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Reference Point Adaptation and Disposition Effect

Abstract

This paper investigates the importance of reference point adaptation in the analysis of the disposition effect. We consider two exogenous factors pertinent to reference point adaptation: prior outcome and recent expectation of future outcome. We show that the incidence of the disposition effect varies in a manner consistent with reference point adaptation. Both prior outcome and recent expectation of future outcome affect the location of the reference point and have a large and significant impact on the incidence of the disposition effect. First, the disposition effect can largely be explained by investors' inability to sufficiently adapt the reference point in response to large capital losses. Second, a negative expectation of future outcome, due to recent unfavorable information and highly speculative investments, accelerates reference point adaptation to price depreciation and dramatically increases loss realization. These effects are economically sizeable and are robust to plausible heterogeneity concerns and alternative explanations such as a belief in mean-reversion and managerial incentives.

The disposition effect, as defined by Shefrin and Statman (1985), describes investors' tendency to hold losing investments too long and to sell winning investments too soon. The disposition effect is commonly explained in terms of Kahneman and Tversky's (1979) prospect theory and Thaler's (1985) mental accounting framework. According to prospect theory, decision makers evaluate outcomes as gains and losses relative to a reference point using an S-shaped value function that is concave (risk averse) for gains and convex (risk seeking) for losses. Reference dependency is the core component of prospect theory because the reference point determines whether an outcome is judged as a gain or loss, which significantly affects the subsequent risk-taking decision. The disposition effect is a manifestation of the prospect theory, under the critical assumption that investors fail to adapt to losses and anchor the reference point at a price level higher than the current price.

Although the essential premise of the prospect theory is that the reference point may change over time, empirical tests of specifically how a shift in the reference point affects the investor's subsequent risk-taking decision and the disposition effect have been almost nonexistent.[1] The existing empirical literature on the disposition effect typically assumes the initial purchase price as a fixed reference point. These studies show that when an investment is trading below the reference point, investors tend to be risk seeking. That is, they hold the losing investment by framing the sell decision as a sure loss and the hold decision as a gamble that provides the opportunity to at least break even. However, as Kahneman and Tversky (1979) and Thaler and Johnson (1990) point out, the reference point in a dynamic setting (e.g., a financial investment) is *not* static and may shift away from the purchase price in response to the change in security price, which defines an adaptation level or adapted reference point..Likewise, Odean (1998) argues that

[1] Arkes, Hirshleifer, Jiang, and Lim (2008, 2010) provide extensive discussion on the relation between dynamic adaptation of reference point and the disposition effect, and a synthesis of the existing evidence on this topic.

although evidence of investors' reluctance to realize capital losses supports the notion that purchase price plays an important role in determining the reference point, it may be only one determinant of the reference point.

In this paper, we examine the implications of reference point adaptation for the disposition effect. Specifically, we empirically investigate the extent to which the incidence of the disposition effect varies in a manner that is consistent with reference point adaptation using a large sample of institutional investors' trading records over a seven-year period. Because investors exhibit distinct risk attitudes in the gain versus loss domain, a shift in the reference point systematically alters the value of an outcome and subsequent risk-taking decisions. In particular, the incidence of the disposition effect depends on the discrepancy between the adapted reference point and the lowered current price. On the one hand, if the reference point has been fully adapted downward to the current price, the investor will less likely be risk seeking. On the other hand, if the adapted reference point remains higher than the current price, the investor is likely to hold onto the losing investment and exhibit the disposition effect.

Motivated by the existing theoretical and experimental studies on reference point adaptation, we consider two exogenous factors pertinent to reference point adaptation—prior outcome (i.e., the magnitude of prior capital losses) and expectation about future outcomes—and examine the link between reference point adaptation and the magnitude of the disposition effect.

First, we consider the influence of prior outcome on risk-taking behavior by examining the extent to which the magnitude of capital loss affects the incidence of the disposition effect. A large capital loss affects investors' willingness to adjust the reference point downward to the lowered current price, creating a discrepancy between the adapted reference point and the current price, and induces risk-seeking behavior. Thaler and Johnson (1990) shows that individuals are more willing to adapt to a small to moderate loss than to a large loss. Specifically, a small to moderate loss increases risk aversion for subsequent gambles whereas a large loss numbs investors to additional losses.[2][3] Furthermore, diminishing sensitivity of prospect theory's value function reinforces the effect of a large loss on risk seeking. When an investor has yet to adapt completely to large loss and is already in the loss domain, a further loss only causes a small decrease in utility whereas a price recovery results in a large increase in utility.[4]

Second, we investigate the extent to which the change in an investor's expectation of future outcome, as a result of recent unfavorable information and the speculative nature of investment, affects the location of the reference point and the incidence of the disposition effect. In a recent reference-dependency model, Köszegi and Rabin (2006, 2007, 2009) posit that the reference point is endogenously determined as rational expectations about future outcomes rather than the initial purchase price. Building on the essential intuitions in Kahneman and Tversky's (1979) prospect theory, they argue that an investor's reference point is his or her recent probabilistic beliefs about future outcomes, which are largely determined by recent value-relevant information and the speculative nature of investments.

In the context of the disposition effect, the location of the reference point depends critically

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[2] In their experimental study on how prior losses affect subsequent risk-taking behavior, Thaler and Johnson (1990, p. 650) find evidence that the disutility of a subsequent loss is not a monotonically increasing function of a prior loss. Specifically, the loss of $9 hurts more after a small to moderate loss ($9 or $30) but less after a large loss ($250 or $1000).

[3] Regret aversion and skill signaling help explain why investors are less able to adapt to a large capital loss. Odean (1998) suggests that investors are most loath to realize their greatest losses due to regret aversion. Harbaugh (2009) argues that investors take risky chances to win back large losses to avoid unfavorable signaling on their skills.

[4] To illustrate how the disposition effect is affected by the magnitude of prior capital losses, consider an investor who bought a stock at $45, and then the stock price goes down to $40. The price drop requires the investor to adjust the reference point downward to the current price by $5 to alleviate any discrepancy between the adapted reference point and the lowered current price. The investor is more likely to accept this small loss and evaluates future prospects relative to the current stock price. Consequently, the investor is unlikely to exhibit the disposition effect. If however, the stock goes down sharply to $25, the investor must adjust the reference point downward by $20. In this case, the investor is less likely to fully accept to this large loss and considers the subsequent decision as a choice between selling the stock for a sure loss of $20 and holding the stock, hoping to eventually break even. Hence, the investor will engage in risk seeking behavior by waiting for a price to recover before selling.

on how investors incorporate recent unfavorable information into their beliefs and update their reference point according to downward expectation about the future asset value. Similarly, a priori expectation of losing money influences the location of reference point. That is, investors are more willing to adjust the reference point downward after they experience a loss if they already foresaw a high possibility of incurring a loss (e.g., due to a highly speculative investment).

We examine three kinds of stock-level and market-level unfavorable information: a stock's recent underperformance, negative earnings news, and down market conditions. We hypothesize that unfavorable information accelerates reference point adaptation to price depreciation and increases loss realization. In the presence of a prior loss, investor updates their expectations about stock value downward after receiving unfavorable information. By equating the reference point with recent expectation, the downward expectation translates into a lower reference point, which, in turn, increases the investor's willingness to sell a losing position.

To examine the impact of the speculative nature of an investment on the disposition effect, we consider speculative nature at the stock level and the market level: namely, stock-level information uncertainty and market-wide investor sentiment, respectively. We hypothesize that investors are less prone to the disposition effect when trading high information uncertainty stocks and during high market-wide investor sentiment. That is, because an investor foresees a high chance of losing money in highly speculative investments, he or she is more willing to adapt the reference point downwards, closer to the lowered current price, after experiencing anticipated losses and is more willing to sell losing positions.

Primary findings presented in this article can be summarized as follows. Prior outcome and recent expectation related to future outcome dramatically influence an investor's subsequent risk-taking decision and the incidence of the disposition effect in systematic ways. First, we find that the incidence of the disposition effect increases with the magnitude of prior losses, consistent with the notion that investors are less willing to adapt the reference point downward to a lowered current price after experiencing a large capital loss. Our finding indicates that the incidence of the disposition effect is largely explained by investors' inability to adapt to large capital loss (i.e., positions that have depreciated more than 20% in value).

Second, institutional investors' propensity to sell losing position depends on their recent expectation of future outcome. Our findings indicate that both recent unfavorable information and the highly speculative nature of an investment accelerates investors' adaptation to price depreciation and significantly increases investors' propensity to sell a losing investment. Particularly, a stock's recent underperformance, negative earnings news, and down market conditions increase the probability of selling a losing investment by 63%, 109%, and 64%, respectively. Similarly, the propensity to sell a losing investment increases by 353% when investors trade in stock with high information uncertainty and 102% during periods of high market-wide investor sentiment.

Finally, we examine the overall impact of recent unfavorable information and the speculative nature of an investment on the disposition effect. Our findings suggest that a combination of recent unfavorable information or the speculative nature of investments can largely eliminate the disposition effect. Specifically, when all three exogenous factors related to recent unfavorable information are considered together, the incidence of the disposition effect is reduced by 90.74% and is effectively eliminated in stock with high idiosyncratic risk and during the period of high market sentiment. Furthermore, we find that the adaptation of reference point proves economically beneficial. The stocks sold that are associated with reference point adaptation consistently underperform those that are not. Our findings are robust to a large battery of model specification checks, including full-set regression and regressions with investor-specific, stock-specific, and year-specific heterogeneity controls. Taken together, the empirical evidence indicates that both prior outcome and recent expectation about future outcome affect the location of a reference point and the incidence of the disposition effect. These results are consistent with the experimental evidence and provide direct empirical support for the recent behavioral models of Köszegi and Rabin (2006, 2007, 2009).

One potential criticism leveled at the results is that they may be driven by the possibility that fund managers choose to hold the losing positions in attempt to improve their performance due to managerial compensation incentives (Brown, Harlow, and Starks 1996; Chevalier and Ellison 1997; Koski and Pontiff 1999). To allay such a concern, we conduct the analysis separately for outperforming fund managers (midyear winners) and underperforming fund managers (midyear losers). We find that both midyear winners and losers are reluctant to realize losing positions relative to winning positions. In fact, midyear winners have a stronger tendency to hold onto losing investments than midyear losers. Our finding suggests that the risk-taking behavior does not depend on the fund manager's interim performance and cannot be explained by managerial compensation concerns.

Our study offers several substantial contributions to the existing literature. First, our study provides empirical evidence on the importance of reference point adaptation in explaining the disposition effect. Although both theoretical and experimental studies acknowledge that investors update the reference point over time, empirical evidence is lacking on whether and, if so, to what extent the shift of the reference point affects the incidence of the disposition effect. Second, we investigate a paramount theoretical model of Köszegi and Rabin (2006, 2007, 2009) which highlights the importance of recent expectation about future outcomes in explaining when and how the disposition effect is likely to be observed. Third, we offer the first-to-date empirical investigation of the disposition effect in U.S. institutional equity trading using high-frequency transaction data. Although the disposition effect is well-documented among retail investors, little is known about the existence of such biases among institutional investors. Our findings should be of interest to a wide audience, as institutions currently hold 74% of common stocks, compared to 8% about 50 years ago. With a large fraction of aggregate wealth under their management, institutions are frequently the marginal price-setting agents in securities markets. An investigation of their trading behavior is necessary to understand the dynamics of stock prices. Lastly, our daily institutional trading data overcome the limitations of quarterly holdings data to allow us to investigate more accurately how institutional investors exhibit the disposition effect in equity markets. That is, the quarterly holdings data cannot accurately identify the timing of trades and do not reflect intra-quarter round-trip trades, which results in a significant number of missing trades.[6] Furthermore, the purchase prices are assumed to be the closing price at the end of each quarter. This treatment deteriorates the accuracy for measuring gains and losses because the actual transaction price is generally different from the quarter-end closing price.

The remainder of the paper is organized as follows. The next section provides a brief review of existing literature and discusses testable hypotheses. Section 2 introduces the data and methodology. Section 3 presents the empirical results. Section 4 presents a battery of robustness checks to validate our results from the baseline model. Conclusion is offered in the last section.

1. Related Literature and Testable Hypotheses

[6] Elton, Gruber, Blake, Krasny, and Ozelge (2009) and Puckett and Yan (2010) estimate that use of quarterly data fails to capture more than 20% of trades due to intra-quarter round-trip transactions.

Prior theoretical and experimental studies show that investors adjust the reference point from the initial purchase price toward the current price in response to the prior outcome and recent expectation of the future outcome. Working from a psychological perspective, Tversky and Kahneman (1974) argue that people adjust the reference point away from the purchase price toward the current price in response to the change in security price, which defines an adaptation level or adapted reference point. Barberis, Huang, and Santos's (2001) model assumes a benchmark, which serves as a secondary reference point that responds sluggishly to changes in the value of the risky asset. When a stock price moves up by a lot, the benchmark also moves up but by less. Conversely, if the stock price falls sharply, the benchmark also falls but not as much. Chen and Rao (2002) suggest that people immediately but incompletely update their reference point after experiencing an event. In recent experimental studies, Arkes, Hirshleifer, Jiang, and Lim (2008, 2010) show that the reference point moves in a manner consistent with the prior outcome, shifting upward following a gain and downward following a loss, but the magnitude of reference point adaptation following a price change is not as large as the magnitude of price change itself.

We consider two exogenous factors pertinent to reference point adaptation—prior outcome (i.e., the magnitude of prior capital losses) and expectation about future outcomes—and examine the link between reference point adaptation and the magnitude of the disposition effect. The magnitude of prior losses affects investors' willingness to adjust the reference point downward to a lowered current price. Failure to fully adapt to a large loss creates a discrepancy between the adapted reference point and the current price, which leaves the investor in the loss domain and induces risk-seeking behavior. Given that an investor has not completely adapted to the large loss, a further loss will cause only a small decrease in utility whereas a price recovery will result in a larger increase in utility. Thus, investors tend to be more disposition-prone after experiencing a large loss. Therefore, we state our first hypothesis as follows:

Hypothesis 1: *Institutional investors' exhibition of the disposition effect increases with the magnitude of prior losses.*

In a recent reference-dependency model, Köszegi and Rabin (2006, 2007, 2009) propose that a person's reference point is his or her recent probabilistic beliefs about outcomes, which are largely determined by recent value-relevant information and the speculative nature of investments. Because public information flows interact with investors' belief formation (Harris and Raviv 1993; Kim and Verrecchia 1994; Wang 1994; Karlson, Loewenstein, and Seppi 2009), investors update beliefs downward on the receipt of recent unfavorable value-relevant information. In the context of the disposition effect, adverse information accelerates reference point adaptation to price depreciation and increases loss realization. We examine three kinds of unfavorable stock-level and market-level information: (a) a stock's recent underperformance, (b) a firm's negative earnings news, and (c) down market conditions.

A stock's recent performance is salient information for investors to form expectations about future performance (Chan, Jegadeesh, and Lakonishok 1996; Chae 2005). When an investor observes the recent price path of a stock, the investor gradually incorporates the information into his or her expectation and thus updates the reference point. If the stock has been underperforming recently, the investor updates his or her beliefs about the stock's price downward. As such, the investor will adjust the referent point to a lower level and will be more willing to sell the losing stock. Therefore, we state the first part of our second hypothesis as follows:

Hypothesis 2a: *Institutional investors' reluctance to realize losses is attenuated by the recent underperformance of the underlying stocks.*

Earnings news spurs investors' revision of expectations and affects their adaptation of the reference point. Bernard and Thomas (1989), Chae (2005) and Chan et al. (1996), show that earnings news provides significant information about a stock's value and that earnings news is positively correlated with subsequent stock returns. When an investor observes negative earnings news, he or she updates the expectation about stock's price downward. By lowering the reference point according to recent expectation, the investor will be more willing to sell the losing stock. Accordingly, we state the first part of our second part of our second hypothesis as follows:

Hypothesis 2b: *Institutional investors' reluctance to realize losses is attenuated by negative earnings news events related to the underlying stock*

Down market conditions lower investors' expectations for an individual stock's performance (Daniel, Hirshleifer, and Subrahmanyam 1998; Cooper, Gutierrez, and Hameed 2004). That is, when the overall market goes down, investors are more likely to update the expectations and reference points downward, closer to the current price, and are more willing to sell losing stocks. Thus, we state the final portion of our second hypothesis as follows:

Hypothesis 2c: *Institutional investors' reluctance to realize losses is attenuated in down market conditions.*

Köszegi and Rabin (2006, 2007) argue that a priori expectation of losing money decreases aversion to realizing actual losses. Because investors foresee a good chance of losing money when investing in a highly speculative investment, they are more willing to adapt the reference point downward after experiencing anticipated losses and are less willing to take chances to break even. We examine whether institutional investors are able to adapt to a large loss when they foresee a probability of losing money in highly speculative investments (as proxied by stock-level information uncertainty) and during highly speculative market periods (as proxied by market-wide investor sentiment).

Previous literature argues that stocks with high information uncertainty are hard to value and difficult to arbitrage (Miller 1977; Shleifer and Vishny 1997; Baker and Wurgler 2006, 2007; Kumar 2009). These stocks are characterized with high idiosyncratic risk, small market capitalization, and high volatility. We conjuncture that institutional investors have an expectation of losing money in high information uncertainty stocks and are thus more willing to liquidate the losing positions. Therefore, we state the first part of our third hypothesis as follows:

Hypothesis 3a: *Institutional investors' reluctance to realize losses is attenuated in high information uncertainty stocks.*

Finally, we examine speculative nature of investments at the market level, using market-wide investor sentiment to represent the biased expectations of market participants: A bullish (bearish) investor overestimates (underestimates) asset value (Brown and Cliff 2004). De Long et al. (1990) and Shleifer and Vishny (1997) argue that rational investors face the risk of sentiment when trading against noise investors. During periods of high sentiment, speculative traders have systematic optimism and increase speculative demand while sophisticated investors face higher risk from trading against them (Baker and Wurgler 2007; Lemmon and Ni 2009). To the extent that institutional investors are sophisticated, we conjecture that they are aware of the high risk associated with trading against noise traders during high sentiment periods and will be more willing to adjust the reference point downward and liquidate losing positions. Consequently, we form the second part of our third hypothesis as follows:

Hypothesis 3b: *Institutional investors' reluctance to realize losses is attenuated during high investor sentiment periods.*

A useful representation of the relation between reference adaptation and the disposition effect using the prospect theory value function is illustrated in Figure 1. In presence of a small capital loss, the investor is at point SL, as shown in Figure 1a. The investor is more likely to accept the small loss and adjusts the reference point downward from the initial purchase price to current price (SL). In doing so, the investor will not be risk seeking. On the other hand, as the capital loss becomes large (LL), the investor is less likely to fully accept the total loss and only partially adjusts the reference point downward to point (R1). As such, a large capital loss creates a discrepancy between the adapted reference point (R1) and current price (LL). If a subsequent decision is made and the reference point is not fully adapted to the initial loss, the investor will likely be risk seeking. That is, a further loss will cause only a small decrease in the utility value, but a further gain will result in a larger increase. Figure 1b illustrates the effect of recent unfavorable information and highly speculative investments on the disposition effect. In the presence of a large loss, an investor updates his or her expectation about the stock's value downward on receipt of unfavorable information. By equating the reference point with recent expectation, the downward expectation accelerates the investor's reference point adaptation (from R1) to a lower level (R2). As a result, the investor will be less risk seeking and will be more willing to sell losing investment. Highly speculative investments enhance reference point adaptation in a similar fashion. Specifically, the investor adjusts the reference point downward (from R1) to R2, closer to the lowered current price (LL), after experiencing anticipated losses in a highly speculative investment, and will less likely be risk seeking.

[FIGURE 1 ABOUT HERE]

2. Data and Methodology

2.1 Data, Sample and Summary Statistics

We obtain proprietary institutional trading data from the Ancerno Ltd. (formerly the Abel/Noser Corporation) for the period of 1999 to 2005. Ancerno is a widely recognized firm that provides consulting and advisory services to institutional investors related to equity trading costs monitoring and measurement. The Ancerno data set identifies institutional investors' decisions to establish or liquidate positions as well as the order execution. The Ancerno data set provides information about stocks traded, number of shares ordered and executed, execution price, order direction (buy or sell), and date of orders and the executions. The identities of the institutions and portfolio managers are not provided due to privacy protection, but the unique identity codes are used to track trades initiated by each institution and portfolio manager.[7] Our analysis focuses on active mutual funds and excludes pension funds that explicitly follow inactive trading strategy. We obtain stock return, share price, and stock turnover from the CRSP daily tape and include only common stocks (share code 10 or 11) traded on NYSE, AMEX, and NASDAQ in our sample. To make sure our results are not driven by very small stocks or by bid–ask bounce, we delete stocks with a price of less than $1. We obtain analysts' consensus quarterly earnings forecast and actual earnings per share from I/B/E/S.

Positions. We define the beginning position as the point at which the investor purchases a stock and ending position as the point at which the investor sells the stock. To maintain the

[7] Compared to the standard mutual fund database (Thomson Financial Mutual Fund Holdings database s12), Ancerno database's distinct feature is that it tracks a complete record of a mutual fund's trading. However, whereas the s12 database contains fund characteristics (fund classification by objectives), the Ancerno database includes no classifications information on funds' miscellaneous attributes.

integrity of the data and filter out possible errors in identifying prior capital gains or losses, we follow Ivkovic, Poterba, and Weisbenner (2005) and restrict the sample to trades for which we can unambiguously match purchase and sale dates. We exclude sales that do not have a preceding purchase and sales that are preceded by multiple purchases.[8] When a single purchase is followed by multiple sales, we choose the first sale as the end of that position.[9]

Gains and losses. On each position-day, we compare the holding period capital loss/gain against the purchase price on each position-day. If the position has a sell order on that day, we compare the volume-weighted executed price of the sell order to that of the buy order, which originates the position. On days that the position is held, we compare the CRSP closing price of that day to the purchase price.[10] All prices are adjusted for stock splits and dividend distributions.

Table 1 provides the descriptive statistics of our sample. The final sample consists of 199 institutions and 469 portfolio managers who place orders in 6,653 common stocks. We identify 890,000 initiations of positions, which results in 23.9 million position-days. The average holding period (from initiation to first sale) is 27 days for a position. Institutions purchase approximately 41.79 billion shares, representing $1.08 trillion in value.

[TABLE 1 ABOUT HERE]

2.2 Cox Proportional Hazard Model

We estimate the extent to which institutional investors are prone to the disposition effect by

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[8] As a robustness check, we repeat our analysis with the sample including sale orders that are preceded by multiple purchase orders by using volume-weighted average purchase prices of each order as the purchase price. The results remain qualitatively unchanged.

[9] Institutional investors in our sample are less likely to engage in portfolio rebalancing when they liquidate their holding, as over 90% of the sales are of entire positions.

[10] We use closing price instead of bid/ask price to identify gain/loss to limit the observations with no price change. We also repeat all analysis using bid/ask price. The results are qualitatively similar to those obtained using closing price.

employing an extended Cox proportional hazard model (hereafter, the Cox-PH model). Recent studies on the disposition effect (e.g., Genesove and Mayer 2001; Ivkovic et al. 2005; Feng and Seasholes 2005; Seru, Shumway, and Stoffman 2010) report the advantages of a hazard model over several traditional approaches as a tool for investigating the disposition effect. In particular, Odean (1998) compares the proportion of losses realized (PLR) to the proportion of gains realized (PGR). A lower PLR than PGR suggests that investors are more reluctant to realize losses than gains.[11] However, it is difficult to control for other factors that could be correlated to investors' trading decision. To facilitate such controls, Grinblatt and Keloharju (2001) use a logit regression by regressing a holding indicator (1 = sell, 0 = hold) at the stock position level on a set of independent variables. The logit regression includes observations for each position on each day when an investor trades at least one security. Days in which an investor does not trade are dropped from their analysis. A potential problem with a logit regression is that it may give incorrect inferences in cases in which capital gains or losses vary over time (i.e., the model ignores the price path during the holding period of a position). The hazard model overcomes this limitation by including each position-day as a separate observation and thus can identify the time-varying nature of the explanatory variables. In addition, this model is especially suited for our setting due to the conditional nature of investors' sale decisions: The probability of selling a position at time *t* is conditional on still holding that position at time *t*–1.

For each day *t* after a position *j* is established (i.e., a stock is bought by an investor), we calculate hazard rate $h_j(t|X)$, the probability of selling position *j* at time *t* conditional on still

[11] We also assess the robustness of our main findings using Odean's (1998) proportional method. The results from proportional method are consistent with our findings using Cox-PH model. Specifically, we find that the ratio of the ratio of the proportion of gains realized (PGR) to the proportion of large losses realized (PLR) is 3.587, indicating that institutional investors exhibit a very strong disposition effect in large losses. In contrast, the ratio of the PGR to the PLR of general losses is 0.963, suggesting that institutional investors do not exhibit the disposition effect overall. In comparison, Odean (1998) reports the ratio of PGR to PLR equals 0.148/0.098=1.510, suggesting that retail investors are strongly disposition-prone.

holding the position until time *t*. We specify the hazard rate as

$$h_j(t|\,\mathbf{X}) = h_0(t)\exp(\boldsymbol{\beta}^*\mathbf{X}). \tag{A}$$

The baseline hazard rate $h_0(t)$ is essentially the hazard rate when all covariates take the value of zero. If we take logarithm of both sides, (A) is transferred to

$$\log[h_j(t|\,\mathbf{X})] = \log[h_0(t)] + \boldsymbol{\beta}^*\mathbf{X}. \tag{B}$$

Equation (B) shows that the log baseline hazard is analogous to the intercept in a linear regression model. The advantage of the Cox-PH model is that it does not impose a specific form of the baseline by allowing for a nonparametric baseline $h_0(t)$, which automatically captures fluctuations in hazard rate caused by differing holding time.

X is the matrix of explanatory variables (i.e., covariates) that can be time invariant or time varying. The estimate for each covariate reflects an average effect of the covariate to increase or decrease the hazard rate during the holding period of a position. The sign of the coefficient indicates the direction of the covariate's effect on the hazard rate. Specifically, a negative β_1 coefficient on X_1 means that 1 unit increase in X_1 lead to an absolute value of $[EXP(\beta_1) - 1]$ decrease in the conditional probability of selling. Because the duration of holding a position is the time between establishing and liquidating a position, a lowered hazard rate implies a longer period of holding the position.

3. Empirical Results

3.1 Disposition Effect (on average)

We begin our analysis by examining whether institutional investors in our sample exhibit the disposition effect on average. To carry out the test, we use the univariate specification of the Cox-PH model:

$$h_j(t) = h_0(t)\exp(\beta_1 * LOSS), \tag{1}$$

where *LOSS* is an indicator variable that equals 1 if the position has depreciated in value from the time of purchase until time *t*.[12] If institutional investors exhibit disposition effect, the coefficient for the capital loss indicator will be negative (i.e., a capital loss decreases the hazard rate), indicating that investors with a losing position will hold the position longer than a winning position.

Model 1 in Table 2 reports the estimated coefficient and standard error for the capital loss indicator. The standard error is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. The result shows weak evidence of the disposition effect among institutional investors. The coefficient on *LOSS* (–0.0334) suggests that an investor holding a losing position reduces his or her probability of selling by only 3.28% (exp (–0.0334) –1= –0.0328= –3.28%) or an equivalent increase in the expected holding time to liquidation. Our result shows a much weaker disposition effect for institutional investors compared to previous findings related to retail investors. For instance, Feng and Seasholes (2005) show that Chinese individual investors decrease the probability of selling by 36% when a stock is trading at a capital loss relative to a capital gain. The comparatively weaker disposition effect is not surprising because institutional investors possess a higher level of sophistication than retail investors. Our results are consistent with a growing body of literature that examines the relation between investor characteristics and the disposition effect and finds that investors that have a higher level of sophistication, literacy, investment knowledge, hold professional occupations, and have more trading experience are better able to adapt to prior losses and exhibit a weaker disposition effect (Shapira and Venezia 2001; Locke and Mann 2005; Feng and Seasholes 2005;

[12] We use the indicator variable of capital loss; the omitted category is capital gain or no price change (in rare instances). According to this setup, the baseline hazard rate $h_0(t)$ corresponds to a capital gain.

Dhar and Zhu 2006; Seru, Shumway, and Stoffman 2010).

[TABLE 2 ABOUT HERE]

3.2 Magnitude of Prior Losses and the Disposition Effect

We investigate whether and to what extent the magnitude of prior losses contributes to variations in the disposition effect. To conduct our tests, we characterize the Cox-PH model using six dummy variables corresponding to six capital loss intervals, with five bands representing an interval that lies within a 10% return band from zero to 50% and one band representing a loss of above 50%. For example, the dummy *LOSS* [0, 10%] equals 1 when the capital loss is greater than zero but less than or equal to 10%. *LOSS* [50%, 100%] equals 1 when the capital loss is greater than 50%. We express this model as

$$\begin{aligned} h_j(t) = h_0(t)\exp(\ &\beta_1 * LOSS\ [0, 10\%] + \beta_2 * LOSS\ [10\%, 20\%] \\ &+ \beta_3 * LOSS\ [20\%, 30\%] + \beta_4 * LOSS\ [30\%, 40\%] \\ &+ \beta_5 * LOSS\ [40\%, 50\%] + \beta_6 * LOSS\ [50\%, 100\%]). \end{aligned} \tag{2a}$$

Panel A of Table 2 presents the estimated coefficients and standard errors for six capital loss indicators. Institutional investors are clearly more likely to hold a stock if it has significantly decreased in value since the date of purchase. The evidence provides strong support for the notion that magnitude of prior loss affects investors' willingness to adjust the reference point downward to a lowered current price and induces risk-seeking behavior, consistent with Hypothesis 1. Specifically, the estimated coefficients on *LOSS* [0, 10%] and *LOSS* [10%, 20%] are positive, suggesting that institutional investors are not disposition-prone with respect to small to moderate losses. In contrast, institutional investors are reluctant to sell a losing position once the loss exceeds 20%. The coefficient of –0.0582 for *LOSS* [20%, 30%] suggests that an investor facing a prior capital loss between 20% and 30% reduces her probability of selling the investment by 5.66%. Moreover, the probability of selling significantly declines as the magnitude of the prior losses exceeds 30%. The estimated coefficients for *LOSS* [30%, 40%], *LOSS* [40, 50%], and *LOSS* [50, 100%] are –0.6617, –1.6585, and –1.5932, respectively, which are associated with a 48.40%, 80.96%, and 79.67% reduction, respectively, in the probability of selling.

Because the coefficients are positive for small to moderate loss dummies but of opposite sign for larger loss dummies, we use more parsimonious representation in subsequent analyses. Specifically, we dichotomize capital losses into large and moderate losses rather than the six capital loss indicators. We characterize the Cox-PH model by including two dummies, *LARGELOSS* and *MODERATELOSS*, for large capital loss (loss >20%) and for moderate capital losses (loss ≤20%), respectively; the baseline is associated with either a capital gain or no price change. The estimation is represented as

$$h_j(t) = h_0(t)\exp(\beta_1 * \mathit{LARGELOSS} + \beta_2 * \mathit{MODERATELOSS}). \quad (2b)$$

The estimated coefficients and standard errors for LARGELOSS and MODERATELOSS are presented in Panel B. As expected, we find opposite signs of the coefficients on the large loss versus moderate loss indicators. The coefficient on *LARGELOSS* (–0.7980) suggests that an investor facing a large capital loss will have a large and economically significant 54.98% reduction in the probability of selling. In contrast, investors are not reluctant to realize a moderate loss. The coefficient on *MODERATELOSS* (0.0427) is positive but economically insignificant. The evidence on the relation between prior losses and investors' subsequent risk attitude is similar to the observed patterns in Thaler and Johnson (1990), Odean (1998), and Grinblatt and Keloharju (2001), although the exact reason for such a trend remains largely unexplained. Given that investors are less likely to fully adapt to large capital losses, the negative relation between the magnitude of prior losses and the propensity to sell a losing position can be explained by the dynamic adaptation of the reference point within the framework of the prospect theory. In prospect theory, the propensity to sell a stock should decline as the stock price moves away from the reference point, given a positive expected return (Gomes 2005; Barberis and Xiong 2009). Our findings suggest that institutional investors are able to adapt to small to moderate losses and adjust the reference point downward closer to the current price, eliminating the discrepancy between the two prices. In contrast, institutions' inability to fully adapt to a large loss creates a large negative deviation between the adapted reference point and the current price, which results in a lower propensity to sell a losing position.

In the subsequent empirical analyses, we focus our discussion on the impact of a large capital loss compared to a moderate loss, given that institutional investors are able to fully adapt when an investment sustains a moderate capital loss but have a propensity to hold onto investments that incur a large capital loss.

3.3. Recent Value-Relevant Information and the Disposition Effect

We investigate the extent to which recent unfavorable information affects the reference point, which, in turn, translates into variations in the disposition effect. We examine three kinds of stock- and market-level unfavorable information: (a) a stock's recent underperformance, (b) a firm's negative earnings news, and (c) down market conditions.

3.3.1 Recent Stock Underperformance

We expand the model to include interaction terms for large and moderate loss indicators with past return variables. The interaction terms allow us to assess how a stock's recent performance together with prior losses affects the disposition effect. We also include past returns as control variables. We estimate the Cox-PH model using the following specification:

$$h_j(t) = h_0(t)\exp(\ \beta_1 * \mathit{LARGELOSS} + \beta_2 * \mathit{MODERATELOSS} \\ + \beta_3 * \mathit{LARGELOSS} * \text{PastRet} + \beta_4 * \mathit{MODERATELOSS} * \text{PastRet} \\ + \beta_5 * \text{PastRet}). \quad (3)$$

We use the market-adjusted returns, calculated as the difference between the buy-and-hold returns of sample stocks and the return of CRSP value-weighted portfolio. We include market-adjusted return variables over seven non-overlapping trading-day intervals in the past one year: trading days –4 to zero (prior one week), days –19 to –5 (prior one month to prior one week), days –39 to –20, days –59 to –40, days –119 to –60, days –179 to –120, and days –239 to –180.

Model 3 in Table 3 reports the estimated coefficients and standard errors for interaction terms of large and moderate loss indicators with past return variables. The coefficients on the interaction terms in intervals from day –4 to zero until days –59 to –40 (prior three months) are negative and statistically significant, which implies that a negative past return accelerates the speed at which investors liquidate losing positions.

To elaborate, consider an investor who holds stocks X and Y, both of which are held as a large loss. Suppose stock X had a –15% market-adjusted return during the prior week, and stock Y had a zero market-adjusted return. The coefficient on the interaction term of the large loss indicator with past returns for days –4 to zero is–3.2966 (LARGELOSS *Ret[day0,–4]). Thus, the probability that the investor will sell stock X is 63.96% higher than the probability she will sell stock Y. In contrast, the marginal effect of a negative return on the propensity to sell moderate losses is economically insignificant. Under the same circumstance, when both stocks X and Y are held as moderate loss, the probability of that the investor will sell stock X is only 4.47%

higher than the probability she will sell stock Y. Moreover, the coefficients on the interaction terms of the large loss indicator with the most recent past return (Ret [day0,–4]) is the largest among all the interaction terms, suggesting that investors pay more attention to the most recent weekly return, consistent with Köszegi and Rabin's (2006, 2007) proposition that investors update the reference point based on recent expectation about the future asset value.

Our results also show that the disposition effect cannot be explained by investors' belief in mean reversion. The coefficient on *LARGELOSS* remains statistically and economically significant after controlling for past return variables. The *LARGELOSS* coefficient of –1.0713 implies that the probability of selling a position with a large loss is 65.74% lower than the probability of selling a position with a capital gain or no price change, ceteris paribas. More importantly, the positive coefficients on past return control variables imply that investors are more likely to sell a stock that has recently performed well, conditional on the position being a capital gain. While recent outperformance induces investors to sell winning positions, recent underperformance increases investors' willingness to liquidate losing positions. The finding suggests that a belief in mean reversion is not a sufficient explanation for the disposition effect. A mean-reversion investor would tend to hold underperforming stocks and sell outperforming stocks, regardless of paper losses or gains.

Overall, our finding is consistent with Hypothesis 2a, which posits that a stock's recent underperformance accelerates investors' adaptation of the reference point to a lower level. Institutional investors are more willing to realize losses and exhibit a weaker disposition effect following a recent price decline.[13]

[13] To capture potential nonlinear relation between past performance and disposition effect, we implement two additional tests: (a). We include dummy variables indicating whether stocks hit recent historical highs/lows over three (overlapped) intervals (past one-month, past three-month, and past six-month), and (b) we include dummy variables representing top/bottom momentum quintiles formed based on returns over three (overlapped) intervals

[TABLE 3 ABOUT HERE]

3.3.2 Negative Earnings News

We characterize the Cox-PH model to include the interaction terms of large and moderate loss indicators with extreme positive and negative earnings surprise dummies. The earnings surprise variables are also included as control variables. We estimate this model as

$$
\begin{aligned}
h_j(t) = h_0(t)\exp(&\beta_1 * \mathit{LARGELOSS} + \beta_2 * \mathit{MODERATELOSS} \\
&+ \beta_3 * \mathit{LARGELOSS} * \text{NegES} + \beta_4 * \mathit{LARGELOSS} * \text{PosES} \\
&+ \beta_5 * \mathit{MODERATELOSS} * \text{NegES} \\
&+ \beta_6 * \mathit{MODERATELOSS} * \text{PosES} \\
&+ \beta_7 * \text{NegES} + \beta_8 * \text{PosES}).
\end{aligned} \tag{4}
$$

We define quarterly standardized unexpected earnings as $(X_{jt}\text{-}X_{jt\text{-}4})/S_{jt}$,, where X_{jt} is actual earnings per share for quarter t, X_{jt-4} is actual earnings per share for quarter t–4, and S_{jt} is the standard deviation of $(X_{jt}–X_{jt\text{-}4})$ in the previous eight quarters (Chordia and Shivakumar 2006).

Following Foster, Olsen, and Shevlin (1984), we rank stocks each calendar quarter based on the standardized unexpected earnings for that quarter to determine the deciles of the distribution. We use these deciles as the cut-offs to assign firms into 1 of 10 earnings surprise portfolios in the quarter subsequent to that quarter in which the cut-off point was determined. We define NegES (PosES) as a dummy variable if the stock is in the bottom (top) decile of the earnings surprise ranking. We also assess the robustness of our findings using dummy variables representing negative and positive earnings surprises; our conclusions remain qualitatively unchanged.

(past one-month, past three-month, and past six-month). The additional tests confirm our main findings. The results indicate that (a) investors are more likely to sell (hold) a losing position if the underlying stock hits the historical low (high), and (b) investors are more likely to sell (hold) a losing position if the underlying stock is in the bottom (top) momentum quintile.

Table 3, Model 4, presents the estimated coefficients and standard errors for the interaction terms of the large loss indicator with a negative earnings surprise (LARGELOSS*NegES) along with other covariates. The positive coefficient of 0.7405 implies that a negative earnings surprise increases an investor's propensity to sell a losing position by a very large and economically significant 109.69%, relative to a losing position without negative earnings news.[14]

3.3.3 Down Market Conditions

We characterize the Cox-PH model to include the interaction terms of large and moderate loss indicators with down market conditions as

$$\begin{aligned} h_j(t) = h_0(t)\exp(&\beta_1 * \mathit{LARGELOSS} + \beta_2 * \mathit{MODERATELOSS} \\ &+ \beta_3 * \mathit{LARGELOSS} * \text{MKTdown} \\ &+ \beta_4 * \mathit{MODERATELOSS} * \text{MKTdown} \\ &+ \beta_5 * \text{MKTdown}), \end{aligned} \tag{5}$$

where MKTdown is an indicator variable that equals 1 for down market conditions, and zero otherwise. Down (up) markets are months in which the market excess return is less (greater) than zero. Market excess return is defined as the difference between the return on the value-weighted CRSP portfolio and the risk-free rate. We also repeat our analysis using an equally weighted CRSP portfolio as well as the Standard & Poor 500 index as a proxy for the market portfolio. The findings are qualitatively unchanged and not reported for brevity.

[14] We also perform additional test to address the possibility that the impact of a stock's underperformance and a firm's negative earnings news may be subsumed by each other (Chan, et al. 1996; Chordia and Shivakumar 2006). We characterize the Cox-PH model to include both past return and earnings news variables. The results confirm our main findings and provide support for Hypotheses 2a and 2b. We find that both stock's recent performance and a firm's earnings news have a strong impact on the incidence of the disposition effect and are not subsumed by each other. Specifically, when both past return and earnings news variables are included in the model, the estimated coefficients on the interaction terms of the large loss indicator with the seven past return variables change only slightly from Model 3 and remain economically and statistically significant. When compared to Model 4, the coefficient on the interaction term of a large loss with negative earnings news falls from 0.7405 in Model 4 to 0.3497 in Model 5 but remains economically and statistically significant. Thus, our results suggest that the economic effect of negative earnings news on the disposition effect is reduced but not subsumed by past return variables.

Table 4 reports the estimated coefficient and standard error for the interaction term of the large loss indicator with the down-market indicator (LARGELOSS*MKTdown). The positive coefficient on the interaction term (0.4933) suggests that institutional investors are 63.77% more likely to realize a large loss in a down market than in an up market. The finding support Hypothesis 2c, which posits that down market conditions accelerate reference point adaptation and increase loss realization. That is, institutional investors are more likely to update their expectations and adapt the reference point downward in a down market after experiencing loss and are more willing to sell a losing position in down-market conditions.

[TABLE 4 ABOUT HERE]

3.4. Speculative Nature of Investment and the Disposition Effect

We investigate how institutional investors' reluctance to realize large losses is affected by stock-level and market-level speculative natures. To carry out our tests, we use information uncertainty proxies to examine the speculative nature of an investment at the stock level, and we use a composite index of investor sentiment to examine the speculative nature of a stock at the market level.

3.4.1 Stock-Level Speculative Nature

We adopt three commonly used proxies for stock-level information uncertainty: idiosyncratic risk, firm size, and return volatility.

Idiosyncratic Risk --- We use the average monthly idiosyncratic risk during the prior quarter before portfolio formation. Following Fu (2009), we define idiosyncratic volatility each month as the product of (a) the standard deviation of the regression residuals of excess daily returns on the daily Fama–French three factors and (b) the square root of the number of observations in the month.

Firm Size --- measured as the market capitalization at the portfolio formation date. Following prior literature (Zhang 2006), we conjecture that small firms are less diversified and have less information available for the market than large firms.

Return Volatility --- calculated as the standard deviation of weekly returns over the year ending at the portfolio formation date. We measure the weekly returns from Thursday to Wednesday to mitigate nonsynchronous trading or the effect of bid–ask bounce in daily price.

For each proxy of information uncertainty (IU), we sort stocks into three groups: IU-High, IU-Mid, and IU-Low. We define a dummy variable that represents the high information uncertainty group and characterize the Cox-PH model to include the interaction terms of large and moderate loss indicators with the high information uncertainty indicator as

$$\begin{aligned} h_j(t) = h_0(t)\exp\big(& \beta_1 * \mathit{LARGELOSS} + \beta_2 * \mathit{LARGELOSS} * \text{IU\_High} \\ & + \beta_3 * \mathit{MODERATELOSS} + \beta_4 * \mathit{MODERATELOSS} * \text{IU\_High} \\ & + \beta_5 * \text{IU\_Mid} + \beta_6 * \text{IU\_High}. \end{aligned} \tag{6}$$

Model 6 in Table 5 presents the estimated coefficients and standard errors for the interaction terms of the large loss indicator with the high information uncertainty indicator. For all three information uncertainty proxies, our findings are consistent with Hypothesis 3a, which posits that institutional investors exhibit a weaker disposition effect when trading in highly speculative stocks. For instance, when using idiosyncratic volatility as the proxy for the speculative nature of an investment, the coefficient of 1.5129 implies that institutional investors are 353% more likely to liquidate a position in stock with high idiosyncratic than in other stocks. Similarly, the coefficients of 1.1519 and 1.2080 for small stocks and high volatility stocks, respectively, imply that a losing position in small stocks and high volatility stocks is 216% and 234% more likely to be realized, respectively. Our results are consistent with the notion that institutional investors anticipate a high probability of losses when trading in highly speculative stocks and are more willing to adapt to losses. In contrast, institutions are more willing to assume risk and hold onto losing positions in the stocks that are perceived to be safer (i.e., low information uncertainty stocks).

[TABLE 5 ABOUT HERE]

3.4.2. Market-Level Investor Sentiment

We now characterize the Cox-PH model to include the interaction terms of large and moderate loss indicators with a market-wide investor sentiment indicator as

$$\begin{aligned} h_j(t) = h_0(t)\exp(&\beta_1 * \textit{LARGELOSS} + \beta_2 * \textit{MODERATELOSS} \\ &+ \beta_3 * \textit{LARGELOSS} * \text{PosSENT} + \beta_4 * \textit{MODERATELOSS} * \text{PosSENT} \\ &+ \beta 5 * \text{PosSENT}), \end{aligned} \tag{7}$$

where PosSENT is a dummy variable that equals 1 if the composite index of investor sentiment is positive in the previous month, and zero otherwise. The positive (negative) sentiment index implies high (low) market-wide investor sentiment. We use the composite index of sentiment developed by Baker and Wurgler (2006). The sentiment index is created from six proxies of investor sentiment based on their first principal component. These proxies include variables that are positively associated with sentiment levels (share turnover, IPO volume, first-day returns, and the equity share in new issues) and variables that are negatively associated with sentiment levels (closed-end fund discount and the dividend premium). We obtain monthly sentiment index from Jeffrey Wurgler’s Web site.

Table 6 reports the estimated coefficient and standard error for the interaction term of the large loss indicator with a positive market sentiment indicator (LARGELOSS*PosSENT).

Consistent with Hypothesis 3b, the positive coefficient for the interaction term of 0.7073 suggests that high market-wide investor sentiment attenuates institutional investors' disposition effect. In a high sentiment period, the probability of selling a large losing position increases by 102.84%. We repeat our analysis, replacing the monthly sentiment index with a yearly sentiment index. We also include each individual component of the composite sentiment index (share turnover, IPO volume and first-day returns, equity share in new issues, closed-end fund discount, and the dividend premium) compiled by Baker and Wurgler (2006) and the market volatility index as an alternative proxy, which measures the implied volatility of options on the S&P 500 stock index. In untabulated results, we find that when investor sentiment is high, institutional investors are less prone to the disposition effect, which is consistent with our main findings.

[TABLE 6 ABOUT HERE]

3.5. The Overall Impact on the Magnitude of the Disposition Effect

The findings thus far indicate that the disposition effect is affected by the magnitude of prior losses, recent unfavorable information, and the speculative nature of investment. We now conduct additional tests to explore the marginal impact of recent unfavorable information and the speculative nature of investments as well as their overall impact on the magnitude of the disposition effect.

To examine the marginal impact of each proxy, we calculate the change in magnitude of the disposition effect from the baseline Model (2b). The marginal impact of recent unfavorable information and the speculative nature of an investment is large and economically significant. Specifically, the incidence of the disposition effect decreases by 20.28%, 87.74%, and 23.27% for recent stock underperformance, negative earnings news, and down market conditions, respectively. Similarly, the incidence of the disposition effect is essentially eliminated for stocks with high information uncertainty and decreases by 38.34% during a high market sentiment period.[15]

To examine the overall impact of recent unfavorable information and the speculative nature of an investment, we estimate two regressions including (a) all three exogenous factors related to recent unfavorable information and (b) two exogenous factors related to the speculative nature of an investment; at a baseline position, all covariates equal zero. Models 9 and 10 in Table 7 reports results for the models including all covariates related to recent unfavorable information and the speculative nature of an investment, respectively. Our findings indicate that a combination of all factors related to recent unfavorable information or the speculative nature of investments can largely eliminate the disposition effect. Specifically, when all three exogenous factors related to recent unfavorable information are considered together, the incidence of the disposition effect is reduced by 90.74% and is effectively eliminated in stock with high idiosyncratic risk and during the period of high market sentiment.

[TABLE 7 ABOUT HERE]

3.6. Ex-Post Performance

We evaluate ex-post outcomes following the sale of winning stock or the holding of a large losing stock. If the stock with a large loss subsequently outperforms the winning stock, then the institutional investor would have been better off holding stock. That is, the disposition effect is

[15] To calculate the reduction in the disposition effect, we first estimate the hazard rate for a large loss with recent unfavorable information and the speculative nature of investment. We then calculate the percentage change relative to the sample average of –54.98% from the baseline model (Model 2b). For example, the hazard rate for a large loss with negative earnings news during the prior week of –6.96% (exp(–0.8126+0.7405)–1 = –6.96%) is used to calculate the change in the disposition effect –(54.98%– (–6.96%))/(–54.98%)= 87.34%).

justified by subsequent performance and making the sale was a poor decision, ex post. We employ an approach similar to Odean (1998) to calculate excess returns for 27 trading days (average holding period), 126 trading days (assuming semi-annual turnover) and 252 trading days after the trade. Returns are calculated in excess of CRSP value-weighted index. Our findings (available from the authors) are consistent with the notion that institutional investors are unable to adapt to the large loss and make poor trading decisions by holding large losing position. The stock with a large loss, on average, underperform the winning stock by 0.72%, 1.87%, and 3.51% for the period of 27 trading days, 176 trading days and 252 trading days, respectively.

Our main interest is to investigate the extent to which reference point adaptation affects ex-post outcomes following the sale of large losing position. If the large losing stocks sold due to reference point adaptation subsequently underperform those unrelated to reference point adaptation, then adaptation of the reference point is economically beneficial. We partition the sample of large loss realizations into two subsamples according to whether or not the sale is associated with recent unfavorable information and the speculative nature of investment, as described in Section 3.3. We then calculate excess returns for 27 trading days, 126 trading days and 252 trading days after the sales. For all three examination periods, we find that the losing stocks sold that are associated with reference point adaptation underperform those that are not. For instance, the underperformance in six month following the sales due to recent unfavorable information and speculative nature of an investment, on average, is 3.55% and 2.78%, respectively.

4. Robustness Checks

4.1. Full-Set Regression

We now examine all factors together—the magnitude of prior losses, recent unfavorable information, and the speculative nature of an investment—and explore whether the impact of some factors on the disposition effect may be subsumed by other factors. We estimate the regression including all the exogenous factors, with the baseline being associated with a position that all covariates take the value of zero.

Model 10 of Table 7 reports the estimated coefficients and standard errors for all covariates. The results from Model 10 show that each exogenous factor pertinent to reference point adaptation has an impact on the disposition effect and that one factor's impact is not subsumed by another.[16] First, the coefficient on *LARGELOSS* is –2.2352, and the coefficient on *MODERATELOSS* is 0.0345, indicating that institutional investors are strongly disposition-prone with respect to large losses while they do not exhibit a disposition effect in moderate losses. Second, the coefficients on the interaction terms of the large loss indicator with each of the factors representing recent stock-level and market-level value-relevant information remain qualitatively unchanged. This result indicates that institutional investors show a weaker disposition effect in large losses when the loss follows recent unfavorable information events. Third, the coefficients on the interaction terms of the large loss indicator with the stock-level information uncertainty proxy and investor sentiment remain qualitatively the same as in our main analysis. This result suggests that institutional investors exhibit a weaker disposition effect when trading in highly speculative stocks and during highly speculative market periods.

4.2. Investor-, Stock-, and Time-Specific Heterogeneity

4.2.1 Investor- and Stock-Specific Heterogeneity

There may be unobserved fixed effects in selling probabilities specific to individual investor or

[16] We report the results using idiosyncratic risk as the proxy for stock-level information uncertainty. The findings are robust to other alternative information uncertainty proxies. The results are available upon request.

stock. To explore the sensitivity of our main findings to such potential unobserved heterogeneities, we follow Ivkovic et al. (2005) to allow for investor- and stock-specific baseline hazard rates. We replace the homogeneous baseline $h_0(t)$ in Model 10 with an investor-specific baseline $h_{0,i}(t)$ that allows the baseline to vary across institutions (Model 11) and across institutions' portfolio managers (Model 12). We also replace $h_0(t)$ with stock-specific $h_{0,s}(t)$, which allows the baseline to vary across stocks (Model 13).

Models 11 and 12 in Table 8 present the estimated coefficients and standard errors for the full regression set with the investor-specific baseline that varies by institution and institutions' portfolio managers, respectively. After controlling for heterogeneity in investors' trading behaviors, institutional investors' reluctance to sell large losing positions is still prominent, and all exogenous factors pertinent to reference point adaptation still have a significant impact on the disposition effect. Model 13 presents the estimated coefficients and standard errors for full set regression with a stock-specific baseline. The magnitudes of all covariates of interests become even larger and remain statistically significant after including the stock-specific baseline. Taken together, the results confirm that our main findings are not simply an artifact of correlated cross-sectional differences in investor trading behavior or stock attributes.

[TABLE 8 ABOUT HERE]

4.2.2 Time-Specific Heterogeneity and Bubble Period

We also address concerns that our findings are driven by specific time period in the sample. For example, during the technology bubble in the late 1990s, mutual funds that actively invested in the technology sector may find it optimal to ride bubbles and engage in post-peak sell-offs (Brunnermeier and Nagel 2004; Griffin, Harris, Shu, and Topaloglu 2009). We address these concerns in three ways. First, we reestimate the regressions in Model 10 by replacing the homogeneous baseline $h_0(t)$ with a year-specific baseline, $h_{0,y}(t)$, to address the possibility of cross-section dependence produced by time-specific heterogeneity (Model 14). Second, we repeat our analysis including an investor–stock-year specific baseline (Model 15). Third, we address the possibility that our findings may be altered by different trading behaviors of institutional investors for tech stocks during the bubble period. To mitigate this concern, we repeat the analysis without technology firms (Model 16). We define technology firms as firms with the SIC codes 3570–3579, 3622, 3660–3692, 3694–3699, 3810–3839, 7370–7379, 7391, and 8730–8734.

The last three columns of Table 8 present the estimated coefficients and standard errors for Models 14–16. Our findings are robust to the inclusion of a year-specific baseline as well as an investor–stock-year specific baseline. The estimated coefficients of all covariates of large losing positions and all exogenous factors pertinent to reference point adaptation are qualitatively unchanged after excluding technology firms. In addition, we estimate the regressions separately for the pre-bubble and post-bubble period of tech bubble. Following Griffin, Harris, Shu, and Topaloglu (2009), we define the run-up as the period from the beginning of our data set to March 27, 2000. In untabulated results, we find that institutional investors tend to ride their losing investments longer than winning investments in both periods and that this tendency is attenuated by the exogenous factors due to reference point adaptation.

4. 3.Managerial Compensation Incentive

One potential criticism leveled at the results is a compensation incentive that may motivate fund managers to hold losing positions.[17] Brown et al. (1996), Chevalier and Ellison (1997), and

[17] Ippolito (1992) and Sirri and Tufano (1998) document that funds with the best recent performance attract higher inflows of new investment, while poorly performing funds are not penalized with significant outflows. Because the

Koski and Pontiff (1999) show that midyear underperforming fund managers have an incentive to gamble toward the end of the year in attempt to improve their performance while outperformers have an incentive to decrease the riskiness and lock in a winning year.

To determine the validity of this concern, we estimate the regressions separately for outperforming fund managers (midyear winners) and underperforming fund managers (midyear losers). Each year, we identify midyear winners and midyear losers based on their portfolio returns for the first half of the year (January to June). The difficulty with our data set to measure fund's portfolio return is that we lack information on share holdings. To construct share holdings, we follow Dvořák (2005) and cumulate trading flows of a given stock initiated by a given fund manager. In some cases, holdings may be established before the start of our data set and those shares are missed in the integration of trades up to holdings. To mitigate this problem, we keep the holdings series of a fund manager after the first year in which the first trade record of the manager appears in the data set. Following Barber and Odean (2000), we apply the CRSP monthly return to each stock in a fund's portfolio at the beginning of the month and then calculate the fund's monthly portfolio return as the beginning-of-the-month market value weighted average returns of all the stocks held in the portfolio. Finally, we derive the January–June performance as the cumulative portfolio returns during the first half of each year. We define funds whose performance is above median as midyear winners and funds whose performance is below median as midyear loser (Brown et al. 1996).

The analysis for the second half of the year is presented in Table 9. If midyear losers have stronger incentives to improve performance due to managerial compensation incentives, we expect them to increase the funds' riskiness in the second half of the year by holding onto losing

fund manager's compensation typically changes in proportion to the fund's inflows, the convex performance–flow relation produces a convex relationship between the fund's past performance and the compensation of the fund's manager.

investments. However, the negative sign on the *LARGELOSS* coefficient for both midyear winners and midyear losers suggests that both subgroups are reluctant to liquidate the losing positions relative to winning positions. Thus, the risk-taking behavior we report in our study does not depend on fund managers' interim performance and cannot be explained by managerial compensation concerns. In fact, midyear winners have a stronger tendency to hold onto losing investments. The coefficient on large loss indicator is –5.2322 for interim winners and –4.1311 for interim losers, suggesting that midyear winners are more likely to hold onto losing stocks than midyear losers. Our finding may reflect that the adjustment of risk taking by mutual fund managers in response to past performance due to managerial compensation incentives operates at the fund portfolio level, while the disposition effect operates at individual position level (O'Connell and Teo 2009).

Some key differences exist with respect to the extent of reference point adaptation for interim winners and losers. First, midyear losers are more sensitive to market conditions. Down market conditions makes midyear losers sell losing investments more aggressively than midyear winners. This result is in line with Kempf, Ruenzi, and Thiele (2009), who find that midyear losers tend to decrease risk to prevent job loss in bearish markets because employment risk is relatively high. Second, we find that although both midyear winners and losers are more willing to sell highly risky losing stocks, midyear losers sell less aggressively than midyear winners. The result agrees with conventional wisdom that midyear winners will not take risky positions to the same extent as do the losers for the second half of the year and suggests that interim good performance does not entice excess managerial overconfidence.

[TABLE 9 ABOUT HERE]

4.4 Tax-Motivated Selling

Previous literature documents evidence that the disposition effect is weakened in the month near the tax year-end as investors sell losing positions in order to reduce tax payment (Shefrin and Statman (1985) and Ivkovic et al. (2005)). Bhabra, Dhillon, and Ramirez (1999) show that mutual funds engage in tax-selling in October just before the end of tax year on October 31. Since tax-related sales typically occur just before funds' October 31 tax year-end and that a significant portion of sale trades likely take place shortly before funds' fiscal year end, portfolio managers may be more willing to sell losing positions in October. To explore the sensitivity of our main findings to tax related sales, we repeat the analysis without (a). Month of October and (b). One quarter prior to October 31. Consistent with prior research, the magnitude of disposition effect is larger for non-tax window than for tax window periods. Our finding of mitigated disposition effect by factors triggering reference point adaptation holds for both periods in and out of the tax window.

5. Conclusion

This study provides empirical examination of the potential role of reference point adaptation on the disposition effect. Our evidence indicates that both prior outcome and recent expectation about future outcome dramatically influence subsequent risk-taking decisions and the incidence of the disposition effect in systematic ways. First, the incidence of the disposition effect increases with the magnitude of prior losses, consistent with the notion that investors are less able to fully adapt to large capital losses. Second, institutional investors' propensity to sell losing position depends on their recent expectation of future outcome, which is largely determined by recent unfavorable information events and the speculative nature of the investments. Our findings indicate that both recent unfavorable information and the speculative nature of the investment accelerate investors' adaptation to price depreciation and significantly increase the propensity to sell a losing investment. These results provide direct empirical support for recent behavioral models of Köszegi and Rabin (2006, 2007). Our findings are robust to various changes in model specification, including full-set regression and regressions with investor-specific, stock-specific, and year-specific heterogeneity controls, and are not subjected to the alternative explanation such as mean-reversion beliefs, managerial compensation incentives and tax-motivated selling. Taken together, the empirical evidence indicates that both prior outcome and recent expectation about future outcome affect the location of a reference point and the incidence of disposition effect.

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Table 1. Summary Statistics

This table reports summary statistics of the data used in the analysis. The positions established are placed by 469 portfolio managers from 199 mutual funds during the sample period from January 1, 1999 to December 31, 2005. A position begins when a portfolio manager purchases a stock and ends when the stock is sold. A position-day refers to a day during the holding period. Following Ivkovic, Poterba and Weisbenner (2005), we restrict the sample to trades for which we can unambiguously match purchase and sale dates. We exclude sales that do not have a preceding purchase and sales that are preceded by multiple purchases. When a single purchase is followed by multiple sales, we choose the first sale as the end of that position.

	1999–2005
Number of institutions	199
Number of portfolio managers	469
Number of stocks	6,653
Number of positions (millions)	0.89
Number of position-days (millions)	23.90
Dollar volume purchased ($trillion)	1.08
Share volume purchased (billion)	41.79

Table 2. Disposition Effect on Average and Impact of Magnitude of Capital Losses

This table shows how holding-period capital loss affects the probability of an investor selling a position by fitting an extended Cox proportional hazard model. The Cox PH-model facilitates both time-invariant and time-varying covariates. A negative estimated coefficient suggests that the covariate decreases the probability of selling; a positive estimated coefficient suggests that the covariate increases the probability of selling. This table reports the estimated coefficients and standard errors for loss indicators and different magnitudes of capital losses. Model 1 reports the estimated coefficient and standard error for the capital loss indicator. *LOSS* is an indicator variable that equals 1 if there is a realized or paper loss for that position-day. Model 2a characterizes the Cox-PH model by six dummy variables corresponding to six capital loss intervals, each representing an interval that lies within a 10% return band from zero to 50% and above 50% loss. For example, the dummy *LOSS* [0, 10%] is equals 1 when capital loss is greater than zero but less than or equal to 10%. *LOSS* [50%, 100%] equals 1 when capital loss exceeds 50%. Model 2b reports estimated coefficients and standard errors for large and moderate losses. *LARGELOSS* is an indicator variable that equals 1 if the holding loss exceeds 20%, and zero otherwise. *MODERATELOSS* is an indicator variable that equals 1 if the loss is between zero and 20%. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. ** indicates significance at the 1% level.

	Model 1	
LOSS	-0.0334	**
	(0.0025)	
	Model 2a	
Panel A 10% Band Dummies		
LOSS [0,10%]	0.0408	**
	(0.0026)	
LOSS [10%,20%]	0.0505	**
	(0.0064)	
LOSS [20%,30%]	-0.0582	**
	(0.0112)	
LOSS [30%,40%]	-0.6617	**
	(0.0172)	
LOSS [40%,50%]	-1.6585	**
	(0.0235)	
LOSS [50%, 100%]	-1.5932	**
	(0.0226)	
	Model 2b	
Panel B LARGELOSS vs. MODERATELOSS		
LARGELOSS	-0.7980	**
	(0.0085)	
MODERATELOSS	0.0427	**
	(0.0025)	

Table 3. Stocks' Recent Performance, Earnings News, and Disposition Effect

This table reports Cox PH models including the interaction terms of large and moderate loss indicators with past return variables and earnings surprise dummies. *LARGELOSS* is the large loss indicator, and *MODERATELOSS* is the moderate loss indicator. Model 3 includes interaction terms of the loss indicators with a stock's percentage market-adjusted return variables over seven non-overlapping trading-day horizons for the prior one year: trading days –4 to zero (past one week), days –19 to –5 (prior one month to one week), days –39 to –20, days –59 to –40, days –119 to –60, days –179 to –120, and days –239 to –180. The regression also includes the seven past return variables as control variables. Model 4 includes interaction terms of the loss indicators with two news dummy variables. NegES is an indicator for stocks with extreme negative earnings news, and PosES is an indicator for stocks with extreme positive earnings news. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. * and ** indicate significance at the 5% and 1% levels, respectively.

	Model 3	Model 4
Loss Indicators		
LARGELOSS	–1.0713**	–0.8126**
	(0.0098)	(0.0087)
MODERATELOSS	0.0438**	0.0431**
	(0.0028)	(0.0026)
Interaction terms with large loss		
*LARGELOSS**Ret[day0,–4]	–3.2966**	
	(0.0674)	
*LARGELOSS**Ret[day–19,–5]	–1.5838**	
	(0.0575)	
*LARGELOSS**Ret[day–39,–20]	–0.7767**	
	(0.0583)	
*LARGELOSS**Ret[day–59,–40]	–0.3805**	
	(0.0605)	
*LARGELOSS**Ret[day–119,–60]	0.1220**	
	(0.0285)	
*LARGELOSS**Ret[day–179,–120]	0.1025**	
	(0.0242)	
*LARGELOSS**Ret[day–239,–180]	0.1082**	
	(0.0224)	
*LARGELOSS**NegES		0.7405**
		(0.0502)
*LARGELOSS**PosES		–0.0495
		(0.0638)

Table 3 continues

Table 3 (*continued*)

Interaction terms with moderate loss		
*MODERATELOSS**Ret[day0,–4]	–0.4379**	
	(0.0473)	
*MODERATELOSS**Ret[day–19,–5]	–0.0725**	
	(0.0238)	
*MODERATELOSS**Ret[day–39,–20]	0.0515**	
	(0.0210)	
*MODERATELOSS**Ret[day–59,–40]	0.0052	
	(0.0210)	
*MODERATELOSS**Ret[day–119,–60]	0.0228	
	(0.0115)	
*MODERATELOSS**Ret[day–179,–120]	–0.0135	
	(0.0106)	
*MODERATELOSS**Ret[day–239,–180]	0.0587	
	(0.0102)	
*MODERATELOSS**NegES		0.0124
		(0.0239)
*MODERATELOSS**PosES		–0.0302
		(0.0180)
Control variables		
Ret[day0,–4]	0.2147**	
	(0.0297)	
Ret[day–19,–5]	0.1819**	
	(0.0163)	
Ret[day–39,–20]	–0.0079	
	(0.0143)	
Ret[day–59,–40]	0.0261	
	(0.0146)	
Ret[day–119,–60]	–0.0660**	
	(0.0080)	
Ret[day–179,–120]	0.0846**	
	(0.0074)	
Ret[day–239,–180]	0.0661**	
	(0.0074)	
NegES		0.1493**
		(0.0124)
PosES		0.2991**
		(0.0172)

Table 4. Market Condition and Disposition Effect

This table reports estimated coefficients and standard errors for interaction terms of large and moderate loss indicators with a down-market indicator. *LARGELOSS* is the large loss indicator, and *MODERATELOSS* is the moderate loss indicator. The dummy variable MKTdown equals 1 if the monthly market excess return is negative, and zero otherwise. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. ** indicates significance at the 1% level.

	Model 5
LARGELOSS	-1.0422^{**}
	(0.0122)
MODERATELOSS	0.0299^{**}
	(0.0033)
*LARGELOSS**MKTdown	0.4933^{**}
	(0.0163)
*MODERATELOSS**MKTdown	0.0173^{**}
	(0.0051)
MKTdown	0.0478^{**}
	(0.0036)

Table 5. Stock-Level Information Uncertainty and Disposition Effect

The table reports the estimated coefficients and standard errors for interaction terms of large and moderate loss indicators with high stock-level information uncertainty indicators. Panel A, B, and C report the relation between disposition effect and information uncertainty, proxied by idiosyncratic risk (IDIO), market capitalization (SIZE), and return volatility (VOL), respectively. Stocks are sorted into tertiles based on each information uncertainty proxy. The regression includes interaction terms of the loss indicators with high information uncertainty dummy; we also include the level of information uncertainty as controls. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. ** indicates significance at the 1% level.

	Model 6
Panel A. Information uncertainty = IDIO	
LARGELOSS	–1.4590**
	(0.0136)
*LARGELOSS**IDIO_High	1.5129**
	(0.0176)
MODERATELOSS	0.0464**
	(0.0028)
*MODERATELOSS**IDIO_High	–0.0234**
	(0.0065)
IDIO_High	–0.2068**
	(0.0044)
Panel B. Information uncertainty = market capitalization (SIZE)	
LARGELOSS	–1.0676**
	(0.0107)
*LARGELOSS**SIZE_Small	1.1519**
	(0.0179)
MODERATELOSS	0.0445**
	(0.0027)
*MODERATELOSS**SIZE_Small	0.0134
	(0.0076)
SIZE_Small	–0.7976**
	(0.0052)
Panel C. Information uncertainty = return volatility (VOL)	
LARGELOSS	–1.3218**
	(0.013)
*LARGELOSS**VOL_High	1.2080**
	(0.0172)
MODERATELOSS	0.0463**
	(0.0028)
*MODERATELOSS**VOL_High	–0.0246**
	(0.0062)
VOL_High	–0.1645**
	(0.0042)

Table 6. Market-Level Investor Sentiment and Disposition Effect

This table reports the estimated coefficients and standard errors for the interaction terms of large and moderate loss indicators with the positive market sentiment indicator. We use the composite investor sentiment index for investor sentiment developed by Baker and Wurgler (2006). The index is calculated from six proxies based on their first principal component. These proxies include share turnover, IPO volume, IPO first-day returns, the equity share in new issues, the closed-end fund discount, and the dividend premium. The dummy variable PosSENT equals 1 if the composite index of sentiment is positive in the previous month, and zero otherwise. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. ** indicates significance at the 1% level.

	Model 7
LARGELOSS	–1.1215**
	(0.0118)
MODERATELOSS	0.0368**
	(0.0030)
*LARGELOSS**PosSENT	0.7073**
	(0.0171)
*MODERATELOSS**PosSENT	0.0093
	(0.0055)
PosSENT	0.3937**
	(0.0038)

Table 7. Full-Set Regressions

This table reports the estimated coefficients and standard errors for interaction terms of the large loss indicator with exogenous factors. Model 8 reports the estimated coefficients and standard errors for interaction terms of the large loss indicator with all covariates related to negative information. Model 9 reports the estimated coefficients and standard errors for interaction terms of the large loss indicator with all covariates related to speculative nature. Model 10 reports results for the full-set regressions. ** indicate significance at the 1% level.

	Model 8	Model 9	Model 10
Loss Indicators			
LARGELOSS	–2.0856**	–1.2682**	–2.2352**
	(0.0219)	(0.0129)	(0.0229)
MODERATELOSS	0.0441**	0.0309**	0.0345**
	(0.004)	(0.0035)	(0.0044)
Interaction terms with large loss			
*LARGELOSS**Ret[day0,-4]		–3.1193**	–2.2307**
		(0.0676)	(0.067)
*LARGELOSS**Ret[day-19,-5]		–1.5300**	–0.6525**
		(0.0572)	(0.0471)
*LARGELOSS**Ret[day-39,-20]		–0.7709**	–0.2529**
		(0.057)	(0.0411)
*LARGELOSS**Ret[day-59,-40]		–0.3921**	–0.2118**
		(0.0584)	(0.0439)
*LARGELOSS**Ret[day-119,-60]		0.1157**	0.1241**
		(0.0274)	(0.0209)
*LARGELOSS**Ret[day-179,-120]		0.1133**	–0.0001
		(0.0234)	(0.0207)
*LARGELOSS**Ret[day-239,-180]		0.0841**	–0.0236
		(0.0222)	(0.02)
*LARGELOSS**NegES		0.3494**	0.2245**
		(0.0542)	(0.0527)
*LARGELOSS**PosES		–0.0385	–0.1146
		(0.064)	(0.0641)
*LARGELOSS**MKTdown		0.3986**	0.2874**
		(0.0169)	(0.0171)
*LARGELOSS**IDIO_Mid	0.8673**		0.9188**
	(0.0275)		(0.0278)
*LARGELOSS**IDIO_High	1.8150**		1.6495**
	(0.0251)		(0.0266)
*LARGELOSS**PosSENT	0.5010**		0.3319**
	(0.0174)		(0.0184)
Interaction terms with moderate loss	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Table 8. Full-Set Regression and Heterogeneity Controls

This table reports results for the full-set regressions for robustness check. Model 11 allows for institution-specific baseline. Model 12 allows for institution-manager-specific baseline. Model 13 allows for stock-specific baseline. Model 14 allows for year-specific baseline. Model 15 allows for manager-stock-year-specific baseline. Model 16 estimates the sample without technology stocks and allows for manager-stock-year-specific baseline. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. * and ** indicate significance at the 5% and 1% levels, respectively.

	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
Loss indicators						
LARGELOSS	–2.2445**	–2.2465**	–5.0097**	–2.2173**	–4.6161**	–4.9304**
	(0.0229)	(0.0229)	(0.0302)	(0.0228)	(0.0503)	(0.0603)
MODERATELOSS	0.0302**	0.0365**	0.0116**	0.0691**	0.0386**	0.0419**
	(0.0043)	(0.0043)	(0.0043)	(0.0044)	(0.0045)	(0.005)
Interaction terms with large loss						
*LARGELOSS**Ret[day0,-4]	–2.3173**	–2.3019**	–5.1527**	–2.1398**	–5.6943 **	–6.3393**
	(0.0652)	(0.0646)	(0.1434)	(0.0619)	(0.1779)	(0.2401)
*LARGELOSS**Ret[day-19,-5]	–0.5901**	–0.5777**	–3.1413**	–0.4788**	–3.1721**	–4.0876**
	(0.0455)	(0.0449)	(0.0997)	(0.0421)	(0.1653)	(0.247)
*LARGELOSS**Ret[day-39,-20]	–0.1900**	–0.1824**	–1.8832**	–0.0356	–1.0402 **	–1.4025**
	(0.0396)	(0.0386)	(0.0966)	(0.0358)	(0.1222)	(0.1919)
*LARGELOSS**Ret[day-59,-40]	–0.1240**	–0.1162**	–1.3515**	0.0394	–0.6859	–0.4108
	(0.041)	(0.0398)	(0.0906)	(0.0371)	(0.1798)	(0.3165)
*LARGELOSS**Ret[day-119,-60]	0.1804	0.1621***	–0.1385***	0.2324***	0.0963	0.0649
	(0.0224)	(0.021)	(0.0465)	(0.0198)	(0.0637)	(0.1114)
*LARGELOSS**Ret[day-179,-120]	0.0624	0.0761**	–0.1970***	0.1076***	0.0031	0.3206**
	(0.0200)	(0.0193)	(0.0441)	(0.0189)	(0.0551)	(0.0977)
*LARGELOSS**Ret[day-239,-180]	0.0306**	0.0426*	0.0242	0.0602***	0.1927**	0.4191**
	(0.0195)	(0.019)	(0.0381)	(0.0187)	(0.0564)	(0.0948)

Table 8 continues

Table 8 (*continued*)

	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
*LARGELOSS**NegES	0.2221**	0.2220**	0.3404**	0.2843**	0.3152*	0.2026**
	(0.052)	(0.0515)	(0.0685)	(0.051)	(0.0206)	(0.0838)
*LARGELOSS**PosES	–0.0952 *	–0.0909	–0.2728 *	–0.0694	–0.2383 **	0.0011 **
	(0.0638)	(0.0637)	(0.0699)	(0.0631)	(0.1171)	(0.1526)
*LARGELOSS**MKTdown	0.2778**	0.2632**	0.4568 **	0.2444 **	0.5622 **	0.6510 **
	(0.017)	(0.017)	(0.0215)	(0.0169)	(0.0363)	(0.0483)
*LARGELOSS**IDIO_Mid	0.9034**	0.9016**	1.2543 **	0.8742 **	1.0931 **	0.9713 **
	(0.0278)	(0.0278)	(0.0309)	(0.0277)	(0.061)	(0.0759)
*LARGELOSS**IDIO_High	1.5957**	1.5768**	2.7390 **	1.5145**	2.3601**	2.3952 **
	(0.0263)	(0.0262)	(0.0355)	(0.0261)	(0.0626)	(0.0794)
*LARGELOSS**PosSENT	0.2899**	0.3220**	0.6556**	0.2780 **	0.6173 **	0.5336 **
	(0.0182)	(0.0179)	(0.023)	(0.018)	(0.0384)	(0.0514)
Interaction terms with moderate loss		Yes	Yes	Yes	Yes	Yes
Control variables		Yes	Yes	Yes	Yes	Yes
Heterogeneity control						
Institution-specific baselines	Yes					
Manager-specific baselines		Yes			Yes	Yes
Stock-specific baselines			Yes		Yes	Yes
Year-specific baselines				Yes	Yes	Yes

Table 9. Full-Set Regression Partitioned by Midyear Winners/Losers

The table reports estimated coefficient and standard error for the full-set regression for the second half of the year (July to December). We estimate the regressions separately for outperforming fund managers (midyear winners) and underperforming fund managers (midyear losers). We identify midyear winners and midyear losers on a yearly basis based on their cumulative portfolio returns for the first half of the year (January to June). We define funds whose performance is above median as midyear winners and funds whose performance is below median as midyear losers. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. * and ** indicate significance at the 5% and 1% levels, respectively.

Variable	Winner	Loser	Difference
Loss Indicators			
LARGELOSS	–5.2322**	–4.1311**	1.0995**
	(0.1875)	(0.0819)	(0.2046)
MODERATELOSS	0.0365**	0.0007	–0.0358**
	(0.0086)	(0.0092)	(0.0126)
Interaction Terms with Large Loss			
*LARGELOSS**Ret[day0,-4]	–6.6548**	–5.8742**	0.7797
	(0.6744)	(0.3465)	(0.7582)
*LARGELOSS**Ret[day-19,-5]	–3.8055**	–2.8321**	0.9729
	(0.5272)	(0.3393)	(0.627)
*LARGELOSS**Ret[day-39,-20]	–1.1227*	–0.6656**	0.4570
	(0.4793)	(0.2564)	(0.5436)
*LARGELOSS**Ret[day-59,-40]	–0.1638	–1.1140**	–0.9505
	(0.4092)	(0.2659)	(0.488)
*LARGELOSS**Ret[day-119,-60]	–0.4362	0.4219**	0.8583**
	(0.2333)	(0.1573)	(0.2814)
*LARGELOSS**Ret[day-179,-120]	0.0355	–0.0243	–0.0598
	(0.152)	(0.1706)	(0.2286)
*LARGELOSS**Ret[day-239,-180]	0.4258**	0.1816	–0.2442
	(0.1634)	(0.1163)	(0.2006)
*LARGELOSS**NegES	0.6897	–0.1285	–0.8183
	(0.6431)	(0.2757)	(0.6998)
*LARGELOSS**PosES	–0.1792	–0.6121	–0.4335
	(0.2786)	(0.3154)	(0.4209)
*LARGELOSS**MKTdown	0.1302	0.9167**	0.7871**
	(0.1409)	(0.0706)	(0.1576)
*LARGELOSS**IDIO_Mid	1.1996**	0.5979**	–0.6009*
	(0.2225)	(0.1022)	(0.2449)
*LARGELOSS**IDIO_High	2.7365**	1.8072**	–0.9283**
	(0.2217)	(0.1002)	(0.2433)

Table 9 continues

Table 9 (*continued*)

	Winner	Loser	Difference
*LARGELOSS**PosSENT	0.8761**	0.6224**	–0.2534
	(0.1555)	(0.077)	(0.1735)
Interaction terms with moderate loss	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Heterogeneity control			
Manager-specific baselines	Yes	Yes	Yes
Stock-specific baselines	Yes	Yes	Yes
Year-specific baselines	Yes	Yes	Yes

Figure 1 The relation between reference adaptation and the disposition effect

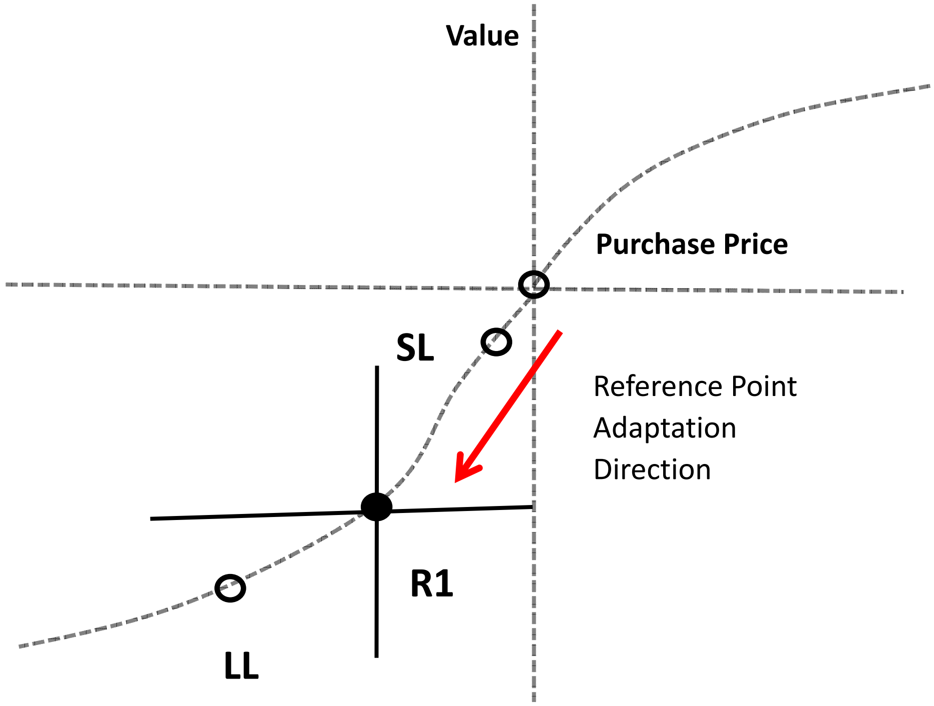

Figure 1a: The effect of prior capital losses on disposition effect

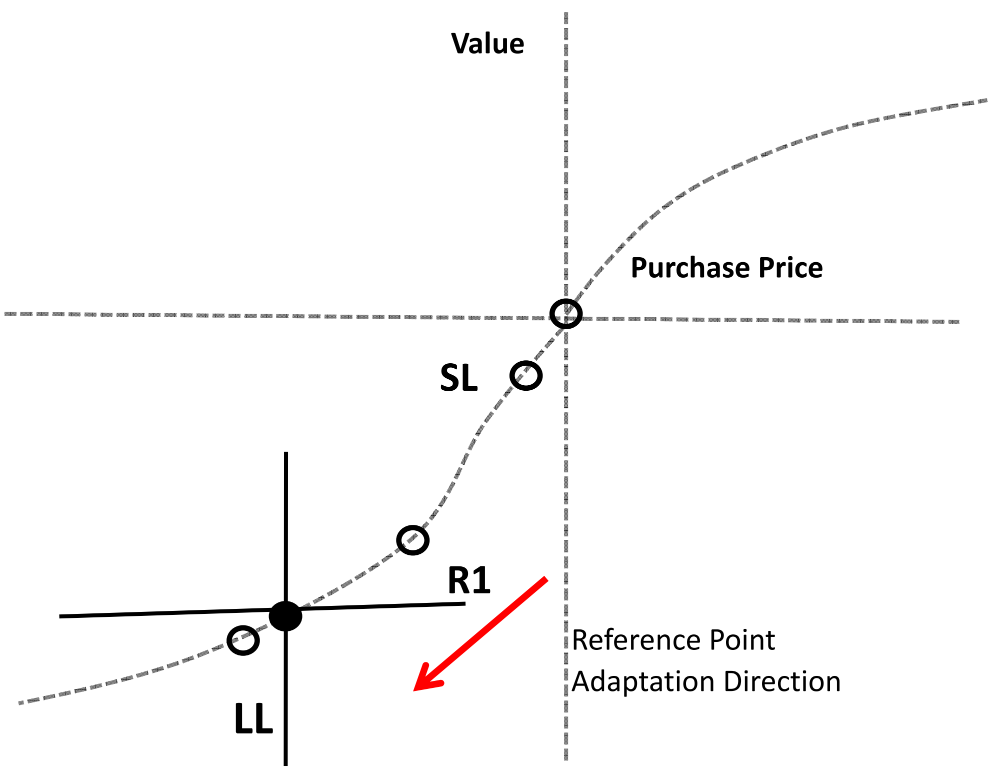

Figure 1b: The effect of recent unfavorable information and highly speculative investments on disposition effect