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Reference Point Adaptation and Disposition Effect: Evidence from Institutional Trading

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Reference Point Adaptation and Disposition Effect

Abstract

Using a large proprietary database of institutional trades, we investigate whether, and to what extent, the dynamic adaptation of reference point translates into variations in the disposition effect, and establish three key results. First, the propensity to realize losses declines sharply with the magnitude of prior losses due to insufficient adaptation of reference point. Second, recent adverse information accelerates investors' adaptation to price depreciation and increases investors' willingness to realize losses. Finally, a priori of losing money in highly speculative investments decreases investors' aversion to realize losses. Collectively, the findings suggest that both prior outcomes and recent expectations contribute to the reference point adaptation and the variations in disposition effect.

“Disposition effect” is labeled by Shefrin and Statman (1985) to describe the tendency of investors to hold losing investments too long and sell winning investments too soon. The prominent explanation for the disposition effect is based on Kahneman and Tversky’s (1979) prospect theory combined with Thaler’s (1985) mental accounting framework. According to prospect theory, decision makers evaluate outcomes in terms of gains and losses relative to a reference point using an S-shaped value function that is concave (risk averse) for gains and convex (risk loving) for losses. Reference-dependency is the essence of the prospect theory because the reference point determines whether an outcome is judged as a gain or loss, which significantly affects subsequent risk-taking decision. The disposition effect is an implication of the prospect theory under the critical assumption that investors fail to adapt to losses and anchor the reference point to a price level higher than the current price.

Existing empirical studies typically assume the initial purchase price as a fixed reference point and show that, when an investment is trading below the reference point, investors tend to be risk seeking and hold the losing investment by framing the sell decision as a sure loss and hold decision as a gamble that gives opportunity to break even. However, as Kahneman and Tversky (1979) and Thaler and Johnson (1990) point out, the reference point in a dynamic setting such as financial investment is *not* static and may shift away from the purchase price depending on how investors consider sequences of gains or losses. If an investor fully adapts to changes in security prices and segregates prior outcomes, she will adjust the reference point to the current price. In contrast, if an investor fails to fully adapt to prior outcomes, there will be a discrepancy between the current price and the reference point. Likewise, Odean (1998) argues that though evidence of investors’ reluctance to realize capital losses vindicates that purchase price plays an important role in determining the reference point, the purchase price may be only one determinant of the reference point and the price path may also affect the level of the reference point.

Motivating our empirical study is the fact that although the reference point plays a critical role in prospect theory, yet little is known about how the shift of reference point over time affects subsequent risk-seeking behavior and the disposition effect. Since investors exhibit distinct risk attitudes in the gain versus loss domain, a shift of reference point systematically alters the value of an outcome and subsequent risk-taking decision. In the presence of a prior loss, investors' hold versus sell decision 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 downwards to the current price, investor will less likely be risk seeking. On the other hand, if the adapted reference point remains at a higher level than the current price, the investor is likely to hold onto the losing investment and exhibits the disposition effect.[1]

Prior theoretical and experimental studies suggest that investors adjust the reference point from the initial purchase price towards current price in response to experienced changes in security value but the adjustment is usually incomplete. Tversky and Kahneman (1974) provide psychological basis that people adjust away from an initial value towards a final estimate based on information, but the adjustment is often insufficient. Barberis, Huang, and Santos' (2001) model assumes a benchmark which serves as a secondary reference point to respond *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 does not adjust downwards by as much. Chen and Rao (2002) suggest that people immediately but incompletely update their reference point after experiencing an event. In recent experimental

[1] See Weber and Camerer (1998) and Arkes, Hirshleifer, Jiang, and Lim (2008, 2009) for more 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.

studies, Arkes, Hirshleifer, Jiang, and Lim (2008, 2009) show that individuals tend to shift reference points upwards after prior gains and downwards after prior losses but the magnitude of reference point adaptation following a price change is not as large as the magnitude of price change itself.

Since investors' propensity to hold losing investments depends on the discrepancy between the adapted reference point and the lowered current price, this study aims to provide empirical evidence on how the dynamic adaptation of reference point affects investors' exhibition of the disposition effect by examining exogenous factors potentially relevant to reference point adaptation. We conjecture that the disposition effect depends on (1) the magnitude of prior losses and (2) the extent to which reference point shifts downwards to the current price.

First, the magnitude of prior losses affects investors' willingness to adjust the reference point downwards to the lowered current price. Thaler and Johnson (1990) show that individuals are more willing to adapt to a small to moderate loss than a large loss in that a small to moderate loss increases risk aversion for subsequent gambles whereas a large loss numbs the individual to additional losses.[2] Failure to fully adapt to a large loss creates a discrepancy between the adapted reference point and current price, leaving an investor in the loss domain, and induces risk-seeking behavior. Further, diminishing sensitivity reinforces the effect of large losses on risk seeking. Given that an investor has not completely adapted to large loss and is already in the loss domain, a further loss will cause only a small decrease in utility whereas a price recovery will result in a large increase in utility. To illustrate how disposition effect is affected by the magnitude of prior losses, imagine an investor who bought a stock at $45, and now the stock price goes down to $40. It requires the investor to adjust the reference point downwards by $5 to

[2] In their experimental study on how prior losses affect subsequent risk taking behavior, Thaler and Johnson (1990) document 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) (P.650).

the current price ($40) so that there will be no discrepancy between the reference point and the current price. The investor is more willing to adapt to this small loss and evaluates future prospects relative to current stock price. In doing so, she is less likely to exhibit the disposition effect. If however, the stock goes down sharply to $25, it requires the investor to adjust the reference point downwards by $20. The investor is less likely to fully adapt to this large loss and considers the subsequent decision as a choice between a sure loss of $20 and a gamble that gives opportunity to break even. Hence, she is likely to exhibit risk seeking behavior and assumes risks otherwise not justified by expected returns.

Second, the disposition effect depends on the extent to which the reference point shifts downwards to the current price. Though Kahneman and Tversky (1979) argue that reference point can be “an expectation or aspiration level that differs from status quo” and “a state to which one has adapted”, they do not specify how the reference point changes over time. In a recent reference-dependency model, Köszegi and Rabin (2006, 2007) posit that a person’s reference point is her *recent probabilistic beliefs* about outcomes. The model helps explain how the reference point changes over time and provides testable implications for the disposition effect. The first testable implication is that investors are less susceptible to disposition effect if they have recently received unfavorable information about stock prices. Since investors form expectations using information available to them, they tend to update expectations about stock value downwards upon receipt of unfavorable information. By equating the reference point with recent expectations, the downward expectation translates into a lower reference point, which in turn makes investors more willing to sell losing positions. The second testable implication is that investors are less prone to disposition effect when trading in highly speculative investments and during highly speculative market periods. Köszegi and Rabin argue that a *priori of losing money* decreases aversion to realize losses. Since investors base the reference point on probabilistic beliefs about outcomes, a high expected probability of losing money increases their willingness to realize losses. Specifically, since investors foresee a good chance of losing money when investing in a highly speculative investment, they will be more willing to adapt the reference point downwards after experiencing anticipated losses, and will be less willing to take chances to break even.

Building on the prior experimental studies and theoretical predictions, we empirically investigate whether, and to what extent, prior outcomes and recent expectations affect the reference point which, in turn, translates into variations in the disposition effect using a large proprietary dataset of institutional trading. We employ an extended Cox proportional hazard model to ascertain the degree of institutional investors' disposition effect. Primary findings presented in this article can be summarized as follows. First, the disposition effect increases with the magnitude of prior losses as a result of insufficient adjustment of reference point. We assess the extent to which disposition effect is sensitive to the magnitude of prior losses by separating the losing positions into 6 capital loss intervals, each representing an interval that lies within a 10% return band from 0 to 50% and above 50% loss. We find that the probability of selling a losing position declines as the magnitude of prior loss becomes larger. Consistent with our conjuncture that a large capital loss creates a discrepancy between the adapted reference point and current price, institutional investors' exhibition of disposition effect is driven by their reluctance to realize large losses (positions that have depreciated more than 20%). Furthermore, the tendency to hold onto losing positions significantly increases once the capital losses exceed 40%, with the probability of selling such a loss is 80% lower than a winning position.

Second, consistent with the theoretical predictions of Köszegi and Rabin (2006, 2007), we find that institutional investors' propensity to sell losing position depends crucially on both recent value-relevant information and speculative natures of investment. Our findings reveal that recent adverse information accelerates investors' adaptation to price depreciation and increases their willingness to realize large capital losses. Specifically, if institutional investors hold a losing position in a stock that a) has been underperforming recently, b) experiences negative earnings news, or c) is traded in down market condition, they are more likely to update the reference point to a lower level and liquidate the losing position. On the other hand, if investors observe recent favorable value-relevant information, they are more likely to hold onto the losing stock in waiting for price recovery as the favorable information raises their hope to break even.[3] Furthermore, institutional investors are more willing to adapt to large capital losses and liquidate losing investments when trading in highly speculative stocks (as proxied by stock-level information uncertainty) and during highly speculative market periods (as proxied by market-wide investor sentiment). In particular, our findings indicate that institutional investors are more willing to realize large capital losses in high idiosyncratic risk, small market capitalization, and high volatility stocks and during the periods of high market-wide investor sentiment.

Our key contributions to the literature are as follows. First, to the best of our knowledge, our study is the first to provide empirical evidence on the importance of reference point adaptation in explaining the disposition effect using the data from financial markets. Although both theoretical and experimental studies acknowledge that investors update the reference point overtime, there has been a lack of empirical evidence on whether, and to what extent, the shift of reference point affects subsequent risk-seeking decision. Second, we investigate a paramount theoretical model

[3] This finding also suggests that a misguided belief in mean-reversion cannot be a sufficient explanation for institutional investors' disposition effect. Mean-reversion beliefs will lead investors to hold underperforming stocks and sell overperforming stocks regardless whether the stocks are held as capital losses.

of Köszegi and Rabin (2006, 2007) which highlights the importance of recent stock-level and market-level value-relevant information and speculative natures in explaining when and how the disposition effect is likely to be observed. Our findings suggest that exogenous factors pertinent to investors' recent expectations affect the reference point and the disposition effect. Third, we offer the first-to-date empirical investigation of disposition effect in U.S. institutional equity trading using high frequency transaction data. Though disposition effect is well-documented among retail investors, little is known about the existence of such biases among institutional investors. Our results should be of interest to a wide audience, as institutions currently hold 74% of common stocks, compared to 8% about 50 years ago (Bogle (2008)). 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. In this respect, the closest work to our study is perhaps Frazzini (2006) which examines whether the presence of mutual funds who display the disposition effect can generate stock price underreaction to news, leading to return predictability and post-announcement price drift using quarterly mutual funds stock holdings data. While his study focuses on the relation of disposition effect and cross-sectional return predictability, our study is devoted to the examination of how prior outcomes as well as recent expectations affect the adaptation of reference point which, in turn, translate into variations in disposition effect. Fourth, our daily institutional trading data enables us to investigate how institutional investors exhibit the disposition effect in equity markets while overcomes the limitations of the quarterly holdings data. The quarterly holdings data cannot accurately identify the timing of trades and does not reflect intra-quarter round-trip trades which results in a significant number of missing trades.[4]

[4] Puckett and Yan (2008) and Elton, Gruber, Blake, Krasny, and Ozelge (2009) estimate that use of quarterly data fails to capture more than 20% of trades due to intra-quarter round-trip transactions.

Moreover, 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 since the actual transaction price is generally different from the quarter-end closing price. Lastly, we estimate the extent to which institutional investors are prone to disposition effect by employing an extended Cox proportional hazard model. The model offers advantages over the traditional approaches used to investigate the disposition effect. Our findings are robust to various changes in model specification (full-set regression and regressions with investor-specific and stock-specific, and year-specific heterogeneity controls) and are not driven by fund manager's managerial compensation incentive.

The balance of the paper is organized as follows. Section 1 reviews related literature and develops testable hypotheses. Section 2 introduces the data and methodology. Section 3 presents the empirical results. Section 4 reports robustness checks. Section 5 concludes.

1. Related Literature and Hypothesis Development

According to Kahneman and Tversky's (1979) prospect theory, decision makers evaluate outcomes in terms of gains and losses relative to a reference point using an S-shaped value function that is concave (risk averse) for gains and convex (risk loving) for losses. Critical to this value function is the reference point which determines whether an outcome is judged as a loss or gain. The original formation of this theory uses the status quo as the reference point for static context whereas Shefrin and Statman (1985) apply the prospect theory to a dynamic setting - security trading - and coin "disposition effect" to describe investors' tendency to hold losing investments too long and sell winning investments too soon.

Initiated by Shefrin and Statman (1985), existing empirical studies typically assume the initial purchase price as a fixed reference point and show that investors are reluctant to sell investments trading below the reference price.[5] Although both theoretical and empirical studies acknowledge that reference point is likely to migrate overtime (Kahneman and Tversky's (1979), Shefrin and Statman (1985), Thaler and Johnson (1990), Odean (1998), Weber and Camerer (1998), Heath, Hudddart, and Lang (1999), Barberis, Huang, and Santos (2001), Chen and Rao (2002), Garvey and Murphy (2004), Crane and Hartzell (2008), Arkes, Hirshleifer, Jiang, and Lim (2008, 2009)), little empirical analysis focuses on whether, and to what extent, the shift of reference point affects investors' exhibition of the disposition effect. Since investors exhibit distinct risk attitudes in the gain versus loss domain, a shift of reference point systematically alters the value of an outcome and subsequent risk-taking decision. Specifically, investors' hold versus sell decision following a loss depends on the discrepancy between the adapted reference point and the lowered current price.

In this paper, we conjecture that the discrepancy between the adapted reference point and the current price is largely determined by the magnitude of prior losses and recent expectations about outcomes. The magnitude of prior losses affects investors' willingness to adjust the reference point downwards to lowered current price. Failure to fully adapt to a large loss creates a discrepancy between the adapted reference point and current price, leaving investor in the loss domain, and induces risk-seeking behavior. Further, diminishing sensitivity reinforces the effect of large loss on risk seeking. Given that an investor has not completely adapted to 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.

Hypothesis 1: *Institutional investors' exhibition of disposition effect increases with the*

[5] See, for example, Odean (1998), Grinblatt and Keloharju (2001), Genesove and Mayer (2001), Garvey and Murphy (2004), Coval and Shumway (2005), Feng and Seasholes (2005), Shumway and Wu (2006), Ivkovic, Poterba, and Weisbenner (2005), Locke and Mann (2005), and Dhar and Zhu (2006).

magnitude of prior losses.

In a recent reference-dependency model, Köszegi and Rabin (2006, 2007, 2009) propose that a person's reference point is her recent probabilistic beliefs about outcomes. Building on the essential intuitions in Kahneman and Tversky's (1979) prospect theory, Köszegi and Rabin (2006, 2007) argue that, by equating the reference point with recent expectations rather than the status quo, their model helps explain how the reference point changes over time and hence provides testable implications for the disposition effect. The first testable implication is that investors are less susceptible to disposition effect if they have recently received unfavorable information about stock prices. Since public information flows interact with investors' belief formation (Harris and Raviv (1993), Wang (1994), and Kim and Verrecchia (1994), and Karlson, Leowenstein, and Seppi (2009)), investors update beliefs downwards (upwards) upon the receipt of recent unfavorable (favorable) value-relevant information. In particular, adverse information accelerates dynamic adaptation to price depreciation and increases their willingness to realize losses. In contrast, favorable information raises their hope to break even, and induces risk-seeking behavior.

We examine three kinds of stock-level and market-level information: 1) stock's recent performance, 2) firm's earnings news, and 3) aggregate market condition. A stock's recent performance is salient information for investors to form expectation about future performance (Chan, Jegadeesh, and Lakonishok (1996), Barberis and Thaler (2003), and Chae (2005)). When an investor observes the recent price path of a stock, she gradually incorporates the information into expectation and updates the reference point. If an investor is holding a losing position, and the underlying stock has been performing poorly recently, she tends to update beliefs about stock's price downwards. By adjusting the reference price to a lower level, closer to the current price, the investor will be more willing to sell the losing stock.

Hypothesis 2a: *Institutional investors' reluctance to realize losses is attenuated when the underlying stocks have been underperforming recently.*

Earnings news spurs investors' revision of expectations and affects their adaptation of the reference point. Bernard and Thomas (1989, 1990), Chan, Jegadeesh, and Lakonishok (1996), and Chae (2005) show that earnings news provides significant information about stock's value and that there is a positive correlation between earnings news and subsequent stock returns. When an investor observes negative earnings news, she updates the expectation about stock's price downwards. By lowering her reference point according to her recent expectation, she will be more willing to sell the losing stock.

Hypothesis 2b: *Institutional investors' reluctance to realize losses is attenuated when the underlying stocks experience negative earnings news.*

Down (up) market condition lowers (raises) investors' expectation for individual stock's performance (Daniel, Hirshleifer, and Subrahmanyam (1998), and Cooper, Gutierrez, and Hameed (2004)). When the overall market goes down, investors are more likely to update the expectations and reference points downwards, closer to current price, and will be more willing to sell losing stocks.

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

The second testable implication is that investors are less prone to disposition effect when trading highly speculative investments or during highly speculative market periods. Köszegi and Rabin (2006, 2007) argue that a *priori of losing money* decreases aversion to realize losses. Since an investor foresees a good chance of losing money, when investing in a highly speculative investment, she is more willing to adapt the reference point downwards after experiencing anticipated losses, and will be 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 (2005, 2006), and Kumar (2009)). These stocks are characterized with high idiosyncratic risks, small market capitalization, and high volatility. We conjuncture that institutional investors have a priori of losing money in high information uncertainty stock and will be more willing to liquidate the losing position.

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

Lastly, we examine market-level speculative nature using market-wide investor sentiment which represents 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 investor sentiment is a risk faced by rational investors 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) and Lemmon and Ni (2009)). To the extent that institutional investors are sophisticated, we conjecture that institutions are aware of high risk associated with trading against noise traders during high sentiment periods and will be more willing to liquidate the losing position.

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

2. Data and Methodology

2.1 Data, Sample and Summary Statistics

We obtain proprietary institutional trading data from the Abel Noser Corporation (thereafter, Abel Noser) for the period of 1999-2005. Abel Noser is a widely recognized firm that provides consulting and advisory services to institutional investors in monitoring their equity trading cost. The Abel Noser dataset identifies institutional investor's decisions to establish or liquidate positions as well as the order execution. The Abel Noser dataset provides information about stock traded, number of shares ordered and executed, execution price, order direction (buy or sell), and the time 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 distinguish trades from different types of institutions and portfolio managers. Our analysis focuses primarily on mutual funds since most pension funds and index funds in our dataset follow an inactive trading strategy.

We obtain stock return, share price, stock turnover from CRSP daily tape, and include only common stocks (share code equals 10 or 11) traded on NYSE/AMEX/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 price less than $1. We obtain analysts' consensus quarterly earnings forecast and actual earnings per share from I/B/E/S.

Positions. A position begins when an investor purchases a stock and ends when the stock is sold. To maintain the integrity of the data and filter out possible errors in identifying prior capital gains or losses, we follow the approach of 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.[6] When a single purchase is followed by multiple sales, we choose the first sale as the end of that position.[7] **Gains and losses.** On each position-day, we identify holding period capital loss/gain against purchase price. 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.[8] All prices are adjusted for stock splits and dividend distributions.

Table I provides the descriptive statistics of our sample. The final sample consists of 199 institutions and 469 portfolio managers who place orders in a total number of 6,653 common stocks. We identify 0.89 million initiations of positions which results in 23.90 million position-days. The average holing 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.

2.2 The Cox Proportional Hazard Model

We estimate the extent to which institutional investors are prone to disposition effect by employing an extended Cox proportional hazard model (thereafter, the Cox-PH model). Recent studies on disposition effect such as Genesove and Mayer (2001), Feng and Seasholes (2005), Ivkovic et al (2005), Shumway and Wu (2006) and Seru, Shumway, and Stoffman (2008)

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[6] 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.

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

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

advocate the advantages of hazard model over several traditional approaches to investigate 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 reluctant to realize losses than gains.[9] However, it is difficult to control for other factors that could be correlated to investors' trading decision, such as stock past returns and stock volatility. 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 most relevant variables to our study are indicators of capital losses. 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 they may give incorrect inferences in cases where capital gains or losses vary over time, i.e. the model ignores the price path during the holding period of a position (Seru et al. (2008)). 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 proper in 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 still time t-1.

For each day t after a position j is established (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 holding the position until time t. We specify the hazard rate as:

$$h_j(t|\mathbf{X}) = h_0(t)\exp(\boldsymbol{\beta}^*\mathbf{X}) \quad \text{(A)}$$

[9] We also repeat our main analysis using Odean's (1998) proportional method. We provide a brief discussion of the findings in robustness check section.

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

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

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 non-parametric baseline $h_0(t)$, which automatically captures fluctuations in hazard rate caused by differing holding time.

X is the matrix of explanatory variables --- 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 hazard rate during the holding period of a position. The economic meaning is easy to interpret. 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 *one unit increase* in X_1 lead to *the absolute value of [EXP(β_1) -1] decrease* in the conditional probability of selling. Since 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

In this section, we present our empirical findings on how the reference point adaptation affects subsequent risk-seeking behavior and the disposition effect. We begin by assessing the general evidence of institutional investors' disposition effect in Section 3.1. We investigate how the magnitude of prior capital losses affects the disposition effect in Section 3.2. We evaluate the impact of recent stock-level and market-level information on disposition effect in Section 3.3. We examine the impact of stock-level and market-level speculative natures on the disposition effect in Section 3.4.

3.1 General Disposition Effect

To examine the general disposition effect, we begin with 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 is equal to one if the position has depreciated in value from the time of purchase until time t.[10] If institutional investors exhibit disposition effect, the coefficient for the capital loss indicator will be negative (capital loss decreases the hazard rate). This implies that investors with a losing position will hold the position longer than a winning position.

Table II Model (1) 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 a weak evidence of disposition effect among institutional investors. The coefficient of -0.0333 on *LOSS* suggests that an investor facing a prior loss will have a 3.28% reduction in the daily hazard (exp (-0.03) -1= -0.0328= -3.28%), or an equivalent increase in the expected holding time to liquidation. Compared to previous findings on retail investors' disposition effect, our result presents a much weaker disposition effect for institutional investors. For instance, Feng and Seasholes (2005) show that Chinese individual investors decrease the hazard rate by 36% if a stock is trading at a capital loss relative to a capital gain. The comparatively weaker disposition effect is not surprising, considering that institutional investors possess a higher level of sophistication than retail investors. Our findings are consistent with a growing body of literature which examines the

[10] We use the indicator variable of capital loss, with the omitted category being capital gain or no price change (in rare instances). By this setup, the baseline hazard rate $h_0(t)$ is the hazard rate corresponding to a capital gain.

relationship between investor characteristics and disposition effect (Locke and Mann (2004), Shapira and Venezia (2001), Feng and Seasholes (2005), Dhar and Zhu (2006), and Seru, Shumway, and Stoffman (2009)) and documents evidence that investors with higher level of sophistication, literacy, investment knowledge, professional occupations, and more trading experience are able to adapt better to prior losses and exhibit weaker disposition effect.

3.2 Magnitude of Prior Losses and Disposition Effect

In this section, we investigate whether, and to what extent, the magnitude of prior losses contributes to variations in disposition effect. We characterize the Cox-PH model by including 6 dummy variables corresponding to 6 capital loss intervals, each representing an interval that lies within a 10% return band from 0 to 50% and above 50% loss. For example, the dummy *LOSS* [0, 10%] is equal to one when capital loss is greater than zero but less than or equal to 10%. *LOSS* [50%, 100%] is equal to one when capital loss is greater than 50%.

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

Table II Panel A Model (2) presents the estimated coefficients and standard errors for six capital loss indicators. Our finding suggests that institutional investors fail to adapt to large losses while they are able to adapt to small to moderate losses. 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 losing position once the loss exceeds 20%. The coefficient of -0.0582 and -0.6617 for *LOSS* [20%, 30%] and *LOSS* [30%, 40%] suggests that an investor facing a prior capital loss between 20% and 30% (and 30% to 40%) will have a 5.66% (and 48.40%) reduction in the probability of selling relative to an investor otherwise facing a gain or no price change. The probability of selling a losing position significantly declines as the magnitude of the prior losses increases beyond 40%. The estimated coefficients for *LOSS* [40, 50%], and *LOSS* [50, 100%] are -1.6585, and -1.5032, respectively, which are associated with an 80.96%, and 79.67% decrease in the probability of selling relative to a stock with capital gain or no price change. In sum, our finding supports *Hypothesis 1* and is consistent with the notion that a large prior loss creates a discrepancy between the adapted reference point and lowered current price which induces risk-seeking behavior.

Since 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, instead of 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, with the baseline being associated with either a capital gain or no price change.

$$h_j(t) = h_0(t)\exp(\beta_1 * \mathit{LARGELOSS} + \beta_2 * \mathit{MODERATELOSS}) \qquad (2')$$

Table II Panel B Model (2') presents the estimated coefficients and standard errors for moderate and large loss indicators. We find opposite signs of the coefficients on the large loss versus moderate loss indicators. The coefficient of -0.7980 on *LARGELOSS* suggests that an investor facing a large capital loss will have a 54.98% reduction in the daily hazard (exp (-0.7980) -1 = -0.5498 = -54.98%) relative to an investor otherwise facing a gain or no price change. In contrast, investors are not reluctant to realize a small to moderate loss. The coefficient on moderate loss of 0.0427 is positive but economically insignificant. Investors facing a moderate loss will increase the hazard rate by 4.36% (exp (0.0427) -1 = 0.0436 = 4.36%). 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 loss, the negative relation between magnitude of prior losses and the propensity to sell losing position can be explained by dynamic adaptation of reference point within the framework of 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) and Barberis and Xiong (2009)). Our findings suggest that institutional investors are able to adapt to small to moderate losses and adjust the reference point downwards closer to current price, resulting in only a small discrepancy between the two prices. In contrast, institutions' inability to fully adapt to large loss creates a large negative deviation between adapted reference point and current price which results in a lower propensity to sell losing position.[11]

In the subsequent empirical analyses, we focus our discussion on the impact of large capital loss rather than moderate loss given that institutional investors are able to adapt to small to moderate losses and have the greater propensity to hold onto losing investments with large capital losses.

3.3 Recent Value-Relevant Information and Disposition Effect

In this section, we investigate the extent to which recent value-relevant information affects the

[11] Skill signaling may also help explain why institutional investors are unable to adapt to large losses. Harbaugh (2009) argues that decision makers take risky chances to win back large losses to avoid unfavorable signaling on their skills.

reference point which, in turn, translates into variations in the disposition effect. We examine three kinds of stock-level and market-level value-relevant information: a) stock's recent performance, b) firm's earnings news, and c) aggregate market condition.

3.3.1 Stock's Recent Performance and Disposition Effect

We expand the model to include interaction terms of large and moderate loss indicators with past return variables. The interaction terms enable us to assess how 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:

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

We use the market-adjusted returns, calculated as the difference between the buy-and-hold returns of sample stocks and the CRSP value-weighted portfolio. We include market-adjusted return variables over 7 non-overlapping trading-day intervals in the past one year: trading days -4 to 0 (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.

Table III Model (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 0 till days -59 to -40 (prior 3 months) are negative and statistically significant which implies that, conditional on a prior loss, negative past return accelerates the speed of investors' liquidation of the losing position. To elaborate on this point, consider the situation of stock X and Y, both of which are held as a large loss. Suppose stock X had a -10% market-adjusted return during the prior week while stock Y had zero market-adjusted return. The coefficient of -3.2965 on the interaction term of large loss indicator with past returns of days -4 to 0 (*LARGELOSS* *Ret[day0,-4]) implies that the hazard rate of stock X is 28.08% higher than that of stock Y (exp(-3.29657 * -10% *1)-1) = 0.2808 = 28.08%). In contrast, the marginal effect of negative return on the propensity to sell moderate losses is economically insignificant. Under the same circumstance, when both stock X and Y are held as moderate loss, the coefficient of -0.4379 on the interaction term of moderate loss indicator and stocks' return of days -4 to 0 (*MODERATELOSS* *Ret[day0,-4]) suggests that the hazard rate of stock X is only 4.47% higher than that of stock Y (exp(-0.4379 * -10% *1)-1) = 0.0447 = 4.47%). Moreover, the coefficients on interaction terms of large loss indicator with most recent past return (*LARGELOSS* *Ret [day0,-4]) is the largest among all the interaction terms, suggesting that investors pay more attention to the most recent past return, consistent with Köszegi and Rabin's (2006, 2007) conjuncture that reference point is based on investors' *recent* expectations about the asset value.

Our results also reveal that the disposition effect cannot be explained by contrarian trading. The coefficient on *LARGELOSS* remains statistically and economically significant after controlling for past return variables. The *LARGELOSS* coefficient of -1.0713 implies that the hazard rate for a position with large loss is 65.74% lower than that for a position with capital gain or no price change (exp (-1.0713) -1 = -0.6574 = 65.74%), ceteris paribas. Moreover, the positive coefficients on past return control variables implies that investors are more likely to sell a stock with good recent performance, 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 could not be a sufficient explanation for the disposition effect. A mean-reversion investor would tend to hold the stocks having been underperforming and sell outperforming stocks, regardless of whether she experiences paper losses or gains.

Overall, our finding is consistent with *Hypothesis 2a* that stock's recent underperformance accelerates adaptation of reference point to a lower level so that institutional investors are more willing to realize losses and exhibit weaker disposition effect following a recent price decline.[12]

3.3.2 Earnings News and Disposition Effect

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.

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

We define quarterly earnings surprise (SUE) as:

$$(X_{jt}-X_{jt-4})/S_{jt}, \tag{C}$$

where X_{jt} is actual earnings per share for quarter t; X_{jt-4} is actual earnings per share for quarter t-4. S_{jt} is the standard deviation of $(X_{jt}-X_{jt-4})$ in the previous eight quarters (Chordia and Shivakumar (2006)).

Following Foster, Olsen, and Shevlin (1984), each calendar quarter, we rank stocks based on the SUE for that quarter to determine the deciles of the distribution. We use these deciles as

[12] To capture potential non-linear relation between past performance and disposition effect, we implement two additional tests: (1). we include dummy variables indicating whether stocks hit recent historical highs/lows over 3 intervals (overlapped): past 1-month, 3-month, and 6-month. (2). we include dummy variables representing top/bottom momentum quintiles formed based on returns over 3 intervals (overlapped): past 1-month, 3-month, 6-month. Our results indicate that (1). Investors are more likely to sell (hold) a losing position if the underlying stock hits the historical low (high). (2). Investors are more likely to sell (hold) a losing position if the underlying stock is in the bottom (top) momentum quintile. Overall, the additional tests confirm our main findings and results are not reported here for brevity.

the cut-offs to assign firms into one of ten earnings surprise portfolios in the quarter subsequent to that quarter in which the cut-off point were determined. We define NegES as a dummy variable if the stock is in the bottom decile of the earnings surprise ranking, and PosES as a dummy variable if the stock is in the top decile of the earnings surprise ranking. We also assess the robustness of our findings using dummy variables representing negative or positive earnings surprise, our conclusion remains qualitatively unchanged.

Table III, Model (4) presents the estimated coefficients and standard errors for interaction term of large loss indicator with negative earnings surprise (*LARGELOSS**NegES) along with other covariates. The positive sign of the coefficient on the interaction term suggests that negative earnings news increases the probability of selling a large losing position. Specifically, the positive coefficient of 0.7405 implies that a negative earnings surprise increases the probability of selling by 109.69% (exp(0.7405* 1*1)-1) = 1.0969) relative to a losing position that is not subject to extreme negative earnings news. This finding is consistent with *Hypothesis 2b* in that recent negative earnings news helps accelerate investors' reference point downwards and attenuates the disposition effect.

In addition, we address the possibility of the correlation between the stock's past performance and firm's earnings news. Prior researches suggest that information in stock price is correlated with information in earnings news to some extent (Chan, Jegadeesh, and Lakonishok (1996) and Chordia and Shivakumar (2006)). As a result, we specify the regression including both past return variables and earnings news variables:

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

$$+ \beta_7 * MODERATELOSS * \text{NegES} + \beta_8 * MODERATELOSS * \text{PosES}$$

$$+ \beta_9 * \text{PastRet} + \beta_{10} * \text{NegES} + \beta_{11} * \text{PosES}) \quad (5)$$

Results from Model (5) confirm our earlier findings and provide support to *Hypothesis 2a* and *Hypothesis 2b*. Stock's recent performance and firm's earnings news both have strong impact on the disposition effect and are not subsumed by each other. Specifically, when both past return and earnings news variables are included in the model, coefficients on the interaction terms of large loss indicator with the seven past return variables change only slightly from Model (3), and remain economically and statistically significant. The coefficient on interaction term of large loss with negative earnings news reduces from 0.7405 in Model (4) to 0.3497 in Model (5), but is still economically and statistically significant, suggesting that the economic effect of negative earnings news on disposition effect is reduced but not subsumed by past return variables.

3.3.3 Aggregate Market Condition and Disposition Effect

We characterize the Cox-PH model to include the interaction terms of large and moderate loss with market condition indicator.

$$h_j(t) = h_0(t)\exp(\beta_1 * LARGELOSS + \beta_2 * MODERATELOSS$$

$$+ \beta_3 * LARGELOSS * \text{MKTdown}$$

$$+ \beta_4 * MODERATELOSS * \text{MKTdown}$$

$$+ \beta_5 * \text{MKTdown}) \quad (6)$$

where the indicator variable "MKTdown" is equal to one for down market condition, and takes the value of 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 risk-free rate. We also repeat our analysis using equal-weighted CRSP portfolio as well as Standard & Poor 500 index as proxy for market portfolio. The findings are qualitatively unchanged and not reported here for brevity.

Table IV reports the estimated coefficient and standard error for interaction term of large loss indicator with down-market indicator (*LARGELOSS* * MKTdown). The positive coefficient on the interaction term of 0.4933 suggests that institutional investors are 63.77% (exp(0.4933 * 1*1)-1) = 0.6377) more likely to realize large loss in down-market than in up-market condition. The finding provides support to *Hypothesis 2c* in that institutional investors are more likely to update the expectations and reference points downwards and will be more willing to sell losing positions in down-market condition.

3.4 Stock-Level and Market-Level Speculative Natures and Disposition Effect

In this section, 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 examine stock-level speculative nature using information uncertainty proxies and market-level speculative nature using composite index of investor sentiment.

3.4.1 Stock-Level Speculative Nature and Disposition Effect

We adopt three commonly used proxies for stock level information uncertainty.

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 (FF3), 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. It seems plausible that small firms are less diversified and have less information available for the market than large firms (Zhang (2006)).

Return Volatility --- return volatility is 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 bid-ask bounce effects in daily price.

For each proxy of information uncertainty, we sort stocks into three groups (High, Mid, Low). We define three dummy variables representing information uncertainty group a stock belongs to. We characterize the Cox-PH model to include the interaction terms of large and moderate loss indicators with three information uncertainty indicators.

$$
\begin{aligned}
h_j(t) = h_0(t)\exp (\ & \beta_1 * \mathit{LARGELOSS} * \text{IU\_High} \\
& + \beta_2 * \mathit{LARGELOSS} * \text{IU\_Mid} \\
& + \beta_3 * \mathit{LARGELOSS} * \text{IU\_Low} \\
& + \beta_4 * \mathit{MODERATELOSS} * \text{IU\_High} \\
& + \beta_5 * \mathit{MODERATELOSS} * \text{IU\_Mid} \\
& + \beta_6 * \mathit{MODERATELOSS} * \text{IU\_Low} \\
& + \beta_7 * \text{IU\_Mid} + \beta_8 * \text{IU\_Low} \qquad (7)
\end{aligned}
$$

Table V Model (7) presents the estimated coefficients and standard errors for interaction terms of large loss indicator with stock-level information uncertainty indicators. For all three information uncertainty proxies, the results are consistent with *Hypothesis 3a* in that institutional investors exhibit weaker disposition effect when trading in highly speculative stocks. For example, when using size as the proxy for information uncertainty, the positive coefficient of the interaction term of small size with large loss indictor (*LARGELOSS* *SIZE_Small) of 0.0778, with small increase in probability of selling a losing position of 8.09%, implies that institutional investors exhibit no disposition effect when trading in small stocks. As firm size becomes larger, institutional investors exhibit stronger disposition effect. The negative coefficient of the interaction term of middle size with large loss indicator (*LARGELOSS* *SIZE_Mid) of -0.6462 suggests that institutional investors are 47.59% (exp(-0.6462 * 1*1)-1) = -0.4759) less likely to realize large losses in middle size stocks. The negative coefficient of the interaction term of the large size with large loss indicator (*LARGELOSS* *SIZE_Large) of -1.4165 indicates that institutional investors are 75.74% (exp(-1.4165 * 1*1)-1) = -0.7574) less likely to realize large loss in large stocks. Our results are consistent with the notion that institutions anticipate a high probability of losing money when trading a highly speculative stock and are more willing to adapt to large losses. In contrast, institutions are more willing to assume risk and hold onto losing positions in the relatively “safe” stocks, i.e., low information uncertainty stocks.

3.4.2 Market-Level Investor Sentiment and Disposition Effect

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

$$
\begin{aligned}
h_j(t) = h_0(t)\exp\,(\; & \beta_1 * \mathit{LARGELOSS} \\
& + \beta_2 * \mathit{MODERATELOSS} \\
& + \beta_3 * \mathit{LARGELOSS} * \mathrm{PosSENT} \\
& + \beta_4 * \mathit{MODERATELOSS} * \mathrm{PosSENT} \\
& + \beta 5 * \mathrm{PosSENT}) \qquad (8)
\end{aligned}
$$

The dummy variable “PosSENT” is equal to one if the composite index of investor sentiment is positive in the previous month. Positive (Negative) sentiment index implies high (low) market-wide investor sentiment. We use a composite index of sentiment developed by Baker and Wurgler (2006). The sentiment index is created from 6 proxies of investor sentiment based on their first principal component. These proxies include such variables positively associated with sentiment levels as share turnover, IPO volume and first-day returns, and the equity share in new issues, and those negatively associated as the closed-end fund discount and the dividend premium. We obtain monthly sentiment index from Jeffrey Wurgler's website.[13]

Table VI reports the estimated coefficient and standard error for interaction terms of large loss indicator with positive market sentiment indicator (*LARGELOSS* * PosSENT). Consistent with *Hypothesis 3b*, the positive coefficient on the interaction term suggests that high investor sentiment attenuates institutional investors' disposition effect. The coefficient on *LARGELOSS**PosSENT of 0.7073 suggests that positive investor sentiment increases the probability of selling a large losing position by 102.84% (exp(0.7073 * 1*1)-1) = 1.0284).

In addition to monthly sentiment index, we repeat our analysis using yearly sentiment index as well as 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 alternative proxy such as Market Volatility Index (VIX) 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 disposition effect, consistent with our main findings.

4. Robustness Checks

4.1 Full-Set Regression

The findings so far indicate that the disposition effect is affected by each of the three aspects pertinent to reference point adaptation: the magnitude of prior losses, recent stock-level and market-level value-relevant information and speculative natures. In this section, we examine all

[13] http://pages.stern.nyu.edu/~jwurgler/

factors together 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.

$$
\begin{aligned}
h_j(t) = h_0(t)\exp(&\beta_1 * \mathit{LARGELOSS} + \beta_2\, \mathit{MODERATELOSS} \\
&+ \beta_3 * \mathit{LARGELOSS} * \text{PastRet} \\
&+ \beta_4 * \mathit{LARGELOSS} * \text{NegES} + \beta_5 * \mathit{LARGELOSS} * \text{PosES} \\
&+ \beta_6 * \mathit{LARGELOSS} * \text{MKTdown} \\
&+ \beta_7 * \mathit{LARGELOSS} * \text{IU\_Mid} + \beta_8 * \mathit{LARGELOSS} * \text{IU\_High} \\
&+ \beta_9 * \mathit{LARGELOSS} * \text{PosSENT} \\
&+ \beta_{10} * \mathit{MODERATELOSS} * \text{PastRet} \\
&+ \beta_{11} * \mathit{MODERATELOSS} * \text{NegES} + \beta_{12} * \mathit{MODERATELOSS} * \text{PosES} \\
&+ \beta_{13} * \mathit{MODERATELOSS} * \text{MKTdown} \\
&+ \beta_{14} * \mathit{MODERATELOSS} * \text{IU\_Mid} + \beta_{15} * \mathit{MODERATELOSS} * \text{IU\_High} \\
&+ \beta_{16} * \mathit{MODERATELOSS} * \text{PosSENT} \\
&+ \beta_{17} * \text{PastRet} + \beta_{18} * \text{NegES} + \beta_{19} * \text{PosES} \\
&+ \beta_{20} * \text{MKTdown} + \beta_{21} * \text{IU\_Mid} + \beta_{22} * \text{IU\_High} \\
&+ \beta_{23} * \text{PosSENT}) \qquad (9)
\end{aligned}
$$

Table VII Model (9) reports the estimated coefficients and standard errors for all covariates. Result from Model (9) shows that each exogenous factor pertinent to reference point adaptation has impact on the disposition effect and that one factor’s impact is not subsumed by another. For brevity, 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.

First, the coefficient on *LARGELOSS* is -2.2352 while 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 disposition effect in moderate losses. Second, the coefficients on the interaction terms of large loss indicator with each of the factors representing recent stock-level and market-level value-relevant information remain qualitatively unchanged, suggesting that institutional investors' exhibition of disposition effect in large losses is weakened by recent adverse information about the stock's value. Third, the coefficients on the interaction terms of large loss indicator with stock-level information uncertainty proxy and investor sentiment remain qualitatively the same as in our main analysis. This suggests that institutional investors exhibit 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 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 (9) with investor-specific baseline $h_{0,i}(t)$, which allows the baseline to vary across portfolio managers (Model 10). We replace $h_0(t)$ with stock-specific $h_{0,s}(t)$, which allows the baseline to vary across stocks (Model 11).

Table VII Model (10) presents the estimated coefficients and standard errors for full set regression with investor-specific baseline. After controlling for heterogeneity in investors' trading behaviors, institutional investors' reluctance to sell large losing positions is still prominent with all the exogenous factors pertinent to reference point adaptation still have significant impact on the disposition effect. Model (11) presents the estimated coefficients and standard errors for full set regression with stock-specific baseline. The magnitudes of all the covariates of interests become even larger and statistically significant after including stock-specific baselines. 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 attribute.

4.2.2 Time-Specific Heterogeneity and Bubble Period

There may be 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 actively invest 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 the concerns in three ways. First, we reestimate the regressions in Model (9) by replacing the homogeneous baseline $h_0(t)$ with year-specific baseline $h_{0,y}(t)$, to address the possibility of cross-section dependence produced by time-specific heterogeneity (Model (12)). Second we repeat our analysis including investor-stock-year specific baseline (Model (13)). 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 redo the analysis without technology firms (Model (14)). We define technology firms as firms with the following SIC codes: 3570-3579, 3622, 3660-3692, 3694-3699, 3810-3839, 7370-7379, 7391, and 8730-8734. The last three columns of Table VIII present the estimated coefficients and standard errors for all three models. Our findings are robust to inclusion of year-specific baseline as well as investor-stock-year specific baseline. Moreover, the estimated coefficients of all the covariates of large losing positions and all the exogenous factors pertinent to reference point adaptation are qualitatively unchanged after excluding technology firms.

4.3 Managerial Compensation Incentive

One criticism leveled at the results is that they may be driven by the possibility that fund managers choose to hold the large losing positions because of their compensation incentive.[14] Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), and Koski and Pontiff (1999) show that midyear underperforming fund managers have an incentive to gamble towards 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 array such a concern, we estimate the regression separately for outperforming fund managers (midyear winners) and underperforming fund managers (midyear losers).[15] 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 dataset 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. There may be cases where some holdings are established before the start of our dataset and those shares will be missed in the integration of trades up to holdings. To mitigate this problem, we keep holdings series of a fund manager after the first year in which the first trade record of the manager appears in the dataset. Following

[14] 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 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.

[15] The empirical evidence of the relation between interim performance and subsequent risk taking due to managerial incentive is inconclusive. For example, Chevalier and Ellison (1997) find that the worst performing funds have the lowest risk-taking incentives due to job losing concerns. Busse (2001) finds that the evidence in favor of the tournament hypothesis based on monthly data is weaken using daily data.

Barber and Odean (2000), we apply 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 beginning-of-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. Following Brown, Harlow, and Starks (1996), we define funds whose performance is above median as midyear winners while funds whose performance is below median as midyear loser.

The analysis for the second half of the year is presented in Table VIII. If midyear losers have stronger incentives to improve performance due to managerial compensation, we expect them to increase the funds' riskiness in the second half of the year by holding onto large losing investments. However, the negative sign on *LARGELOSS* coefficient for both midyear winners and midyear losers suggests that both are reluctant to realize large losing positions relative to winning positions. Our finding implies that the risk taking behavior does not depend on fund manager's midyear performance and cannot be explained by managerial compensation concerns. Moreover, midyear winners have a stronger tendency to hold onto large losing investments. Midyear winners are 92.50% less likely to sell a losing stock than to sell a winning stock compare to only 77.16% for midyear losers. Our finding may reflect the fact 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)).

It's interesting to note that there are some key differences with respect to the extent of reference point adaptation to the exogenous factors. First, midyear losers are more sensitive to stock's recent performance and market conditions. Specifically, the negative market-adjusted return during the prior week has stronger influence for midyear losers in selling a losing position than for midyear winners. Similarly, down market condition makes midyear losers sell losing investments more aggressively than midyear winners. Our finding 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 though 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.

4.3 Odean's (1998) Proportional Method

We assess the robustness of our main findings using Odean's (1998) proportional method. This also facilitates a comparison of our findings to previous studies. 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 reluctant to realize losses. The results using proportional method is consistent with our findings from Cox-PH model. In untabulated result, we find that 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 very strong disposition effect in *large* losses. In contrast, the ratio of the proportion of gains realized (PGR) to the proportion of losses realized

(PLR) of *general* losses is 0.963, suggesting that institutional investors do not exhibit disposition effect. 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.

4.4 Evidence on Tax-Selling/Window-Dressing Motivations

We assess the extent to which institutional investors' exhibition of the disposition effect is affected by tax-motivation or window dressing. Previous literature documents evidence that the disposition effect is weakened in month near the deadline for realizing capital losses in order to reduce tax payment (Shefrin and Statman (1985), Odean (1998), and Ivkovic et al. (2005)). Bhabra, Dhillon, and Ramirez (1999) document evidence that mutual funds engage in window dressing or 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 window-dressing trades likely take place shortly before funds' fiscal year end, portfolio managers may be more willing to sell losing positions in October. We use an October dummy to investigate whether there is tax motivated selling or window dressing for institutional investors. We find that institutional investors are more readily to sell large losing positions in October than during the rest of the year, which is consistent with tax motivated selling or window dressing.

5 Conclusion

We provide empirical evidence on whether, and to what the extent, the dynamic adaptation of reference point affects investors' exhibition of the disposition effect by examining exogenous factors potentially relevant to reference point adaptation. Our findings indicate that the probability of selling a losing position declines as the magnitude of prior capital losses increases due to insufficient adaptation of reference point to large capital losses. Furthermore, institutional investors' willingness to realize large losses is accelerated by recent adverse value-relevant information as well as speculative natures, consistent with the theoretical predictions of Köszegi and Rabin (2006, 2007). Collectively, our findings highlight that both prior outcomes and recent expectations contribute to the reference point adaptation and the disposition effect.

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Table I Summary Statistics

Table I reports summary statistics of the data in our sample. 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. We follow the approach of 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. 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 II General Disposition Effect Magnitude of Capital Loss and Disposition Effect

We analyze 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 which takes the value of one if there is a realized or paper loss for that position-day. Model (2) characterizes the Cox-PH model by 6 dummy variables corresponding to 6 capital loss intervals, each representing an interval that lies within a 10% return band from 0 to 50% and above 50% loss. For example, the dummy *LOSS* [0, 10%] is equal to one when capital loss is greater than zero but less than or equal to 10%. *LOSS* [50%, 100%] is equal to one when capital loss exceeds 50%. Model (2') reports estimated coefficient and standard error for large and moderate losses. *LARGELOSS* is an indicator variable that takes the value of one if the holding loss exceeds 20%, and takes the value of zero otherwise. *MODERATELOSS* is an indicator variable that takes the value of one if the loss is between 0% and 20%. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. *, ** indicate significance at the 5% and 1% levels, respectively.

	Model (1)	
LOSS	-0.0334	**
	(0.0025)	
	Model (2)	
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 (2')	
Panel B *LARGE* versus *MODERATE* LOSSES		
LARGELOSS	-0.7980	**
	(0.0085)	
MODERATELOSS	0.0427	**
	(0.0025)	

Table III Stocks' Recent Performance, Earnings News, and Disposition Effect

The table reports the estimated coefficients and standard errors for interaction terms of large and moderate loss indicators with past return variables and earnings surprise dummies. *LARGELOSS* is the large loss indicator; *MODERATELOSS* is the moderate loss indicator. Model (3) includes interaction terms of the loss indicators with stock's percentage market-adjusted return variables over 7 non-overlapping trading-day horizons for prior one year: trading days -4 to 0 (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 7 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 while PosES is an indicator for stocks with extreme positive earnings news. Model (5) includes both past return variables and earnings surprise dummies in one regression. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. *, ** indicate significance at the 5% and 1% levels, respectively.

	Model (3)		Model (4)		Model (5)	
Loss Indicators						
LARGELOSS	-1.0713	**	-0.8126	**	-1.0769	**
	(0.0098)		(0.0087)		(0.0098)	
MODERATELOSS	0.0438	**	0.0431	**	0.0438	**
	(0.0028)		(0.0026)		(0.0028)	
Interaction Terms with Large Loss						
*LARGELOSS**Ret[day0,-4]	-3.2966	**			-3.2193	**
	(0.0674)				(0.0675)	
*LARGELOSS**Ret[day-19,-5]	-1.5838	**			-1.584	**
	(0.0575)				(0.0573)	
*LARGELOSS**Ret[day-39,-20]	-0.7767	**			-0.7714	**
	(0.0583)				(0.0582)	
*LARGELOSS**Ret[day-59,-40]	-0.3805	**			-0.385	**
	(0.0605)				(0.0604)	
*LARGELOSS**Ret[day-119,-60]	0.1220	**			0.1248	**
	(0.0285)				(0.0283)	
*LARGELOSS**Ret[day-179,-120]	0.1025	**			0.1071	**
	(0.0242)				(0.0242)	
*LARGELOSS**Ret[day-239,-180]	0.1082	**			0.1137	**
	(0.0224)				(0.0224)	
*LARGELOSS**NegES			0.7405	**	0.3497	**
			(0.0502)		(0.0548)	
*LARGELOSS**PosES			-0.0495		-0.0042	
			(0.0638)		(0.0641)	
Interaction Terms with Moderate Loss						
*MODERATELOSS**Ret[day0,-4]	-0.4379	**			-0.404	**
	(0.0473)				(0.0472)	

	Model (3)	Model (4)	Model (5)
*MODERATELOSS**Ret[day-19,-5]	-0.0725 **		-0.0709 **
	(0.0238)		(0.0238)
*MODERATELOSS**Ret[day-39,-20]	0.0515 **		0.0515 *
	(0.0210)		(0.0210)
*MODERATELOSS**Ret[day-59,-40]	0.0052		0.0056
	(0.0210)		(0.0210)
*MODERATELOSS**Ret[day-119,-60]	0.0228		0.023
	(0.0115)		(0.0116)
*MODERATELOSS**Ret[day-179,-120]	-0.0135		-0.0129
	(0.0106)		(0.0106)
*MODERATELOSS**Ret[day-239,-180]	0.0587		0.0589 **
	(0.0102)		(0.0102)
*MODERATELOSS**NegES		0.0124	0.0235
		(0.0239)	(0.0247)
*MODERATELOSS**PosES		-0.0302	-0.0304
		(0.0180)	(0.0180)
Control Variables			
Ret[day0,-4]	0.2147 **		0.1954 **
	(0.0297)		(0.0297)
Ret[day-19,-5]	0.1819 **		0.1814 **
	(0.0163)		(0.0163)
Ret[day-39,-20]	-0.0079		-0.0066
	(0.0143)		(0.0143)
Ret[day-59,-40]	0.0261		0.0262
	(0.0146)		(0.0146)
Ret[day-119,-60]	-0.0660 **		-0.0668 **
	(0.0080)		(0.0080)
Ret[day-179,-120]	0.0846 **		0.0826 **
	(0.0074)		(0.0074)
Ret[day-239,-180]	0.0661 **		0.0639 **
	(0.0074)		(0.0074)
NegES		0.1493 **	0.1563 **
		(0.0124)	(0.0179)
PosES		0.2991 **	0.2886 **
		(0.0172)	(0.0124)

Table IV Market Condition and Disposition Effect

The table reports estimated coefficient and standard error for interaction term of large and moderate loss indicators with down-market indicator. *LARGELOSS* is the large loss indicator; *MODERATELOSS* is the moderate loss indicator. The dummy variable "MKTdown" takes on the value of one if the monthly market excess return is negative, and takes the value of zero otherwise. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. *, ** indicate significance at the 5% and 1% levels, respectively.

	Model (6)	
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 V Stock-Level Information Uncertainty and Disposition Effect

The table reports the estimated coefficients and standard errors for interaction terms of large and moderate loss indicator with stock-level information uncertainty indicators. Panel A to Panel C report the relationship 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 rank dummies based on information uncertainty (High, Medium, Low); we also control the level of information uncertainty. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. *, ** indicate significance at the 5% and 1% levels, respectively.

Model (7)

Panel A **IU Proxy= Idiosyncratic Risk (IDIO)**			***Panel B*** **IU Proxy=Market Capitalization (SIZE)**			***Panel C*** **IU Proxy=Return Volatility (VOL)**		
*LARGELOSS**IDIO_High	0.0532	**	*LARGELOSS**SIZE_Small	0.0778	**	*LARGELOSS**VOL_High	-0.0796	**
	(0.0109)			(0.0142)			(0.0113)	
*LARGELOSS**IDIO_Mid	-1.0483	**	*LARGELOSS**SIZE_Mid	-0.6462	**	*LARGELOSS**VOL_Mid	-0.7158	**
	(0.0171)			(0.0145)			(0.0155)	
*LARGELOSS**IDIO_Low	-2.3646	**	*LARGELOSS**SIZE_Large	-1.4165	**	*LARGELOSS**VOL_Low	-2.2176	**
	(0.0275)			(0.0162)			(0.0255)	
*MODERATELOSS**IDIO_High	0.0195	**	*MODERATELOSS**SIZE_Small	0.0594	**	*MODERATELOSS**VOL_High	0.0534	**
	(0.0058)			(0.0072)			(0.0055)	
*MODERATELOSS**IDIO_Mid	0.0422	**	*MODERATELOSS**SIZE_Mid	0.0223	**	*MODERATELOSS**VOL_Mid	0.0482	**
	(0.0044)			(0.0047)			(0.0044)	
*MODERATELOSS**IDIO_Low	0.0356	**	*MODERATELOSS**SIZE_Large	0.0458	**	*MODERATELOSS**VOL_Low	0.0365	**
	(0.0036)			(0.0033)			(0.0037)	
IDIO_Mid	0.1499	**	SIZE_Mid	0.5256	**	VOL_Mid	0.1317	**
	(0.0049)			(0.0058)			(0.0047)	
IDIO_Low	0.2542	**	SIZE_Large	0.9738	**	VOL_Low	0.2585	**
	(0.0045)			(0.0054)			(0.0045)	

Table VI Market-Level Investor Sentiment and Disposition Effect

This table reports the estimated coefficient and standard error for interaction terms of large and moderate loss indicator with 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 6 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" is equal to one if the composite index of sentiment is positive in the previous month, and equal to zero otherwise. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. *, ** indicate significance at the 5% and 1% levels, respectively.

	Model (8)	
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 VII Full-Set Regression and Heterogeneity Controls

This table reports results for the full set regressions. Model (9) reports the homogeneous baseline model as in the main analysis. Model (10) allows for investor-specific baseline. Model (11) allows for stock-specific baseline. Model (12) allows for year-specific baseline. Model (13) allows for manager-stock-year-specific baseline. Model (14) 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. *, ** indicate significance at the 5% and 1% levels, respectively.

	Model (9)	Model (10)	Model (11)	Model (12)	Model (13)	Model (14)
Loss Indicators						
LARGELOSS	-2.2352 **	-2.2465 **	-5.0097 **	-2.2173 **	-4.6161 **	-4.9304 **
	(0.0229)	(0.0229)	(0.0302)	(0.0228)	(0.0503)	(0.0603)
MODERATELOSS	0.0345 **	0.0365 **	0.0116 **	0.0691 **	0.0386 **	0.0419 **
	(0.0044)	(0.0043)	(0.0043)	(0.0044)	(0.0045)	(0.005)
Interaction Terms with Large Loss						
*LARGELOSS**Ret[day0,-4]	-2.2307 **	-2.3019 **	-5.1527 **	-2.1398 **	-5.6943 **	-6.3393 **
	(0.067)	(0.0646)	(0.1434)	(0.0619)	(0.1779)	(0.2401)
*LARGELOSS**Ret[day-19,-5]	-0.6525 **	-0.5777 **	-3.1413 **	-0.4788 **	-3.1721 **	-4.0876 **
	(0.0471)	(0.0449)	(0.0997)	(0.0421)	(0.1653)	(0.247)
*LARGELOSS**Ret[day-39,-20]	-0.2529 **	-0.1824 **	-1.8832 **	-0.0356	-1.0402 **	-1.4025 **
	(0.0411)	(0.0386)	(0.0966)	(0.0358)	(0.1222)	(0.1919)
*LARGELOSS**Ret[day-59,-40]	-0.2118 **	-0.1162 **	-1.3515 **	0.0394	-0.6859	-0.4108
	(0.0439)	(0.0398)	(0.0906)	(0.0371)	(0.1798)	(0.3165)
*LARGELOSS**Ret[day-119,-60]	0.1241 **	0.1621 **	-0.1385 **	0.2324 **	0.0963	0.0649
	(0.0209)	(0.021)	(0.0465)	(0.0198)	(0.0637)	(0.1114)
*LARGELOSS**Ret[day-179,-120]	-0.0001	0.0761 **	-0.1970 **	0.1076 **	0.0031	0.3206 **
	(0.0207)	(0.0193)	(0.0441)	(0.0189)	(0.0551)	(0.0977)
*LARGELOSS**Ret[day-239,-180]	-0.0236	0.0426 *	0.0242	0.0602 **	0.1927 **	0.4191 **
	(0.02)	(0.019)	(0.0381)	(0.0187)	(0.0564)	(0.0948)
*LARGELOSS**NegES	0.2245 **	0.2220 **	0.3404 **	0.2843 **	0.3152 *	0.2026
	(0.0527)	(0.0515)	(0.0685)	(0.051)	(0.0206)	(0.1838)
*LARGELOSS**PosES	-0.1146 *	-0.0909	-0.2728 **	-0.0694	-0.2383 **	0.0011
	(0.0641)	(0.0637)	(0.0699)	(0.0631)	(0.1171)	(0.1526)
*LARGELOSS**MKTdown	0.2874 **	0.2632 **	0.4568 **	0.2444 **	0.5622 **	0.6510 **
	(0.0171)	(0.017)	(0.0215)	(0.0169)	(0.0363)	(0.0483)
*LARGELOSS**IDIO_Mid	0.9188 **	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	1.6495 **	1.5768 **	2.7390 **	1.5145 **	2.3601 **	2.3952 **
	(0.0266)	(0.0262)	(0.0355)	(0.0261)	(0.0626)	(0.0794)
*LARGELOSS**PosSENT	0.3319 **	0.3220 **	0.6556 **	0.2780 **	0.6173 **	0.5336 **
	(0.0184)	(0.0179)	(0.023)	(0.018)	(0.0384)	(0.0514)
Interaction Terms with Moderate Loss	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES
Heterogeneity Control						
Manager-specific baselines		YES			YES	YES
Stock-specific baselines			YES		YES	YES
Year-specific baselines				YES	YES	YES

Table VIII Full-Set Regression Partitioned by Midyear Winners/Losers

The table reports estimated coefficient and standard error for full-set regression in 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 while funds whose performance is below median as midyear loser. Robust standard error (in parentheses) is calculated using the robust covariance matrix clustered by each position to derive the statistic inference. *, ** indicate significance at the 5% and 1% levels, respectively.

	Midyear Winners		Midyear Losers		Difference	
Loss Indicators						
LARGELOSS	-2.5908	**	-1.4767	**	1.1140	**
	(0.0496)		(0.0328)		(0.0595)	
MODERATELOSS	-0.0002		0.0842	**	0.0844	**
	(0.008)		(0.0085)		(0.0117)	
Interaction Terms with Large Loss						
*LARGELOSS**Ret[day0,-4]	-1.8287	**	-2.5956	**	-0.7669	**
	(0.1666)		(0.109)		(0.199)	
*LARGELOSS**Ret[day-19,-5]	-0.5537	**	-0.7465	**	-0.1928	
	(0.118)		(0.0856)		(0.1457)	
*LARGELOSS**Ret[day-39,-20]	-0.3402	**	-0.1701	**	0.1701	
	(0.1063)		(0.0787)		(0.1322)	
*LARGELOSS**Ret[day-59,-40]	-0.0620		-0.2688	**	-0.2068	
	(0.114)		(0.0844)		(0.1418)	
*LARGELOSS**Ret[day-119,-60]	0.1447	*	0.2345	**	0.0898	
	(0.0662)		(0.0443)		(0.0796)	
*LARGELOSS**Ret[day-179,-120]	0.0474		0.0396		-0.0078	
	(0.0475)		(0.034)		(0.0584)	
*LARGELOSS**Ret[day-239,-180]	0.0694		-0.2044	**	-0.2738	**
	(0.0439)		(0.0358)		(0.0567)	
*LARGELOSS**NegES	0.2778	*	0.1187		-0.1591	
	(0.1407)		(0.0942)		(0.1693)	
*LARGELOSS**PosES	-0.3813	**	-0.0430		0.3382	*
	(0.1411)		(0.1219)		(0.1865)	
*LARGELOSS**MKTdown	0.1840	**	0.4025	**	0.2185	**
	(0.0423)		(0.0289)		(0.0512)	
*LARGELOSS**IDIO_Mid	0.7986	**	0.6075	**	-0.1912	*
	(0.0641)		(0.0415)		(0.0764)	
*LARGELOSS**IDIO_High	1.6546	**	1.2032	**	-0.4515	**
	(0.0611)		(0.0393)		(0.0727)	
*LARGELOSS**PosSENT	0.8144	**	0.0119		-0.8026	**
	(0.0486)		(0.0312)		(0.0578)	
Interaction Terms with Moderate Loss	YES		YES		YES	
Control Variables	YES		YES		YES	