V-Shaped Disposition:

Mutual Fund Trading Behavior and Price Effects

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Abstract

This study investigates the trading behavior and price effects of mutual fund managers by examining their selling schedules in response to unrealized profits. We present two main findings: first, mutual fund managers tend to sell relatively big winners and big losers – a 1% increase in the magnitude of unrealized gains (losses) is associated with a 2.7% (1.1%) higher probability of selling. Second, we link this selling behavior to equilibrium prices by aggregating unrealized profits across funds for each security. Consistent with the relative magnitude of the selling behavior results, we find that a 1% increase in the magnitude of the security-level unrealized gains (losses) predicts a 1.4 (.9) bp increase in future monthly returns. We further explore the link between trading behavior and price effects by examining the cross-sectional heterogeneity of fund characteristics - funds with higher turnover, shorter holding period, and higher expense ratios are significantly more likely to manifest such a trading pattern, and securities held by such funds have stronger return predictability.

Keywords: mutual funds, trading behavior, price pressure, cross-sectional return predictability

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In the field of asset pricing, researchers have documented many return anomalies, each with various potential explanations; however, pinning down the specific source of a return pattern is difficult. As John Cochrane put it in his 2010 AFA presidential address, "A crucial question is, as always, what data will this class of theories use to measure discount rates? ... Ideally, one should tie price or discount-rate variation to central items in the models, such as the balance sheets of leveraged intermediaries, data on who is actually active in segmented markets, and so forth." Behavioral theories, in particular, have applied findings from the field of psychology to suggest that behavioral biases can cause market prices to systematically deviate from their "rational" benchmark, and yet it has remained a challenging task in the literature to empirically link investors' behaviors to equilibrium price dynamics.

In this paper, we speak directly to this challenge by studying how mutual fund managers' trading behavior affects stock prices. We present two main findings: first, we document a behavioral pattern that mutual fund managers are more likely to sell holdings with relatively large unrealized gains and losses (rather than those with small unrealized gains and losses); second, we explicitly link this behavior to stock price deviations, by constructing stock-level variables to capture the pressure from such selling behavior and showing that these variables strongly predict stock returns in the cross section.

This research bears on the most recent studies of the disposition effect. First introduced to the finance literature by Shefrin and Statman (1985), the disposition effect refers to investors' tendency to sell their winning securities more readily than their losers. Since then, this trading behavior has been documented using evidence from both individual and institutional investors[1], across different asset markets[2], and around the world[3]; however, previous research mostly focuses on the difference in selling propensity when investors experience a gain versus a loss, rather than the full functional form of how investors trade in response to past profits. In a recent study, Ben-David and Hirshleifer (2012) take a closer look at individual trading account data (as in Barber and Odean (2000)) and document a refinement of the disposition effect: individual investors do not increase their selling

[1]See Odean (1998) and Grinblatt and Keloharju (2001) as examples for individual investors. See Locke and Mann(2000), Shapira and Venezia (2001), and Coval and Shumway (2001) for institutional investors.

[2]See, for example, Genesove and Mayor (2001) in housing markets, Heath, Huddart, and Lang (1999) for stock options, and Camerer and Weber (1998) in experimental markets.

[3]See Grinblatt and Keloharju (2001), Shapira and Venezia (2001), Feng and Seasholes (2005), among others. For a thorough survey of the disposition effect, please see the review article by Barber and Odean (2013).

probability monotonically from the extreme losers to the extreme winners. Instead, they have a V-shaped selling schedule in response to past profit - selling their biggest winners *and* their biggest losers. Moreover, the gain side of the V is steeper than the loss side of the V - the average propensity to sell following a gain is higher than the average propensity to sell following a loss.

We examine the selling schedule of mutual fund managers in response to unrealized profits. While studying the trading behavior of retail investors is interesting and significant, mutual fund managers represent more capital, resemble more of a representative investor, and play a larger role in deciding equilibrium prices. We find that mutual fund managers, like individual traders, exhibit a V-shaped selling schedule. Pushing beyond previous research, we argue that such trading behavior can generate price pressure and subsequent return predictability in the cross section. As mutual fund managers are more likely to sell securities with large gains and losses (relative to securities with smaller gains and losses), it increases the supply of such stocks and in turn presses the equilibrium price down from its fundamental value. As future prices revert to fundamental values in subsequent periods, stocks with large gains and losses will outperform.

To test this hypothesis, we construct price pressure variables directly from mutual fund holdings data. We follow the methodology developed by Frazzini (2006) to measure the aggregate cost base for a particular stock using the time series of net purchases across the mutual fund universe. Taking into account investors' V-shaped selling schedule, we separate unrealized gains from unrealized losses. Empirical results confirm our hypothesis: stocks with large gain overhang and large loss overhang indeed outperform in the next month, and the price effect is both economically and statistically significant: a 1 percentage point increase in the aggregate unrealized gains (losses) for a stock predicts a 1.4 (0.9) basis point increase in the next month return. A trading strategy based on this effect can generate a Sharpe ratio of 1.4. These result are consistent with price effects documented by An (2014), where investors' aggregate cost base is approximated based on trading volume.

To further explore the link between investors' trading behavior and the associated price effect, we conduct a series of tests examining the cross-sectional variation of the V-shaped disposition effect across various mutual fund characteristics. We find that more "speculative" mutual fund managers (characterized by shorter average holding periods, higher expense ratios, and higher turnover ratios) tend to have a significantly steeper V-shaped selling schedule. Decomposing our security-level overhang variables into unrealized gains and losses from “speculative” and “nonspeculative” funds, we show that the former overhang variables are stronger in predicting future returns. Our dataset and our measurement of selling pressure allow us to offer unique insight into the source of return predictability by connecting manager characteristics to disposition effect-related price movements.

We contribute to the literature on the disposition effect in two ways. First, in addition to the empirical observation that investors sell more winners than losers, we document a functional form of how investors trade in response to past profit. The evidence of a V-shaped selling schedule among mutual fund managers corroborates the findings by Ben-David and Hirshleifer (2012) for individual traders. This contribution is important because it refutes the common presumption that investors' selling propensity is monotonically increasing in past profits, upon which much empirical work has been based. Also, it calls into question commonly offered explanations for the disposition effect. Prevalent theories, either prospect theory (Kahneman and Tversky (1979)) which posits loss-averse investors or the realization utility developed by Barberis and Xiong (2009, 2012), all rely on investors' utility being concave over gains and convex over losses. While these preference-based interpretations can generate a monotonic selling schedule, they are difficult to reconcile with the V-shaped selling schedule that we document.

Second, this paper expands our understanding of the pricing implications of behavioral biases. Particularly, for selling behaviors, the early literature on pricing impact is exclusively based on the premise that investors have a monotonic selling schedule. For instance, Grinblatt and Han (2005) develop an equilibrium model where the disposition effect influences investors' demand for a stock and in turn causes the equilibrium price to deviate from the fundamental value in a predictable way. They show that capital gains overhang, an empirical measure that linearly aggregates all investors' unrealized gains and losses, predicts future returns. Frazzini (2006) constructs a linear capital gains overhang measure using mutual fund holdings data and shows that the disposition effect can cause price underreaction to news. Pricing implications of the V-shaped selling schedule have only been taken into account very recently - motivated by Ben-David and Hirshleifer (2012), An (2014) separates the capital gains overhang of Grinblatt and Han (2005) into gain overhang and loss overhang and finds that stocks with both large unrealized gains and losses outperform in the next month. Her measures for unrealized gains and losses, as in Grinblatt and Han (2005), are aggregate approximations based on trading volume. Our measure employs the mutual fund holdings data and is thus able to accurately track unrealized profits instead of a proxy based on trading volume. Our methodology eliminates the ambiguity in using aggregate approximate measures; moreover, it allows us to further explore the link between mutual fund managers' selling schedules and price impact by exploiting the cross-sectional variation in the characteristics of fund managers.

Our paper also extends the literature on the price impact of mutual fund managers' uninformed trades. Among others, Coval and Stafford (2007) show that mutual funds who experience large outflows are forced to decrease existing positions, and this creates price pressure on stocks that are commonly held by distressed funds. Argyle (2013) finds that idiosyncratic shocks to firms in a mutual fund's portfolio can induce portfolio flows and cause price pressure on other firms in common portfolios. Overall, most of the documented price effects are due to the liquidity channel[4] and imply the agency problems and institutional constraints modeled by Shleifer and Vishny (1997). On the contrary, the price impact found in our paper is orthogonal to flow controls; in this paper, the behavioral tendencies of mutual fund managers is the source of the price deviation from fundamentals. It is a unique contribution of this paper to tie the variation in price patterns to the variation in investor behavior.

The rest of the paper is organized as follows. Section 1 provides on overview of the datasets used. Section 2 constructs the necessary variables and outlines the specification strategy. Section 3 discusses the results. Section 4 examines heterogeneity across funds and the resulting cross-sectional variation in selling behavior and pricing implications. Section 5 explores various robustness checks of the main finding, and Section 6 concludes.

I Data description

Data are collected from three datasets. Mutual funds holding data are taken from the Thomson Reuters Mutual Fund and Institutional Holdings databases from the S12 Master Files. The data span the time series from January 1980 to December 2012, inclusively. These data are crosschecked at the fund-date level against the CRSP Mutual Fund Summary database as discussed below. The CRSP Mutual Fund Summary database is also used to construct some of the fund-date level control

[4] See Blocher (2011), Hau and Lai (2011), Hau and Lai (2012), Lou (2012), and Anton and Polk (2013), among others.

variables. Security prices and accounting information are taken from the CRSP Security File. We excludes ADRs, ATCs, REIT, and closed-end funds, and focus on common shares of domestic securities with a share code of 10 or 11. Similar to previous literature, we employ the following filters:

1. We exclude all fund-date combination in which the Total Net Assets reported by Thomson Reuters differs from the CRSP database by more than 100%.

2. We exclude all fund-date-holding combinations in which the number of shares of firm i reported to be held by a given fund exceeds the number of shares outstanding of firm i on a given date.

3. We exclude all fund-date-holding combinations in which the market value of a reported holding of firm i exceeds the Total Net Assets of the reporting fund on a given date.

4. We exclude all fund-date-holding combinations in which the price of one share of the security is below $2.

Applying these filters, and merging with the CRSP Security File, results in roughly 20M valid fund-quarter-holding combinations. We assume that holdings are constant during the quarter and that all trading takes place at the end of the reporting quarter. Previous research has discussed and demonstrated the reality of intraquarterly trading[5], but given that the ratio of the size of trading to Total Net Assets is relatively small, we abstract away from these realities to focus on the capital overhang effects. At best, daily trading simply adds noise to our estimation, and at worst it biases against our results. As a final note on the construction of our dataset, the CRSP/Compustat manual reports that fund numbers (variable "*fundno*") are often reused for unrelated funds. We assume that a gap of more than 2 years between reporting dates implies the cessation of the previous fund and the outset of a new fund. Summary statistics and correlation tables of the filtered dataset are show in the panels of Table I.

Insert Table I about here.

[5] See Busse (1999), Bollen & Busse (2001), Green & Hodges (2002), Puckett and Yan (2011), Bobson, Cavenaile, & Sougné (2012), and Argyle (2013).

II Specification

II.A Trading Behavior

We refer to the overhang of a single holding in the portfolio of a single manager as the "holding period overhang" (*hp_overhang*) and the aggregate overhang across all mutual funds for a single security as the "capital overhang" (*overhang*). To examine the trading behavior of fund managers, we construct our primary measure of the holding period overhang for a given security in the portfolio of fund f at time t as:

$$hp\_overhang_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{p_t - p_{t-n}}{p_t} \right] \tag{1}$$

where $V_{f,t,t-n}$ is the number of shares purchased at time $t-n$ that are still held in the fund at time t, and p_t is the price of the security at time t. The holding period overhang variable is a weighted average of the deviation of the current price from the purchase price ($p_t - p_{t-n}$) as a percentage of the current price (p_t). To be consistent with the construction of the capital overhang variables (discussed below), the denominator of the unweighted component of $hp\_overhang_{ft}$ is the current price (as opposed to the purchase price). In this way, $hp\_overhang_{ft}$ is simply the capital overhang at the fund-holding level. The alternative measure (constructed in the Appendix) is normalized by the purchase price[6]. We follow the argument laid out in Frazzini (2006) and employ a First In First Out (FIFO) assumption to characterize the mental accounting of fund managers and to populate $V_{f,t,t-n}$. When part (or all) of a position is sold, shares are sold in the order that they were purchased. For example, if in time period 0, the fund manager of a given fund purchases 500 shares of a security, and in time period 1 she adds another 1000 shares, then the fund manager now owns 1500 shares, and the net positions for the fund are given by $V_{f,1,0} = 500$ and $V_{f,1,1} = 1000$. If the fund manager decides to sell 700 shares in time period 2, then we would assume that the shares that were purchased first are sold first, such that $V_{f,2,0} = 0$, $V_{f,2,1} = 800$, and $V_{f,2,2} = 0$.

In order to examine a V-shaped selling schedule, we further separate the holding period overhang

[6]We argue that the measures normalized by the current price (p_t) are preferred because when aggregated to the security level, capital gains overhang constructed this way can be interpreted as the holding period overhang of a representative investor ($\sum \omega_{t-n} \frac{P_t - P_{t-n}}{Pt} = \frac{P_t - \sum \omega_{t-n} P_{t-n}}{Pt}$), while the alternative measures that normalize by purchase price (p_{t-n})do not offer this convenient interpretation.

into unrealized gains and losses for a given security in the portfolio of fund f at time t:

$$hp\_gain_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} \leq p_t}}{p_t} \right] \tag{2}$$

and

$$hp\_loss_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} > p_t}}{p_t} \right], \tag{3}$$

where the indicator variables $\mathbb{I}_{p_{t-n} \leq p_t}$ and $\mathbb{I}_{p_{t-n} > p_t}$ indicate that the current price is greater than or equal to the purchase price and that the current price is less than the purchase price, respectively. This construction implies that $hp\_overhang = hp\_gain + hp\_loss$, for every fund-holding-period. We also construct the variable hp_time to capture the weighted average amount of time that the shares have been held. For a given security, this is defined as:

$$hp\_time_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} [t-n]\,. \tag{4}$$

Our primary selling specification, similar to Ben-David and Hirschleifer (2012), is thus a logit regression:

$$\begin{aligned} \mathbb{I}(selling)_{fit} \quad = \quad & \alpha + \beta^{+} hp\_gain_{fit} + \beta^{-} hp\_loss_{fit} + \\ & \zeta^{+} hp\_gain_{fit} \times \sqrt{hp\_time_{fit}} + \zeta^{-} hp\_loss_{fit} \times \sqrt{hp\_time_{fit}} \\ & + \zeta \sqrt{hp\_time_{fit}} + \text{Controls}_{fit} \boldsymbol{\gamma} + \epsilon_{fit} \end{aligned} \tag{5}$$

where Controls_{fit} is a vector of fund-level and security-level control variables and $\boldsymbol{\gamma}$ is a vector of corresponding coefficients. We address potential concerns that our observed effect is mechanically influenced by the assumption of constant holdings between reporting months by excluding all months that are not reporting months for the fund - results are qualitatively unchanged if we include these observations. We also exclude outlier funds whose Total Net Assets are in either .5% tail. As an exploration of robustness, we use fund-level flow at various horizons (when our data permit) and daily security-level volatility calculated over the previous year as controls. Several alternative measures, including normalization by current price, are explored in the Appendix.

II.B Price Effect

In our primary analysis of the pricing implications of a V-shaped selling schedule, the capital overhang for a given security at time t is calculated at a monthly horizon and is defined similarly to the holding period overhang above:

$$overhang_t = \sum_{n=0}^{t} \frac{V_{t,t-n}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{p_t - p_{t-n}}{p_t} \right], \tag{6}$$

where $V_{t,t-n}$ is the aggregate sum of the shares purchased at time $t-n$ that are still held at time t across all funds:

$$V_{t,t-n} = \sum_{f=1}^{F} V_{f,t,t-n}, \tag{7}$$

and F is the total number of funds. We construct the capital gains overhang due to unrealized gains and unrealized losses similar to the fund-level variables such that $overhang = gain\_overhang + loss\_overhang$. For every security-period:

$$gain\_overhang_t = \sum_{n=0}^{t} \frac{V_{t,t-n}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} \leq p_t}}{p_t} \right] \tag{8}$$

and

$$loss\_overhang_t = \sum_{n=0}^{t} \frac{V_{t,t-n}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} > p_t}}{p_t} \right] \tag{9}$$

We consider two empirical models. The first model estimates how gain overhang and loss overhang predict future returns separately :

$$Ret_{i,t} = \alpha + \beta_1 gain\_overhang_{i,t-1} + \beta_2 loss\_overhang_{i,t-1} + \gamma_1 Ctrl1_{i,t-1} + \gamma_2 Ctrl2_{i,t-1} + \epsilon_{i,t}, \tag{10}$$

We expect $\beta_1$to be positive, β_2 to be negative, and the relation between these two price effects ($\frac{\beta_1}{\beta_2}$) to match the relative selling sensitivity we find in the selling behavior regressions (equation 5).

To better connect this work to the literature, we pit the linear $CGO_{i,t}$ (Capital Gains Overhang as in Frazzini (2006)) against our V-shaped construction *V-shaped Selling Pressure (VSP)*, defined as $(gain\_overhang_{i,t} + \phi|loss\_overhang_{i,t}|)$, where the parameter ϕ is the relative relationship between selling pressure from unrealized gains and from unrealized losses. We consider the following model:

$$Ret_{i,t} = \alpha + \beta_1 CGO_{i,t-1} + \beta_2 VSP_{i,t-1} + \gamma_1 Ctrl1_{i,t-1} + \gamma_2 Ctrl2_{i,t-1} + \epsilon_{i,t}, \tag{11}$$

The results from the selling behavior regressions (discussed in the following section and modeled in equation 5) suggest that, given an unrealized gain and loss of the same magnitude, mutual fund managers are twice as likely to sell the gain as to sell the loss - thus, we expect a gain overhang to result in twice the selling pressure as a similarly sized loss overhang, and we set $\phi = .5$.

We are concerned that the overhang variables may be correlated with other return predictors, and we include two sets of control variables in our estimates of the price effect. The first set of controls ($Ctrl1_{i,t-1}$) is designed to control for the momentum effect. As we would expect, stocks with large unrealized gains (losses) tend to be those who performed well (poorly) in the past, and the past one year return is a well-documented predictor of future return (see Jegadeesh (1990) and Jegadeesh and Titman (1993)). Thus, we include the past 12-to-2 month return, but we separate the raw return by sign: $Ret^{+}_{i,t-12,t-2} = Max\{0, Ret_{i,t-12,t-2}\}$, and $Ret^{-}_{i,t-12,t-2} = Min\{0, Ret_{i,t-12,t-2}\}$. We do this to address the asymmetry of momentum's predictive power - Hong, Lim, and Stein (2000) find that the loser leg of momentum is markedly stronger than the winner leg in predicting future return which implies that the raw return may not be a good functional form for capturing the proper return-momentum relationship. This is particularly relevant for our purpose, because if we artificially equate the coefficient for momentum winners and momentum losers, the rest of the predictive power may be picked up by our gain/loss overhang.

In addition to momentum, we also control for other common return predictors in $Ctrl2_{i,t-1}$ which includes the following variables. The past one month return ($Ret_{i,t-1}$) and the past 3-to-1 year return ($Ret_{i,t-36,t-13}$) address potential contamination from short-term and long-term reversal, respectively. $ivol$ is the idiosyncratic volatility with respect to a Fama-French three factor model calculated using daily stock return data in the past one year. $logBM$ is the logarithm of the book-to-market ratio; the calculation follows Daniel and Titman (2006) in which this variable remains the same from July of year t through June of year $t+1$, and there is at least a 6 months lag between the fiscal year end and the measured return, allowing adequate time for this information to become public. $logMktcap$ is the logarithm of a firm's market capitalization. $turnover$ is the average daily turnover ratio ($\frac{trading\_volume}{shares\_outstanding}$) in the past one year; this is meant to capture any volume effects that may relate to future returns[7].

We conduct predictive Fama-MacBeth regressions. To avoid the liquidity bias in estimations, we follow the suggestion by Asparouhova, Bessembinder, and Kalcheva (2010) and run weighted least square (WLS) regressions with the weight equal to past one-month gross return. OLS results

[7]See Lee and Swaminathan (2000) and Gervais, Kaniel, and Mingelgrin (2001)

(not reported) are qualitatively the same, suggesting that liquidity bias is not a severe issue in our exercises. We follow An (2014) and run tests using all months as well as excluding January, to demonstrate that our results are not driven by the January effect[8].

Finally, it is important to discuss the timing of information availability. Holdings data that are reported by Thomson Reuters include both the effective date of holdings data (variable *"rdate"*) as well as the date that these holdings were filed with the SEC (variable *"fdate"*). It is not uncommon, especially in the early sample, for the difference between when the information is relevant (*rdate*) and when it is reported (*fdate*) to be severe (up to 24 months in extreme cases). This is seemingly less common in the latter portion of the data. Though the selling behavior can and should be identified using the data as of the corresponding *rdate*, the correct course of action is less clear when examining the price effect regressions (equations 10 and 11). While using the holdings data as of the *rdate* is justifiable to identify a pure price effect, these results would not speak to a viable trading strategy. To this end, for the selling behavior regressions, we use the data as of the corresponding *rdate*, but for the price effect regressions we estimate holdings based on the most recent filing date (with at least a 1 month lag). This is identical to the argument formulated in Frazzini (2006) and ensures that overhang data are publicly available.

III Results

III.A Trading Behavior

Results from the selling behavior regressions are shown in Table II. All errors are clustered at the fund level except regression 6, where the errors are two-way clustered at the fund-time level. The results from regression (1) shows a strong overhang effect. We see that both the hp_gain_{fit} (4.10) and hp_loss_{fit} (-1.64) coefficients are strongly significant with t-stats of 43.4 and -38.1, respectively. The coefficients on the interaction of $hp_gain_{fit}$and hp_loss_{fit} with $\sqrt{hp\_time}$ are -0.72 and o.28 respectively, suggesting that fund managers' selling response to unrealized profit weakens as holding time becomes longer. At the mean value of holding time, 3.62 months, the magnitude of these coefficients implies that a 1% increase in the holding period gain implies a 2.74% ($4.10\% - 0.72\% \times \sqrt{3.62}$) higher

[8]For tax purposes, investors in December tend to sell off losing stocks to offset capital gains. The price of such stocks tends to decline in December and then reverses in January. See, for example, Roll (1983), Lakonishok and Smidt (1988), and Grinblatt and Keloharju (2004).

probability that some or all of the security will be sold this period; a 1% more extreme holding period loss implies a 1.09% ($1.64\% - 0.28\% \times \sqrt{3.62}$) higher probability of being sold. These results confirm the V-shaped disposition effect, and the relatively magnitude ($\frac{1.09}{2.74} = .4$) further suggests an asymmetric V-shaped effect. Regressions (2) and (3) repeat this regression, but separate the sample based on "short" holding period $\left(\sqrt{hp\_time} \leq 3.5\right)$ and "long" holding period $\left(\sqrt{hp\_time} > 3.5\right)$. Both subsamples manifest a strongly V-shaped disposition effect - the ratio of loss to gain coefficients taking into account the time interaction effect $\left(\left|\frac{\beta(hp\_loss)+\beta(hp\_loss\times\sqrt{hp\_time})\times\sqrt{mean(hp\_time)}}{\beta(hp\_gain)+\beta(hp\_gain\times\sqrt{hp\_time})\times\sqrt{mean(hp\_time)}}\right|\right)$ is equal to .407 and .425 for short-term and long-term holding periods, respectively. However, the magnitude of the coefficients and the corresponding t-stats are bigger for shorter holding periods.

Regressions (4) and (5) split the data into a "past" subsample spanning 1980 to 2001 and a "recent" subsample spanning 2002 to 2012. We see that coefficient estimates are qualitatively identical to the original regression with t-stats above 30, though the magnitude of the results in the recent sample is slightly smaller. Regression (6) uses the logit2 code written by Jingling Guan and Mitchell Petersen (2008) to perform logit regressions using two-way clustering at the fund-quarter level. T-stats are reduced (as expected), but remain highly statistically significant. Finally, regression (7) is a further robustness check including an outflow dummy equal to 1 if the monthly flow of the fund is less than zero and an interaction between outflow and the holding period overhang. The usage of the flow data reduces the sample to only those funds in the CRSP universe for which flow data can be calculated (reducing the number of observations from roughly 20.4 million to 7.4 million). The resulting coefficient estimates have slightly smaller magnitudes (3.64 for the holding period gains, -1.37 for the holding period losses, 0.58 for the interaction term of hp_gain and holding time, and 0.24 for the interaction term of hp_loss and holding time), but are close to the original estimates. We also explore various windows for the measurement of the fund flows, at 3 month and 12 months horizons, without notable change in the coefficient estimates (results omitted). We conclude that the observed V-shaped disposition effect is orthogonal to fund flow effects[9] .

Insert Table II about here.

[9]See Lou (2012) for an example of the effects of fund flows on mutual fund trading behavior at the quarterly horizon.

III.B Pricing Effect

Table III presents results from estimating equation 10 using Fama-MacBeth regressions. In these regressions, we expect the coefficients on gain overhang and loss overhang be positive and negative, respectively. Note that by construction, all values of the loss overhang variable are negative, so an increase in loss overhang means a decrease in the magnitude of loss. In columns (1) and (2), we regress future one-month returns onto gain overhang and loss overhang only, and we see that the coefficients on loss overhang (0.002 in all months, and 0.004 in Feb to Dec) have opposite signs than expected. This is due to the fact that stocks with large unrealized losses tend to be momentum losers, and failing to properly control for momentum masks the true marginal effect of the overhang variables. Indeed, adding the two legs of momentum, $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$, we see in regressions (3) and (4) that the gain and loss overhang variables have the expected sign. Notably, the coefficient for $Ret^{-}_{-12,-2}$ is roughly an order of magnitude larger than the coefficient for $Ret^{+}_{-12,-2}$, underlining the importance of separating these two legs and suggesting that the loser leg of momentum is a better predictor of returns than the winner leg (consistent with Hong, Lim, and Stein (2000)). In regressions (5) and (6), we omit momentum controls and add other common return predictors ($Ctrl2$). Finally, regressions (7) and (8) add all relevant controls and present our full model. In these two regressions, gain overhang positively predicts future return and loss overhang negatively predicts future return, both as expected; focusing on the all-month estimation, the coefficients suggest that a 1 percentage point increase in gain (loss) overhang is associated with a 1.4 (0.9) basis point increase (decrease) in next month returns. The t-statistics (6.02 and -8.65) are very large - given 391 months are used in the estimation, these numbers imply that a trading portfolio based on gain (loss) overhang with zero loading on other control variables would have a Sharpe ratio of $\left(6.02\sqrt{\frac{12}{391}}\right) = 1.05$ and $\left(8.6\sqrt{\frac{12}{391}}\right) = 1.51$, respectively.

Grinblatt and Han (2005) discuss the important relation between the momentum effect and capital overhang; in fact, they find that capital overhang subsumes momentum in their sample and suggest that the disposition effect may be the source of momentum. On the contrary, An (2014) argues that, if investors tend to sell big losers as well as big winners, the loss part of capital gains overhang will predict future return in the opposite direction as momentum would. This claim is also supported by empirical evidence by Novy-Marx (2012) and Birru (2012). Our results here support the second view that the disposition effect can not be the source of the momentum effect, as loss overhang and the loser leg in momentum have opposite return predictions.

We also draw attention to the relationship between idiosyncratic volatility and the overhang effects. It has been documented that high idiosyncratic volatility stocks are associated with low future returns[10], and perhaps unsurprisingly, stocks with large gain and loss overhang tend to be those with high idiosyncratic volatility. This result biases against our results since our model predicts the opposite relationship: stocks with large gain and loss overhang will outperform in the next month as prices return to fundamentals. Indeed, controlling for idiosyncratic volatility strengthens the predictive power of our overhang variables - note the change in overhang coefficient estimates from columns (1) and (2) to columns (5) and (6) and the change from columns (3) and (4) to columns (7) and (8).

Insert Table III about here.

To compare with previous literature, we also construct a single V-shaped selling pressure variable, *V-shaped Selling Pressure (VSP)*, equal to $(gain\_overhang + \phi|loss\_overhang|)$ with $\phi = .5$. We conduct a horse race between *VSP* and the linear Capital Gains Overhang (CGO) variable as in Frazzini (2006). Table IV presents the results. We see that with control variables included, CGO loses all of its predictive power, while VSP remains highly significant. The coefficient of 0.016 in the all-month estimation suggests that a 1 percentage point increase in *VSP* would lead to 1.6 basis point increase in future one-month return; given that the average 10th and 90th percentile of monthly *VSP* sample is 0.04 and 0.36, a portfolio that longs the top *VSP* decile and shorts the bottom *VSP* decile would generate a monthly return spread of approximately $(.36 - .04) \times .0016 = 51.2$ basis points, and a t-statistic $= 8.44$ implies that the Sharpe ratio is approximately $8.44\sqrt{\frac{12}{391}} = 1.48$.

Insert Table IV about here.

IV Fund Characteristic Heterogeneity

In this section, we examine how heterogeneity in mutual funds' behavior affects price patterns. We first explore the cross-sectional heterogeneity in trading behavior that is related to fund character-

[10]see Ang, Hodrick, Xing, and Zhang (2006, 2009), among others

istics. We then link this heterogeneity in fund behaviors to price effects, by examine if securities held by funds who manifest a stronger behavior pattern have stronger return predictability. This provides further evidenceve that the return pattern we find is indeed coming from mutual funds' V-shaped selling schedule.

IV.A Selling Behavior

We repeat the selling behavior regressions on subsamples of the fund universe, splitting the data based on fund characteristics designed to capture activeness and speculation by the fund manager. These characteristic variables are the expense ratio, the turnover, and the average holding period within a portfolio. The expense ratio is the ratio of operating expenses to total investment. The turnover is the ratio of aggregated purchases ($) divided by the average 12-month Total Net Assets. Average holding period is the average number of months that a security is held by a fund (from inception to liquidation). With the exception of average holding period, these fund characteristics data are only available for the subset of funds that are in the CRSP Mutual Fund database, and the universe is reduced to roughly 7.4 million fund-holding-period observations.

A given portfolio in the CRSP database will have almost always (at most) a single corresponding fund in the Thomson Reuters data. However, a single portfolio in the Thomson Reuters data may correspond to several separate share classes in the CRSP database (varying by fee structures, eligibility requirements, etc.). Treating these share classes as separate portfolios would bias the results toward funds with more share classes. To address this bias, we instead construct weighted averages of the characteristic variables based on the Total Net Assets of the various share classes. For example, consider a single portfolio with two share classes: Fund A with Total Net Assets of $400M and Fund B with Total Net Assets of $200M. Both of these funds represent exposure to the same portfolio (and trading behavior), but they may have very different characteristics. For instance, assume that the expense ratio of Fund A is 2% and the expense ratio of Fund B is 5%. For the purpose of classifying this fund, we calculate the weighted average expense ratio: $\frac{400}{600}.02+\frac{200}{600}.05 = .03$ for the portfolio. Though this method is not without alternatives, our primary goal is simply to categorize funds, and this procedure allows us to parsimoniously parse the characteristics of varied share classes in an intuitive manner. We thus obtain weighted averages of the fund expense ratio and turnover. We form the average holding period directly from the holdings data using *hp_time*. Summary statistics for the weighted versions of these variables are shown in Table I labeled as *wt_exp_ratio*, *wt_turn_ratio*, $\overline{hp\_time}$, respectively.

Insert Table V about here.

Selling behavior results splitting funds based on the expense ratio are shown in Table V. We see that funds with higher expense ratios manifest a much more significant V-shaped disposition effect - the coefficient for holding period gain (*hp_gain*) for funds in the top third by expense ratio is a highly significant 4.27, whereas the corresponding coefficient for funds in the bottom third by expense ratio is 2.34. The difference is statistically significant, and we see a similar difference in the coefficients for holding period loss (*hp_loss*). We interpret high fee as a proxy for active investment style, which allows room for fund managers' trading tendency. In the extreme, index funds with very low fees only passively follow the index and should not manifest any V-shaped disposition effect; indeed, our placebo test in Section 5.2 confirms this conjecture.

Insert Table VI about here.

Another way to measure fund activeness and speculation is to look at fund turnover. We proxy for this characteristic by using two variables - dollar turnover and average holding period. Though these two variables are related, they capture different behavior; high turnover implies a large portion of the portfolio's value is being traded while low average holding period implies frequent trading. Selling behavior results, splitting funds based on turnover and average holding period are shown in Table VI. We find that the V-shaped disposition effect is more severe among funds with higher trading turnover and short average holding period; the gain and loss coefficients for high turnover funds (5.1 and -2.1, respectively) are roughly twice the size of the gain and loss coefficients for funds with low relative turnover (2.43 and -0.93, respectively). Similarly, funds with the shortest average holding period have coefficients almost twice the magnitude of funds with the longest average holding period. These results suggest that relatively active managers are more prone to evince a V-shaped disposition effect.

IV.B Fund Characteristics and Return Predictability

We link the heterogeneity in mutual funds' selling behavior to equilibrium prices by decomposing the overhang variables, *gain_overhang* and *loss_overhang*. Recalling that *gain_overhang* and *loss_overhang* (defined in equations 8 and 9) are a decomposition of the total capital overhang, we can further decompose the overhang for a given fund characteristic. To be consistent with our hypothesis, securities with overhang from funds that exhibit the most extreme V-shaped disposition effect should exhibit the most significant return predictability.

To test this hypothesis, we sort all funds in the Thomson Reuters database into three categories based on the fund characteristics discussed in the previous section: the low group (the bottom half, denoted as L), the high group (the top half, denoted as H), and the undefined group (denoted as U). We then aggregate paper gains and losses for funds in these three categories respectively. For instance, gain and loss decomposition based on fund turnover is specified as the following:

$$gain\_overhang\_turnL_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnL}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} \leq p_t}}{p_t} \right], \tag{12}$$

$$gain\_overhang\_turnH_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnH}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} \leq p_t}}{p_t} \right], \tag{13}$$

$$gain\_overhang\_turnU_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnU}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} \leq p_t}}{p_t} \right], \tag{14}$$

$$loss\_overhang\_turnL_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnL}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} > p_t}}{p_t} \right], \tag{15}$$

$$loss\_overhang\_turnH_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnH}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} > p_t}}{p_t} \right], \tag{16}$$

and

$$loss\_overhang\_turnU_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnU}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} > p_t}}{p_t} \right] \tag{17}$$

where $turnL$, $turnH$, $turnU$ denote the sets of funds that fall into the bottom half, top half, and undefined group based on turnover at time t, respectively, and

$$V_{t,t-n}^{turnL} = \sum_{f \in turnL} V_{f,t,t-n}, \tag{18}$$

$$V_{t,t-n}^{turnH} = \sum_{f \in turnH} V_{f,t,t-n}, \tag{19}$$

$$V_{t,t-n}^{turnU} = \sum_{f \in turnU} V_{f,t,t-n}. \tag{20}$$

The undefined group exists because not all funds in the Thomson Reuters database can be matched with fund characteristic information in the CRSP database. We keep this category so that the overhangs from these three groups of funds sum to the original overhang variables - i.e. taking turnover as an example, $gain\_overhang = gain\_overhang\_turnL + gain\_overhang\_turnH + gain\_overhang\_turnU$ and similarly $loss\_overhang = loss\_overhang\_turnL + loss\_overhang\_turnH + loss\_overhang\_turnU$. The same decomposition technique applies to the fund expense ratio and average holding period. Note that since calculating average holding period only requires holding information in the Thomson Reuters database, all funds fall into either the high group or the low group in this decomposition, and the undefined group is an empty set.

We repeat the pricing effect exercises using the empirical model of equation 10, and we now replace both $gain\_overhang$ and $loss\_overhang$ with its respective three-part decomposition. Recall that we reported in the previous subsection that mutual funds with higher expense ratio, higher turnover, and lower average holding time are more likely to exhibit a V-shaped selling schedule. We expect overhangs from the high expense ratio group, the high turnover group, and the low average holding time group to have stronger return predictability (larger regression coefficients), and we have no prior predictions for overhangs from the undefined group.

Insert Table VII about here.

Regression results reported in Table VII generally confirm our conjecture. On the gain side, overhangs from all three more-biased groups have a larger regression coefficient, and the difference in coefficient magnitude between the more-biased group and the less-biased group ranges from 1 to 3 multiples of the coefficient. On the loss side, the coefficient of the high-group overhang is about two times as large as that of the low-group overhang for the turnover sort; the difference in coefficients based on expense ratio sort and average holding time sort is almost zero for all-month estimation, and small but in the right direction for February to December estimation.

These results help to further validate the link between the biases of mutual fund managers and the observed price pattern: it is the positions of those who exhibit a stronger behavioral tendency that predict future returns.

V Robustness checks

V.A Extreme Rank Dependency

There is some evidence that the absolute best performer in a portfolio or the absolute worst performer in a portfolio is treated and traded materially differently by the manager. See Hartzmark (2013). To address this possibility, we rerun the primary selling regression and include a dummy variable signifying that the security is the best performing in the portfolio in a given period ($best\_dummy_{fit}$) and also a separate dummy variable if the security is the worst performing in the portfolio in a given period ($worst\_dummy_{fit}$), defined in the following manner:

$$best\_dummy_{fit} = \begin{cases} 1 & \text{if security } i \text{ has the highest } hp\_overhang \\ & \text{in the portfolio of fund } f \text{ in period } t \\ 0 & \text{otherwise} \end{cases} \tag{21}$$

and

$$worst\_dummy_{fit} = \begin{cases} 1 & \text{if security } i \text{ has the lowest } hp\_overhang \\ & \text{in the portfolio of fund } f \text{ in period } t \\ 0 & \text{otherwise} \end{cases}. \tag{22}$$

We also control for the security-level, capital overhang versions of the Hartzmark dummies in the pricing effect regressions, defined as:

$$best\_dummy_{i,t} = \begin{cases} 1 & \text{if security } i \text{ has the highest } hp\_overhang \\ & \text{in the portfolio of at least one fund in period } t \\ 0 & \text{otherwise} \end{cases} \tag{23}$$

and

$$worst\_dummy_{i,t} = \begin{cases} 1 & \text{if security } i \text{ has the lowest } hp\_overhang \\ & \text{in the portfolio of at least one fund in period } t\ . \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

Insert Table VIII about here.

Selling behavior regressions using both the original and alternative measure - the alternative measure is normalized by the purchase price and constructed in the Appendix, that include these dummies are shown in Table VIII. Regression 1 repeats the main regression without subsample splits. Both the coefficient estimates and the resulting ratios of gain and loss coefficients are practically unchanged from the regressions omitting these extreme rank dummies. Regression 2 substitutes the alternatives measures and finds similar results. Though these dummies do not effect our overhang findings, the corresponding coefficient are persistently significant even when controlling for fund flow variables at 1 month, 3 month, and 12 month horizons (results omitted). The standardized coefficients for the *best_dummy* is equal to $.0938\frac{.497}{.494} = .0944$ whereas the standardized coefficient of the *hp_gain* variable is equal to $3.9974\frac{.128}{.494} = 1.04$ which speaks to the relatively explanatory significance. Also, the R^2 improvement from adding these rank dummies is minimal (.0129 versus .0112).

We also find that including similar security-level dummies in the pricing equations has virtually no qualitative effect on the overhang coefficient estimates. These results are shown in Table IX.

Insert Table IX about here.

V.B Placebo Test

We would predict that the disposition effect would not be observed among passive index funds, given that these funds are not making active trading decisions. We test this hypothesis by first isolating the index funds from our sample. The CRSP Mutual Fund database categorizes index funds into three distinct groups: B-funds are "mostly" index funds but engage in an amount of active trading, D-funds are "pure" index funds, and E-funds seek to augment or lever exposure to an underlying index. Though we examine all three classes of index fund, we focus our placebo test on those D-funds that are not open to investors; selling occurs in these funds when the underlying index is rebalanced - which usually occurs with a frequency of between every month and every six months, depending on the fund. There are 71 pure index funds spanning 43,933 observations in our sample.

Insert Table X about here.

Results from the selling behavior regressions, using only this subset of mutual funds are shown in Table X. We see that for index-based and pure-index funds, the coefficients on the overhang variables are not statistically different from zero. The gain coefficient when looking at enhanced-index funds is statistically significant, but the loss coefficient is not, and the strategies of these funds are arguably very different from a passive index fund. We interpret these results as broadly supportive of our work.

VI Conclusions

This paper has sought to robustly establish three contributions to the current literature. First, we show that mutual fund managers, like the individual retail investors of previous research, also exhibit a V-shaped disposition effect - they are more likely to sell both their past relative winners and losers. We found that the slope of the selling schedule for past winners is roughly twice the magnitude of the slope of the selling schedule for past losers, and we established this results using both a weighted measure of holding period overhang, which took into account the net purchases of a fund's holdings, as well as a simple measure focusing solely on the purchase price (shown in the Appendix). This discovery and these results are in contrast to the assumption of a monotonic selling schedule proposed elsewhere in the literature.

The second major contribution of this research has been to demonstrate that this observed behavior, aggregated across fund managers, has an observable impact on equilibrium prices. When properly controlling for momentum, we found that a 1 percentage point increase in the magnitude of the gain (loss) overhang implied a 1.4 (.9) basis point increase in future one-month returns. The relative magnitude of the gain and loss effect $\left(\frac{.9}{1.44}\right) = .625$ is consistent with the estimates of the relative impact of holding period gain and loss on the selling behavior of individual mutual fund managers. With these results in hand, we are able to directly pit a monotonic capital gains overhang measure (widespread in the literature) against a V-Shaped capital gains overhang measure. Properly controlling for momentum and short- and long-term reversal, the monotonic measure loses all of its predictive power (point estimate of -.0012 with a t-stat of 1.28) against the V-shaped measure (point estimate of .0156 with a t-stat of 8.44). This is further evidence of the superiority of the V-shaped disposition effect in capturing the trading behavior of institutional investors.

Third, we further establish the link between selling behaviors and the price effects by exploring heterogeneity in fund characteristics. We find that the subset of funds with higher turnover, shorter holding period, and higher fees are more likely to exhibit the V-shaped disposition effect, and paper gains and losses aggregated across this subset of funds have stronger return predictability. This evidence closely ties the observed price variation to investors' behavior, and sheds further light on the underlying mechanism of the V-shaped disposition effect.

Appendix

A. Alternative Measures

We propose an alternative measure of overhang that is consistent with the usual definition of returns - we normalize based of the purchase price instead of the current price. This alternative holding period overhang is defined as:

$$hp\_overhang\_alt_{ft} = \frac{\sum_{n=0}^{t} V_{f,t,t-n}\left(p_t - p_{t-n}\right)}{\sum_{n=0}^{t} V_{f,t,t-n} p_{t-n}}, \tag{A1}$$

and the alternative holding period gain and loss overhang variables are constructed accordingly:

$$hp\_gain\_alt_{ft} = \frac{\sum_{n=0}^{t} V_{f,t,t-n}\left(p_t - p_{t-n}\right) \mathbb{I}_{p_{t-n} \leq p_t}}{\sum_{n=0}^{t} V_{f,t,t-n} p_{t-n}} \tag{A2}$$

and

$$hp\_loss\_alt_{ft} = \frac{\sum_{n=0}^{t} V_{f,t,t-n}\left(p_t - p_{t-n}\right) \mathbb{I}_{p_{t-n} > p_t}}{\sum_{n=0}^{t} V_{f,t,t-n} p_{t-n}}. \tag{A3}$$

and the alternative gain and loss capital overhang variables for a given security (where the $V_{f,t,t-n}$ are aggregated across funds) are:

$$gain\_overhang\_alt_t = \frac{\sum_{n=0}^{t} V_{t,t-n}\left(p_t - p_{t-n}\right) \mathbb{I}_{p_{t-n} \leq p_t}}{\sum_{n=0}^{t} V_{t,t-n} p_{t-n}} \tag{A4}$$

and

$$loss\_overhang\_alt_t = \frac{\sum_{n=0}^{t} V_{t,t-n}\left(p_t - p_{t-n}\right) \mathbb{I}_{p_{t-n} > p_t}}{\sum_{n=0}^{t} V_{t,t-n} p_{t-n}}. \tag{A5}$$

We argue that the measures normalized by current price (p_t) are preferred, because the aggregate capital gains overhang variable can be interpreted as the holding period overhang of a representative investor ($\sum \omega_{t-n} \frac{P_t - P_{t-n}}{Pt} = \frac{P_t - \sum \omega_{t-n} P_{t-n}}{Pt}$). The alternative measure offers no such intuitive interpretation, though it is consistent with the usual definition of holding period returns. Previous literature has focused solely on the original measure of overhang (normalized by current price) and has failed to explore this interesting alternative. Selling behavior results are shown in Table AI. Many of the observations drawn using the original measures are maintained. We see highly significant overhang coefficients that persist throughout a number of subsample and error-clustering specifications. Also, results are much more prevalent for shorter holding periods (regression (2)) than for longer holding periods (regression (3)) which is consistent with the findings presented in the body of the paper. The most interesting observation from these results is that the overhang coefficients are still very statistically and economically significant, but the relative magnitude between holding period gain and loss is opposite the original measure. From regression (1), we see that the ratio of coefficients $\left|\frac{\beta(hp\_loss)+\beta(hp\_loss\times\sqrt{hp\_time})\times\sqrt{mean(hp\_time)}}{\beta(hp\_gain)+\beta(hp\_gain\times\sqrt{hp\_time})\times\sqrt{mean(hp\_time)}}\right| = 1.75$. This relationship is consistent across all of the selling behavior regressions for the alternative measures.

Insert Table AI about here.

We examine the pricing effects of the alternative measure in Table AII. Interestingly, we see that the relative impact of the gain overhang and the loss overhang have reversed from the results using the original measure - consistent with the selling behavior regressions using the alternative measures. In the fully controlled regressions (7) and (8), the significant gain and loss coefficients (t-stats are greater than 7) are .0115 and -.0225, respectively, in the all-months case, implying a ratio of $\left|\frac{-.0225}{.0115}\right| = 1.96$.

Insert Table AII about here.

These results further instantiate the robustness of the V-shaped disposition effect. Though the relative slope of the gain and loss overhang is dependent on the choice in normalizing price, both measures result in statistically and economically significant coefficient estimates whose predictions for fund managers' selling behavior are consistent with the estimated effects on equilibrium price.

B. Unweighted Measures

We examine two simpler measures of overhang in which fund managers consider the unweighted overhang based on purchase price of only the "oldest" shares that have not yet been sold. We examine both the original measure (normalized by current price p_t) and also the alternative measure (normalized by the purchase price). Given the FIFO assumption about the construction of $V_{f,t,t-n}$, managers only consider the purchase price (p_{t-n}) associated with the nonzero value of $V_{f,t,t-n}$ with the greatest value of n. That is:

$$hp\_overhang\_simple_{ft} = \frac{p_t - p_{t-n^*}}{p_t}, \tag{A6}$$

and

$$hp\_overhang\_alt\_simple_{ft} = \frac{p_t - p_{t-n^*}}{p_{t-n^*}}, \tag{A7}$$

where $n^* = \max(n)$ such that $V_{f,t,t-n} > 0$. We construct the holding period gain and loss variables similar to the original construction:

$$hp\_gain\_simple_{ft} = \frac{[p_t - p_{t-n^*}]\, \mathbb{I}_{p_{t-n} \leq p_t}}{p_t} \tag{A8}$$

and

$$hp\_loss\_simple_{ft} = \frac{[p_t - p_{t-n^*}]\, \mathbb{I}_{p_{t-n} > p_t}}{p_t}. \tag{A9}$$

The corresponding simple alternative measures $hp\_gain\_alt\_simple_{ft}$ and $hp\_loss\_alt\_simple_{ft}$ are constructed similarly, though normalized by the purchase price (p_{t-n^*}) instead of the current price

(p_t) .

We similarly construct the simpler measures of the holding period :

$$hp\_time\_simple_{ft} = t - n^*. \tag{A10}$$

We examine the same logit selling regression as before (equation 5) but use the simple measures of holding period overhang (based on the "oldest" surviving holding of a security according to a FIFO assumption). Results are shown in Table AIII. We see that for both the main and alternative measures, the coefficients of the simple versions are within an order of magnitude of the original weighted measures. Though the t-stats are still highly significant (above 7), they are much lower than the original measures. This suggests that fund managers are much more inclined to process overhang that is based on the average of the purchase prices as opposed to simply the first-purchase price. We interpret this as justification for the original, V-weighted versions of the overhang measures. The relative magnitude, however, of $\left|\frac{\beta(hp\_loss\_simple)+\beta(hp\_loss\_simple\times\sqrt{hp\_time})\times\sqrt{mean(hp\_time)}}{\beta(hp\_gain\_simple)+\beta(hp\_gain\_simple\times\sqrt{hp\_time})\times\sqrt{mean(hp\_time)}}\right| =$ 0.58 is very similar and suggests a similar V-shaped disposition structure. Including a battery of control variables including various flow measures, we see that the magnitude and statistical significance of the overhang coefficients are qualitatively unchanged.

Insert Table AIII about here.

Tables and Figures

Panel A: Summary statistics for fund-holding-level selling behavior variables.

Variable	N	Mean	p25	p50	p75	Standard Deviation	Skewness	Kurtosis
hp_overhang_alt	20400376	-0.113	-0.251	0.02	0.2	0.538	-2.333	10.915
hp_overhang	20400376	-0.074	-0.185	0.016	0.157	0.399	-2.068	9.134
$\mathbb{I}(selling)$	20400376	0.421	0	0	1	0.494	0.321	1.103
assets	16911988	91735.896	6173	20817	71955	218634.576	4.918	32.286
$flow1m$	10729332	0.005	-0.013	-0.001	0.014	0.05	2.434	19.392
$flow3m$	10729523	0.022	-0.036	-0.003	0.045	0.131	3.639	26.928
$flow12m$	10732271	0.494	-0.123	0.005	0.24	4.807	21.915	564.986
$fret1m$	10791576	0.006	-0.017	0.01	0.034	0.05	-0.436	5.653
$fret3m$	10803061	0.021	-0.028	0.027	0.079	0.099	-0.34	4.901
$fret12m$	10839309	0.082	-0.025	0.098	0.198	0.209	0.159	5.903
ivol	20399540	0.025	0.016	0.022	0.03	0.013	1.944	12.7
best_dummy	20400376	0.446	0	0	1	0.497	0.219	1.048
worst_dummy	20400376	0.496	0	0	1	0.5	0.016	1
wt_exp_ratio	7954084	0.01	0.006	0.009	0.013	0.005	0.371	2.675
wt_mgmt_ratio	7954084	0.446	0.229	0.38	0.709	0.343	-0.135	3.484
wt_turn_ratio	7954084	0.687	0.29	0.502	0.84	0.667	2.827	14.757
wt_inst	7954084	0.537	8.644	12.674	19.756	10.951	1.947	8.315
outflow_dummy	20400376	0.53	0	1	1	0.499	-0.121	1.015
hp_gain_alt	20400376	0.15	0	0.035	0.215	0.235	2.219	8.441
hp_loss_alt	20400376	-0.084	-0.124	0	0	0.141	-1.906	6.084
hp_gain	20400376	0.095	0	0.023	0.161	0.129	1.399	4.181
hp_loss	20400376	-0.157	-0.17	0	0	0.321	-3.212	15.393
$\sqrt{(hp\_time\_simple)}$	20400376	4.315	2.449	3.873	5.477	2.107	1.021	3.932
$\sqrt{(hp\_time)}$	20400376	3.622	2.449	3.382	4.568	1.663	0.988	4.168
shares	20399450	212951.2	3200	15200	70000	18742105.31	294.974	87620.163
hp_gain_simple	20400376	0.119	0	0.029	0.209	0.158	1.271	3.67
hp_loss_simple	20400376	-0.223	-0.239	0	0	0.462	-3.348	16.848
hp_gain_alt_simple	20400376	-0.118	-0.193	0	0	0.183	-1.578	4.553
hp_loss_alt_simple	20400376	0.15	0	0.035	0.215	0.235	2.219	8.441
net_trading	16756850	0.102	-0.039	0	0.106	0.507	3.005	16.841
$\mathbb{I}(buying)$	16756850	0.307	0	0	1	0.461	0.836	1.699

Table I: Summary Statistics. Panel (A) describes the data used to examine selling behavior. *hp_overhang* is the measure of overhang expressed in equation 1. *hp_overhang_alt* is the alternative measure of overhang expressed in equation A1. $\mathbb{I}(selling)$ is a fund-security-period dummy equal to 1 if the part or all of the security was sold in a given period. *assets* are the Total Net Assets of the fund expressed in thousands ($). $flow1m$, $flow3m$, and $flow12m$ are the 1 month, 3 month, and 12 month fund flow, respectively. $fret1m$, $fret3m$, and $fret12m$ are the 1 month, 3 month, and 12 month fund return, respectively. *ivol* is the average daily residual from a 3 factor Fama-French model over the previous year. *best_dummy* is a dummy equal to 1 for the highest ranked security according to *hp_overhang* in the portfolio of the fund in a given period. *worst_dummy* is a dummy equal to 1 for the lowest ranked security according to *hp_overhang* in the portfolio of the fund in a given period. *wt_exp_ratio*, *wt_mgmt_ratio*, *wt_turn_ratio* are the weighted-average expense ratio, management fee, and turnover ratio for the fund, respectively. *outflow_dummy* is equal to 1 if the $flow1m < 0$. *hp_gain* is the holding period gain defined in equation 2. *hp_loss* is the holding period loss defined in equation 3. *hp_gain_alt* and *hp_loss_alt* are the alternative holding period gain and loss as defined in equations A2 and A3, respectively. *hp_time* is the net purchase-weighted holding period at the fund-security-period level. *hp_time_alt* is the corresponding alternative holding period measure. *shares* is the number of shares held at the fund-security-period level.

Panel B: Summary statistics for stock-level pricing variables.

	N	mean	p25	p50	p75	Std	Skewness	Kurtosis
gain_overhang	1164236	0.121	0.008	0.074	0.192	0.135	1.381	4.766
loss_overhang	1164236	-0.300	-0.327	-0.085	-0.006	0.631	-7.099	123.274
CGO	1164236	-0.168	-0.299	-0.015	0.167	0.604	-3.362	22.782
VSP	1164236	0.178	0.081	0.142	0.240	0.134	1.778	9.502
gain_overhang_alt	1164236	0.170	0.006	0.069	0.227	0.294	12.973	871.968
loss_overhang_alt	1164236	-0.160	-0.253	-0.086	-0.008	0.188	-1.361	4.233
CGO_alt	1164236	0.006	-0.230	-0.015	0.201	0.367	0.790	5.402
VSP_alt	1164236	0.197	0.081	0.142	0.240	0.225	3.012	17.618
Ret	1164212	0.012	-0.057	0.006	0.073	0.134	0.752	7.909
$Ret^{+}_{-12,-2}$	1136148	0.257	0	0.079	0.349	0.449	4.417	41.372
$Ret^{-}_{-12,-2}$	1136148	-0.103	-0.156	0	0	0.174	-1.827	5.651
$Ret_{-12,-2}$	1136148	0.154	-0.156	0.079	0.349	0.534	2.737	23.244
$Ret_{-36,-13}$	1027333	0.402	-0.145	0.209	0.675	0.929	3.200	24.982
$logBM$	992424	-0.631	-1.066	-0.545	-0.100	0.794	-0.899	5.751
$logMktcap$	1164236	12.508	11.135	12.324	13.691	1.843	0.515	3.077
$ivol$	1161670	0.028	0.017	0.024	0.035	0.015	1.340	5.359
$turnover$	1164236	0.005	0.002	0.003	0.007	0.006	2.529	11.415
$best$	1164236	0.155	0	0	0	0.362	1.908	4.641
$worst$	1164236	0.149	0	0	0	0.356	1.974	4.895

Table I: Summary Statistics (Continued). Panels (B) describes the data used to examine pricing effects. *gain_overhang* and *loss_overhang* are the security level overhang variables expressed in equations 8 and 9, respectively. CGO is the monotonic disposition effect overhang documented in Frazzini (2006). VSP is the V-shaped disposition effect overhang as is defined as $VSP = gain\_overhang + .5\,|loss\_overhang|$. Ret is the one-month security return. $Ret_{-36,-13}$ is the lagged 24-month return. $Ret_{-12,-2}$ is the lagged 11-month cumulative return, and $Ret^{+}_{i,t-12,t-2} = Max\{0, Ret_{i,t-12,t-2}\}$, and $Ret^{-}_{i,t-12,t-2} = Min\{0, Ret_{i,t-12,t-2}\}$. $logBM$ is the logarithm of the book-to-market ratio. $logMktcap$ is the logarithm of market capitalization. $turnover$ is the average daily turnover ratio $\left(\frac{trading\_volume}{shares\_outstanding}\right)$ over the past year. $best$ ($worst$) is a dummy variable that is equal to 1 if a security has the highest (lowest)*hp_verhang* in the portfolio of at least one fund.

Panel C: Correlation table of stock-level pricing variables.

	$gain\_overhang$	$loss\_overhang$	CGO	VSP	Ret_{-1}	$Ret^{+}_{-12,-2}$	$Ret^{-}_{-12,-2}$	$Ret_{-12,-2}$	$Ret_{-36,-13}$	$logBM$	$logMktcap$	$ivol$	$turnover$	$best$	$worst$
$gain\_overhang$	1														
$loss\_overhang$	0.36	1													
CGO	0.58	0.93	1												
VSP	0.69	-0.39	-0.19	1											
Ret	0.28	0.19	0.25	0.12	1										
$Ret^{+}_{-12,-2}$	0.49	0.18	0.28	0.33	0.01	1									
$Ret^{-}_{-12,-2}$	0.39	0.59	0.65	-0.11	-0.03	0.34	1								
$Ret_{-12,-2}$	0.54	0.34	0.45	0.25	0.00	0.95	0.61	1							
$Ret_{-36,-13}$	0.06	0.03	0.04	0.04	-0.02	-0.05	-0.11	-0.08	1						
$logBM$	0.01	0.03	0.03	-0.01	0.02	0.01	0.11	0.04	-0.30	1					
$logMktcap$	0.13	0.19	0.21	-0.02	0.04	0.04	0.19	0.10	0.09	-0.29	1				
$ivol$	-0.09	-0.39	-0.39	0.24	0.02	0.14	-0.38	0.00	-0.02	-0.08	-0.47	1			
$turnover$	0.05	-0.14	-0.12	0.17	-0.01	0.14	-0.17	0.07	0.17	-0.29	0.30	0.24	1		
$best$	0.44	0.15	0.23	0.05	0.13	0.25	0.16	0.26	0.09	-0.16	0.39	-0.08	0.25	1	
$worst$	-0.26	-0.39	-0.40	0.29	-0.13	-0.11	-0.30	-0.19	0.01	-0.11	0.20	0.07	0.25	-0.06	1

Table I: Summary Statistics (Continued). Panel (C) reports a correlation matrix of primary variables. $gain\_overhang$ and $loss\_overhang$ are the security level overhang variables expressed in equations 8 and 9, respectively. CGO is the monotonic disposition effect overhang documented in Frazzini (2006). VSP is the V-shaped disposition effect overhang as is defined as $VSP = gain\_overhang + .5\,|loss\_overhang|$. Ret is the one-month security return. $Ret_{-36,-13}$ is the lagged 24-month return. $Ret_{-12,-2}$ is the lagged 11-month cumulative return, and $Ret^{+}_{i,t-12,t-2} = Max\{0, Ret_{i,t-12,t-2}\}$, and $Ret^{-}_{i,t-12,t-2} = Min\{0, Ret_{i,t-12,t-2}\}$. $logBM$ is the logarithm of the book-to-market ratio. $logMktcap$ is the logarithm of market capitalization. $turnover$ is the average daily turnover ratio $\left(\frac{trading\_volume}{shares\_outstanding}\right)$ over the past year. $best$ ($worst$) is a dummy variable that is equal to 1 if a security has the highest (lowest)$hp\_verhang$ in the portfolio of at least one fund.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Data Filter	None	$\sqrt{hp\_time} \leq 3.5$	$\sqrt{hp\_time} > 3.5$	$1980 \leq year \leq 2001$	$2002 \leq year \leq 2012$	None	None
hp_gain	4.1043***	6.7636***	1.5892***	4.8019***	4.0412***	4.1043***	3.6388***
	[43.41]	[67.75]	[17.64]	[51.08]	[35.87]	[31.85]	[26.77]
hp_loss	-1.6404***	-2.1572***	-0.8094***	-1.6782***	-1.6179***	-1.6404***	-1.3666***
	[-38.09]	[-48.49]	[-17.66]	[-36.80]	[-30.51]	[-24.21]	[-20.05]
$hp\_gain \times \sqrt{hp\_time}$	-0.7193***	-1.9502***	-0.2061***	-0.9600***	-0.6812***	-0.7193***	-0.5790***
	[-31.31]	[-57.27]	[-12.10]	[-35.44]	[-26.46]	[-22.92]	[-18.49]
$hp\_loss \times \sqrt{hp\_time}$	0.2851***	0.5630***	0.1116***	0.2869***	0.2804***	0.2851***	0.2441***
	[26.81]	[37.27]	[12.17]	[23.58]	[22.66]	[20.28]	[16.15]
$\sqrt{hp\_time}$	0.1207***	0.7321***	-0.0400***	0.1945***	0.0965***	0.1207***	0.0845***
	[13.60]	[76.90]	[-2.78]	[13.05]	[10.68]	[10.09]	[7.38]
$outflow\_dummy$							0.8315***
							[23.43]
$outflow\_dummy \times$ $hp\_overhang$							-0.0601*
							[-1.87]
$ivol$	-1.9053***	1.5013***	-4.7824***	6.0914***	-3.8651***	-1.9053*	-1.1410
	[-2.64]	[2.71]	[-4.06]	[5.90]	[-4.82]	[-1.92]	[-1.32]
$Constant$	-0.9083***	-2.4002***	-0.1157*	-1.5513***	-0.7141***	-0.9083***	-1.2893***
	[-29.90]	[-97.34]	[-1.67]	[-33.53]	[-21.60]	[-18.69]	[-30.57]
Error Cluster Level	Fund	Fund	Fund	Fund	Fund	Fund-Quarter	Fund
Observations	20,399,540	11,449,063	8,950,477	5,266,244	15,133,296	20,399,540	7,384,251
Pseudo R-squared	0.0112	0.0382	0.00382	0.0209	0.00973	0.0112	0.0375

Table II: Selling Behavior Regressions. For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. hp_gain and hp_loss represent the holding period gain and holding period loss as defined in equations 2 and 3, respectively. hp_time is equal to the weighted average holding period, in unit of months. $flow1m$ is the one month flow calculated for the subset of funds in the CRSP Mutual Fund Holdings database. $outflow\_dummy$ is equal to one if $flow1m < 0$. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. With the exception of regression 6 (which calculates two-way clustered errors at the fund-time level), all errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Data Filter	All months	Feb-Dec	All months	Feb-Dec	All months	Feb-Dec	All months	Feb-Dec
gain_overhang	0.0202***	0.0248***	0.0062*	0.0105***	0.0277***	0.0307***	0.0144***	0.0154***
	[4.61]	[5.50]	[1.72]	[2.86]	[8.45]	[9.12]	[6.02]	[6.08]
loss_overhang	0.0020	0.0038**	-0.0064***	-0.0048***	-0.0041***	-0.0033**	-0.0090***	-0.0085***
	[1.07]	[2.07]	[-4.97]	[-3.72]	[-2.94]	[-2.30]	[-8.65]	[-7.89]
$Ret^{+}_{-12,-2}$			0.0041**	0.0041**			0.0061***	0.0075***
			[2.47]	[2.52]			[4.93]	[6.11]
$Ret^{-}_{-12,-2}$			0.0493***	0.0515***			0.0299***	0.0315***
			[12.73]	[12.72]			[9.70]	[10.03]
Ret_{-1}					-0.0516***	-0.0456***	-0.0432***	-0.0363***
					[-12.86]	[-10.98]	[-10.60]	[-8.76]
$Ret_{-36,-13}$					-0.0016***	-0.0011**	-0.0009*	-0.0004
					[-3.06]	[-2.06]	[-1.85]	[-0.72]
$logBM$					0.0010*	0.0010*	0.0008	0.0007
					[1.87]	[1.76]	[1.49]	[1.35]
$logMktcap$					-0.0005*	-0.0003	-0.0008***	-0.0006**
					[-1.89]	[-1.00]	[-2.89]	[-2.11]
$ivol$					-0.2513***	-0.3271***	-0.2353***	-0.3149***
					[-4.45]	[-5.70]	[-4.29]	[-5.67]
$turnover$					-0.1411	-0.1624	-0.2176	-0.2578
					[-0.80]	[-0.89]	[-1.30]	[-1.49]
$constant$	0.0089***	0.0077***	0.0113***	0.0103***	0.0213***	0.0186***	0.0252***	0.0232***
	[3.78]	[3.17]	[5.24]	[4.62]	[5.37]	[4.53]	[6.52]	[5.77]
Observations	1,164,212	1,067,071	1,136,140	1,040,886	932,310	852,065	932,140	851,911
R-squared	0.017	0.016	0.030	0.029	0.061	0.059	0.067	0.065
# of months	393	360	393	360	391	358	391	358

Table III: Pricing effect Fama-Macbeth regressions. For ease of notation, subscripts have been omitted. Cross-sectional WLS regressions are run for each month with the weight equal to the previous month gross return, and coefficient estimates and t-statistics (shown in square brackets) are calculated using the time series of cross-sectional estimations. The dependent variable is return in month t, and the explanatory variables are all available at the end of month t-1. *gain_overhang* and *loss_overhang* are stock-level unrealized gains and loss aggregated across all mutual funds, as defined in equation 8 and 9. $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$are the positive part and the negative part of cumulative return from month $t-12$ to $t-2$; Ret_{-1} is return in month $t-1$; $Ret_{-36,-13}$ is cumulative return from past three year to past one year. $logBM$ and $logMktcap$ are the logarithm of a firm's book-to-market ratio and market capitalization, respectively. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. $turnover$ is the average daily turnover ratio in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-squared is the average R^2 from the cross-sectional regressions.

	(1)	(2)
Data Filter	All months	Feb-Dec
CGO	-0.0012	-0.0005
	[-1.28]	[-0.53]
VSP	0.0156***	0.0159***
	[8.44]	[8.19]
$Ret^+_{-12,-2}$	0.0061***	0.0075***
	[4.93]	[6.11]
$Ret^-_{-12,-2}$	0.0299***	0.0315***
	[9.70]	[10.03]
Ret_{-1}	-0.0432***	-0.0363***
	[-10.60]	[-8.76]
$Ret_{-36,-13}$	-0.0009*	-0.0004
	[-1.85]	[-0.72]
$logBM$	0.0008	0.0007
	[1.49]	[1.35]
$logMktcap$	-0.0008***	-0.0006**
	[-2.89]	[-2.11]
$ivol$	-0.2353***	-0.3149***
	[-4.29]	[-5.67]
$turnover$	-0.2176	-0.2578
	[-1.30]	[-1.49]
$constant$	0.0252***	0.0232***
	[6.52]	[5.77]
Observations	932,140	851,911
R-squared	0.067	0.065
# of months	391	358

Table IV: Horse race between CGO and VSP, Fama-Macbeth regressions. For ease of notation, subscripts have been omitted. Cross-sectional WLS regressions are run for each month with the weight equal to the previous month gross return, and coefficient estimates and t-statistics (shown in square brackets) are calculated using the time series of cross-sectional estimations. The dependent variable is return in month t, and the explanatory variables are all available at the end of month t-1. Capital Gains Overhang (CGO) and V-shaped Selling Pressure (VSP) are stock-level variables that capture selling pressure from unrealized gains and loss aggregated across all mutual funds. $CGO = gain\_overhang + loss\_overhang$ and $VSP = gain\_overhang + 0.5|loss\_overhang|$. $Ret^+_{-12,-2}$ and $Ret^-_{-12,-2}$are the positive part and the negative part of cumulative return from month $t-12$ to $t-2$; Ret_{-1} is return in month $t-1$; $Ret_{-36,-13}$ is cumulative return from past three year to past one year. $logBM$ and $logMktcap$ are the logarithm of a firm's book-to-market ratio and market capitalization, respectively. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. $turnover$ is the average daily turnover ratio in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-squared is the average R^2 from the cross-sectional regressions.

Sort Variable	*wt_exp_ratio*		
	LOW	MED	HIGH
hp_gain	2.2209***	3.9391***	4.1592***
	[10.06]	[17.23]	[28.67]
hp_loss	-1.0195***	-1.6066***	-1.6853***
	[-12.77]	[-13.24]	[-24.21]
$hp\_gain \times \sqrt{hp\_time}$	-0.2953***	-0.6915***	-0.7976***
	[-7.28]	[-12.80]	[-22.11]
$hp\_loss \times \sqrt{hp\_time}$	0.1532***	0.2743***	0.3106***
	[8.63]	[8.95]	[17.05]
$\sqrt{hp\_time}$	0.0889***	0.1364***	0.1663***
	[4.67]	[7.31]	[10.93]
ivol	-5.6123***	1.3826	2.3780***
	[-3.25]	[0.69]	[3.25]
Constant	-0.9366***	-1.1709***	-0.9714***
	[-12.54]	[-16.07]	[-20.69]
Error Cluster Level	Fund	Fund	Fund
Observations	2,585,470	2,584,334	2,584,837
Pseudo R-squared	0.00661	0.0123	0.0141

Table V: Selling Behavior Regressions - Characteristic Splits - Expense Ratio. For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. *hp_gain* and *hp_loss* represent the holding period gain and holding period loss as defined in equations 2 and 3, respectively. *hp_time* is equal to the weighted average holding period. *ivol* is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. All errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

Sort Variable	wt_turn_ratio			$\overline{hp\_time}$		
	LOW	MED	HIGH	LOW	MED	HIGH
hp_gain	2.3066***	3.9285***	4.9288***	6.0177***	4.9142***	2.9303***
	[10.99]	[24.05]	[31.66]	[58.84]	[66.47]	[21.66]
hp_loss	-0.8816***	-1.6704***	-2.0591***	-2.0353***	-1.6144***	-1.0776***
	[-12.93]	[-15.60]	[-30.51]	[-39.08]	[-52.11]	[-19.98]
$hp\_gain \times \sqrt{hp\_time}$	-0.2991***	-0.7148***	-1.1087***	-1.6781***	-1.0096***	-0.4304***
	[-8.15]	[-18.46]	[-24.58]	[-52.51]	[-54.42]	[-18.04]
$hp\_loss \times \sqrt{hp\_time}$	0.1203***	0.2931***	0.4371***	0.4844***	0.3041***	0.1537***
	[8.98]	[10.67]	[22.95]	[31.57]	[38.89]	[14.98]
$\sqrt{hp\_time}$	0.1085***	0.1739***	0.3319***	0.6429***	0.3053***	0.1081***
	[6.83]	[10.83]	[20.15]	[74.54]	[48.44]	[13.23]
$ivol$	-6.4301***	0.5969	1.4047*	2.5407***	-0.1455	-9.1692***
	[-3.68]	[0.35]	[1.83]	[4.52]	[-0.19]	[-5.90]
$Constant$	-1.1047***	-1.4087***	-1.2094***	-2.0995***	-1.4563***	-1.0707***
	[-16.46]	[-20.99]	[-25.40]	[-80.27]	[-59.45]	[-25.77]
Error Cluster Level	Fund	Fund	Fund	Fund	Fund	Fund
Observations	2,598,329	2,571,856	2,584,456	6,681,751	6,682,111	6,682,215
Pseudo R-squared	0.00827	0.0136	0.0242	0.0428	0.0177	0.00645

Table VI: Selling Behavior Regressions - Characteristic Splits - Trading Frequency and Magnitude. For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. hp_gain and hp_loss represent the holding period gain and holding period loss as defined in equations 2 and 3, respectively. hp_time is equal to the weighted average holding period. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. All errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

characteristic variable	*wt_exp_ratio*		*wt_turn_ratio*		$\overline{hp\_time}$	
Data Filter	All months	Feb-Dec	All months	Feb-Dec	All months	Feb-Dec
gain_overhang_charaL	0.0130***	0.0134***	0.0143***	0.0148***	0.0173***	0.0207***
	[4.81]	[4.64]	[5.04]	[4.90]	[3.84]	[4.51]
gain_overhang_charaH	0.0399***	0.0464***	0.0207***	0.0239***	0.0144***	0.0147***
	[3.84]	[4.20]	[2.71]	[3.03]	[5.51]	[5.33]
gain_overhang_charaU	0.0288***	0.0333***	0.0343***	0.0386***		
	[2.95]	[3.20]	[3.47]	[3.66]		
loss_overhang_charaL	-0.0109***	-0.0099***	-0.0094***	-0.0087***	-0.0096***	-0.0103***
	[-8.27]	[-7.21]	[-6.14]	[-5.89]	[-4.99]	[-5.08]
loss_overhang_charaH	-0.0108***	-0.0102**	-0.0165***	-0.0169***	-0.0097***	-0.0086***
	[-2.63]	[-2.30]	[-4.94]	[-4.80]	[-6.89]	[-5.98]
loss_overhang_charaU	-0.0104***	-0.0118***	-0.0097***	-0.0102***		
	[-2.95]	[-3.40]	[-2.95]	[-3.03]		
$Ret^{+}_{-12,-2}$	0.0055***	0.0068***	0.0055***	0.0068***	0.0060***	0.0072***
	[4.46]	[5.55]	[4.36]	[5.43]	[4.90]	[5.98]
$Ret^{-}_{-12,-2}$	0.0308***	0.0323***	0.0300***	0.0314***	0.0300***	0.0318***
	[9.66]	[9.93]	[9.27]	[9.48]	[9.97]	[10.36]
Ret_{-1}	-0.0430***	-0.0363***	-0.0431***	-0.0363***	-0.0426***	-0.0358***
	[-10.64]	[-8.81]	[-10.68]	[-8.83]	[-10.64]	[-8.79]
$Ret_{-36,-13}$	-0.0009*	-0.0003	-0.0010**	-0.0005	-0.0010*	-0.0004
	[-1.77]	[-0.64]	[-2.03]	[-0.99]	[-1.91]	[-0.81]
$logBM$	0.0010*	0.0010*	0.0009	0.0009	0.0008	0.0008
	[1.96]	[1.86]	[1.61]	[1.54]	[1.60]	[1.52]
$logMktcap$	-0.0007**	-0.0005*	-0.0008***	-0.0006**	-0.0008***	-0.0006**
	[-2.47]	[-1.70]	[-2.90]	[-2.19]	[-2.85]	[-2.06]
ivol	-0.2399***	-0.3221***	-0.2458***	-0.3275***	-0.2369***	-0.3168***
	[-4.37]	[-5.80]	[-4.49]	[-5.92]	[-4.31]	[-5.71]
turnover	-0.2669	-0.3119*	-0.2974*	-0.3531**	-0.2496	-0.2988*
	[-1.63]	[-1.85]	[-1.85]	[-2.13]	[-1.51]	[-1.76]
constant	0.0229***	0.0210***	0.0245***	0.0228***	0.0251***	0.0232***
	[6.01]	[5.29]	[6.32]	[5.66]	[6.48]	[5.75]
Observations	909,116	830,261	885,022	808,048	930,833	850,731
R-squared	0.070	0.069	0.072	0.070	0.070	0.068
# of months	385	352	385	352	391	358

Table VII: Pricing Effect Fama-Macbeth regressions - Characteristic Decomposition. For ease of notation, subscripts have been omitted. Cross-sectional WLS regressions are run for each month with the weight equal to the previous month gross return, and coefficient estimates and t-statistics (shown in square brackets) are calculated using the time series of cross-sectional estimations. The dependent variable is return in month t, and the explanatory variables are all available at the end of month t-1. *gain_overhang_charaL*, *gain_overhang_charaH*, and *gain_overhang_charaU*, as defined in equation 12, 13, and 14, are stock-level unrealized gains aggregated across mutual funds in the low group, the high group, and the undefined group based on fund characteristics; the fund characteristics are expense ratio, turnover ratio, and average holding time in columns (1) and (2), columns (3) and (4), and columns (5) and (6), respectively. *loss_overhang_charaL*, *loss_overhang_charaH*, and *loss_overhang_charaU* are similarly defined, with the only difference that they aggregate unrealized losses instead of unrealized gains. $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$are the positive part and the negative part of cumulative return from month $t-12$ to $t-2$; Ret_{-1} is return in month $t-1$; $Ret_{-36,-13}$ is cumulative return from past three year to past one year. $logBM$ and $logMktcap$ are the logarithm of a firm's book-to-market ratio and market capitalization, respectively. *ivol* is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. *turnover* is the average daily turnover ratio in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-squared is the average R^2 from the cross-sectional regressions.

Original Measure	(1)	Alternative Measure	(2)
hp_gain	3.9974***	*hp_gain_alt*	2.3876***
	[41.33]		[36.61]
hp_loss	-1.6130***	*hp_loss_alt*	-4.2751***
	[-37.92]		[-47.63]
$hp\_gain \times \sqrt{hp\_time}$	-0.7076***	$hp\_gain\_alt \times \sqrt{hp\_time}$	-0.4216***
	[-30.70]		[-28.63]
$hp\_loss \times \sqrt{hp\_time}$	0.2830***	$hp\_loss\_alt \times \sqrt{hp\_time}$	0.7125***
	[26.96]		[31.13]
$\sqrt{hp\_time}$	0.1209***	$\sqrt{hp\_time}$	0.1285***
	[14.05]		[15.58]
best_dummy	0.0938***	*best_dummy*	0.0502***
	[7.51]		[4.18]
worst_dummy	0.1498***	*worst_dummy*	0.1907***
	[9.73]		[12.08]
ivol	-1.0863*	*ivol*	-3.2361***
	[-1.73]		[-5.09]
Constant	-1.0374***	*Constant*	-1.0564***
	[-44.92]		[-47.32]
Error Cluster Level	Fund	Error Cluster Level	Fund
Observations	20,399,540	Observations	20,397,229
Pseudo R-squared	0.0129	Pseudo R-squared	0.0156

Table VIII: Selling Behavior Regressions - Extreme Rank Dependency. For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. *hp_gain* and *hp_loss* represent the holding period gain and holding period loss as defined in equations 2 and 3, respectively. The alternative measures (*hp_gain_alt* and *hp_loss_alt*) are normalized by the purchase price instead of the current price as defined in equations A2 and A3, respectively. *hp_time* is equal to the weighted average holding period. *best_dummy* is a dummy identifying that the security is the best performing security (ranked by *hp_overhang*) in the portfolio in a given period; *worst_dummy* is a dummy identifying that the security is the worst performing security (again ranked by *hp_overhang*) in the portfolio in a given period. *ivol* is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. All errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

Original Measure	(1)	(2)	Alternative Measure	(3)	(4)
Data Filter	All months	Feb-Dec	Data Filter	All months	Feb-Dec
$gain\_overhang$	0.0158***	0.0171***	$gain\_overhang\_alt$	0.0114***	0.0115***
	[6.55]	[6.68]		[7.77]	[7.37]
$loss\_overhang$	-0.0071***	-0.0064***	$loss\_overhang\_alt$	-0.0179***	-0.0148***
	[-6.42]	[-5.58]		[-7.02]	[-5.67]
$best\_dummy$	-0.0004	-0.0007	$best\_dummy$	-0.0003	-0.0005
	[-0.70]	[-1.21]		[-0.44]	[-0.87]
$worst\_dummy$	0.0049***	0.0053***	$worst\_dummy$	0.0048***	0.0054***
	[7.78]	[8.43]		[7.30]	[8.12]
$Ret^+_{-12,-2}$	0.0059***	0.0073***	$Ret^+_{-12,-2}$	0.0059***	0.0073***
	[4.80]	[6.00]		[4.65]	[5.91]
$Ret^-_{-12,-2}$	0.0306***	0.0322***	$Ret^-_{-12,-2}$	0.0307***	0.0321***
	[10.01]	[10.35]		[10.07]	[10.32]
Ret_{-1}	-0.0420***	-0.0350***	Ret_{-1}	-0.0419***	-0.0350***
	[-10.34]	[-8.48]		[-10.58]	[-8.70]
$Ret_{-36,-13}$	-0.0010*	-0.0004	$Ret_{-36,-13}$	-0.0009*	-0.0003
	[-1.94]	[-0.80]		[-1.81]	[-0.61]
$logBM$	0.0008	0.0007	$logBM$	0.0008	0.0007
	[1.44]	[1.29]		[1.54]	[1.37]
$logMktcap$	-0.0010***	-0.0008***	$logMktcap$	-0.0009***	-0.0007**
	[-3.51]	[-2.69]		[-3.37]	[-2.56]
$ivol$	-0.2306***	-0.3093***	$ivol$	-0.2323***	-0.3082***
	[-4.19]	[-5.55]		[-4.23]	[-5.53]
$turnover$	-0.2442	-0.2846*	$turnover$	-0.2366	-0.2762
	[-1.47]	[-1.66]		[-1.42]	[-1.61]
$constant$	0.0270***	0.0250***	$constant$	0.0255***	0.0238***
	[7.06]	[6.26]		[6.69]	[5.98]
Observations	932,140	851,911	Observations	932,140	851,911
R-squared	0.069	0.067	R-squared	0.068	0.066
# of months	391	358	# of months	391	358

Table IX: Pricing effect Fama-Macbeth regressions - Extreme Rank Dependency. For ease of notation, subscripts have been omitted. Cross-sectional WLS regressions are run for each month with the weight equal to the previous month gross return, and coefficient estimates and t-statistics (shown in square brackets) are calculated using the time series of cross-sectional estimations. The dependent variable is return in month t, and the explanatory variables are all available at the end of month t-1. $gain\_overhang$ and $loss\_overhang$ are stock-level unrealized gains and loss aggregated across all mutual funds, as defined in equation 8 and 9. The alternative measures ($gain\_overhang\_alt$ and $loss\_overhang\_alt$) are normalized by the purchase price instead of the current price as defined in equations A4 and A5, respectively. $best\_dummy$ ($worst\_dummy$) is a dummy variable that equals to 1 if the security is the best-performing (worst-performing) security in at least one fund's portfolio at the end of month t-1 (according to publicly available information), 0 otherwise.$Ret^+_{-12,-2}$ and $Ret^-_{-12,-2}$are the positive part and the negative part of cumulative return from month $t-12$ to $t-2$; Ret_{-1} is return in month $t-1$; $Ret_{-36,-13}$ is cumulative return from past three year to past one year. $logBM$ and $logMktcap$ are the logarithm of a firm's book-to-market ratio and market capitalization, respectively. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. $turnover$ is the average daily turnover ratio in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-squared is the average R^2 from the cross-sectional regressions.

Data Filter	(1) Index-Based funds	(2) Pure Index Funds	(3) Enhanced Index Funds
hp_gain	0.8636	1.7085	7.6087***
	[0.58]	[1.46]	[4.29]
hp_loss	-0.1912	-0.2259	-0.7832
	[-0.66]	[-0.58]	[-0.98]
$\frac{hp\_gain\times}{\sqrt{hp\_time}}$	0.0304	-0.1769	-2.1444***
	[0.09]	[-1.27]	[-5.04]
$\frac{hp\_loss\times}{\sqrt{hp\_time}}$	0.0405	0.0170	0.2224
	[0.51]	[0.33]	[0.91]
$\sqrt{hp\_time}$	0.1557**	0.1351***	0.4802***
	[2.09]	[3.62]	[3.32]
$ivol$	18.1652**	-8.9578	49.0930***
	[2.18]	[-0.70]	[3.96]
$Constant$	-2.1722***	-0.6618	-2.2040***
	[-5.21]	[-1.25]	[-5.13]
Observations	37,101	37,857	2,370
Pseudo R-squared	0.0181	0.0176	0.0750

Table X: Selling Behavior Regressions - Placebo Test With Index Funds. For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%

	(1)	(2)	(3)	(4)	(5)	(6)
Data Filter	None	$\sqrt{hp\_time} \leq 3.5$	$\sqrt{hp\_time} > 3.5$	$1980 \leq year \leq 2001$	$2002 \leq year \leq 2012$	None
hp_gain_alt	2.4814***	4.4986***	0.8984***	2.9865***	2.4128***	2.4814***
	[38.51]	[69.43]	[18.22]	[49.80]	[31.49]	[31.09]
hp_loss_alt	-4.2487***	-5.6394***	-2.3078***	-4.6647***	-4.0796***	-4.2487***
	[-46.83]	[-63.66]	[-20.29]	[-45.81]	[-37.62]	[-36.46]
$hp\_gain\_alt \times \sqrt{hp\_time}$	-0.4303***	-1.2958***	-0.1178***	-0.5776***	-0.4057***	-0.4303***
	[-29.13]	[-61.05]	[-13.23]	[-36.11]	[-24.35]	[-23.18]
$hp\_loss\_alt \times \sqrt{hp\_time}$	0.7079***	1.4140***	0.3023***	0.7594***	0.6807***	0.7079***
	[30.63]	[45.41]	[13.05]	[25.72]	[26.22]	[26.26]
$\sqrt{hp\_time}$	0.1273***	0.7407***	-0.0349**	0.2007***	0.1021***	0.1273***
	[14.93]	[78.47]	[-2.51]	[13.94]	[11.71]	[10.95]
$ivol$	-3.9540***	-0.7919	-6.4337***	3.4975***	-5.7698***	-3.9540***
	[-5.46]	[-1.45]	[-5.42]	[3.50]	[-7.13]	[-3.77]
$Constant$	-0.9240***	-2.4206***	-0.1289*	-1.5825***	-0.7206***	-0.9240***
	[-31.40]	[-98.70]	[-1.92]	[-36.22]	[-22.24]	[-19.12]
Error Cluster Level	Fund	Fund	Fund	Fund	Fund	Fund-Quarter
Observations	20,397,229	11,448,252	8,948,977	5,266,107	15,131,122	20,397,229
Pseudo R-squared	0.0137	0.0414	0.00449	0.0260	0.0115	.0137

Table AI: Selling Behavior Regressions - Alternative Measure. For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. The alternative measures (hp_gain_alt and hp_loss_alt) are normalized by the purchase price instead of the current price as defined in equations A2 and A3, respectively. hp_time is equal to the weighted average holding period. $best\_dummy$ is a dummy identifying that the security is the best performing security (ranked by $hp\_overhang$) in the portfolio in a given period; $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. With the exception of regression 7 (which calculates two-way clustered errors at the fund-time level), all errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Data Filter	All months	Feb-Dec	All months	Feb-Dec	All months	Feb-Dec	All months	Feb-Dec
gain_overhang_alt	0.0115***	0.0127***	0.0078***	0.0089***	0.0172***	0.0181***	0.0115***	0.0115***
	[5.01]	[5.21]	[4.52]	[4.85]	[10.04]	[10.00]	[7.70]	[7.25]
loss_overhang_alt	0.0058	0.0127**	-0.0195***	-0.0133***	-0.0082**	-0.0044	-0.0225***	-0.0198***
	[1.16]	[2.59]	[-5.16]	[-3.57]	[-2.30]	[-1.23]	[-9.03]	[-7.77]
$Ret^{+}_{-12,-2}$			0.0036**	0.0038**			0.0060***	0.0074***
			[2.15]	[2.31]			[4.74]	[5.98]
$Ret^{-}_{-12,-2}$			0.0507***	0.0525***			0.0303***	0.0316***
			[13.67]	[13.44]			[9.85]	[10.08]
Ret_{-1}					-0.0516***	-0.0456***	-0.0429***	-0.0362***
					[-13.06]	[-11.16]	[-10.83]	[-8.98]
$Ret_{-36,-13}$					-0.0015***	-0.0011**	-0.0008*	-0.0002
					[-3.02]	[-2.03]	[-1.69]	[-0.49]
$logBM$					0.0010*	0.0010*	0.0008	0.0008
					[1.93]	[1.81]	[1.58]	[1.42]
$logMktcap$					-0.0005	-0.0002	-0.0008***	-0.0006**
					[-1.62]	[-0.74]	[-2.75]	[-1.97]
$ivol$					-0.2511***	-0.3230***	-0.2394***	-0.3165***
					[-4.48]	[-5.65]	[-4.38]	[-5.70]
$turnover$					-0.1251	-0.1417	-0.2135	-0.2518
					[-0.70]	[-0.77]	[-1.27]	[-1.46]
$constant$	0.0095***	0.0093***	0.0095***	0.0093***	0.0203***	0.0181***	0.0234***	0.0217***
	[4.48]	[4.21]	[4.75]	[4.50]	[5.16]	[4.41]	[6.03]	[5.35]
Observations	1,164,212	1,067,071	1,136,140	1,040,886	932,310	852,065	932,140	851,911
R-squared	0.018	0.017	0.030	0.029	0.061	0.059	0.067	0.065
# of months	393	360	393	360	391	358	391	358

Table AII: Pricing effect Fama-Macbeth regressions - alternative overhang measures. For ease of notation, subscripts have been omitted. Cross-sectional WLS regressions are run for each month with the weight equal to the previous month gross return, and coefficient estimates and t-statistics (shown in square brackets) are calculated using the time series of cross-sectional estimations. The dependent variable is return in month t, and the explanatory variables are all available at the end of month t-1. *gain_overhan_alt* and *loss_overhang_alt* are stock-level unrealized gains and loss aggregated across all mutual funds, as defined in equation A4 and A5. $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$are the positive part and the negative part of cumulative return from month $t-12$ to $t-2$; Ret_{-1} is return in month $t-1$; $Ret_{-36,-13}$ is cumulative return from past three year to past one year. $logBM$ and $logMktcap$ are the logarithm of a firm's book-to-market ratio and market capitalization, respectively. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. $turnover$ is the average daily turnover ratio in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-squared is the average R^2 from the cross-sectional regressions.

Simple Version of Original Measure	(1)	(2)	Simple Version of Alternative Measure	(3)	(4)
hp_gain_simple	0.4540***	0.4798***	$hp\_gain\_alt\_simple$	0.3530***	0.3512***
	[8.98]	[7.59]		[11.45]	[9.29]
hp_loss_simple	-0.2478***	-0.2234***	$hp\_loss\_alt\_simple$	-0.8409***	-0.7470***
	[-11.82]	[-8.68]		[-17.11]	[-11.39]
$\frac{hp\_gain\_simple\times}{\sqrt{hp\_time\_simple}}$	-0.0896***	-0.0831***	$\frac{hp\_gain\_alt\_simple\times}{\sqrt{hp\_time\_simple}}$	-0.0631***	-0.0574***
	[-10.08]	[-8.10]		[-12.15]	[-9.55]
$\frac{hp\_loss\_simple\times}{\sqrt{hp\_time\_simple}}$	0.0440***	0.0387***	$\frac{hp\_loss\_alt\_simple\times}{\sqrt{hp\_time\_simple}}$	0.1425***	0.1234***
	[10.87]	[7.79]		[13.90]	[9.11]
$\sqrt{hp\_time\_simple}$	-0.0529***	-0.0529***	$\sqrt{hp\_time\_simple}$	-0.0462***	-0.0473***
	[-9.07]	[-6.30]		[-8.76]	[-5.93]
$ivol$	0.5184	2.4124***	$ivol$		1.8986**
	[0.75]	[2.83]			[2.26]
$flow1m$		-7.2858***	$flow1m$		-7.2774***
		[-18.48]			[-18.45]
$Constant$	-0.1169***	-0.2442***	$Constant$	-0.1509***	-0.2707***
	[-4.71]	[-7.39]		[-9.52]	[-8.53]
Observations	20,399,540	10,728,704	Observations	20,400,376	10,728,704
Pseudo R-squared	0.00462	0.0223	Pseudo R-squared	0.00491	0.0225

Table AIII: Selling Behavior Regressions - Simple Measures. For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. The simple measures (hp_gain_simple, hp_loss_simple, hp_time_simple) are constructed using only the "oldest" position in the security that is still in the portfolio assuming a FIFO mental accounting. $hp\_gain\_alt\_simple$, $hp\_loss\_alt\_simple$ are normalized by the purchase price instead of the current price. $best\_dummy$ is a dummy identifying that the security is the best performing security (ranked by $hp\_overhang$) in the portfolio in a given period; $worst\_dummy$ is a dummy identifying that the security is the worst performing security (again ranked by $hp\_overhang$) in the portfolio in a given period. $flow1m$ is the one month flow calculated for the subset of funds in the CRSP Mutual Fund Holdings database. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%