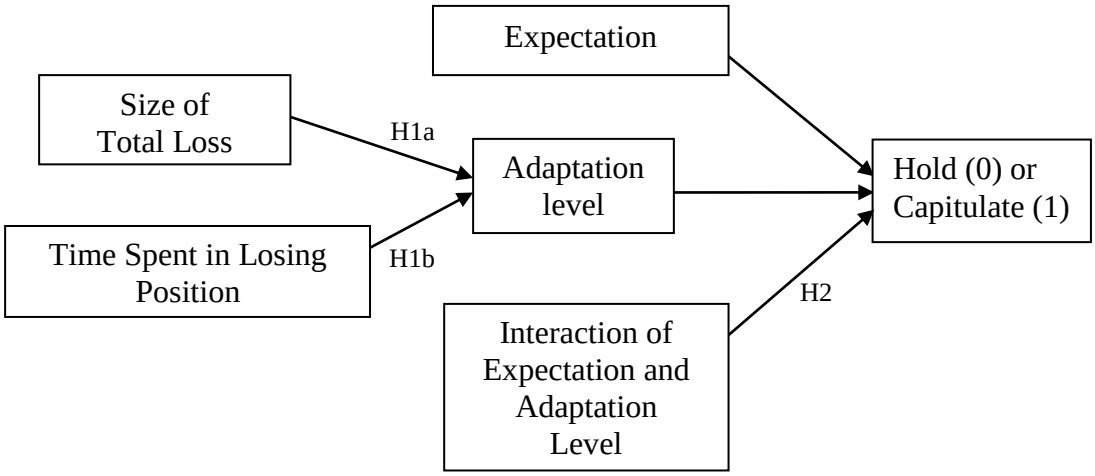
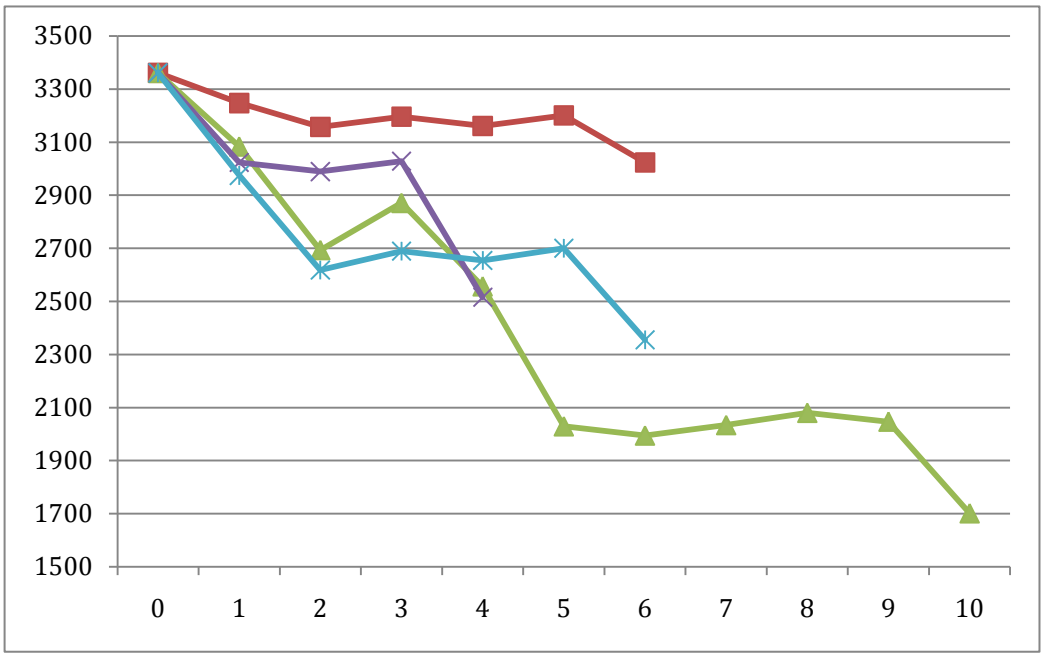
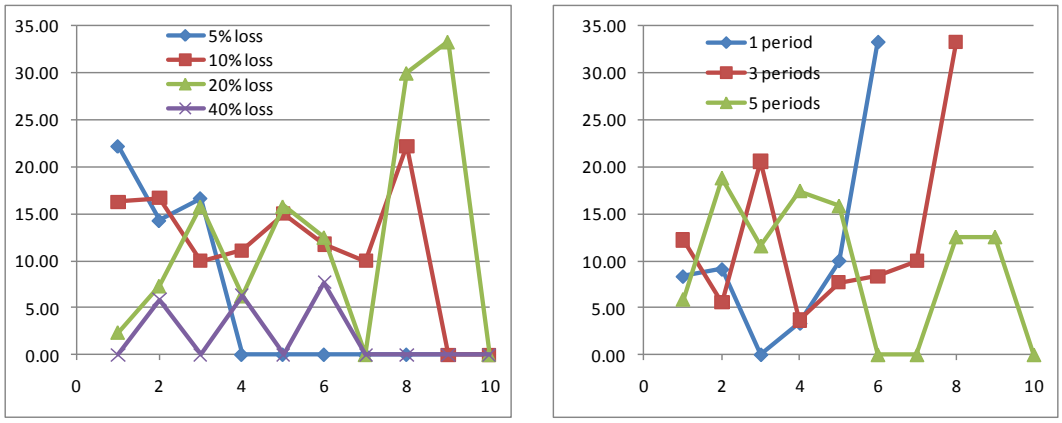


Figure 4. Four sample price patterns presented to participants in the experiment.



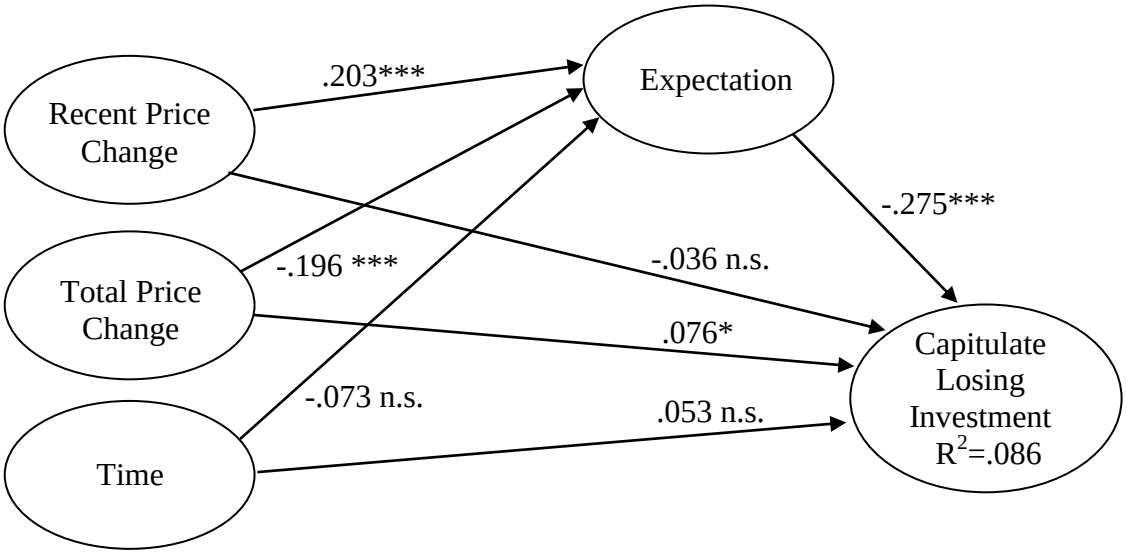
Notes: Participants considered various combinations of price patterns, based on randomly assigned sizes and durations of losses (see table 1 for details) and there are some mild upward movements in the intermediate stages.

Figure 5. Descriptive statistics: empirical capitulation frequencies over time



Notes: The left-hand panel shows the empirical capitulation frequencies over the 10 stages of the experiment, disaggregated with respect to the size of the first-stage loss. For example, for the 10% loss curve in period 2, we divide the number of subjects that were administrated a 10% first-stage loss and capitulated in the second period, by the number of 10% first-stage loss subjects still participating at the start of period 2. The right-hand panel holds similar empirical capitulation frequencies, but disaggregated over the duration of the first-stage loss (see also Table 1).

Figure 6. Results of preliminary model (no adaptation level or interaction with expectation).

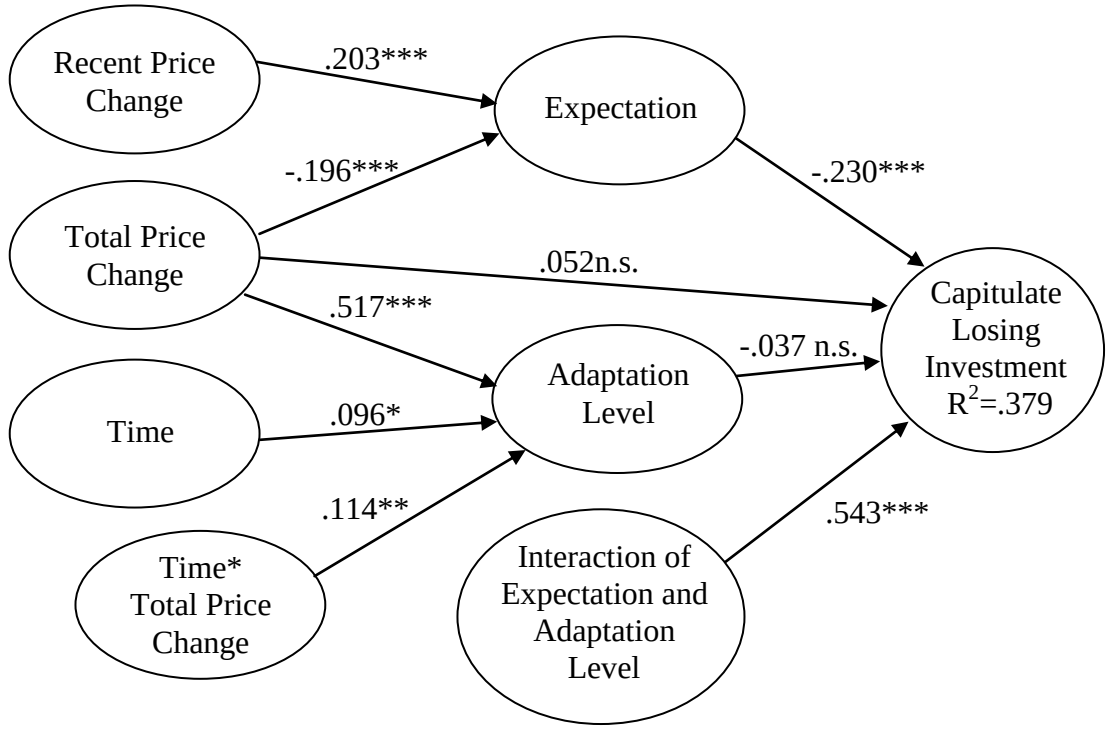


* $p < .05$.

*** $p < .001$.

n.s. = not significant, results based on two-tailed *t*-test.

Figure 7. Results of the complete proposed model (including adaptation level and interaction with expectation).



* $p < .05$.

** $p < .01$.

*** $p < .001$.

n.s. = not significant, results based on two-tailed *t*-test.

Notes: The insignificant effects of recent price change and time on capitulation probability and effect of time on expectation remain insignificant in this analysis. For simplicity, we do not show these relations this figure.

Table 1. Price changes presented in the experiment.

a. Block 1 (Start wealth level $3361)

	First major loss			
	≈ -5%	**≈ -10%**	**≈ -20%**	**≈ -40%**
Number of periods	Price change at each period (in $)			
1	-165.06	-337.38	-674.76	-1331.36
3	-113.95	-193.24	-386.48	-834.24
	-89.56	-178.23	-356.46	-698.46
	38.45	35.36	70.72	201.34
5	-38.27	-99.21	-198.42	-277.33
	-55.68	-89.43	-178.86	-390.12
	40.36	40.32	80.64	177.45
	-61.49	-109.31	-218.62	-314.05
	-49.98	-78.47	-156.94	-527.31

b. Block 2

	Stable prices
	≈ 1%
Number of periods	Price change at each period (in $)
2	-34.78
	39.32
4	-34.78
	39.32
	46.18
	-33.20

c. Block 3

	Second major loss		
	≈ -5%	**≈ -10%**	**≈ -15%**
Number of period	Price change at each period (in $)		
1	-177.23	-345.31	-512.89

Notes: We divide the prices presented to participants into three blocks. The initial value of stock X starts at $3361 ($33.61 × 100 shares). Participants were randomly assigned to incur approximately a 5%, 10%, 20%, or 40% first major loss in block 1 (over 1, 3, or 5 periods). In block 2, participants experienced price changes of approximately 1% (2 or 4 periods). In block 3, participants incur a second major loss of approximately 5%, 10%, or 15% in 1 period. The order of price presentations in blocks 1 and 2 were random.

Table 2. Probability of capitulation with respect to expectation (high vs. low) and adaptation level (high vs. low)

Capitulation Probability			
		Adaptation level	
		High	Low
Expectation	Negative	0.155	0.255
	Positive	0.037	0.036

Notes: A median split was performed on all adaptation levels obtained in the experiment. To distinguish between positive and negative expectations, expectations of 6 to 9 were labeled as positive, and of 1 to 5 as negative expectations. The capitulation probability is small when the expectation is positive, regardless of the adaptation level. When the expectation is negative though, the capitulation probability is greater when the adaptation level is low than when it is high.

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