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Overselling winners and losers: How mutual fund managers' trading behavior affects asset prices ☆

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ABSTRACT

We link a seemingly biased trading behavior to equilibrium asset prices. U.S. equity mutual fund managers tend to sell both their big winners and big losers. This selling pressure pushes down current prices and leads to higher future returns; aggregating across funds, we find that securities for which investors have large unrealized gains and losses outperform in the subsequent month. Funds with larger turnover, shorter holding period, and higher expense ratios, are significantly more likely to manifest this trading pattern, and unrealized profits from such funds have stronger return predictability. This cross-sectional return predictability is difficult to reconcile with alternative explanations.

A primary hurdle of behavioral explanations of asset pricing phenomena has been to directly and unambiguously tie the examined behavioral bias to changes in equilibrium prices. Lacking direct measures of the central items in behavioral asset pricing models, most studies have relied on indirect tests, which typically do not have sufficient power to reject competing explanations. In this research, we speak directly to this challenge in a well-defined context by documenting equilibrium stock price responses to the biased trading behavior of mutual fund managers.

Using data on mutual fund holdings and fund characteristics, we present three sets of main findings. First, we document that mutual fund managers are, like presumably less sophisticated retail investors, more likely to sell holdings with large unrealized gains and losses rather than those with small unrealized gains and losses. Second, we link this behavior to fluctuations in stock prices by constructing stock-level variables to capture this selling pressure. We show that these variables produce cross-sectional return predictability. Third, we pin down the link between the selling behavior and the price impact by exploring the heterogeneity across fund characteristics and their ensuing price impact. This cross-fund variation in return predictability is

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difficult to reconcile with alternative explanations and strongly links the underlying trading behavior to changes in aggregate prices.

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, this research has predominantly focused on the difference in selling propensity when investors experience a gain versus a loss, rather than a more flexible form of how investors trade in response to unrealized profits. Ben-David and Hirshleifer (2012) take a closer look at the individual trading account data as used by Strahilevitz et al. (2011) and discover a refinement in retail investor behavior: individual investors do not increase their selling probability monotonically from the extreme losers to the extreme winners; instead, they employ a V-shaped selling schedule in response to unrealized 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, meaning that the average propensity to sell following a gain is higher than the average propensity to sell following a loss. We refer to this asymmetric V-shaped selling schedule as the V-shaped disposition effect, as opposed to the disposition effect in its traditional monotonic sense.

In this paper, we first 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 command much more capital, are arguably more sophisticated than retail investors, and play a larger role in deciding equilibrium prices. Moreover, while the binary pattern of the original disposition effect is widely documented under numerous settings, the prevalence of the newly documented V-shape remains an open question. Among retail investors around the world, the evidence seems to be mixed. Though not the focus of their studies, several papers provide insight on the *shape* of investors' selling schedule: Seru et al. (2009, Fig. 3) show a similar asymmetric V-shape in Finnish investors from 1995 to 2003; in contrast, Grinblatt and Keloharju (2001, Table 1, Panels A and B), using the first two years of data from the same Finnish source, find the relation between selling and unrealized profits is generally monotonically increasing; finally, using Chinese retail brokerage account data, Frydman and Wang (2020, Table 2, Panel B) present a pattern that appears to be an inverted V-shape. As the prevalence (or the lack thereof) of this refined pattern would provide important empirical fodder for theories that aim to explain the disposition effect, there is a need for more evidence from other asset classes[4] and other investor categories where the original disposition effect has been shown to exist. We find that mutual fund managers, like individual traders in the Ben-David and Hirshleifer (2012) study, exhibit a V-shaped disposition effect.

Second, we argue that such trading behavior can generate a price impact and subsequent return predictability in the cross-section. How investors trade is interesting in and of itself, but it is relevant to asset pricing only to the extent that it impacts equilibrium price dynamics. As mutual fund managers are more apt to sell securities with large unrealized gains and losses (relative to securities with smaller gains and losses), this leads to selling pressure for such stocks for non-fundamental reasons.[5] This temporarily depresses the price of affected securities, and as future prices revert to fundamental values, affected stocks will outperform. To test this hypothesis, we construct stock-level price impact 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 fund managers' V-shaped selling schedule, we separate unrealized gains from unrealized losses. The results confirm our hypothesis: stocks with large unrealized gains and losses indeed outperform in the next month, and the price effect is both economically and statistically significant. A 10 percentage point increase in the aggregate unrealized gains (losses) for a stock predicts a 9 (5) bps increase in next month's returns. A long-short portfolio strategy based on this effect can generate a monthly alpha of approximately 0.5%, with a Sharpe ratio equal to 1.2. These results are consistent with price effects documented by An (2016) where investors' aggregate cost base is approximated based on past prices and trading volumes.

Third, with a focus on establishing the link between fund managers' trading behavior and the associated price effect, we conduct a series of tests to exam the cross-sectional variation of the V-shaped disposition effect across various mutual fund characteristics. We find that mutual funds with higher turnover ratios, shorter average holding periods, and higher expense ratios tend to have a steeper V-shaped selling schedule. This tendency does not appear to be stronger among funds whose managers graduated from institutions with higher average SAT scores, consistent with this being a biased behavior. We then decompose our security-level unrealized gains and losses into those from "more-disposition-prone" funds and those from"less-disposition-prone" funds; we show that unrealized profits from the more-disposition-prone funds are stronger in predicting future returns.

This exercise offers several benefits. First, it allows us to pin down the source of the return predictability we document.

[1] See Odean (1998) and Grinblatt and Keloharju (2001) as examples for individual investors. See Locke and Mann (2005), Shapira and Venezia (2001), and Coval and Shumway (2005) for institutional investors.

[2] See, for example, Genesove and Mayer (2001) in housing markets, Heath et al. (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 evidence of the disposition effect in various countries. For a thorough survey of the disposition effect, see the review article by Barber and Odean (2013).

[4] Korteweg et al. (2016) find an asymmetric V-shaped selling schedule in the arts market.

[5] The V-shaped selling schedule is not necessarily a behavioral bias per se. However, if it is driven by informed trading, then such selling reflects the process of information being incorporated into prices, and it is thus unlikely to generate return reversal in the future. Our test of price impact is then essentially a joint test of (1) the V-shaped disposition effect is a biased behavior, and (2) such behavior can impact equilibrium prices.

Although our selling pressure variable is motivated by and constructed according to a specific model, the unrealized gain and loss measures are essentially particular linear combinations of past returns; even though we control for past returns at various horizons, one might still be concerned that the return predictability somehow originates from past returns rather than the V-shaped disposition effect. Unlike the typical examination of cross-sectional variation in return predictability based on stock characteristics (such as size and institutional ownership), the cross-fund variation in selling behavior and the ensuing impact on asset prices is a unique prediction of our conjectured mechanism. Second, this cross-fund variation in selling behavior provides insight on the source of the V-shaped selling schedule. For instance, this trading pattern seems to be related to investors' speculativeness, measured by a higher turnover ratio and a lower average holding period; this is consistent with the finding on retail investors of Ben-David and Hirshleifer (2012).

This seemingly biased trading pattern may seem related to the rank effect documented by Hartzmark (2015), who finds that the extreme best and worst performer, relative to other stocks in the same portfolio, are more likely to be sold. We find that our results remain robustly strong after controlling in various ways for the rank effect, including explicitly excluding extremely ranked stocks. Our evidence corroborates the claim by Hartzmark (2015) that the disposition effect and the rank effect are distinct, simultaneously robust patterns of investor trading. Our work also relates to previous studies that examine the disposition effect among mutual fund managers. A few previous studies (e.g., Jin and Scherbina, 2011; Cici, 2012) find that (the binary pattern of) the disposition effect is absent or weak in the whole sample, but exists among a subset of mutual fund managers. Our findings suggest, if allowed for the refined V-shaped pattern, the disposition effect is much more prevalent in the mutual fund sample.

This V-shaped selling schedule we document sheds light on theories that seek to account for investors' trading patterns. Prospect theory (Kahneman and Tversky, 1979) has been commonly, yet informally, offered as an explanation for the disposition effect; however, Barberis and Xiong (2009) and Hens and Vlcek (2011) point out that prospect theory often fails to generate even the binary pattern of the disposition effect. The V-shaped selling schedule, as a refinement of the disposition effect, further raises the hurdle for theories that aim to explain investors' trading pattern in response to past profits. Several recent models, based on either prospect theory or realization utility, have successfully produced a binary pattern of the disposition effect (e.g., Barberis and Xiong, 2012; Ingersoll and Jin, 2012; Li and Yang, 2013; Meng and Weng, 2017). Among them, Ingersoll and Jin (2012) point out that under certain parameter values, an aggregation effect of their heterogeneous agents model can produce a V-shaped selling schedule. The model of Meng and Weng (2017) emphasizes the role of reference point adjustment in determining the shape of the selling schedule, and their model can generate both the V-shape and the inverted V-shape, depending on the adjustment speed of the reference point. The authors suggest that market experience and sophistication would make investors adjust their reference point more quickly; thus, they more likely to have a V-shaped selling schedule. Our finding of the V-shaped selling schedule among mutual fund managers is generally consistent with this view.

This paper also expands our understanding of the pricing implications of investor behavior. Looking at the relation between capital gains and selling behavior, the early literature on the pricing impact of the disposition effect is based exclusively 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. An (2016) 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 past prices and trading volumes. In this paper, we study manager trading behavior directly to explore the aggregate pricing implications of the V-shaped disposition effect and then explores how the correlates of manager trading behavior can explain stock price deviations from fundamentals.

Finally, our paper also extends the literature on the price impact of mutual fund managers' uninformed trades. Among others, Coval and Stafford (2007), Frazzini and Lamont (2008), and Lou (2012) show that mutual funds that experience outflows (inflows) would decrease (expand) existing positions, and this creates price pressure on stocks that are commonly held by these funds. Anton and Polk (2014) and Argyle (2015) find 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 originate from flow-induced trading and reflect the agency problems and institutional constraints modeled by Shleifer and Vishny (1997). On the contrary, the price impact we find is unrelated to flow pressure; the trading tendency of mutual fund managers *is* the source of the price deviation from fundamentals.

The rest of the paper is organized as follows. In Section 1, we describe the analytical framework of how the V-shaped disposition effect can affect asset prices. In Section 2, we provide an overview of the datasets we use. In Section 3, we construct the necessary variables and outline the specification strategy. We discuss the results in Section 4. In Section 5, we examine heterogeneity across funds, as well as the resulting cross-sectional variation in selling behavior and pricing implications. In Section 6, we explore various robustness checks and discuss additional analysis. Finally, we conclude in Section 7.

1. Hypothesis development

To better understand how the V-shaped disposition effect can affect asset prices, consider the analytical framework of Grinblatt and Han (2005). In their model, the supply of a stock is fixed and the disposition effect leads to a demand perturbation:

disposition-prone investors' demand function depends on their unrealized profits, in addition to the fundamental value of the stock. The authors show that the equilibrium price is a linear combination of the stock's fundamental value and the average investor's purchase price; therefore, the *percentage of unrealized profit* for the average investor can predict future returns. Now consider the price impact of the V-shaped disposition effect: because mutual fund managers are more likely to sell big winners/losers and hold small winners/losers, there is effectively excess demand for firms whose current share holders are facing small gains and losses, and there is a shortage of demand for firms whose average investors are facing large gains and losses. Consequently, the former group of stocks is relatively overvalued and the latter is relatively undervalued. Our empirical measures for price impact, the gain and loss overhang, are directly motivated by this insight.

It is worth noting that according to this model, the price impact induced by the V-shaped disposition effect is directly linked to the *unrealized* gains and losses (the ex-ante selling propensity) but not necessarily to the actual sales of the stock (the ex-post sales). The reason is twofold. First, in this framework, stocks with large (small) unrealized gains and losses are relatively undervalued (overvalued). This undervaluation (overvaluation) in equilibrium price can happen when the price at which the current holders *are willing to* sell is lower (higher) than the fundamental value of stock, due to the V-shaped disposition effect. This misvaluation does not have to take the form of actual sales and purchases. More importantly, the actual sales may contain confounding information: suppose that $\alpha\%$ of selling is driven by the V-shaped disposition effect and $(1-\alpha)\%$ is driven by other factors (information, rebalancing decisions, liquidity needs, etc.), then actual sales also capture the latter, which may have distinct pricing implications and will confound the price effect of the former. Particularly, if the $(1-\alpha)\%$ of sales is driven by private negative information, it would have an opposite pricing prediction from our proposed mechanism (e.g., Kelly, 2018).[6] Our approach is reminiscent of the construction of the hypothetical sales driven by fund flow as in Edmans et al. (2012). In that paper, in order to identify selling pressure that is unrelated to information about the firm, the authors employ hypothetical sales predicted by fund flow, instead of the actual fund sales.

One might naturally compare our setting to those in the studies on mutual fund flow-induced price pressure (e.g., Coval and Stafford, 2007; Lou, 2012). The timing of the return pattern we document is similar to that in Coval and Stafford (2007) where the reversal of the price pressure starts right after the formation period, but is distinct from Lou (2012) in which the price pressure reverts only after four quarters. We discuss this point in more detail in the Online Appendix.

We derive the pricing implications with a focus on fund managers' selling behavior rather than their buying behavior. In unreported results, we find that mutual fund managers seem to have an inverted V-shaped buying schedule; they tend to buy *less* when the magnitude of a gain or loss increases. Thus, the predicted price impact of buying is in line with the selling side, although this differs from the behavior of retail investors documented by Ben-David and Hirshleifer (2012). We focus on the selling side for two reasons. First, the disposition effect, i.e., the relation between unrealized capital gains and selling, has been robustly documented in numerous settings. The relation between unrealized profits and selling behavior is better defined given that investors are limited to securities in the portfolio when they sell (if we ignore short selling), but they face the entire market when they buy. Second, the focus on the selling side is in line with the finding that institutional investors are more prone to behavioral biases when selling but not when buying (Akepanidtaworn et al., 2019).

2. Data description

We collect data from several 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 from January 1980 to December 2018. Since the fund numbers (variable *fundno*) in Thomson Reuters database are often reused for unrelated funds, as reported in the data manual. We use WFICN from the MFLINKS database to identify mutual funds. These data are cross-checked at the fund-date level against the CRSP Mutual Fund Summary data as discussed below. We also use data from the CRSP Mutual Fund Summary database to construct some of the fund-date level control variables. Security prices and accounting information are taken from the CRSP Security File and Compustat, respectively. We excludes ADRs, ATCs, REITs, and closed-end funds, and focus on the common shares of domestic securities with a share code of 10 or 11. Similar to previous studies, we employ the following filters:

1. We exclude all fund-date combinations 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.

[6] Kelly (2018) shows that an *observed* sale of stock at a loss by an insider conveys more negative information than a sale at a gain. The reason is that if investors sell a stock at a loss despite the tendency to hold on to losers (the original disposition effect), then they must have very negative information about the stock, and thus such stocks will have low returns in the future. In other words, observing a sale in a region where investors tend not to sell implies that the posterior probability that they have negative information is higher. Kelly's (2018) study and our study are similar – both try to establish return predictability of selling related to unrealized profits. However, the underlying mechanisms are different and the return predictions are opposite. In the previous example, we are interested in measuring the unconditional selling propensity that contributes to the $\alpha\%$ of selling driven by the disposition effect; in contrast, Kelly (2018) tries to infer the posterior probability of information-induced selling conditional on observing an actual sale, which is related to the $(1-\alpha)\%$ of selling driven by information and other factors.

Applying these filters results in roughly 27 million 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 (e.g., Busse, 1999; Bollen and Busse, 2001; Greene and Hodges, 2002; Puckett and Yan, 2011; Bodson et al., 2013; Argyle, 2015), but given that the ratio of the size of trading to total net assets is relatively small, we abstract away from these realities. At best, daily trading simply adds noise to our estimation, and at worst it biases against our results.

3. Specification

Our selling behavior analysis is conducted at the fund-security-date level, and our pricing effect analysis is at the security-date level. We refer to the overhang (unrealized profit) of a single holding in the portfolio of a single fund as the "fund-holding overhang" (*fh_overhang*), and the aggregate overhang (unrealized profit) across all mutual funds for a single security as the "capital gains overhang" (*CGO*).

3.1. Trading behavior

To measure the unrealized profit since purchase, we construct the fund-holding overhang variable for a given security in the portfolio of fund f at time t as:

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

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 fund-holding overhang variable is a weighted average of the deviations of the current price from the purchase prices $(p_t - p_{t-n})$ as a percentage of the current price (p_t), where the weight is equal to the percentage of shares that were purchased at time $t - n$. Note that instead of using the purchase price (similar to a holding period return), the denominator is the current price; this is to be consistent with the construction of the capital gains overhang variables (discussed below). When aggregated to the security level, capital gains overhang constructed this way can be interpreted as the fund-holding 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 measure normalized by purchase price (p_{t-n}) does not offer this convenient interpretation.[7] 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 $V_{f,t,t-n}$.[8] 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 fund-holding overhang into fund-holding gain (*fh_gain*) and fund_holding loss (*fh_loss*), such that for a given security in the portfolio of fund f at time t:

$$fh\_gain_{ft} = Max\left\{\sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{(p_t - p_{t-n})}{p_t}\right], 0\right\} \tag{2}$$

and

$$fh\_loss_{ft} = Min\left\{\sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{(p_t - p_{t-n})}{p_t}\right], 0\right\}. \tag{3}$$

This construction implies that $fh\_overhang = fh\_gain + fh\_loss$ for every fund-holding-date. We also construct the variable *fh_time* to capture the weighted average amount of time that the shares have been held. For a given security, this is defined as:

$$fh\_time_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[t - (t-n)\right]. \tag{4}$$

Our primary model to examine fund managers' selling behavior is given by:

$$selling\%\_of\_shrout_{fit} = \alpha_{it} + \beta^{+} fh\_gain_{fit} + \beta^{-} fh\_loss_{fit} + \zeta^{+} fh\_gain_{fit} \times \sqrt{fh\_time_{fit}} + \zeta^{-} fh\_loss_{fit} \times \sqrt{fh\_time_{fit}} \tag{5}$$

[7] We also consider an alternative measure (constructed in Section 7) that is normalized by the purchase price; it does not qualitatively change our results.

[8] Frydman et al. (2017) provide insight on the rolling mental accounting of fund managers.

$$+\zeta\sqrt{fh\_time_{fit}} + \text{Controls}_{ft}\boldsymbol{\gamma} + \epsilon_{fit},$$

where $selling\%\_of\_shrout_{fit} = \left[\frac{\#\text{of shares sold}_{fit}}{\#\text{of shares outstanding}_{it}}\right] \times 100$ is the percentage of shares outstanding of stock i that were sold by fund f at time t, Controls_{ft} is a vector of fund-level control variables, and the regressions are run with stock-time fixed effects. Since our focus is to link selling behavior to price effects, the model specification has been designed to capture the potential price impact.

First, while most studies of investors' selling behavior examine the propensity to sell by employing a dummy variable as the dependent variable, we are more interested in the magnitude of trades that can potentially affect price. Normalizing the number of shares sold by the total number of shares outstanding makes the estimated coefficient comparable across funds and stocks. Second, by adding fixed effects at the stock-time level, we capture the difference in selling for the same stock at the same time that is purely driven by a fund's different level of unrealized profits. Also, this fixed effects model of selling behavior matches closely with the Fama-MacBeth (1973) regression we later employ in Section 3.2 in testing the price impact.

To address concerns that our observed effect may be mechanically influenced by the assumption of no intraquarterly trading between reporting months, we exclude 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 0.5% tail. As an exploration of robustness, we control for fund-level flows (when our data permit). Several alternative measures, including normalization by current price and using a selling dummy as the dependent variable, are explored in Section 7.

In Table 1, we report summary statistics for all fund-holding-date-level and fund-date-level variables used to examine fund managers' selling behavior.

3.2. Price effect

In our analysis of the pricing implications of a V-shaped selling schedule, we aggregate unrealized profit for a given security across all mutual funds. The capital gains overhang for a given security at time t is calculated at a monthly horizon and is defined similarly to the fund-holding overhang above:

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

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. This variable is the same as the capital gains overhang variable in Frazzini (2006). It is essentially the weighted average of unrealized profits for shares purchased at different times by the entire mutual fund sector, where the weight is equal to the percentage of shares that are purchased by the sector at a particular previous time, $t - n$. We then separate the gain part from the loss part of unrealized profits at the stock level. For every security-date:

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

and

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

Note that this definition is different from $Max\{CGO, 0\}$ and $Min\{CGO, 0\}$. In order to capture the V-shape in fund managers' selling schedule, it is crucial to separate gains and losses for each purchase. Consider for instance a stock with only two current holders; one made a purchase at t_1 with a 60% gain and the other made a purchase at t_2 with a 60% loss. According to the V-shaped selling schedule, both unrealized profits are large in magnitude and both would generate downward pressure on the current price. However, if one aggregates the two purchases first, the average unrealized profit would be close to zero. Based on this measure, one might wrongly predict that the stock is relatively overvalued. This simple example illustrates how the separated gain and loss overhang can better capture the price pressure over the CGO measure. Also, this construction implies

Table 1
Summary statistics for selling behavior variables. This table describes the data used to examine selling behavior. $Selling\%\_of\_shrout = \left[\frac{\#\text{of shares sold}}{\#\text{of shares outstanding}}\right] \times 100$ is the percentage of shares outstanding sold for a given stock by a given fund in a given time period. $\mathbb{I}(selling)$ is a fund-security-period dummy equal to 1 if the part or all of the security was sold in a given period. *fh_overhang* is the measure of overhang expressed in equation (1). *fh_overhang_alt* is the alternative measure of overhang expressed in equation (25). *fh_gain* is the fund-holding gain defined as $fh\_gain = Max\{fh\_overhang, 0\}$, while *fh_loss* is the fund-holding loss defined as $fh\_loss = Min\{fh\_overhang, 0\}$. *fh_gain_alt* and *fh_loss_alt* are the alternative holding period gain and loss as defined as $Max\{fh\_overhang\_alt, 0\}$ and $Min\{fh\_overhang\_alt, 0\}$, respectively. *fh_time* is the net purchase-weighted holding period at the fund-security-period level. *assets* are the Total Net Assets of the fund expressed in thousands ($). *shares* is the number of shares held at the fund-security-period level. *flow*1*m* is the 1 month flow, and *fret*1*m* is the 1 month fund return. *best_dummy* is a dummy equal to 1 for the highest ranked security according to *fh_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 *fh_overhang* in the portfolio of the fund in a given period. *wt_exp_ratio* is the weighted-average expense ratio for the fund. *turn_ratio* is the turnover ratio of the fund. *SAT* is the entrance SAT score (in 2005) of the fund manager's undergraduate institution.

Variable	N	Mean	p10	p25	p50	p75	p90	Std	Skewness	Kurtosis
Selling%_of_shrout	27,576,203	0.016	0	0	0	0.001	0.023	0.067	6.645	54.535
$\mathbb{I}(selling)$	27,576,203	0.391	0	0	0	1	1	0.488	0.448	1.2
fh_overhang	27,576,203	−0.001	−0.395	−0.09	0.015	0.184	0.344	0.326	−1.391	6.319
fh_overhang_alt	27,576,203	0.137	−0.253	−0.066	0.027	0.253	0.595	0.41	1.966	8.649
fh_gain	27,576,203	0.109	0	0	0.015	0.184	0.344	0.153	1.477	4.425
fh_loss	27,576,203	−0.11	−0.395	−0.09	0	0	0	0.243	−2.937	12.139
fh_gain_alt	27,576,203	0.2	0	0	0.027	0.253	0.595	0.357	2.835	12.179
fh_loss_alt	27,576,203	−0.063	−0.253	−0.066	0	0	0	0.123	−2.162	6.988
$\sqrt{(fh\_time)}$	27,576,203	3.462	0	1.909	3.262	4.791	6.433	2.245	0.600	3.629
assets	21,400,789	350,178	2600	9085	32,878	115,410	413,501	2357.987	17.147	353.591
shares	25,114,641	235,299	870	3561	18,100	89,500	345,858	4728.682	365.617	190,971.117
*flow*1*m*	23,965,987	0.008	−0.038	−0.014	−0.002	0.014	0.053	0.088	4.198	41.477
*fret*1*m*	25,172,717	0.008	−0.048	−0.013	0.009	0.031	0.059	0.046	0.273	50.425
best_dummy	27,576,203	0.27	0	0	0	1	1	0.444	1.036	2.073
worst_dummy	27,576,203	0.364	0	0	0	1	1	0.481	0.564	1.318
wt_exp_ratio	27,576,203	0.009	0.001	0.004	0.008	0.013	0.022	0.007	0.586	2.477
turn_ratio	27,576,203	1.11	0.03	0.16	0.455	0.98	5.65	1.741	2.152	6.186
$\overline{fh\_time}$	27,576,203	17.116	4.521	7.553	12.626	22.209	35.625	14.482	2.116	9.84
SAT	1,249,962	1321.019	1121	1205	1355	1450	1480	136.403	−0.571	2.23

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that $CGO = gain\_overhang + loss\_overhang$, for every security-date.[9]

We employ Fama-MacBeth (1973) regressions and consider two empirical models. The first model is used to estimate how gain 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 β_1 to be positive, β_2 to be negative, and the relation between these two price effects ($\frac{\beta_1}{\beta_2}$) to be similar to 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 *capital gains overhang* (*CGO*) construction against our V-shaped construction *V-shaped selling propensity (VSP)*, defined as $\left(gain\_overhang_{i,t} + \varphi \mid loss\_overhang_{i,t} \mid\right)$, where the parameter φ is the relative relation between selling pressure from unrealized gains and 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 1.8 times as likely to sell the gain as to sell the loss. Thus, we expect a gain overhang to result in about 1.8 times of the price effect as a similarly sized loss overhang, and we set $\varphi = 1/1.8 = 0.6$ (from Table 2, column (2), the relative magnitude of selling induced by loss relative to gain is 0.6). We view this regression design as a horse race between the two underlying models of how investors trade in response to unrealized capital gains.

We include two sets of control variables in our regressions 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 that performed well (poorly) in the past, and the past one-year return is a well-documented predictor of future returns (Jegadeesh, 1990; Jegadeesh and Titman, 1993). There are many theories of momentum that use various mechanisms other than the disposition effect story from Grinblatt and Han (2005). If there is truth to any of these alternative stories, then any tests of the price impact of capital gains and losses without controlling for past returns are likely to be severely biased. Here we are interested in testing whether selling propensities affect future returns, without taking a stand on what drives momentum. It is therefore important to control for momentum returns. Moreover, we separate the raw past 12-to-2 month 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 et al. (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 relation. 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 ($Ret_{i,t-36,t-13}$) are included to address potential contamination from short- 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 the approach in 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 six-month 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, which is meant to capture any volume effects that may relate to future returns.

We conduct predictive Fama-MacBeth (1973) regressions at a monthly horizon. At the end of every month, we exclude stocks whose price is lower than five dollars, and those that are traded for less than 10 days in the previous month. To avoid liquidity bias, we follow the suggestion by Asparouhova et al. (2010) and run weighted least squares (WLS) regressions with the weight equal to past one-month gross return. The OLS results (not reported) are very similar, suggesting that liquidity bias is not a severe issue in our exercises. We follow An (2016) and run tests using all months as well as excluding January, to demonstrate that our results are not driven by the January effect.[10]

Besides Fama-MacBeth (1973) regressions, we also conduct portfolio sorts based on VSP and CGO. To control for the confounding effects, we also sort portfolios based on residual VSP and CGO where the residual variables are constructed by regressing the raw values of VSP and CGO onto contemporaneous $Ret_{i,t-1}$, $Ret^{+}_{i,t-12,t-2}$, $Ret^{-}_{i,t-12,t-2}$, $Ret_{i,t-36,t-13}$, *logMktcap*, *turnover*, and *ivol*.

In Panel A of Table 2, we report summary statistics for *gain_overhang*, *loss_overhang*, *CGO*, and *VSP*, as well as the other control variables. The numbers are the time series averages of statistics calculated at a monthly level. Panel B in Table 1 shows

[9] This construction of gain and loss overhang treats the net purchases at different dates of a fund manager on a single stock as independent positions. It allows the possibility that a fund manager has both a realized gain and a loss on a single stock at the same time given that she purchased the shares at different prices. Although this specification might be a deviation from the most realistic modeling of how fund mangers think about their positions, this event is relatively rare (in our sample, only 7.8% of all fund-security-date observations have a single fund manager who has both a gain and a loss for the same security at the same time). The impact of this construction is small, and it affords an intuitive decomposition of the capital gains overhang, i.e., CGO = gain overhang + loss overhang.

[10] 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, Lakonishok and Smidt (1988) and Grinblatt and Keloharju (2001).

Table 2
Summary statistics for stock-level variables. Panel (A) describes the stock-level variables used to examine pricing effects, and Panel (B) reports a correlation matrix of these variables. All numbers presented are the time-series average of the cross-sectional statistics. *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 constructed as in Frazzini (2006). *VSP* is the V-shaped disposition effect overhang defined as $VSP = gain\_overhang + .6\,|loss\_overhang|$. Ret_{-1} is return in month $t-1$. $Ret_{-36,-13}$ is the cumulative return from the past three year to the past one year. $Ret_{-12,-2}$ is the cumulative return from month $t-12$ to $t-2$, 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_d* (*worst_d*) is a dummy variable that is equal to 1 if a security has the highest (lowest) *fh_verhang* in the portfolio of at least one fund, and *best_pct* (*worst_pct*) is the percentage of funds who have the security as best (worst) ranked in their portfolio among all funds holding this security. All variables in raw values are winsorized at the 1% level.

Panel A: Summary statistics for stock-date-level pricing variables.

Variable	N	mean	p10	p25	p50	p75	p90	Std	Skewness	Kurtosis
gain_overhang	2691	0.139	0.001	0.025	0.101	0.217	0.337	0.136	1.103	3.796
loss_overhang	2691	−0.207	−0.570	−0.253	−0.074	−0.012	−0.001	0.343	−3.347	17.865
CGO	2691	−0.068	−0.545	−0.206	0.017	0.189	0.327	0.420	−2.034	10.139
VSP	2691	0.263	0.070	0.136	0.220	0.337	0.487	0.203	2.119	11.582
Ret_{-1}	2690	0.018	−0.104	−0.046	0.009	0.069	0.144	0.121	2.119	38.987
$Ret^{+}_{-12,-2}$	2690	0.284	0.003	0.025	0.139	0.359	0.699	0.481	6.100	93.019
$Ret^{-}_{-12,-2}$	2690	−0.080	−0.258	−0.102	−0.021	−0.002	0.000	0.130	−2.586	12.511
$Ret_{-12,-2}$	2690	0.204	−0.255	−0.077	0.117	0.357	0.699	0.540	4.277	64.786
$Ret_{-36,-13}$	2558	0.451	−0.300	−0.054	0.252	0.662	1.292	1.022	6.056	105.366
logBM	2431	−0.638	−1.658	−1.076	−0.525	−0.096	0.235	0.805	−1.054	6.496
logMktcap	2691	12.826	10.781	11.603	12.665	13.877	15.124	1.681	0.490	3.069
turnover	2653	0.006	0.001	0.002	0.004	0.007	0.012	0.007	5.166	86.616
ivol	2689	0.025	0.013	0.016	0.022	0.031	0.039	0.012	2.703	35.995
best_d	2684	0.118	0.000	0.000	0.000	0.006	0.478	0.303	2.498	7.868
worst_d	2684	0.095	0.000	0.000	0.000	0.000	0.387	0.277	2.891	10.015
best_pct	2684	0.009	0.000	0.000	0.000	0.000	0.006	0.045	10.018	161.449
worst_pct	2684	0.008	0.000	0.000	0.000	0.000	0.003	0.041	10.082	155.579

Panel B: 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_pct*	*worst_pct*
gain_overhang	1														
loss_overhang	0.41	1													
CGO	0.68	0.94	1												
VSP	0.33	−0.69	−0.42	1											
Ret_{-1}	0.24	0.18	0.23	0.00	1										
$Ret_{-12,-2}$	0.43	0.31	0.40	−0.01	0.00	1									
$Ret^{+}_{-12,-2}$	0.38	0.18	0.28	0.10	0.01	0.95	1								
$Ret^{-}_{-12,-2}$	0.34	0.53	0.54	−0.28	−0.03	0.54	0.29	1							
$Ret_{-36,-13}$	0.07	0.03	0.04	0.03	−0.03	−0.06	−0.04	−0.08	1						
logMktcap	0.11	0.11	0.13	−0.03	0.02	0.05	0.01	0.15	0.08	1					
logBM	−0.01	0.05	0.03	−0.06	0.03	0.00	−0.03	0.10	−0.31	−0.24	1				
turnover	0.03	−0.12	−0.09	0.15	0.00	0.10	0.17	−0.16	0.16	0.13	−0.25	1			
ivol	−0.05	−0.24	−0.21	0.21	0.07	0.11	0.22	−0.28	0.01	−0.40	−0.12	0.34	1		
best_pct	0.31	0.09	0.18	0.13	0.12	0.29	0.30	0.09	0.08	0.11	−0.07	0.12	0.06	1	
worst_pct	−0.15	−0.46	−0.42	0.35	−0.11	−0.15	−0.08	−0.29	0.03	0.02	−0.05	0.12	0.11	−0.03	1

the average monthly correlation between these variables. A somewhat surprising observation is that the correlation between *loss_overhang* and *CGO* is 0.94. This is because the overhang variables are aggregations of $fh\_overhang = \frac{P_t - P_0}{P_t}$ where the denominator is the current price; the gain side is bounded above from 1, and the loss side can take any value. Therefore, *loss_overhang* has larger absolute values than *gain_overhang*, and the value of *CGO* is mainly driven by the loss side. In a similar vein, we see that the correlation between $Ret_{-12,-2}$ and $Ret^{+}_{-12,-2}$ is 0.95. In this case, $Ret_{-12,-2}$ is defined as the price change normalized by the purchase price, where the winner side has larger absolute values and dominates the variation of $Ret_{-12,-2}$. Note that a high correlation between two variables does not necessarily suggest that the two variables have similar impacts on price; for instance, in the case of $Ret_{-12,-2}$, the price effect of momentum is actually driven mainly by the loser leg [see Hong et al. (2000); in our sample, Table 4 shows that the pricing coefficient of $Ret^{-}_{-12,-2}$ is 5–10 times as large as that of $Ret^{+}_{-12,-2}$].

Finally, it is important to discuss the timing of information availability. The holdings data reported by Thomson Reuters include both the effective date of holdings data (variable "*rdate*") as well as the file date (variable "*fdate*") that corresponds to a vintage date assigned by Thomson Reuters.[11] It is not uncommon, especially in the early sample, for the difference between when the information is relevant (*rdate*) and the vintage date (*fdate*) to be severe (up to 24 months in extreme cases). This is seemingly less common in the latter portion of the data. Although 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. 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. Schwarz and Potter (2016) show that most funds take at least 57 days to disclose their portfolios to SEC, which publishes them on EDGAR on the next business day. To this end, for the selling behavior regressions (equation (5)), we use the data as of the corresponding *rdate*. For the price effect regressions (equations (10) and (11)) we construct security-level overhang variables based on holdings with a 2-month lag from the file date. This is similar but more conservative than the argument formulated in Frazzini (2006), who uses a 30-day lag from the file date.

4. Results

This section presents results for both mutual fund managers' selling behavior and the ensuing price impacts, using empirical models and specifications discussed in Section 3.

4.1. Trading behavior

Results from the selling behavior regressions are shown in Table 3. All errors are clustered at the fund level except regression 8, where the errors are two-way clustered at the fund-quarter level for robustness. Column (1) shows results from a pooled OLS regression. We find that larger magnitudes in both unrealized gains and losses are associated with more selling. Including stock-time fixed effects that absorb variations within stock-time, we see in column (2) that the coefficients for both fh_gain_{fit} (0.029) and fh_loss_{fit} (−0.016) have the expected signs and are strongly significant, with *p-values* well below 1%. These figures imply that a 1% more extreme realization of the fund-holding gain (loss) implies a 2.9 bps (1.6 bps) increase in the percentage of shares outstanding that are sold; the relative magnitude of loss versus gain ($\frac{1.6}{2.9} = 0.56$) further suggests an asymmetric V-shape. When we include the interaction terms with holding period, the coefficients in column (3) on the interaction of fh_gain_{fit} and fh_loss_{fit} with $\sqrt{fh\_time}$ are −0.012 and 0.008, respectively. This suggests that fund managers' selling response to unrealized profit weakens as the holding time becomes longer, which is consistent Ben-David and Hirshleifer's (2012) findings on retail investors. Further, for the average stock held for the average time (about 17 months), the coefficients in column (3) demonstrate that a 1% more extreme realization of the fund-holding gain (loss) implies a $7.7 - 1.2 \times 4.12 = 2.73$ bps ($4.6 - 0.8 \times 4.12 = 1.37$ bps) increase in the percentage of shares outstanding that are sold. In columns (4) and (5), we repeat this regression, but separate the sample based on the "short" holding period ($fh\_time \leq 1$ year) and the "long" holding period ($fh\_time > 1$ year). The V-shaped disposition effect is more pronounced for shorter holding periods.

We next split the data into a "past" subsample spanning 1980 to 2001 and a "recent" subsample spanning 2002 to 2018. As shown in columns (6) and (7), coefficient estimates are qualitatively identical to the original regression with *t*-statistics above 5, although the magnitude of the results in the recent sample is smaller. For robustness, we repeats the main specification for column (2) and additionally use two-way clustering at the fund-quarter level; the results remain highly statistically significant, as shown in column (8). Similar results are obtained by clustering at only the quarter level, as well. Finally, we conduct a further robustness check controlling for fund flows from the past 1 month. The usage of the flow data restricts the sample to only those funds in the CRSP universe for which flow data can be calculated, which reduces the number of observations from roughly 27 million to 24 million. The resulting coefficient estimates in column (9) are virtually unchanged from those in column (3); controlling for fund flows, a 1% more extreme gain (loss) implies a 3.08 bps (1.52 bps) increase in the percentage of shares

[11] From the Thomson Reuters User Guide, the "fdate" corresponds to the "last day of the quarter for which the data items were generally available for public information such as stock prices, and for holdings, theoretically available through fund or investment company records."

Table 3
Selling behavior regressions. For ease of notation, subscripts have been omitted. The dependent variable is $Selling\%\_of\_shrout = \left[\frac{\#\text{of shares sold}}{\#\text{of shares outstanding}}\right] \times 100$ which is the percentage of shares outstanding sold for a given stock by a given fund in a given time period. *fh_gain* and *fh_loss* represent the gain and loss calculated for each fund-holding pair as defined in equations (2) and (3), respectively. *fh_time* is equal to the weighted average holding period, in unit of months. *flow1m* is the one-month flow. With the exception of regression 8 (which calculates two-way clustered errors at the fund-time level), all errors are clustered at the fund level. *P-values* are reported in parentheses. $*$, $**$, and $***$ denote significance levels at 10%, 5%, and 1% levels, respectively.

Data Filter	(1) None	(2) None	(3) None	(4) $fh\_time \leq 1yr$	(5) $fh\_time > 1yr$	(6) $1980 \leq year \leq 2001$	(7) $2002 \leq year \leq 2018$	(8) None	(9) None
fh_gain	0.023***	0.029***	0.079***	0.053***	0.008***	0.076***	0.020***	0.029***	0.072***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)
fh_loss	−0.018***	−0.016***	−0.047***	−0.027***	0.001*	−0.035***	−0.010***	−0.016***	−0.044***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.0005)	(0.002)	(0.001)	(0.001)	(0.002)
$fh\_gain \times \sqrt{fh\_time}$			−0.012***						−0.010***
			(0.0001)						(0.001)
$fh\_loss \times \sqrt{fh\_time}$			0.008***						0.007***
			(0.0001)						(0.0001)
$\sqrt{fh\_time}$			0.002***						0.002***
			(0.0001)						(0.0001)
flow1m									−0.019***
									(0.001)
Constant	0.011***								
	(0.0001)								
Stock-Time FEs		YES	YES	YES	YES	YES	YES	YES	YES
Error Cluster Level	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund-Quarter	Fund
Observations	27,582,450	27,582,450	27,582,450	21,435,011	6,147,439	4,983,892	22,598,558	23,970,498	23,970,498
R^2	0.005	0.13	0.135	0.147	0.23	0.186	0.09	0.136	0.136

outstanding that are sold.[12] We conclude that the V-shaped disposition effect we observe is orthogonal to fund flow effects.[13]

4.2. Pricing effect

Table 4 presents return prediction results from estimating equation (10) using Fama-MacBeth regressions. In these regressions, we expect the coefficients on gain overhang and loss overhang to 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. We regress future one-month returns onto gain overhang and loss overhang only. We see in column (1) that the coefficients on gain overhang have a positive sign, but those on loss overhang (0 in all months, and 0.001 in February to December) in column (2) have the opposite sign 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 columns (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 which is consistent with Hong et al. (2000). Finally, we add other common return predictors and present our full model in columns (5) and (6). In these two regressions, gain overhang positively predicts future return while loss overhang negatively predicts future return, both as expected. Focusing on the all-month estimation, the coefficients suggest that a 10 bps increase in gain (loss) overhang is associated with a 9 (5) basis point increase (decrease) in next month returns. The price effect of gain overhang is 1.8 times as large as that of loss overhang. This matches well with the relative magnitude between the gain and loss of our selling regression results (1.8 times from Table 3 column (2)). The t-statistics are 5.35 and −6.40 for gain overhang and loss overhang, respectively. Given that 463 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 $\left(5.35\sqrt{\frac{12}{463}}\right) = 0.86$ and $\left(6.40\sqrt{\frac{12}{463}}\right) = 1.03$, respectively.[14]

Grinblatt and Han (2005) discuss the important relation between the momentum effect and capital overhang. They find that capital overhang subsumes momentum in their sample and suggest that the disposition effect may be the source of momentum. In contrast, An (2016) argues that, if investors tend to sell big losers as well as big winners, the loss part of capital gains overhang will predict future returns in the opposite direction as momentum. This claim is also supported by empirical evidence by Novy–Marx (2012) and Birru (2015). Our results support the second view that investors' selling response to unrealized profit is not likely 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 relation between idiosyncratic volatility and the overhang effects. It has been documented that high idiosyncratic volatility stocks are associated with low future returns,[15] and perhaps unsurprisingly, stocks with large gain and loss overhangs tend to be those with high idiosyncratic volatility. This result biases against our results since our model predicts the opposite relation: stocks with large gain and loss overhangs 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 (3) and (4) to columns (5) and (6).

To capture the overall price impact from the V-shaped disposition effect, we also construct *the V-shaped selling propensity (VSP) variable, which is, equal to* $(gain\_overhang + \varphi|loss\_overhang|)$ with $\varphi = 0.6$ [recall that from Column (2) in Table 3 the relative selling sensitivity of *loss* versus *gain* is 0.60]. We conduct a horse race between *VSP* and the linear capital gains overhang (CGO). Table 5 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 0.009 in the all-month estimation suggests that a 1 percentage point increase in *VSP* would lead to 0.9 bps increase in future one-month return. Given that the average 10th and 90th percentile of the monthly *VSP* sample is 7% and 49%, respectively, a portfolio that goes long the top *VSP* quintile and shorts the bottom *VSP* quintile would generate a monthly return spread of approximately $(49 - 7) \times 0.9 = 38$ bps, and a t-statistic of 7.35 implies that the Sharpe ratio is approximately $7.35\sqrt{\frac{12}{463}} = 1.2$.

In addition to employing Fama-MacBeth regressions, we also examine returns predicted by *VSP* in portfolio sorts in Table 6. We sort firms into five quintiles at the end of each month based on their *VSP*, with quintile 5 representing the portfolio with the largest *VSP*; returns of these portfolios in the next month are reported in Panel A. The left side of the table reports the gross-return-weighted portfolio returns and the right side shows value-weighted results. For each weighting method, we show results

[12] We also explore various windows for the measurement of the fund flows, at 3-month and 12-month horizons, without notable change in the coefficient estimates (results omitted).

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

[14] The t-statistic estimated through the Fama-MacBeth approach corresponds to the Sharpe ratio of a hedged portfolio. For each cross-sectional estimate, $\beta_t = (X'_{t-1}X_{t-1})^{-1}X'_{t-1}r_t$; since R_t is the return in month t and $(X'_{t-1}X_{t-1})^{-1}X'_{t-1}$ is all available at the end of month $t-1$, β_t can be interpreted as the return of a tradable portfolio in which the portfolio weight is equal to $(X'_{t-1}X_{t-1})^{-1}X'_{t-1}$. The annualized Sharpe ratio of this portfolio (SR) is $\frac{\overline{\hat{\beta}}\times\sqrt{12}}{std(\hat{\beta})}$, and the t-statistic in the Fama-MacBeth regression (t_{FM}) is calculated as $\frac{\overline{\hat{\beta}}}{std(\hat{\beta})/\sqrt{T}}$. Thus, $SR = \frac{t_{FM}}{\sqrt{T}} \times \sqrt{12}$.

[15] See Ang et al. (2006, 2009), among others.

Table 4
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 parentheses) are calculated using the time series of cross-sectional estimates. 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 equations (8) and (9). For the definition of other control variables, please see Table 2. R-squared is the average R^2 from the cross-sectional regressions. ∗, ∗∗, and ∗∗∗ denote significance levels at 10%, 5%, and 1%.

Data Filter	(1) All months	(2) Feb–Dec	(3) All months	(4) Feb–Dec	(5) All months	(6) Feb–Dec
gain_overhang	0.015***	0.018***	0.005**	0.008***	0.009***	0.010***
	(4.44)	(5.22)	(1.98)	(3.04)	(5.35)	(5.47)
loss_overhang	0.000	0.001	−0.005***	−0.005***	−0.005***	−0.005***
	(0.30)	(0.88)	(−5.00)	(−4.11)	(−6.40)	(−5.81)
$Ret^{+}_{-12,-2}$			0.004***	0.004***	0.005***	0.006***
			(2.91)	(3.03)	(5.04)	(5.91)
$Ret^{-}_{-12,-2}$			0.039***	0.041***	0.022***	0.024***
			(9.26)	(9.12)	(7.23)	(7.33)
Ret_{-1}					−0.031***	−0.025***
					(−8.75)	(−6.99)
$Ret_{-36,-13}$					−0.001*	−0.000
					(−1.74)	(−0.55)
logBM					0.001*	0.001
					(1.72)	(1.49)
logMktcap					−0.001***	−0.001**
					(−2.76)	(−2.14)
ivol					−0.224***	−0.275***
					(−4.67)	(−5.73)
turnover					−0.021	−0.085
					(−0.15)	(−0.60)
constant	0.009***	0.008***	0.010***	0.010***	0.024***	0.023***
	(4.15)	(3.79)	(5.30)	(4.95)	(6.90)	(6.36)
Ave. monthly obs.	2666	2668	2666	2668	2353	2354
R^2	0.015	0.015	0.029	0.029	0.067	0.066
# of months	463	425	463	425	463	425

in the forms of portfolio raw returns, Carhart four-factor alphas (Fama and French, 1993; Carhart, 1997), and Fama-French five-factor alphas (Fama and French, 2015). For comparison, Panel B shows a similar set of results for portfolio returns based on CGO. Panel A shows that portfolio returns increase monotonically with their *VSP* quintile. The differences between quintiles 5 and 1 for the gross return-weighted portfolios range from 0.4% to 0.5% per month, and they are all significant. For value-weighted portfolios, the results are weaker, which is consistent with An's (2016) findings that the price effect of the disposition effect is absent in the largest firms. In Panel B, gross-return-weighted portfolio returns significantly increase with capital gains overhang, while the value-weighted portfolios do not have the expected pattern. Overall, these results suggest that without controlling for other effects, both *VSP* and CGO capture to some extent the price impacts of the disposition effect.

To better control for confounding factors, we repeat the exercises we conducted for the results in Panels A and B, but now sort firms by residual selling propensity variables instead of the raw values. The residuals are constructed by regressing VSP and CGO on past returns, size, turnover, and idiosyncratic volatility. Focusing on the gross-return-weighted results in Panel C, the return spreads between the top and bottom quintiles based on residual VSP (0.5%–0.6% per month) are of similar magnitude as those in Panel A, and the t-statistics become much larger (around 7). In contrast, after controlling for other return predictors, CGO's predictive power in Panel D becomes very weak, or even reversed, which is consistent with the regression results in Table 5. The value-weighted portfolios in Panels C and D do not have the expected pattern, which suggests that the V-shaped selling propensity effect is more pronounced among smaller firms.

5. Fund characteristic heterogeneity

In this section, we examine how heterogeneity in fund manager characteristics affects trading behavior and price patterns. We first explore the cross-sectional heterogeneity in trading behavior related to fund characteristics. Second, we examine whether the return predictability is indeed stronger for the gain and loss overhang of funds whose managers have characteristics more strongly associated with a V-shaped disposition effect.

5.1. Selling behavior

We repeat the selling behavior regressions on subsamples of the fund universe, splitting the data based on fund characteristics designed to capture speculation, activeness, and raw ability of the fund manager. These characteristic variables are the turnover, the average holding period, the expense ratio, and the average SAT score (in 2005) of the entering class of the undergraduate institution that the manager attended. The turnover is the ratio of aggregated purchases ($) divided by the average

Table 5
Horserace between *CGO* and *VSP*, Fama-MacBeth regressions. For ease of notation, subscripts have been omitted. 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 parentheses) are calculated using the time series of cross-sectional estimates. 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 equations (8) and (9). For the definition of other control variables, please see Table 2. R-squared is the average R^2 from the cross-sectional regressions. ∗, ∗∗, and ∗∗∗ denote significance levels at 10%, 5%, and 1%.

Data Filter	(1) All months	(2) Feb–Dec
CGO	0.000	0.001
	(0.37)	(0.76)
VSP	0.009***	0.009***
	(7.35)	(7.26)
$Ret^{+}_{-12,-2}$	0.005***	0.006***
	(5.04)	(5.91)
$Ret^{-}_{-12,-2}$	0.022***	0.024***
	(7.23)	(7.33)
Ret_{-1}	−0.031***	−0.025***
	(−8.75)	(−6.99)
$Ret_{-36,-13}$	−0.001*	−0.000
	(−1.74)	(−0.55)
logBM	0.001*	0.001
	(1.72)	(1.49)
logMktcap	−0.001***	−0.001**
	(−2.76)	(−2.14)
ivol	−0.224***	−0.275***
	(−4.67)	(−5.73)
turnover	−0.021	−0.085
	(−0.15)	(−0.60)
constant	0.024***	0.023***
	(6.90)	(6.36)
Ave. monthly obs.	2353	2354
R^2	0.067	0.066
# of months	463	425

12-month total net assets. The average holding period is the average number of months that a security is held by a fund in the past year. The expense ratio is the ratio of operating expenses to total investment. With the exception of average holding period, these fund characteristics data are only available for a subset of funds, and the universe is reduced in these regressions. We find it more intuitive to bin based on fund, not on fund-holding-time observation. For this reason, there are a third of funds in each bin and not necessarily a third of the fund-holding-time 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 potential 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 a weighted averages of the fund expense ratio - the other characteristic variables are constant across share classes and thus do not require this aggregation. We form the average holding period directly from the holdings data using *fh_time*. Summary statistics for these variables are shown in Table 1 labeled as *turn_ratio*, $\overline{fh\_time}$, *wt_exp_ratio*, and *SAT*.

One way to measure fund speculation and activeness is to look at fund turnover. We use two variables to proxy for this characteristic: dollar turnover (*turn_ratio*) and average holding period ($\overline{fh\_time}$). Although 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 7, regressions (1-6), with corresponding coefficient difference tests. We find that the V-shaped disposition effect is more severe among funds with higher trading turnover and shorter average holding period; the gain and loss coefficients for high turnover funds (0.050 and −0.030, respectively) are roughly four times the size of the gain and loss coefficients for funds with low relative turnover (0.013 and −0.005, respectively). Similarly, funds with the shortest average holding period have

Table 6

Portfolio sorts. This table reports returns to long-short portfolios constructed based on selling propensity variables. In Panel A, stocks are sorted by their V-shaped selling propensity (VSP) into quintiles at the end of each month, with portfolio 5 containing stocks with the highest VSP. Portfolios are constructed using gross return weights and value weights, reported in the left side and the right side, respectively. Each portfolio is to be held for the following one month, and the time-series average of portfolio returns is reported. For each weighting scheme, we show raw portfolio returns, Carhart (1997) four-factor alphas, and Fama-French five-factor (2014) alpha. Panel B presents the same set of results sorted on capital gains overhang (CGO) instead. Panels C and D repeat the same exercises, but base the sorts on residual VSP and residual CGO. The residuals are constructed by regressing raw selling propensity variables (VSP or CGO) on past returns, firm size, turnover, and idiosyncratic volatility. The returns are in monthly percent, *t*-statistics for the difference between portfolios 5 and 1 are in the parentheses, and *, **, and *** denote significance levels at 10%, 5%, and 1%.

Panel A: portfolio return, sorted on V-shaped selling propensity (VSP)

VSP	Gross-Return Weighted			Value Weighted		
	raw return	Carhart-4 alpha	FF-5 alpha	raw return	Carhart-4 alpha	FF-5 alpha
1	0.98	−0.03	−0.15	0.97	0.06	−0.09
2	0.94	−0.1	−0.28	0.93	−0.06	−0.19
3	1.02	−0.06	−0.18	1	−0.02	−0.04
4	1.22	0.13	0.06	1.12	0.06	0.1
5	1.35	0.36	0.32	1.26	0.29	0.36
5–1	0.37**	0.38***	0.47***	0.3	0.22	0.44***
t-stat	(2.48)	(3.88)	(4.50)	(1.59)	(1.48)	(3.03)

Panel B: portfolio return, sorted on capital gains overhang (CGO)

CGO	Gross-Return Weighted			Value Weighted		
	raw return	Carhart-4 alpha	FF-5 alpha	raw return	Carhart-4 alpha	FF-5 alpha
1	0.95	0.07	−0.22	1.12	0.26	0.03
2	0.92	−0.07	−0.32	0.89	−0.04	−0.21
3	1.05	0.02	−0.14	1.03	0.04	−0.09
4	1.15	0.04	−0.02	0.98	−0.05	−0.1
5	1.42	0.24	0.41	1.23	0.06	0.3
5–1	0.47**	0.17	0.63***	0.12	−0.2	0.27
t-stat	(2.34)	(1.57)	(3.29)	(0.59)	(−1.58)	(1.36)

Panel C: portfolio return, sorted on residual V-shaped selling propensity (res VSP)

res VSP	Gross-Return Weighted			Value Weighted		
	raw return	Carhart-4 alpha	FF-5 alpha	raw return	Carhart-4 alpha	FF-5 alpha
1	0.77	−0.17	−0.36	0.93	0.10	−0.15
2	1.1	0.12	−0.1	1.06	0.18	−0.06
3	1.15	0.08	−0.07	1.02	0.00	−0.07
4	1.25	0.14	0.05	0.98	−0.09	−0.02
5	1.38	0.29	0.28	1.09	0.10	0.18
5–1	0.61***	0.46***	0.63***	0.17	0.00	0.33
t-stat	(7.34)	(6.94)	(7.43)	(1.18)	(0.00)	(2.31)

Panel D: portfolio return, sorted on residual capital gains overhang (res CGO)

res CGO	Gross-Return Weighted			Value Weighted		
	raw return	Carhart-4 alpha	FF-5 alpha	raw return	Carhart-4 alpha	FF-5 alpha
1	1.17	0.13	0.00	0.99	0.04	0.01
2	1.12	0.08	−0.07	1.01	0.03	−0.03
3	1.14	0.07	−0.05	1.03	0.02	−0.05
4	1.2	0.14	0.02	1.18	0.17	0.13
5	1.02	0.03	−0.08	1.06	0.07	0.04
5–1	−0.15**	−0.11*	−0.08	0.07	0.03	0.03
t-stat	(−2.29)	(−1.66)	(−1.14)	(0.49)	(0.24)	(0.26)

coefficients that are much larger than funds with the longest average holding period. These results suggest that relatively speculative managers are more prone to manifest a V-shaped disposition effect. This corroborates Ben-David and Hirshleifer's (2012) finding on retail investors in which they show that the V-shaped selling schedule is associated with investors' speculativeness using gender and trading frequency as proxies.

Selling behavior results splitting funds based on the expense ratio are shown in Table 7, columns (7-9). We see that funds with higher expense ratios manifest a more significant V-shaped disposition effect. The coefficient for fund-holding gain (fund-holding loss) for funds in the top third by expense ratio is a highly significant 0.045 (−0.026), whereas the corresponding coefficient for funds in the bottom third by expense ratio is 0.009 (−0.004). The difference is statistically significant. We view high fees as indicative of an active investment style. 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 the robustness section confirms this conjecture.

Finally, we bin funds based on the average entrance SAT score of the fund manager's undergraduate institution, using fund managers' education background data from Cohen et al. (2008) from 1980 to 2006. The availability of fund managers' education background information and the corresponding SAT score decreases our sample from approximately 6000 total funds to around 1200 unique funds with a corresponding reduction in fund-holding-time observations from approximately 27 million to around

Table 7

Selling behavior regressions - characteristic decomposition. For ease of notation, subscripts have been omitted. The dependent variable is $Selling\%\_of\_shrout = \left[\frac{\#\text{of shares sold}}{\#\text{of shares outstanding}}\right] \times 100$, which is the percentage of shares outstanding sold for a given stock by a given fund in a given time period. *fh_gain* and *fh_loss* represent the gain and loss calculated for each fund-holding pair as defined in equations (2) and (3), respectively. Funds are binned at every time period based on the sort variable. *turn_ratio* represents the turnover ratio for a given fund. $\overline{fh\_time}$ is the average holding period for each fund-holding pair. *wt_exp_ratio* represents the TNA-weighted expense ratio across different share classes for a given fund. *SAT* is the average entrance SAT score (in 2005) of the undergraduate institution that the fund manager attended (when available). All regressions include stock-time fixed effects. All errors are clustered at the fund level, and p-values are reported in parentheses. ∗, ∗∗, and ∗∗∗ denote significance levels at 10%, 5%, and 1%.

Sort Variable:	*Selling%_of_shrout*							
	(1)	(2)	(3)	HIGH-LOW	(4)	(5)	(6)	HIGH-LOW
		turn_ratio				$\overline{fh\_time}$		
	LOW	MED	HIGH		LOW	MED	HIGH	
fh_gain	0.013***	0.046***	0.050***	0.037***	0.091***	0.042***	0.013***	−0.078***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
fh_loss	−0.005***	−0.022***	−0.030***	−0.025***	−0.047***	−0.020***	−0.001***	0.046***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Stock-Time FEs	YES	YES	YES		YES	YES	YES	
Observations	9,231,321	9,154,288	9,196,841		9,197,816	9,180,902	9,203,732	
R^2	0.002	0.007	0.01		0.022	0.006	0.001	
Sort Variable:	*Selling%_of_shrout*							
	(7)	(8)	(9)	HIGH-LOW	(10)	(11)	(12)	HIGH-LOW
		wt_exp_ratio				*SAT*		
	LOW	MED	HIGH		LOW	MED	HIGH	
fh_gain	0.009***	0.041***	0.045***	0.036***	0.069***	0.095***	0.066***	−0.003
	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.012)
fh_loss	−0.004***	−0.022***	−0.026***	−0.022***	−0.032***	−0.046***	−0.039***	−0.007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.009)
Stock-Time FEs	YES	YES	YES		YES	YES	YES	
Observations	9,246,292	9,141,768	9,194,390		422,969	416,770	410,795	
R^2	0.001	0.006	0.009		0.012	0.016	0.01	

1.2 million. In results shown in Table 6 Columns (10)-(12), we find that managers in all three bins exhibit this behavior without any obvious pattern (quintile sorts produce similar findings). These results suggest that the V-shaped selling schedule is unlikely to be the result of intellectual sophistication or superior financial training.

5.2. Fund characteristics and return predictability

We link the heterogeneity in mutual fund managers' 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 unrealized gains and losses aggregated from *all* mutual funds, we can decompose the overhang variables based on fund characteristics. To be consistent with our hypothesis, overhang from funds that exhibit a more extreme V-shaped disposition effect should exhibit stronger 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 follows:

$$gain\_overhang\_turnL_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnL}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{\left(p_t - p_{t-n}\right) \mathbb{1}_{p_{t-n} \le p_t}}{p_t} \right], \tag{12}$$

$$gain\_overhang\_turnH_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnH}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{\left(p_t - p_{t-n}\right) \mathbb{1}_{p_{t-n} \le p_t}}{p_t} \right], \tag{13}$$

$$gain\_overhang\_turnU_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnU}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{\left(p_t - p_{t-n}\right) \mathbb{1}_{p_{t-n} \le p_t}}{p_t} \right], \tag{14}$$

$$loss\_overhang\_turnL_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnL}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{\left(p_t - p_{t-n}\right) \mathbb{1}_{p_{t-n} > p_t}}{p_t} \right], \tag{15}$$

$$loss\_overhang\_turnH_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnH}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{\left(p_t - p_{t-n}\right) \mathbb{1}_{p_{t-n} > p_t}}{p_t} \right], \tag{16}$$

and

$$loss\_overhang\_turnU_t = \sum_{n=0}^{t} \frac{V_{t,t-n}^{turnU}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{\left(p_t - p_{t-n}\right) \mathbb{1}_{p_{t-n} > p_t}}{p_t} \right], \tag{17}$$

where *turnL*, *turnH*, and *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 we decompose the loss overhang 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 the 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. For the SAT score sort, we cannot conduct a meaningful test of the pricing effect based on high and low SAT score decomposition. This is because funds with the manager's educational background are only a small proportion of funds in our holding database, thus the majority of funds fall into the undefined group, and the overhang variables from the undefined group would detect most of the pricing effects.

We repeat the pricing effect exercises using equation (10), and we replace both *gain_overhang* and *loss_overhang* with their respective three-part decomposition. Recall that we reported in the previous subsection that mutual funds with higher turnover, lower average holding time, and higher expense ratio are more likely to exhibit a V-shaped selling schedule. We thus expect

Table 8
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 parentheses) are calculated using the time series of cross-sectional estimates. The dependent variable is return in month t, and the explanatory variables are all available at the end of month $t-1$. Overhang variables are defined according to equations (12)–(17). *turn_ratio* represents the turnover ratio for a given fund. $\overline{fh\_time}$ is the average holding period for each fund-holding pair. *wt_exp_ratio* represents the TNA-weighted expense ratio across different share classes for a given fund. For the definition of other control variables, please see Table 2. ∗, ∗∗, and ∗∗∗ denote significance levels at 10%, 5%, and 1%. R-squared is the average R^2 from the cross-sectional regressions.

Fund Characteristic Data Filter	*turn_ratio* All months	 Feb–Dec	$\overline{fh\_time}$ All months	 Feb–Dec	*wt_exp_ratio* All months	 Feb–Dec
gain_overhang_charaL	0.009***	0.009***	0.022***	0.027***	0.008***	0.008***
	(5.16)	(4.91)	(3.89)	(5.04)	(4.25)	(4.17)
gain_overhang_charaH	0.021***	0.023***	0.009***	0.009***	0.038***	0.042***
	(4.24)	(4.57)	(4.54)	(4.28)	(3.93)	(4.12)
gain_overhang_charaU	0.008	0.028			0.026	0.052
	(0.29)	(0.94)			(0.78)	(1.46)
loss_overhang_charaL	−0.004***	−0.004***	−0.009***	−0.010***	−0.005***	−0.005***
	(−4.97)	(−4.59)	(−3.67)	(−3.86)	(−6.21)	(−5.67)
loss_overhang_charaH	−0.009***	−0.009***	−0.005***	−0.005***	−0.007	−0.007
	(−3.56)	(−3.38)	(−4.68)	(−4.05)	(−1.51)	(−1.52)
loss_overhang_charaU	−0.020	−0.028*			−0.029*	−0.041**
	(−1.36)	(−1.83)			(−1.76)	(−2.39)
$Ret^{+}_{-12,-2}$	0.005***	0.006***	0.005***	0.005***	0.005***	0.006***
	(4.87)	(5.70)	(4.25)	(4.89)	(4.79)	(5.56)
$Ret^{-}_{-12,-2}$	0.023***	0.024***	0.025***	0.026***	0.023***	0.024***
	(7.42)	(7.53)	(7.22)	(7.18)	(7.32)	(7.42)
Ret_{-1}	−0.031***	−0.025***	−0.030***	−0.024***	−0.031***	−0.026***
	(−8.87)	(−7.11)	(−8.26)	(−6.55)	(−8.91)	(−7.17)
$Ret_{-36,-13}$	−0.001**	−0.000	−0.001**	−0.001	−0.001*	−0.000
	(−2.10)	(−0.91)	(−2.43)	(−1.30)	(−1.80)	(−0.64)
logBM	0.001*	0.001*	0.001**	0.001*	0.001*	0.001
	(1.88)	(1.65)	(2.07)	(1.87)	(1.86)	(1.63)
logMktcap	−0.001***	−0.001**	−0.001***	−0.001**	−0.001***	−0.001*
	(−2.96)	(−2.35)	(−3.02)	(−2.37)	(−2.60)	(−1.96)
ivol	−0.224***	−0.275***	−0.184***	−0.238***	−0.222***	−0.272***
	(−4.71)	(−5.76)	(−3.69)	(−4.76)	(−4.63)	(−5.67)
turnover	−0.064	−0.134	−0.132	−0.203	−0.041	−0.107
	(−0.47)	(−0.96)	(−0.94)	(−1.40)	(−0.30)	(−0.76)
constant	0.025***	0.024***	0.025***	0.024***	0.023***	0.022***
	(7.08)	(6.54)	(7.05)	(6.49)	(6.75)	(6.17)
Ave. monthly obs.	2353	2354	2353	2354	2353	2354
R^2	0.071	0.069	0.067	0.065	0.070	0.069
# of months	463	425	463	425	463	425

overhangs from the high turnover group, the low average holding time group, and the high expense ratio group to have stronger return predictability (larger regression coefficients), and we have no prior predictions for overhangs from the undefined group.

The results in Table 8 generally confirm our conjecture. On the gain side, overhangs from the high turnover, low average holding period, and high expense ratio all have larger regression coefficients, and their coefficients range from 2 to 5 multiples of the coefficients for the corresponding less-biased group. On the loss side, overhangs from the high turnover and low average holding period funds generate pricing coefficients about twice as large as the coefficients for low turnover and high average holding period overhang. The differences in coefficients between the high and low expense ratio overhangs are less significant, but the signs are in the right direction.

These results help to further validate the link between the biases of mutual fund managers and the observed price pattern; it is the unrealized profits of those who exhibit a stronger V-shaped selling tendency that predict future returns.

6. Robustness

6.1. V-shaped disposition trading behavior and the rank effect

Hartzmark (2015) documents that the extreme best performer or the extreme worst performer in a portfolio, relative to other stocks in the same portfolio, is treated and traded materially differently by the manager. He argues extensively that the disposition effect and the rank effect are two distinct behaviors; our results concur with his assessment. To address the concern that our V-shaped selling schedule is just a proxy for this rank effect, we rerun the primary selling regressions, controlling for the rank effect in three separate scenarios. First, we include the rank effect dummy variables as in Hartzmark (2015) – 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:

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

and

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

Second, if the V-shaped disposition effect originates from the rank effect, then the behavior should disappear when excluding the 5–10 best and worst performers in a given quarter for a given fund. Hartzmark (2015) shows that the rank effect is no longer significant outside the top and bottom 10 extreme performers [see Fig. 3 of Hartzmark (2015)]. Results of selling behavior regressions controlling for the rank effect are shown in Table 9. We repeat the main regressions for Table 3 but include *best_dummy* and *worst_dummy* dummies; the results are in columns (1)-(3). We next exclude the 5 best and 5 worst performers and present the results in columns (4)-(6). Next, we exclude the 10 best and 10 worst performers and give the results in columns (7)-(9). In all of these regressions, the *fh_gain* and *fh_loss* coefficients remain extremely significant and the magnitudes are very similar to those without rank effect controls. These results suggest that the V-shaped disposition effect and the rank effect reflect related but distinct aspects of investor behavior.

6.2. V-shaped disposition pricing effects and the rank effect

We also compare the V-shaped disposition effect with the rank effect at the security-level in predicting future returns, using two sets of rank effect variables. First, we construct two dummy variables that are equal to 1 if a security is best-ranked (worst-ranked) in the portfolio of at least one fund in a given period. Specifically,

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

and

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

Second, we take the average of $best\_dummy_{fit}$ and $worst\_dummy_{fit}$ across all funds holding a given security and name the variables as $best\_pct_{i,t}$ and $worst\_pct_{i,t}$. Therefore, *best_pct* (*worst_pct*) captures the percentage of funds that have the security ranked as the best (worst) in their portfolio among all funds holding this security.

Table 10 presents the results. We first run predictive Fama-MacBeth regressions on the rank effect variables, together with our main set of control variables [as for Table 4, columns (5) and (6)]. Columns (1) and (2) show that the best and worst dummies positively and significantly predict future one-month returns, consistent with the notion that the extreme ranked stocks are likely to be over-sold currently and the prices are likely to revert in the future. In columns (3) and (4), the coefficients for *best_pct* and *worst_pct* are both positive and significant. We include both gain and loss overhang and the rank effect variables in the regressions for the results in columns (5) -(8). We find that including rank effect variables has almost no impact on the magnitude as well as the significance of the gain and loss overhang compared to the results in columns (5) and (6) of Table 4), while the rank effect coefficients generally become smaller and less significant after controlling for the V-shaped disposition effect. Therefore, the V-shaped disposition effect seems to dominate the rank effect in generating return predictability.

6.3. Alternative measures

We perturb our empirical model on selling behavior in two ways. First, for better comparison with previous studies, we adopt the specifications found in the literature by collapsing the *selling%_of_shrout* variable to be an indicator for selling – $\mathbb{I}(selling_{fit})$ equals one if any selling occurs by fund f of stock i in time period t and zero otherwise. Second, we propose an alternative measure of fund holding overhang that is consistent with the usual definition of holding period returns - we normalize based of the purchase price instead of the current price. This alternative fund-holding overhang is defined as:

$$fh\_overhang\_alt_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{p_t - p_{t-n}}{p_{t-n}} \right], \tag{25}$$

Table 9

Selling behavior regressions - compare with the rank effect. For ease of notation, subscripts have been omitted. The dependent variable is $Selling\%\_of\_shrout = \left[\frac{\#\text{of shares sold}}{\#\text{of shares outstanding}}\right] \times 100$ which is the percentage of shares outstanding sold for a given stock by a given fund in a given time period. *fh_gain* and *fh_loss* represent the gain and loss calculated for each fund-holding pair as defined in equations (2) and (3), respectively. *fh_time* is equal to the weighted average holding period, in unit of months. *best_dummy* (*worst_dummy*) indicates that a security is the best (worst) performer in a fund's portfolio in a given period. Columns (4–6) exclude the 5 best and 5 worst performers in each portfolio and Columns (7–9) exclude the 10 best and 10 worst performers. All errors are clustered at the fund level, and p-values are reported in parentheses. $*$, $**$, and $***$ denote significance levels at 10%, 5%, and 1%.

Data Filter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	None	None	None	exclude 5 best and 5 worst			exclude 10 best and 10 worst		
fh_gain	0.021***	0.027***	0.077***	0.021***	0.027***	0.077***	0.021***	0.027***	0.077***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
fh_loss	−0.017***	−0.015***	−0.046***	−0.017***	−0.015***	−0.046***	−0.017***	−0.015***	−0.046***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
$fh\_gain \times \sqrt{fh\_time}$			−0.012***			−0.012***			−0.012***
			(0.001)			(0.001)			(0.001)
$fh\_loss \times \sqrt{fh\_time}$			0.008***			0.008***			0.008***
			(0.001)			(0.001)			(0.001)
$\sqrt{fh\_time}$			0.002***			0.002***			0.002***
			(0.001)			(0.001)			(0.001)
best_dummy	0.017***	0.012***	0.012***	0.017***	0.012***	0.013***	0.017***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
worst_dummy	0.015***	0.014***	0.012***	0.016***	0.015***	0.013***	0.015***	0.015***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.011***			0.011***			0.011***		
	(0.001)			(0.001)			(0.001)		
Stock-Time FEs	NO	YES	YES	NO	YES	YES	NO	YES	YES
Error Cluster Level	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund
Observations	27,576,203	27,576,203	27,576,203	27,492,540	27,492,540	27,492,540	27,332,988	27,332,988	27,332,988
R^2	0.006	0.13	0.134	0.006	0.129	0.134	0.006	0.127	0.132

Table 10

Pricing effect, Fama-MacBeth regressions - compare with the rank effect. 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 parentheses) are calculated using the time series of cross-sectional estimates. 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 equations (8) and (9). *best_d* (*worst_d*) is a dummy variable that equals 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). *best_pct* (*worst_pct*) is the percentage of funds who have the security as best (worst) ranked in their portfolio among all funds holding this security. For the definition of other control variables, please see Table 2. R-squared is the average R^2 from the cross-sectional regressions. ∗, ∗∗, and ∗∗∗ denote significance levels at 10%, 5%, and 1%.

Data Filter	(1) All months	(2) Feb–Dec	(3) All months	(4) Feb–Dec	(5) All months	(6) Feb–Dec	(7) All months	(8) Feb–Dec
gain_overhang					0.009∗∗∗	0.010∗∗∗	0.009∗∗∗	0.009∗∗∗
					(5.57)	(5.73)	(5.14)	(5.20)
loss_overhang					−0.004∗∗∗	−0.004∗∗∗	−0.005∗∗∗	−0.004∗∗∗
					(−5.30)	(−4.71)	(−5.30)	(−4.69)
best_d	0.001∗∗	0.001∗∗			0.000	0.000		
	(2.55)	(2.53)			(0.76)	(0.70)		
worst_d	0.004∗∗∗	0.003∗∗∗			0.003∗∗∗	0.003∗∗∗		
	(5.99)	(5.67)			(4.55)	(4.51)		
best_pct			0.009∗	0.013∗∗∗			0.005	0.008∗
			(1.89)	(2.64)			(1.04)	(1.78)
worst_pct			0.031∗∗∗	0.031∗∗∗			0.013∗∗	0.015∗∗
			(4.73)	(4.51)			(2.04)	(2.24)
$Ret^{+}_{-12,-2}$	0.007∗∗∗	0.008∗∗∗	0.006∗∗∗	0.007∗∗∗	0.005∗∗∗	0.006∗∗∗	0.005∗∗∗	0.006∗∗∗
	(6.05)	(7.02)	(5.69)	(6.60)	(4.96)	(5.80)	(4.82)	(5.64)
$Ret^{-}_{-12,-2}$	0.021∗∗∗	0.023∗∗∗	0.020∗∗∗	0.022∗∗∗	0.023∗∗∗	0.025∗∗∗	0.023∗∗∗	0.024∗∗∗
	(6.22)	(6.51)	(6.10)	(6.46)	(7.22)	(7.29)	(7.38)	(7.50)
Ret_{-1}	−0.029∗∗∗	−0.023∗∗∗	−0.030∗∗∗	−0.023∗∗∗	−0.030∗∗∗	−0.024∗∗∗	−0.031∗∗∗	−0.025∗∗∗
	(−7.96)	(−6.18)	(−8.09)	(−6.31)	(−8.55)	(−6.77)	(−8.69)	(−6.91)
$Ret_{-36,-13}$	−0.001∗	−0.000	−0.001∗	−0.000	−0.001∗	−0.000	−0.001∗	−0.000
	(−1.73)	(−0.54)	(−1.80)	(−0.67)	(−1.94)	(−0.74)	(−1.96)	(−0.80)
logBM	0.001∗	0.001∗	0.001∗∗	0.001∗	0.001∗	0.001∗	0.001∗	0.001∗
	(1.96)	(1.74)	(2.05)	(1.83)	(1.87)	(1.66)	(1.95)	(1.74)
logMktcap	−0.001∗∗∗	−0.001∗∗∗	−0.001∗∗∗	−0.001∗∗	−0.001∗∗∗	−0.001∗∗	−0.001∗∗∗	−0.001∗∗
	(−3.35)	(−2.66)	(−2.70)	(−2.09)	(−3.14)	(−2.48)	(−2.73)	(−2.12)
ivol	−0.213∗∗∗	−0.265∗∗∗	−0.212∗∗∗	−0.266∗∗∗	−0.224∗∗∗	−0.275∗∗∗	−0.224∗∗∗	−0.275∗∗∗
	(−4.32)	(−5.40)	(−4.32)	(−5.40)	(−4.65)	(−5.69)	(−4.65)	(−5.70)
turnover	−0.062	−0.128	−0.049	−0.116	−0.047	−0.112	−0.040	−0.106
	(−0.45)	(−0.91)	(−0.35)	(−0.82)	(−0.34)	(−0.80)	(−0.29)	(−0.75)
constant	0.027∗∗∗	0.026∗∗∗	0.025∗∗∗	0.024∗∗∗	0.025∗∗∗	0.024∗∗∗	0.024∗∗∗	0.023∗∗∗
	(7.82)	(7.19)	(7.27)	(6.72)	(7.29)	(6.71)	(6.96)	(6.44)
Ave. monthly obs.	2359	2360	2359	2360	2359	2360	2359	2360
R^2	0.066	0.064	0.066	0.065	0.068	0.067	0.069	0.067
# of months	461	423	461	423	461	423	461	423

Table 11
Selling behavior regressions - alternative measures. For ease of notation, subscripts have been omitted. The dependent variable is either $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund *f* sold part or all of its position in security *i* in time period *t*, or $Selling\%\_of\_shrout = \left[\frac{\#\text{of shares sold}}{\#\text{of shares outstanding}}\right] \times 100$ which is the percentage of shares outstanding sold for a given stock by a given fund in a given time period. *fh_gain* and *fh_loss* represent the gain and loss calculated for each fund-holding pair as defined in equations (2) and (3), respectively. The alternative measures (*fh_gain_alt* and *fh_loss_alt*) are normalized by the purchase price instead of the current price as defined in equations (26) and (27), respectively. *fh_time* is equal to the weighted average holding period. All errors are clustered at the fund level, and p-values are reported in parentheses. $*$, $**$, and $***$ denote significance levels at 10%, 5%, and 1%.

Dependent Variable	(1) $\mathbb{I}(selling)$	(2) $\mathbb{I}(selling)$	(3) $\mathbb{I}(selling)$	(4) $\mathbb{I}(selling)$	(5) *Selling%_of_shrout*	(6) *Selling%_of_shrout*
fh_gain	0.550***	1.377***				
	(0.023)	(0.032)				
fh_loss	−0.285***	−0.706***				
	(0.012)	(0.013)				
$fh\_gain \times \sqrt{fh\_time}$		−0.213***				
		(0.006)				
$fh\_loss \times \sqrt{fh\_time}$		0.116***				
		(0.003)				
$\sqrt{fh\_time}$		0.046***		0.045***		0.002***
		(0.002)		(0.002)		0
fh_gain_alt			0.154***	0.505***	0.008***	0.031***
			(0.01)	(0.015)	(0.001)	(0.001)
fh_loss_alt			−0.701***	−1.567***	−0.041***	−0.103***
			(0.022)	(0.025)	(0.002)	(0.003)
$fh\_gain\_alt \times \sqrt{fh\_time}$				−0.079***		−0.004***
				(0.003)		0
$fh\_loss\_alt \times \sqrt{fh\_time}$				0.248***		0.016***
				(0.006)		(0.001)
Stock-Time FEs	YES	YES	YES	YES	YES	YES
Observations	27,582,450	27,582,450	27,582,450	27,582,450	27,582,450	27,582,450
R^2	0.219	0.247	0.215	0.244	0.13	0.134

and the alternative fund-holding gain and loss variables are constructed accordingly:

$$fh\_gain\_alt_{ft} = Max\{\sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{p_t - p_{t-n}}{p_{t-n}}\right], 0\} \tag{26}$$

and

$$fh\_loss\_alt_{ft} = Min\{\sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{p_t - p_{t-n}}{p_{t-n}}\right], 0\}. \tag{27}$$

We rerun selling behavior regressions with these variations and the results are shown in Table 11. We use the indicator $\mathbb{I}(selling_{fit})$ as the dependent variable and present the results in columns (1)-(4). Next, we employ the original fund-holding overhang measures defined in Subsection 3.1 and find in columns (1)-(2) that the results that conform to those using the original LHS variable. We allow for time interactions in the regression for column (2), and find that at the average holding period (about 17 months), a 1% more extreme fund-holding gain (loss) results in a 0.50% (0.23%) higher probability of selling. In the regressions s for columns (3-4), we use the alternative fund-holding overhang variables defined in equations (26) and (27). An interesting observation from these results is that the overhang coefficients are still very statistically and economically significant, but the relative magnitude between fund-holding gain and loss is opposite the original measure. In column (3), we see that the ratio of coefficients for fund-holding loss over fund-holding gain is $\left|\frac{\beta^{fh\_loss\_alt}}{\beta^{fh\_gain\_alt}}\right| = 4.5$. Doing panel regressions with stock-time fixed effects, using the percentage of shares outstanding sold as the LHS variable and the alternative measures of fund-holding overhang, we find highly significant coefficients in columns (5)-(6) for both gain and loss, respectively, and the relative magnitude of gain and loss is similar to the relations implied in columns (3) and (4). The V-shaped selling schedule holds across all of the selling behavior coefficients using the alternative measures. Moreover, using a selling indicator as the LHS variable and splitting the data along the dimensions presented in Table 3 or in the fund characteristic split analysis from Table 7 does not qualitatively change our findings.

In untabulated results, we aggregate unrealized profits normalized by purchase price to the security level, and rerun predictive Fama-MacBeth regressions (as in equation (10)) using the alternative gain and loss overhang. The alternative gain and loss overhang still significantly predict future returns with expected signs, and the effect of loss is about two to three times as large as the effect of gain, which is largely consistent with the selling regression results using the alternative measures.

These results further substantiate the robustness of the V-shaped disposition effect. Although the relative slope of the gain and loss overhang is dependent on the choice in normalizing price, both measures result in statistically and economically signif-

Table 12
Selling behavior regressions - placebo test. For ease of notation, subscripts have been omitted. The dependent variable is $Selling\%\_of\_shrout = \left[\frac{\#\text{of shares sold}}{\#\text{of shares outstanding}}\right] \times 100$ which is the percentage of shares outstanding sold for a given stock by a given fund in a given time period. *fh_gain* and *fh_loss* represent the gain and loss calculated for each fund-holding pair as defined in equations (2) and (3), respectively. All errors are clustered at the fund level, and p-values are reported in parentheses. $*$, $**$, and $***$ denote significance levels at 10%, 5%, and 1%.

Data Filter	(1) Index Funds
fh_gain	0.0046
	(0.0035)
fh_loss	(0.0012)
	(0.0019)
$fh\_gain \times \sqrt{fh\_time}$	(0.0005)
	(0.0003)
$fh\_loss \times \sqrt{fh\_time}$	0.0004
	(0.0004)
$\sqrt{fh\_time}$	0.0002
	(0.0001)
Stock-Time FEs	YES
Observations	1,231,515
R^2	0.241

icant coefficients whose predictions for fund managers' selling behavior are consistent with the estimated effects on equilibrium prices.

6.4. Placebo test

We predict that the V-shaped 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. In the CRSP Mutual Fund database, index funds are categorized 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. Even pure index funds may hold portfolios that differ greatly from a broad equity index; for example, a number of the "pure" index funds are equity growth index funds or equity funds that target specific market capitalization. Alternatively, we use the Lipper objective codes to isolate the S&P 500 index funds.

Results from the selling behavior regressions, using only this subset of mutual funds, are shown in Table 12. We see that the coefficients on the fund holding gain and loss variables are not statistically different from zero for these index funds.

7. Conclusion

Linking seemingly irrational behavior to fluctuations in equilibrium prices is difficult. In the well-defined context of mutual fund portfolio management, we document a seemingly biased trading behavior that affects equilibrium asset prices. Both the cross-sectional and cross-fund return predictability support our interpretation. Mutual fund managers, like individual retail investors, exhibit a V-shaped disposition effect - they are more likely to sell both their big winners and losers. Aggregated across fund managers, this behavior has an impact on equilibrium prices. The subset of funds with higher turnover, shorter holding period, and higher expense ratios are more likely to exhibit the V-shaped disposition effect, and paper gains and losses aggregated across these subsets of funds have stronger return predictability.

Taken together, this evidence provide insight on the pattern, the pricing implications, and the underlying mechanism of the disposition effect. Our results closely tie observed price variation to investors' behavior and suggest that seemingly biased trading tendencies can aggregate to predictably affect equilibrium prices.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.finmar.2020.100580.

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