Asset Pricing When Traders Sell Extreme Winners and Losers

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Abstract

This study investigates the asset pricing implications of a newly documented refinement of the disposition effect, characterized by investors being more likely to sell a security when the magnitude of their gains or losses on it increases. I find that stocks with both large unrealized gains and large unrealized losses outperform others in the following month (trading strategy monthly alpha = 0.5–1%, Sharpe ratio = 1.5). This supports the conjecture that these stocks experience higher selling pressure, leading to lower current prices and higher future returns. Overall, this study provides new evidence that investors' trading behavior can aggregate to affect equilibrium price dynamics. (*JEL* G11, G12, G14)

This paper was previously circulated under the title “The V-Shaped Disposition Effect,” and is based on a portion of my thesis at Columbia University. I am deeply indebted to Kent Daniel and Paul Tetlock for invaluable discussions, guidance, and encouragement. Thanks also to David Hirshleifer (the editor), two anonymous referees, Patrick Bolton, Joe Stiglitz, Jianfeng Yu, Paul Gao, Gur Huberman, Bob Hodrick, Hao Zhou, and Xuan Tian, and to seminar participants at Columbia University, Tsinghua University PBC School of Finance, Research Affiliates, Moodys Analytics, Cornerstone Reserch, Brattle Group, Analysis Group, PanAgora Asset Management 2014 Crowell Prize, and Chicago Quantitative Alliance 2014 Academic Competition. I thank Terrance Odean for generously providing trading data, and Zahi Ben-David and David Hirshleifer for kindly sharing their scripts. All remaining errors are my own. Send correspondence to Li An, Tsinghua University, PBC School of Finance, 43 Chengfu Road, Beijing 100083, P.R. China; telephone: +86-10-62797840. E-mail: anl@pbcsf.tsinghua.edu.cn.

The disposition effect, first described by Shefrin and Statman (1985), refers to investors' tendency to sell securities whose prices have increased since purchase rather than those that have fallen in value. This trading behavior is well documented by evidence from both individual investors and institutions,[1] across different asset markets,[2] and around the world.[3] Several recent studies further explore the asset pricing implications of this behavioral pattern and propose it as the source of a few return anomalies, such as price momentum (e.g., Grinblatt and Han 2005). In these studies, the binary pattern of the disposition effect (a difference in selling propensity, conditional on gain versus loss) is commonly presumed as a monotonically increasing relation of investors' selling propensity in response to unrealized profits.

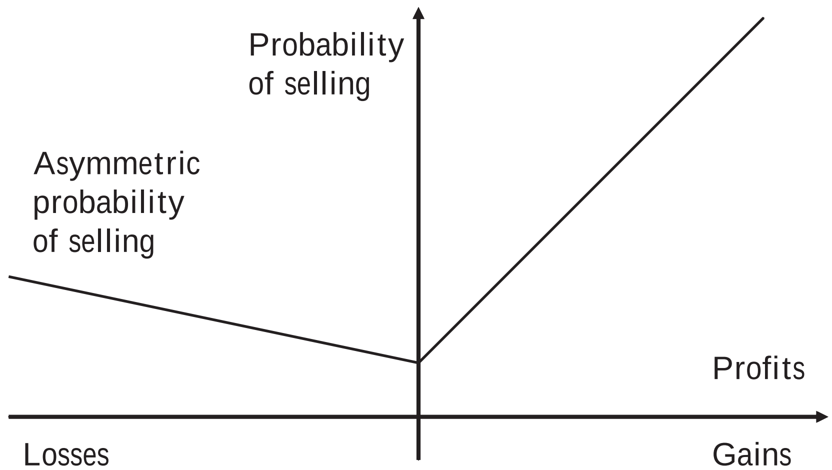
However, new evidence calls this view into question. Ben-David and Hirshleifer (2012) examine individual investor trading data and show that investors' selling propensity is actually a V-shaped function of unrealized profits: selling probability increases as the magnitude of gains or losses increases, with the gain side having a larger slope than the loss side. The V-shaped selling schedule documented also appears in other studies, such as Barber and Odean (2013) and Seru, Shumway, and Stoffman (2010), although it is not their focus. Figure 1 illustrates this relation. Notably, this asymmetric V-shaped selling schedule remains consistent with the empirical regularity that investors sell more gains than losses: since the gain side of the V is steeper than the loss side, the average selling propensity is higher for gains than for losses. This observed V calls into question the current understanding of how investors sell as a function of profits. Moreover, it also challenges the studies on equilibrium prices and returns that presume a monotonically increasing relation between selling propensity and profits.

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

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

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

Figure 1
V-shaped selling propensity in response to profits



Source: Ben-David and Hirshleifer (2012), Figure 2B. Reprinted by permission of Oxford University Press on behalf of the Society for Financial Studies.

The current study investigates the pricing implications and consequent return predictability of this newly documented re nement of the disposition e ect. I refer to the asymmetric V-shaped selling schedule, which Ben-David and Hirshleifer (2012) suggest underlies the disposition e ect, as the V-shaped disposition e ect. If investors sell more when they have larger gains and losses, then stocks with both larger unrealized gains and larger unrealized losses (in absolute value) will experience higher selling pressure. This will temporarily push down current prices and lead to higher subsequent returns when future prices revert to the fundamental values.

To test this hypothesis, I use stock data from 1963 to 2013 and construct stock-level measures for unrealized gains and losses. In contrast to previous studies, I isolate the e ect from gains and that from losses to recognize the pronounced kink and non-monotonicity in the investors' selling schedule. The results show that stocks with larger unrealized gains and those with larger unrealized losses (in absolute value) indeed outperform others in the following month. This return predictability is stronger on the gain side than on the loss side, consistent with the asymmetry documented on the individual level. In terms of magnitude, a trading strategy based on this e ect generates a monthly alpha of approximately 0.5%{1%, with an annualized Sharpe ratio as high as 1.5; in comparison, for the same sample period, the Sharpe ratios of momentum, value, and size strategies are 0.9, 0.6, and 0.7, respectively. Thus, the nding in this paper is comparable to the strongest available evidence on price pressure.

To place my ndings into the context of existing research, I compare a net selling propensity measure that recognizes the V-shaped disposition e ect, the V-shaped net selling propensity, with the capital gains overhang variable, which is motivated by a model that assumes a monotonically increasing selling propensity in response to pro ts. Grinblatt and Han (2005) propose the latter variable, which is also studied in subsequent research. A horse race between these two variables shows that once the V-shaped net selling propensity is controlled, the e ect of capital gains overhang disappears.

To gain insight into the source of the V-shaped disposition e ect, I conduct tests in cross-sectional subsamples based on institutional ownership, rm size, turnover ratio, and stock volatility. In more speculative subsamples (stocks with lower institutional ownership, smaller size, higher turnover, and higher volatility), the e ects of unrealized gains and losses are stronger. This nding supports the conjecture that a speculative trading motive underlies the observed V. It is also consistent with Ben-David and Hirshleifer's (2012) nding that the strength of the V-shape at the individual level is related to investors' \speculative" characteristics, such as trading frequency and gender.

This paper connects to three strands of the literature. First, this study adds to the literature on the disposition e ect being relevant to asset pricing. While investor tendencies and biases are of interest on their own, they relate to asset pricing only when individual behaviors aggregate to a ect equilibrium price dynamics. Grinblatt and Han (2005) develop a model in which the disposition e ect creates a wedge between price and fundamental value. Predictable return patterns are generated as the wedge converges in subsequent periods. Empirically, they construct a stock-level measure of capital gains overhang and show that it predicts future returns and subsumes the momentum effect. Frazzini (2006) measures capital gains overhang with mutual fund holding data and shows that underreaction to news caused by the disposition effect can explain post-earning announcement drift. Goetzmann and Massa (2008) show that the disposition effect goes beyond predicting stock returns: it helps to explain volume and volatility as well. Shumway and Wu (2007) find evidence in China that the disposition effect generates momentum-like return patterns. The measures used in these studies are based on the premise that investors' selling propensity is a monotonically increasing function of past profits. This study is the first one to recognize the non-monotonicity when measuring stock-level selling pressure from unrealized gains and losses and to show that it better captures the predictive return relation.

Return patterns documented in this study emphasize the importance of price path, together with trading volume along the path, in predicting future price movement, above and beyond the mere magnitude of past return. A related but distinct price effect is Da, Gurun, and Warachka's (2014) "frog-in-the-pan" (FIP) effect. Based on the intuition that investors underreact to frequent gradual changes relative to infrequent dramatic changes, the authors find that the momentum effect is stronger after continuous information, which is defined by frequent arrival of small signals and empirically proxied by a high percentage of days in the formation period in which daily returns have the same sign as the cumulative formation-period return. Both FIP and the V-shaped disposition effect emphasize the relevance of price path in predicting returns, yet their implications are considerably different. Consider a case in which a stock with a specific return has a volatile price path. In the FIP story, such a price path would be interpreted as discrete information arrival and thus would predict little return continuation. In contrast, in the V-shaped disposition effect story, the volatile price path is likely to result in both large unrealized gains and large unrealized losses and therefore would predict higher future return.

Second, this paper contributes to the literature on the extent to which investors' selling propensity in response to gains and losses can explain the momentum effect. Grinblatt and Han (2005) and Weber and Zuchel (2002) develop models in which the disposition effect generates momentum-like returns, and Grinblatt and Han (2005) and Shumway and Wu (2007) provide empirical evidence to support this view. In contrast, Birru (2015) disputes the causality between the disposition effect and momentum. He finds that momentum remains robustly present following stock splits, which he shows lack the disposition effect. Novy-Marx (2012) shows that a capital gains overhang variable, constructed as in Frazzini (2006) using mutual fund holding data, does not subsume the momentum effect. My study examines the pricing implications of the full functional form of investors' selling schedule. I show that selling propensities in light of capital gains and losses do not contribute unambiguously to the momentum effect: the tendency to sell more in response to larger losses tends to generate a price impact that opposes the momentum effect.

Third, it also bears on the research on investors' trading behaviors, particularly how investors trade in light of unrealized profits and what theories may explain this behavior. Although it has become an empirical regularity that investors sell more gains than losses, most studies focus on the sign of profit (gain or loss) rather than its size. The full functional form has not been fully resolved yet. Unlike the V-shape recently documented, Odean (1998) and Grinblatt and Keloharju (2001) show a selling pattern that appears as a monotonically increasing function of past profits.[4] More recently, several concurrent studies examine how institutional investors trade in light of unrealized profits; most but not all of them find a V-shaped pattern similar to that in Ben-David and Hirshleifer (2012).[5] My findings show that the return patterns in relation to investors' gains and losses are

[4] These studies do not focus on examining the shape of investors' selling schedule.

[5] An and Argyle (2015) find that mutual fund managers tend to sell in a V-shape in response to gains and losses. Hartzmark (2015) shows that investors are more likely to sell extreme winning and extreme losing positions in their portfolio; this is generally in line with the V-shape. Weisbrod (2015) confines the sample to fund managers' trading in the three-day window around earnings announcements and finds a V-shape in selling schedule in a short holding period; however, when the holding period exceeds 100 days, the V-shape becomes inverted.

consistent with the V-shaped selling schedule; though not a direct test, this is the first price-level evidence we have, which complements previous studies using trading data.

The shape of the full trading schedule is important because it provides clues for the source of this behavior. Prevalent explanations for the disposition effect attribute this behavioral tendency to investors' preferences. Prospect theory (Kahneman and Tversky 1979) has been commonly yet informally argued to lead to the disposition effect; however, the insights from Barberis and Xiong (2009) and Hens and Vlcek (2011) suggest that prospect theory often fails to generate the binary pattern of the disposition effect. Several recent models, built on realization utility or prospect theory, succeed in producing a higher selling probability conditioned on gain versus loss (see Barberis and Xiong 2012; Ingersoll and Jin 2012; Meng 2014; and Li and Yang 2013), yet the V-shaped selling schedule further raises the hurdle for preference-based theories to explain investors' trading pattern in light of unrealized profits.[6]

On the other hand, Ben-David and Hirshleifer (2012) point out that the disposition effect is not necessarily evidence in support of preference-based explanations; instead, belief-based interpretations may come into play. Cross-sectional subsample return patterns found in this paper are consistent with the view that a speculative trading motive (based on investors' beliefs) is a general cause of this behavior. Moreover, while several interpretations based on investors' beliefs are consistent with the V-shape on the individual level, they are likely to diverge on implications for stock-level return predictability. Thus, the stock-level evidence in this paper provides tentative insights on which mechanisms may hold promise for explaining the V-shaped disposition effect. Section 4 discusses this point in detail.

[6] Ingersoll and Jin (2012) point out that, under certain parameter values, an aggregation effect of their heterogeneous agents model can match the V-shaped selling schedule. In contrast, Meng (2014)'s model tends to generate an inverted V-shape.

1. Analytical Framework and Hypothesis

1.1 Analytical framework

How does investors' tendency to trade in light of unrealized profits affect equilibrium prices? I adopt Grinblatt and Han's (2005) analytical framework to answer this question. In this framework, the disposition effect leads to a demand perturbation, which in turn drives stock return predictability. There exists one risky stock and two types of investors in this model: type I investors have rational demand, which only depends on the stock's fundamental value; type II investors are disposition-prone, and their demand is a linear function of the stock's fundamental value and their purchase price. Moreover, the supply of the stock is assumed to be fixed, normalized to one unit. By aggregating the demand from all investors, the authors show that the equilibrium price is a linear combination of the stock's fundamental value and the disposition-prone investors' purchase price. I refer the readers to Grinblatt and Han's (2005) paper for further details.

For one stock at one time point, investors who do not own the stock are not subject to the disposition effect; they therefore have rational demand for the stock (as potential buyers). For current stockholders, all or a fraction of them may be prone to the disposition effect and have demand perturbation. Thus, for the purpose of studying the pricing implications, I need to focus only on the demand function of current stockholders. I empirically estimate it in the following subsection, using retail investors' trading data.

1.2 A revisit of trading evidence and quantitative derivation of hypothesis

In this subsection, I revisit the trading evidence documented by Ben-David and Hirshleifer (2012) and quantitatively derive its pricing implications. I answer two questions here. First, Ben-David and Hirshleifer (2012) find that both selling and buying schedules have a V-shaped relation with unrealized profits; thus, for the purpose of gauging the price effects, I estimate the net selling schedule (selling – buying), which corresponds to investors' demand. Second, I estimate the relative magnitude of demand perturbation on the gain side versus that on the loss side, so that later we can see if the price effects from the two sides are consistent with this relation.

I conduct analysis on how paper gains and losses affect selling and buying in a similar fashion to that in Ben-David and Hirshleifer (2012). I use the same retail investor trading data (the Odean dataset) and follow Ben-David and Hirshleifer (2012) for their data screening criteria and variable specifications. I perform regressions of selling or buying on investor's return since purchase and control variables, based on trading records of all 77,037 accounts in the dataset. Unrealized returns are separated by their signs ($Ret2^+ = Max\{Ret2; 0\}$ and $Ret2^- = Min\{Ret2; 0\}$; the definition of $Ret2$ is given in the next paragraph). The controls include an indicator variable if returns are positive, an indicator variable if returns are zero, the square root of the prior holding period measured in holding days, the logged purchase price (raw value, not adjusted for stock splits and distributions), and two stock return volatility variables (calculated using the previous 250 trading days). One volatility variable is equal to stock volatility when the return is positive and is zero otherwise; the other variable is equal to stock volatility when the return is the negative and is zero otherwise. Regressions are run at different holding horizons (1 to 20 days, 21 to 250 days, and greater than 250 days), and the observations are at investor-stock-day level. I refer to Ben-David and Hirshleifer (2012) for more details.

To better map trading to price impact, I make two major changes from Ben-David and Hirshleifer's (2012) specification. First, the price effect should depend on the size of trades, not just the probability of selling or buying for a given unrealized capital gain. Thus, the dependent variable I use is the number of shares sold or bought, normalized by the shares outstanding. This choice of normalizer fits best to Grinblatt and Han's (2005) theoretical framework where the supply of the stock is fixed and normalized to one, and it makes it comparable to price impact induced by trading across di erent stocks. The dependent variable is multiplied by 1,000,000.

Second, Ben-David and Hirshleifer (2012) de ne return since purchase as the di erence between purchase price and current price, normalized by purchase price (i.e., $Ret = \frac{P_t - P_0}{P_0}$). On the other hand, in previous literature on the pricing implications of the disposition e ect (e.g., Grinblatt and Han 2005 and Frazzini 2006), the stock-level aggregation of investors' gains and losses is all de ned as a weighted sum of the percentage deviation of purchase price from current price, $\frac{P_t - P_0}{P_t}$. I refer to the latter de nition as $Ret2$ henceforth. Which de nition is better? For aggregation at the stock level, $Ret2$ has a unique advantage in that the weighted sum of all investors' unrealized pro ts can be interpreted as the unrealized pro t of a representative investor ($\sum_i !_i \frac{P_t - P_{0i}}{P_t} = \frac{P_t - \sum_i !_i P_{0i}}{P_t}$). On the contrary, the de nition of Ret Han 2005T4n12hiclized93 period less than 20 days, a 1% increase in $Ret2^{+}$ induces the investor to sell 4.2 more parts per million (ppm) of shares outstanding and buy 1.0 more ppm of shares outstanding. Thus the increase in net selling is 3.2 ppm of shares outstanding. On the loss side, a 1% increase in $|Ret2^{-}|$ induces the investor to sell 1.4 more ppm of shares outstanding and buy 0.6 more ppm of shares outstanding. Thus the increase in net selling is 0.8 ppm of shares outstanding. This suggests that investors' net selling schedule is a V-shaped function, with the gain side having a steeper slope than the loss side.

What is the relation between net selling probability upon a gain and net selling probability upon a loss? Because the selling schedule becomes flat beyond one year of holding time, I estimate this relation using results in columns (1), (2), (4), and (5). Given that the numbers of observations are 8.9 million and 63.1 million at 1–20 days horizon and 21–250 days horizon, respectively, we can use these numbers to proxy for their representation in the investor pool. The overall net selling increase caused by a 1% increase in $Ret2^{+}$ is $(4.209 - 0.972) \times \frac{8.9}{8.9+63.1} + (0.069 - 0.013) \times \frac{63.1}{8.9+63.1} = 0.449$; the overall net selling increase caused by a 1% increase in $|Ret2^{-}|$ is $(1.353 - 0.563) \times \frac{8.9}{8.9+63.1} + (0.014 - 0.007) \times \frac{63.1}{8.9+63.1} = 0.104$. Thus, we have the relation between the gain arm and the loss arm of the V-shaped net selling schedule as a multiple of $\frac{0.449}{0.104} = 4.3$.

I now link the estimated investors' demand perturbation to the pricing implications and arrive at the following main hypothesis:

HYPOTHESIS PI (PRICE IMPACT): The V-shaped-disposition-prone investors tend to (net) sell more when their unrealized gains and losses increase in magnitude; the gain side of this effect is about 4.3 times as strong as the loss side. Consequently, at the stock level, stocks with larger gain overhang and larger (in absolute value) loss overhang will experience higher selling pressure, resulting in lower current prices and higher future returns as future prices revert to the fundamental values. Moreover, the price effect on the gain side and that on the loss side shall be in line with the relative magnitude.

The rest of the paper focuses on testing the pricing implications. All remaining empirical exercises will be conducted on the stock level.

2. Data and Key Variables

2.1 Stock samples and filters

I use daily and monthly stock data from CRSP. The sample covers all U.S. common shares (with CRSP share codes equal to 10 and 11) listed in NYSE, AMEX, and NASDAQ from January 1963 to December 2013. To avoid the impact of the smallest and most illiquid stocks, I eliminate stocks worth less than two dollars in price at the time of portfolio formation, and I require that the stock was traded for at least 10 days in the past month. I focus on monthly frequency when assessing how gain and loss overhangs affect future returns. My sample results in 2.1 million stock-month combinations, which is approximately 3,400 stocks per month on average.

Accounting data are from Compustat. Institutional ownership data are from Thomson-Reuters Institutional Holdings (13F) Database, and this information extends back to 1980.

2.2 Gains, losses, and the V-shaped net selling propensity

For each stock, I measure the aggregate unrealized gains and losses at each month end by using the volume-weighted percentage deviation of the past purchase price from the current price. The construction of variables is similar to that in Grinblatt and Han (2005), but with the following major differences: (i) instead of aggregating all past prices, I measure gains and losses separately; (ii) I use daily as opposed to weekly past prices in the calculation.

Specifically, I compute the *Gain Overhang* (*Gain*) as the following:

$$
\begin{aligned}
Gain_t &= \sum_{n=1}^{\infty} \omega_{t-n} gain_{t-n} \\
gain_{t-n} &= \frac{P_t - P_{t-n}}{P_t} \mathbf{1}_{\{P_{t-n} \leq P_t\}} \\
\omega_{t-n} &= \frac{1}{k} V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}]
\end{aligned} \tag{1}
$$

where V_{t-n} is the turnover ratio at time $t - n$. The aggregate *Gain Overhang* is measured as the weighted average of the percentage deviation of the purchase price from the current price if the purchase price is lower than the current price. The weight (ω_{t-n}) is a proxy for the fraction of stocks purchased at day $t - n$ that are not traded afterward.

Symmetrically, the *Loss Overhang* (*Loss*) is computed as:

$$
\begin{aligned}
Loss_t &= \sum_{n=1}^{\infty} \omega_{t-n} loss_{t-n} \\
loss_{t-n} &= \frac{P_t - P_{t-n}}{P_t} \mathbf{1}_{\{P_{t-n} > P_t\}} \\
\omega_{t-n} &= \frac{1}{k} V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}]
\end{aligned} \tag{2}
$$

The *Loss Overhang* variable has negative value, and an increase in *Loss Overhang* means a decrease in the magnitude of loss.

Because NASDAQ volume data are subject to double counting, I cut the volume numbers by half for all stocks listed on NASDAQ to make it roughly comparable to stocks listed on other exchanges. I do not adjust purchase prices for stock splits and dividends. The reason is the following: Birru (2015) points out that investors may naively calculate their gains and losses based on their nominal purchase price, without adjusting for stock splits and dividends. He shows that the disposition effect is absent after stock splits and attributes this observation to investors' confusion. In the robustness check section, I construct gain and loss measures using adjusted purchase prices; the results remain very similar to those of unadjusted variables. If the current stock price exceeds all the historical prices within the past five years, *Loss* is set to be 0, and vice versa for *Gain*. Moreover, to be included in the sample, a stock must have at least 60% nonmissing values within the measuring window or since the time it appears in CRSP.

Following Grinblatt and Han (2005), I truncate price history at five years and rescale the weights for all trading days (with both gains and losses) to sum up to one. In Equations (1) and (2), k is the normalizing constant such that $k = \sum_{n} V_{t-n} \prod_{i=1}^{n-1}[1 - V_{t-n+i}]$. The choice of a five-year window is due to three reasons. First, Ben-David and Hirshleifer (2012) document the refinement of the disposition effect among individual traders, and they show that the effect flattens after a one-year holding period (see Table 4 in their paper; see also Table 1 in this paper); however, the disposition effect is not restrained to this group of investors.[8] Using a five-year window allows the possibility that other types of investors may have different trading horizons. Indeed, using mutual fund holding data, An and Argyle (2015) show that mutual fund managers also exhibit a V-shaped selling schedule, and this trading pattern lasts beyond one year of the holding period. Although often regarded as sophisticated investors, mutual funds, as Arif, Ben-Rephael, and Lee (2015) show, tend to trade in opposite directions of long-term price movement, resulting in substantial losses; thus it is not ungrounded to conjecture that mutual funds' V-shaped selling schedule at horizons longer than a year would contribute to price pressure in a similar way as that of retail investors.

Second, even if all investors are inclined to sell big winners and losers only at a short holding horizon, driving the price too low, it says little about how long it takes for the price to correct itself. It may take several years. Thus the horizon for return predictability may last longer than investors' trading horizon. Third, a five-year window allows a convenient comparison with the previous literature: the sum of *Gain Overhang* and *Loss Overhang* is equal to *Capital Gains Overhang* (*CGO*)

[8] See Frazzini (2006), Locke and Mann (2005), Shapira and Venezia (2001), and Coval and Shumway (2005), among others.

in Grinblatt and Han (2005).

Putting together the effects of unrealized gains and losses, I name the overall variable the *V-shaped Net Selling Propensity* ($VNSP$):

$$VNSP_t = Gain_t - 0.23 Loss_t \tag{3}$$

The coefficient -0.23 indicates the asymmetry in the V-shape of investors' net selling schedule. According to the regression results in Section 1.2, the slope on the the gain side of the V is about 4.3 times as large as that on the loss side. Thus, the coefficient in front of $Loss$ is set to be $-\frac{1}{4.3} = -0.23$.

Panel A in Table 2 presents the time-series average of the cross-sectional summary statistics for *Gain Overhang*, *Loss Overhang*, *Capital Gains Overhang*, and *V-shaped Net Selling Propensity*. *Gain* and *Loss* are winsorized at the 1% level in each tail, while CGO and $VNSP$ are linear combinations of *Gain* and *Loss*.

Insert Table 2 about here.

2.3 Other control variables

To tease out the effects of gain and loss overhang, I control for other variables known to affect future returns. By construction, gain and loss overhang utilize prices from the past five years and thus correlate with past returns; therefore, I control past returns at different horizons. The past twelve- to two-month cumulative return $Ret_{-12,-2}$ is designed to control the momentum effect documented by Jegadeesh (1990), Jegadeesh and Titman (1993), and De Bondt and Thaler (1985). In particular, I separate this return into two variables, with one taking on the positive part ($Ret^{+}_{-12,-2} = Max\{Ret_{-12,-2}, 0\}$) and the other adopting the negative part ($Ret^{-}_{-12,-2} = Min\{Ret_{-12,-2}, 0\}$). This approach addresses the concern that, if the momentum effect is markedly stronger on the loser side (as documented by Hong, Lim, and Stein 2000), then imposing the loser and the winner to have the same coefficient in predicting future returns will tilt the effects from gains and losses. Specifically, the loss overhang variable would bear part of the momentum loser effect that is not completely captured by the model specification, as the losers' coefficient is artificially dragged down by the winners'. Other return controls include the past one-month return Ret_{-1} for the short-term reversal effect, and the past three- to one-year cumulative return $Ret_{-36;-13}$ for the long-term reversal effect.

Since net selling propensity variables are constructed as volume-weighted past prices, turnover is included as a regressor to address the possible effect of volume on predicting returns, as shown in Lee and Swaminathan (2000) and Gervais, Kaniel, and Mingelgrin (2001). The variable *turnover* is the average daily turnover ratio in the past year. Idiosyncratic volatility is particularly relevant here because stocks with large unrealized gains and losses are likely to have high price volatility, and volatility is well documented (as in Ang et al. 2006, 2009) to relate to low subsequent returns. Thus, I control idiosyncratic volatility (*ivol*), which is constructed as the volatility of daily return residuals with respect to the Fama-French three-factor model in the past one year. Book-to-market (*logBM*) is calculated as 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, so that there is enough time for this information to become public. Firm size (*logmktcap*) is measured as the logarithm of market capitalization in units of millions.

Table 2, Panel B, summarizes these control variables. All control variables in raw values are winsorized at the 1% level in each tail. Panel C presents correlations of gain and loss variables with control variables. Both panels report the time-series average of statistics calculated at monthly level. A somewhat surprising number is the negative correlation of -0.11 between *CGO* and *VNSP*, as both variables intend to capture some kind of the disposition effect. I interpret this negative correlation as follows. The overhang variables are aggregations of $Ret2 = \frac{P_t - P_0}{P_t} = \frac{P_t - P_0}{P_0} \times \frac{P_0}{P_t}$. If $P_t > P_0$ (gain), then the value of *Ret* is lessened; if $P_t < P_0$ (loss), then the value of *Ret* is amplified. Therefore, compared with the normal definition of return, *Ret*2 has larger absolute values on the loss side than on the gain side. Indeed, *Loss* has a standard deviation four times the size of that of *Gain*. On the other hand, as we will see later, the gain side has return predictive power about four times the size of loss. Thus, while the loss side dominates in value, the gain side is stronger in predicting future returns. This is why *CGO* and *VNSP* are negatively correlated in value (through the loss side), but their predictive powers are to some extent aligned (through the gain side).

3. Empirical Setup and Results

To examine how gain and loss overhangs affect future returns, I present two sets of findings. First, I examine returns in sorted portfolios based on gains, losses, and the *V-shaped Net Selling Propensity*. I then employ Fama and MacBeth (1973) regressions to better control for other known characteristics that may affect future returns.

3.1 Sorted portfolios

In Table 3, I investigate returns of double-sorted portfolios on the basis of gain and loss separately. This illustrates a simple picture of how average returns vary across different levels of gain and loss. At the end of each month, I sort stocks into ten groups, based on their residual gains and the negative values of residual losses independently.[9] G1 (L1) represents the portfolio with the smallest gain (loss), and G10 (L10) represents that with the largest gain (loss). The residual values are constructed from simultaneous cross-sectional regressions of *Gain* and *Loss* on past returns, size, turnover, and idiosyncratic volatility. Specifically, the residuals are constructed using the following

[9] I sort by the negative value of residual loss, so that as the loss group increases from L1 to L10, the magnitude of loss increases.

models:

$$
\begin{aligned}
Gain_{t-1} = &\quad + \quad {}_1Ret_{t-1} + \quad {}_2Ret^{+}_{t-12;t-2} + \quad {}_3Ret^{-}_{t-12;t-2} + \quad {}_4Ret_{t-36;t-13} \\
& + \quad {}_5logmktcap_{t-1} + \quad {}_6turnover_{t-1} + \quad {}_7ivol_{t-1} + \quad {}_t \\
Loss_{t-1} = &\quad + \quad {}_1Ret_{t-1} + \quad {}_2Ret^{+}_{t-12;t-2} + \quad {}_3Ret^{-}_{t-12;t-2} + \quad {}_4Ret_{t-36;t-13} \\
& + \quad {}_5logmktcap_{t-1} + \quad {}_6turnover_{t-1} + \quad {}_7ivol_{t-1} + \quad {}_t
\end{aligned}
\tag{4}
$$

I conduct sorting on the basis of the residuals, instead of on the raw values of *Gain* and *Loss*, for the following two reasons. First, there are many known return predictors that correlate with *Gain* and *Loss*. Among all confounding e ects, idiosyncratic volatility and the momentum e ect are of particular concern. For idiosyncratic volatility, stocks with larger gains and losses tend to have higher idiosyncratic (as well as total) volatility, and they are thus expected to have lower future returns (see Ang et al. 2006, 2009, among others). For momentum, raw capital gains and losses are highly correlated with past one-year returns. There are many theories of momentum that use various mechanisms other than Grinblatt and Han's (2005) disposition e ect story.[10] If there is truth to any of these alternative stories, then any tests using raw capital gains and losses without controlling for past returns are likely to be severely biased in measuring the price e ect of selling propensity. Here the purpose is to test whether selling propensities a ect future returns, without taking a stand on what drives momentum;[11] it is therefore important to control for past returns.

Second, the values of *Gain* and *Loss* are highly correlated (stocks with large unrealized gains tend to have small unrealized losses), with a Spearman correlation coe cient of 0.76. Thus, independent sorts based on the raw values of *Gain* and *Loss* will result in too few observations for the small

[10] For behavioral theories, see, for instance, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999). For risk-based explanations, an incomplete list includes Johnson (2002), Sagi and Seasholes (2007), Bansal, Dittmar, and Lundblad (2005), Chordia and Shivakumar (2002), and Liu and Zhang (2011).

[11] To clarify, using residual gains and losses (orthogonal to momentum returns by construction), the portfolio sorting tests do not attempt to directly examine whether selling propensities contribute to the momentum e ect.

gain/small loss portfolios and the large gain/large loss portfolios. In contrast, using residual gain and loss largely alleviates this problem: the Spearman correlation coe cient between residual gain and residual loss drops to around 0.3.

Stocks in a portfolio are weighted by the gross return in the previous month.[12] Panel A shows raw portfolio returns, while Panel B presents the DGTW characteristics-adjusted returns,[13] both in units of monthly percent.

Insert Table 3 about here.

We see that in both Panel A and Panel B, for a given level of gain, subsequent returns increase with the magnitude of loss, and vice versa. It supports the hypothesis that stocks with large gains and losses tend to have higher selling pressure, which leads to lower current prices and higher subsequent returns.

After showing portfolio results based on gains and losses separately, I now examine returns predicted by *V-shaped Net Selling Propensity*, a variable that captures selling pressure from both sides, in Table 4. In Panel A, I sort rms into ve quintiles at the end of each month based on their *VNSP*, with quintile 5 representing the portfolio with the largest *VNSP*. The left side of the table reports gross-return-weighted portfolio returns, and the right side shows value-weighted results. For each weighting method, I show results in the forms of portfolio raw returns, DGTW characteristics-adjusted returns, and Carhart four-factor alphas (Fama and French 1993 and Carhart 1997). All speci cations are examined using all months and using February to December separately.[14] For

[12] This follows the weighting practice suggested by Asparouhova, Bessembinder, and Kalcheva (2010) to minimize confounding microstructure e ects. As they demonstrate, this methodology allows for a consistent estimation of the equal-weighted mean portfolio return. The numbers reported here are almost identical to the equal-weighted results.

[13] The adjusted return is de ned as raw return minus DGTW benchmark return, as developed in Daniel et al. (1997) and Wermers (2003). The benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm, and they range from 1975 to 2012.

[14] Grinblatt and Han (2005) show that their capital gains overhang e ect is very di erent in January compared with other months. They attribute this pattern to return reversal in January caused by tax-loss selling in December. To rule out the possibility that the results are mainly driven by stocks with large loss overhang (in absolute value) having high returns in January, I separately report results using February to December only.

comparison, Panel B shows the same set of results for portfolio returns sorted on capital gains overhang.

Insert Table 4 about here.

Panel A shows that portfolio returns increase monotonically with their *VNSP* quintile. The difference between quintiles 5 and 1 is generally significant for both gross-return-weighted portfolios and value-weighted portfolios. In Panel B, the results confirm Grinblatt and Han's (2005) finding that equal-weighted portfolio returns increase with capital gains overhang. However, the value-weighted portfolios do not have the expected pattern. Moreover, the *VNSP* effect shows little seasonality, whereas the *CGO* effect is stronger from February to December than it is across all months. This pattern occurs because *VNSP* accounts for the negative impact from the loss side, which can capture the January reversal caused by tax-loss selling. Overall, these results suggest that, without controlling for other effects, both *VNSP* and *CGO* capture to some extent the price impacts of the disposition effect.

To better control for confounding factors, in Panels C and D I repeat the exercises in Panels A and B, sorted by residual selling propensity variables instead of the raw values. The residuals are constructed by regressing *VNSP* and *CGO* on past returns, size, turnover, and idiosyncratic volatility (the same set of concurrent variables as in Equation (4)).

Focusing on the gross-return-weighted results in Panel C, the return spreads between top and bottom quintiles based on residual *VNSP* (0.5%–0.8% per month) are of larger magnitude than those in Panel A, and the *t*-statistics become much larger (around 8 to 10, for risk-adjusted returns). In contrast, in Panel D, after controlling for other return predictors, *CGO*'s predictive power becomes very weak; this finding is consistent with the regression results in Table 6, Panel A. The value-weighted portfolios in Panels C and D do not have the expected pattern; the return spread between high- and low-selling propensity portfolios even becomes negative in some columns. As shown in

Section 4, in which I examine results in subsamples, the V-shaped net selling propensity effect is stronger among small firms. In fact, the effect from the gain side disappears among firms with size comparable to the largest 30% of firms in NYSE.

3.2 Fama-MacBeth regression analysis

This subsection explores the pricing implications of the V-shaped disposition effect in Fama-MacBeth regressions. While the results using the portfolio approach suggest a positive relation between the V-shaped net selling propensity and subsequent returns, Fama-MacBeth regressions are more suitable for discriminating the unique information in gain and loss variables. I answer two questions here: (i) Do gain and loss overhangs predict future returns if other known effects are controlled; and (ii) Can this V-shaped net selling propensity subsume the previously documented capital gains overhang effect?

3.2.1 The price effects of gains and losses. I begin by testing Hypothesis PI (in Section 1.2), which states that the V-shaped net selling schedule on the individual level can generate price impacts. This means, ceteris paribus, the *Gain Overhang* will positively predict future return, and the *Loss Overhang* will negatively predict future return (because an increase in value of *Loss Overhang* means a decrease in the magnitude of loss); the former should have a stronger effect compared with the latter. To test this, I consider Fama and MacBeth (1973) regressions in the following form:

$$Ret_t = \alpha + \beta_1 Gain_{t-1} + \beta_2 Loss_{t-1} + \gamma_1 X_{1;t-1} + \gamma_2 X_{2;t-1} + \epsilon_t \quad (5)$$

where *Ret* is monthly return, *Gain* and *Loss* are gain overhang and loss overhang, X_1 and X_2 are two sets of control variables, and subscript t denotes variables with information up to the end of month t. $X_{1;t-1}$ is designed to control the momentum effect and consists of the twelve- to two-month return separated by sign, $Ret^{+}_{t-12;t-2}$ and $Ret^{-}_{t-12;t-2}$. $X_{2;t-1}$ includes the following standard characteristics that are also known to affect returns: past one-month return Ret_{t-1}, past three- to one-year cumulative return $Ret_{t-36;t-13}$, log book-to-market ratio $logBM_{t-1}$, log market capitalization $logmktcap_{t-1}$, average daily turnover ratio in the past year $turnover_{t-1}$, and idiosyncratic volatility $ivol_{t-1}$. Details of these variables' construction are discussed in Section 2.3.

I perform the Fama-MacBeth procedure using weighted least square regressions with the weights equal to the previous one-month gross return to avoid microstructure noise contamination. This follows the methodology developed by Asparouhova, Bessembinder, and Kalcheva (2010) to correct the bias from microstructure noise in estimating cross-sectional return premiums. The gross-return-weighted results reported here are almost identical to the equal-weighted results, which suggests that liquidity bias is not a severe issue here.

Insert Table 5 about here.

Table 5 presents results from estimating Equation (5) and variations of it that omit certain regressors. For each specification, I report regression estimates for all months in the sample and for February to December separately. Grinblatt and Han (2005) show strong seasonality in their capital gains overhang effect. They attribute this pattern to the return reversal in January caused by tax-loss selling in December. To address the concern that the estimation is mainly driven by stocks with large loss overhang (in absolute value) having high returns in January, I separately report results that exclude January from the sample.

Columns (1) and (2) regress future returns on the gain and loss overhang variables only; columns (3) and (4) add the past twelve- to two-month returns, separated by their signs, as regressors; columns (5) and (6) add controls in X_2 to columns (1) and (2). Columns (7) and (8) show the marginal effects of gain and loss overhang, controlling both past return variables and other standard characteristics; these two are considered as the most proper specification. Finally, to facilitate comparison with previous literature, I replace the momentum control variables that allow for potential asymmetry, namely $Ret^{+}_{-12;-2}$ and $Ret^{-}_{-12;-2}$, with the standard return variable $Ret_{-12;-2}$.

Columns (7) and (8) show that with proper control, the estimated coefficient is positive for the gain overhang and negative for the loss overhang, both as expected. To illustrate, consider the all-month estimation in column (7). If the gain overhang increases by 1%, then the future one-month return will increase by 3.2 basis points, and if the loss overhang increases by 1% (the magnitude of loss decreases), then the future one-month return will decrease by one basis point. The *t*-statistics are 9.06 and -10.02 for *Gain* and *Loss*, respectively. Since 611 months are used in the estimation, these *t*-statistics imply that the annualized Sharpe ratios are 1.3 ($\frac{9.06}{\sqrt{611}} \times \sqrt{12} = 1.3$) and 1.4 ($\frac{10.02}{\sqrt{611}} \times \sqrt{12} = 1.4$) for strategies based on gain overhang and loss overhang, respectively.[15] The gain effect estimated here is three to four times as large as the loss effect (in all months and in February to December), and this is well in line with the asymmetric V-shape in individual traders' selling schedule (4.3 times, as estimated in section 1.2). A comparison of estimates for all months and for February to December shows that the coefficients are close, suggesting that the results are not driven by the January effect.

From columns (1) and (2) to columns (3) and (4), and from columns (5) and (6) to columns (7) and (8), the change in coefficients shows that controlling the past twelve- to two-month return is important in order to observe the true effect from gains and losses. Otherwise, stocks with gain (loss) overhang would partly pick up the winner (loser) stocks' effect, and the estimates would contain an upward bias, because high (low) past returns are known to predict high (low) future returns. Moreover, the estimated coefficients of $Ret^{+}_{-12;-2}$ and $Ret^{-}_{-12;-2}$ have a magnitude of difference:

[15] 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 $\frac{\bar{\beta}\sqrt{12}}{std(\beta)}$, and the *t*-statistic in the Fama-MacBeth regression (t_{FM}) is calculated as $\frac{\bar{\beta}}{std(\beta)/\sqrt{T}}$. Thus, $SR = \frac{t_{FM}}{\sqrt{T}} \times \sqrt{12}$.

$Ret^{-}_{-12;-2}$ is about 5 to 10 times stronger than $Ret^{+}_{-12;-2}$ in predicting returns. This suggests that allowing winners and losers to have different coefficients can better capture the momentum effect.[16] Meanwhile, columns (9) and (10) show that the gain and loss effects still hold well with the standard momentum return as control.

These results support Hypothesis PI: stocks with larger gain and loss overhangs (in absolute value) would experience higher selling pressure, leading to lower current prices, thus generating higher future returns when prices revert to the fundamental values. This means that future returns are higher for stocks with large gains compared with those with small gains, and they are higher for stocks with large losses compared with those with small losses. This challenges the current understanding that a monotonic selling schedule underlies the disposition effect, which would instead predict higher returns for large gains over small gains, but also small losses over large losses. This evidence also implies that the asymmetric V-shaped selling schedule of disposition-prone investors is not only relevant on the individual level, but also that this behavior aggregates to affect equilibrium prices and generate predictable return patterns.

3.2.2 Comparing V-shaped net selling propensity with capital gains overhang. After showing the gain effect and loss effect separately, I examine in this subsection the overall price impact from investors' trading schedule. I compare the V-shaped net selling propensity variable, which recognizes different effects for gains and losses, with the capital gains overhang variable, which aggregates all purchase prices while assuming they have the same impact. Specifically, I test the hypothesis that the previously documented capital gains overhang effect, as shown in Grinblatt and Han (2005) and other studies that adopt this measure, actually originates from this V-shaped disposition effect.

[16] This is consistent with the evidence in Hong, Lim, and Stein (2000), who show that the bulk of the momentum effect comes from losers, as opposed to winners. However, Israel and Moskowitz (2013) argue that this phenomenon is specific to Hong, Lim, and Stein's (2000) sample of 1980 to 1996 and is not sustained in a larger sample from 1927 to 2011. In my sample from 1963 to 2013, Hong, Lim, and Stein's (2000) conclusion seems to prevail.

Before I run a horse race between the old and new variables, I first re-run Grinblatt and Han's (2005) best model in my sample and show how adding additional control variables affects the results.

Insert Table 6 about here.

Columns (1) and (2) in Table 6, Panel A, report Fama-MacBeth regression results from the following equation (taken from Grinblatt and Han (2005), Table 3, Panel C):

$$\begin{aligned} Ret_t = \;\; + {}_1CGO_{t-1} + {}_1Ret_{t-1} + {}_2Ret_{t-12;t-2} \\ + {}_3Ret_{t-36;t-13} + {}_4logmktcap_{t-1} + {}_5turnover_{t-1} + {}_t \end{aligned} \tag{6}$$

Focusing on the all-month estimation in column (1), a 1% increase in *CGO* will lead to a 0.4-basis-point increase in the subsequent one-month return; this effect is weaker compared with Grinblatt and Han's (2005) estimation, in which a 1% increase in *CGO* results in a 0.4-basis-point increase in weekly returns. Additionally, controlling capital gains overhang in my sample will not subsume the momentum effect; rather, the momentum effect is actually stronger and more significant than the capital gains overhang effect.

The following four columns show the importance of additional control variables. Columns (3) and (4) separate the past twelve- to two-month return by its sign. The losers' effect is five times as large as the winners' effect, with a much larger *t*-statistic. Allowing winners and losers to have different levels of effect largely brings down the coefficient for capital gains overhang. Indeed, artificially equating the coefficients for winners and losers does not fully capture the strong effect on the loser side; the remaining part of this "low past return predicts low future return" effect is picked up by stocks with large unrealized losses (which are likely to have low past returns). This will artificially associate large unrealized losses with low future returns. Columns (5) and (6) further control for idiosyncratic volatility and book-to-market ratio; this further dampens the effect of capital gains overhang, which even becomes negative. This outcome arises because stocks with large unrealized losses are more likely to have high idiosyncratic volatility, a characteristic that is associated with low future returns.

Table 6, Panel B, compares the effects of *CGO* and *VNSP* by estimating models that take the following form:

$$Ret_t = \alpha + \beta_1 CGO_{t-1} + \beta_2 VNSP_{t-1} + \gamma_1 X_{1,t-1} + \gamma_2 X_{2,t-1} + \epsilon_t \tag{7}$$

where the two sets of control variables X_1 and X_2 are the same as in Equation (5). In columns (1), (2), (5), and (6), where I do not control the momentum effect, both variables positively predict the subsequent one-month return, but *VNSP* has a much larger economic magnitude. Moving to columns (7) and (8), which include momentum and the whole set of control variables, *CGO* has the wrong sign in predicting return, while *VNSP* remains highly significantly positive.

Focusing on the price effect of $VNSP$, a 1% increase in *VNSP* raises the subsequent one-month return by 3.4 basis points in the all-month estimation (column (7)). Because the average monthly difference between the 10th and 90th percentiles is 26%, a long-short trading strategy based on *VNSP* would generate returns of $26\% \times 0.034\% = 0.88\%$ per month. The t-statistic for the *VNSP* coefficient is larger than 10. Becuase 611 months are used in the estimation, this t-statistic translates into an annualized Sharpe ratio as high as 1.5 ($\frac{10.76}{\sqrt{611}} \times \sqrt{12} = 1.5$) for a hedged portfolio based on V-shaped net selling propensity. For comparison, the momentum strategy presents a Sharpe ratio of 0.9 ($\frac{6.46}{\sqrt{611}} \times \sqrt{12} = 0.9$) for the same sample period (1963–2013), while the numbers for value and size are 0.6 ($\frac{4.13}{\sqrt{611}} \times \sqrt{12} = 0.6$) and 0.7 ($\frac{5.13}{\sqrt{611}} \times \sqrt{12} = 0.7$), respectively. Overall, these results show that V-shaped net selling propensity has very strong return predictability and it subsumes the capital gains overhang effect.

4. The Source of the V-shaped Disposition Effect and Cross-Sectional Analysis

This section is devoted to obtaining deeper understanding of the source of the V-shaped disposition effect. I first discuss several possible mechanisms that may generate the observed V-shape on the individual level; however, the pricing implications of these interpretations are likely to diverge. Thus, the price-level evidence shown in the previous section helps to provide clues on which mechanism may hold promise as a potential explanation. I then examine the effect of gain and loss overhang in different cross-sectional subsamples. This evidence is consistent with the general conjecture that the speculative trading motive leads to the V-shaped disposition effect.

4.1 The source of the V-shaped disposition effect

An important insight from Ben-David and Hirshleifer (2012) is that investors' higher propensity to sell upon gains over losses is not necessarily driven by a preference for realizing gains over losses per se. Indeed, although commonly regarded as a source of the disposition effect, prospect theory (Kahneman and Tversky 1979) is shown to often fail to generate a higher selling propensity upon gain versus loss (Barberis and Xiong 2009 and Hens and Vlcek 2011). While recent studies have proposed several preference-based models that can reconcile the binary pattern of the disposition effect (see, among others, Barberis and Xiong 2012; Ingersoll and Jin 2012; Meng 2014; and Li and Yang 2013), the newly discovered V-shape seems to further raise the hurdle for preference-based theories to explain such trading behavior. Instead, Ben-David and Hirshleifer (2012) suggest that belief-based explanations may underlie this observed V.

This perspective suggests that changes in beliefs, rather than features of preferences, generate the V-shaped selling schedule. A general conjecture is that investors have a speculative trading motive: they think they know better than the market does (which may arise from genuine private information or psychological reasons), so they actively trade in the hope of profits. Investors generally update their beliefs on a stock after large gains and losses, and this leads to trading activities.

To be more specific, the speculative trading hypothesis encompasses at least three possibilities that could explain the V-shaped selling schedule observed at the individual level. First, the V-shape may originate from investors' limited attention (see Barber and Odean 2008 and Seasholes and Wu 2007, among others). Investors may buy a stock and not reexamine their beliefs until the price fluctuates enough to attract their attention. Thus, large gains and losses are associated with belief updating and trading activities. The asymmetry may come from investors being more inclined to reexamine a position when their profits are higher.

Second, the V-shape in selling may result from rational belief-updating. Assume that investors have private information of a stock and have bought the stock accordingly. As the price rises, they may think their information has been incorporated in the market price and thus want to realize the gain; as the price declines, they may reevaluate the validity of their original beliefs and sell after the loss.

A third possibility, irrational belief-updating, conflicts with the second mechanism. For example, one particular case could be the result of investors' overconfidence. Think of an extreme case in which investors initially receive private signals that have no correlation with the true fundamental value; however, they are overconfident about the signal and think their original beliefs contain genuine information. When price movements lead to gains and losses, they update their beliefs as in the rational belief-updating case; however, their trading activities now reflect only noise.

Although all three explanations are consistent with the individual-level V-shape, they are likely to generate differing price-level implications. First, the limited attention scenario predicts more selling of stocks with large gains and losses, but the same mechanism is likely to generate more buying of these stocks as well, because potential buyers are also attracted by the extreme returns (see Barber and Odean 2008), regardless of whether they currently hold the stock or not. Though we know that for current stockholders the selling effect seems to dominate, the pricing implication is still ambiguous because buying from non-holders also comes into play. As to the second interpretation, the rational belief-updating scenario suggests that trading after gains and losses reflects the process of information being absorbed into price. While we cannot completely rule out the possibility that a rational frictionless model can generate return predictability caused by trading, the magnitude of the return impact seems to raise a challenge for such models.

Finally, in the third possibility, irrational belief-updating, selling is caused by belief changes based on misperceptions and does not draw on genuine information, so the downward pressure on current price is temporary and future returns are predictable. Given the different implications, the return predictability shown in Section 3 is easier to reconcile with the irrational belief-updating scenario than with the other two.

4.2 Subsample analysis: The impact of speculativeness

In this subsection, I test the broad conjecture that speculative trading incurs the V-shaped disposition effect. This conjecture, encompassing all three possibilities discussed in Section 4.1, is in contrast to preference-based explanations. To assess whether speculative trading can serve as a possible source, I examine how the effects of gains and losses play out in subsamples based on institutional ownership, firm size, turnover, and volatility. In general, stocks with low institutional ownership, smaller size, higher turnover, and higher volatility are associated with more speculative activities, and I test whether the gain and loss overhang effects are stronger among these stocks.

The categorizing variables are defined as follows: institutional ownership is the percentage of shares outstanding held by institutional investors; firm size refers to a firm's market capitalization; turnover, as in Section 3, is the average daily turnover ratio within one year; and volatility is calculated as daily stock return volatility in the past one year. Since institutional ownership, turnover, and volatility are all largely correlated with firm size, sorting based on the raw variables may end up testing the role of size in all exercises. To avoid this situation, I base subsamples on size-adjusted characteristics. Specifically, I first sort all firms into ten deciles according to their market capitalization; within each decile, I then equally divide firms into three groups according to the characteristic of interest (calling them low, medium, and high); and finally I collapse across the size groups. This way, each of the characteristic subsamples contains firms of all size levels. As for size, the three groups are divided by NYSE break points; the high group contains firms with size in the largest 30% of NYSE firms category, and the low group corresponds to the bottom 30%.

Insert Table 7 about here.

In each high and low subsample, I reexamine Equation (5) using Fama and MacBeth (1973) regressions. I only report the results from the best model, with all proper controls for all months and for February to December (corresponding to Table 4, columns (7) and (8)). Table 7 presents the results.

In the four more speculative subsamples (low institutional ownership, low market capitalization, high turnover, and high volatility), the effects of gains and losses are indeed economically and statistically stronger than they are in the less speculative subsamples. This finding is consistent with the investor-level evidence from Ben-David and Hirshleifer (2012), in which the strength of the V-shape in the selling schedule is found to be associated with the investor's "speculative" characteristics, such as trading frequency and gender. As more speculative investors are more likely to be prevalent in speculative stocks, the return pattern across subsamples is consistent with the view that speculation is a source of this selling tendency.

In the subsample of high market capitalization, the gain effect completely disappears. This suggests that the V-shaped net selling propensity effect is most prevalent among middle and small firms. In all other groups, the gain and loss variables exhibit significant predictive power for future returns with the expected sign, and the gain effect is two to six times as large as the loss effect. This suggests that the asymmetry between gains and losses is a relatively stable relation.

There are, however, alternative interpretations for the different strength of this effect across different stock groups. One possibility is that the V-shaped net selling propensity effect is stronger among stocks for which there is a high limit to arbitrage. Low institutional ownership may reflect less presence of arbitragers; small firms may be illiquid and relatively hard to arbitrage on; volatility (especially idiosyncratic volatility) may also represent a limit to arbitrage, as pointed out in Shleifer and Vishny (1997). However, this interpretation is not consistent with the pattern observed in the turnover groups: high-turnover stocks that attract more arbitragers exhibit stronger gain and loss effects.

5. Robustness Checks

I now conduct a battery of robustness checks of my results under alternative empirical specifications.

5.1 Alternative specifications and alternative samples

5.1.1 Adjusting prices for stock splits and dividends. In the main specification, I aggregate purchase prices without adjusting for stock splits and dividends. To ensure that the findings of this paper are not driven by this issue, I construct alternative overhang variables, adjusting for stock splits and dividends, and then repeat the tests of Equation (5). Table 8, columns (1) and (2), reports the results. Compared with the estimates for unadjusted variables in Table 4, columns (7) and (8), the results remain very similar.

5.1.2 Aggregation frequency. Grinblatt and Han (2005) use weekly prices and volumes to measure capital gains overhang, whereas my study uses daily variables. To show that the findings in this paper are not artifacts caused by aggregation frequency, I construct overhang variables using weekly prices and volumes. Table 8, columns (3) and (4), shows these results. The estimated coe cients are qualitatively the same as those of daily aggregated variables.

5.1.3 Stock sample. A potential concern is that volume data from NASDAQ, even with adjustment, may create problems for my measures of gains and losses. I thus run the best model on a sample that excludes NASDAQ stocks. The results are reported in Table 8, columns (5) and (6). Gain and loss overhangs still have the expected signs, and both are highly signi cant. The magnitude of gain overhang is smaller compared with the whole sample estimation. I interpret this di erence mainly as a size e ect: NYSE and AMEX rms are generally larger in size, and from Table 7, columns (5){(8), we know that the gain e ect becomes smaller as rm size increases, but the loss e ect is less a ected. Indeed, the change in estimated coe cients from the whole sample to the NYSE and AMEX sample (presumably a change in average rm size) mainly lies in the gain side.

5.1.4 Horizon of gains and losses. In the main speci cation, I use a ve-year window to measure unrealized gains and losses, and I discuss the reasons why the return predictability may last longer than the trading horizon of retail investors. Here, I provide a robustness check on the horizon by constructing gain and loss overhangs using a one-year window. By sticking to the trading horizon of retail investors, this serves as the most conservative range where the price e ect should originate, assuming that (i) no other types of investors have the V-shaped selling schedule at a longer horizon and (ii) there is fast price recovery. The results are presented in Table 8, columns (7) and (8), and they remain qualitatively similar to estimations using ve-year overhangs.[17]

[17] Untabulated results show that, using a one-year time window, a long-short portfolio based on residual VNSP generates a monthly return of 0.77%, 0.53%, and 0.60%, with *t*-statistics of 2.3, 7.8, and 9.4, in the forms of raw return, DGTW characteristics-adjusted return, and Carhart (1997) four-factor alpha, respectively (corresponding to all-month gross-return weighted portfolio results in Table 4, Panel C). In Fama-MacBeth regressions, a 1% increase in one-year VNSP is associated with a 4.5-basis-point (*t*-statistic=8.8) increase in next-month return; in comparison, this

Insert Table 8 about here.

5.2 Impact of liquidity effects

The construction of gain and loss overhang variables utilizes prices from five years to one day prior to the portfolio formation time. One potential concern is that microstructure effects, such as bid-ask bounce, might drive the results. Here, I run robustness checks to address this concern.

First, I skip ten days in measuring *Gain* and *Loss* (i.e., $Gain_t$ and $Loss_t$ use past prices up to $t - 10$ day). Second, I lag *Gain* and *Loss* for one whole month in predicting future returns. Table 9, columns (1)–(2) and columns (3)–(4), reports the results for these two specifications, respectively. The estimated coefficients with lags are smaller compared with those without the lag, but all are still significant. The smaller magnitude is consistent with Ben-David and Hirshleifer's (2012) finding that the V-shaped disposition effect is strong for very recent gains and losses and that the effect gradually weakens as the holding period becomes longer. Indeed, skipping one month in measuring gains and losses would miss a significant amount of the effect.

Third, I run value-weighted regressions to predict returns. In previous sections, all regressions are weighted by the stock's past gross return, a methodology designed to correct liquidity bias in asset pricing tests. Here, the value-weighting scheme is another way to ensure that the findings are not artifacts caused by microstructure noise. Table 9, columns (5) and (6), reports value-weighted regression results. The coefficient of gain overhang is almost zero, while that of loss overhang is still significantly negative. These results are driven by large firms, and we know from Table 7 that the gain effect is absent among mega-sized firms, which dominate in market capitalization but make up a relatively small proportion of the total number of firms in the market. Table 9, columns (7) and (8), shows value-weighted results in a sample that excludes firms in the top size quintile

number for five-year VNSP, presented in Table 6, Panel B, column (7), is 3.4 basis points (t-statistic=10.8). Given the average monthly difference between the 10th and 90th percentiles of one-year VNSP is 18%, it implies that a hedge portfolio based on one-year VNSP can generate $4.5 \times 18 = 81$ basis points in monthly return.

in each month. Both gain and loss overhangs show the expected signs and are highly significant. This suggests that the return predictability of gain and loss overhangs is not likely to be driven by liquidity reasons.

Insert Table 9 about here.

Overall, my findings are robust to alternative specifications in measuring gain and loss overhangs, as well as to the exclusion of NASDAQ stocks; moreover, they are not artifacts caused by liquidity effects. In the Internet Appendix, I also report evidence that suggests these findings are not driven by binding short-sale constraints.

6. Conclusions

This study provides new evidence that investors' selling tendency in response to unrealized profits will result in stock-level selling pressure and generate return predictability. Built on the stylized fact that investors tend to sell more when the magnitude of either gains or losses increases, this study suggests that stocks with both large unrealized gains and unrealized losses will experience higher selling pressure, which will push down current prices temporarily and lead to higher subsequent returns. Using U.S. stock data from 1963 to 2013, I construct variables that measure stock-level unrealized gains and losses and establish cross-sectional return predictability based on these variables.

The return predictability is stronger from the gain side than from the loss side, and it is stronger among more speculative stocks. These patterns are consistent with the individual trading tendencies documented by Ben-David and Hirshleifer (2012). Overall, they help to elucidate the pattern, source, and pricing implication of the disposition effect.

In terms of pricing, I propose a novel measure for stock-level selling pressure from unrealized gains and losses that recognizes the V-shape in investors' selling propensity. I show that the V-shaped net selling propensity subsumes the previous capital gains overhang variable in capturing selling pressure and predicting subsequent returns. This study also bears on the discussion of whether investors' selling tendency in response to gains and losses can explain momentum: the findings suggest that investors' selling propensities do not contribute unambiguously to the momentum effect; the tendency to sell more in light of larger losses tends to oppose the momentum effect.

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Table 1
Selling and buying in response to unrealized profits

This table reports regression results for selling and buying on unrealized pro ts and a set of control variables. The analysis is based on 77,037 retail accounts from a brokerage rm from 1991 to 1996 (the Odean dataset). Observations are at investor-stock-day level. For columns (1){(3), the dependent variable is the number of shares sold normalized by shares outstanding; for columns (4){(6), the dependent variable is the additional number of shares bought (for currently owned stocks) normalized by shares outstanding. $Ret2^{+} = Max\{Ret2; 0\}$ and $Ret2 \; = Min\{Ret2; 0\}$, where $Ret2 = \frac{P_t \;\; P_0}{P_t}$. $I(ret = 0)$ is an indicator if return is zero, $I(ret > 0)$ is an indicator if return is positive, *sqrt(Time owned)* is the square root of prior holding period measured in holding days, *log(Buy price)* is the logged purchase price, *volatility*$^{+}$ is equal to stock volatility when return is positive, and *volatility* is equal to stock volatility when return is negative. The coe cients are multiplied by 1,000,000. Standard errors are clustered at the investor level. T-statistics are reported in square brackets. *, **, and *** denote signi cance levels at 10%, 5%, and 1%.

	Shares sold/shares outstanding × 1 million			Shares bought/shares outstanding × 1 million		
	(1)	(2)	(3)	(4)	(5)	(6)
Prior holding period (days):	1 to 20	21 to 250	>250	1 to 20	21 to 250	>250
Ret2	{1.353***	{0.014***	{0.004	{0.563***	{0.007	0.002***
	[{12.25]	[{2.75]	[{0.74]	[{4.19]	[{1.4]	[3.55]
Ret2^{+}	4.209***	0.069***	{0.007	0.972***	0.013	{0.005**
	[16.3]	[3.35]	[{1.42]	[5.94]	[0.89]	[{2.28]
I(ret=0)	{0.054***	{0.003	0.009	0.492***	0.001	{0.015***
	[{2.84]	[{0.36]	[1.08]	[11.31]	[0.03]	[{5.11]
I(ret>0)	{0.407***	{0.140***	{0.019***	{0.034***	{0.007	0.004*
	[{10.05]	[{16.22]	[{4.6]	[{0.99]	[{0.9]	[1.74]
sqrt(Time owned)	{0.151***	{0.013***	{0.003***	{0.144***	{0.005***	{0.001***
	[{12.57]	[{22.77]	[{14.59]	[{19.88]	[{15.43]	[{8.84]
log(Buy price)	{0.006	{0.056***	{0.023***	{0.146***	{0.037***	{0.014***
	[{0.28]	[{20.19]	[{14.53]	[{10.88]	[{12.41]	[{8.33]
volatility	9.780***	1.939***	0.435*	7.628***	1.307***	0.317***
	[7.92]	[9.55]	[1.84]	[7.92]	[4.9]	[3.12]
volatility^{+}	25.413***	9.182***	1.925***	10.475***	1.476***	0.084
	[12.05]	[24.46]	[13.15]	[7.53]	[4.47]	[0.73]
constant	0.316***	0.326***	0.141***	0.763***	0.171***	0.062***
	[4.02]	[22.71]	[13.73]	[11.83]	[10.56]	[8.76]
Obs.	8.9m	63.1m	78.8m	8.9m	63.1m	78.8m
R^2	0.0012	0.0005	0.0002	0.0010	0.0001	0.0001

Table 2
Summary statistics of net selling propensity variables and control variables

Panel A and B report summary statistics for selling propensity variables and control variables, respectively, and Panel C presents a correlation table of all these variables. *Gain Overhang* is defined as $Gain_t = \sum_{n=1}^{N} \omega_{t-n} \frac{P_t - P_{t-n}}{P_t} \cdot \mathbf{1}_{\{P_{t-n} \le P_t\}}$ using daily price P_{t-n} within five years prior to time t, and ω_{t-n} is a volumed-based weight that serves as a proxy for the fraction of stockholders at time t who bought the stock at P_{t-n}; *Loss Overhang* is defined as $Loss_t = \sum_{n=1}^{N} \omega_{t-n} \frac{P_t - P_{t-n}}{P_t} \cdot \mathbf{1}_{\{P_{t-n} > P_t\}}$ using P_{t-n} from the same period. $Gain$ and $Loss$ are winsorized at 1% level in each tail. *Capital Gains Overhang (CGO)* = $Gain + Loss$, and *V-shaped Net Selling Propensity (VNSP)* = $Gain - 0.23 Loss$. $Ret_{-12,-2}$ is the previous twelve- to two-month cumulative return, $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$ are the positive part and the negative part of $Ret_{-12,-2}$, Ret_{-1} is the past one-month return, $Ret_{-36,-13}$ is the past three- to one-year cumulative return, $logBM$ is the logarithm of book-to-market ratio, $logmktcap$ is the logarithm of a firm's market capitalization, $turnover$ is the average daily turnover ratio in the past one year, and finally, $ivol$ is the idiosyncratic volatility, calculated as the daily volatility of return residuals with respect to Fama-French three-factor model in the past one year. All control variables in raw values are winsorized at 1% level in each tail. All numbers presented are the time-series average of the cross-sectional statistics.

Panel A: Summary stats for net selling propensity variables

	Gain	Loss	CGO	VNSP
Mean	0.102	{0.290	{0.188	0.169
p50	0.073	{0.150	{0.079	0.142
SD	0.097	0.375	0.431	0.108
Skew	1.391	{2.398	{1.656	1.286
p10	0.007	{0.759	{0.734	0.059
p90	0.242	{0.012	0.216	0.317

Panel B: Summary stats for control variables

	Ret_{-1}	$Ret_{-12,-2}$	$Ret_{-36,-13}$	logBM	logmktcap	turnover	ivol
Mean	0.015	0.156	0.332	{0.476	4.921	0.004	0.028
p50	0.005	0.080	0.167	{0.391	4.759	0.003	0.025
SD	0.116	0.453	0.766	0.752	1.780	0.004	0.013
Skew	0.708	1.381	1.800	{0.784	0.422	2.124	1.106
p10	{0.115	{0.305	{0.384	{1.432	2.733	0.001	0.013
p90	0.151	0.676	1.186	0.369	7.359	0.009	0.046

Panel C: Correlation table

	Gain	Loss	CGO	VNSP	Ret_{-1}	$Ret_{-12,-2}$	$Ret^{+}_{-12,-2}$	$Ret^{-}_{-12,-2}$	$Ret_{-36,-13}$	logmktcap	logBM	turnover	ivol
Gain	1.00												
Loss	0.46	1.00											
CGO	0.65	0.96	1.00										
VNSP	0.61	{0.33	{0.11	1.00									
Ret_{-1}	0.33	0.22	0.28	0.15	1.00								
$Ret_{-12,-2}$	0.53	0.40	0.48	0.19	0.01	1.00							
$Ret^{+}_{-12,-2}$	0.52	0.24	0.34	0.31	0.01	0.92	1.00						
$Ret^{-}_{-12,-2}$	0.34	0.54	0.55	{0.11	0.00	0.64	0.36	1.00					
$Ret_{-36,-13}$	0.13	0.15	0.16	0.00	{0.02	{0.03	{0.02	{0.03	1.00				
logmktcap	0.04	0.27	0.23	{0.20	0.03	0.11	0.03	0.24	0.16	1.00			
logBM	0.01	0.02	0.02	0.01	0.03	0.05	0.01	0.10	{0.28	{0.24	1.00		
turnover	{0.01	0.04	0.03	{0.05	{0.01	0.13	0.21	{0.10	0.18	0.05	{0.18	1.00	
ivol	0.03	{0.35	{0.29	0.33	0.03	0.00	0.15	{0.32	{0.14	{0.59	{0.02	0.28	1.00

Table 3
Portfolio sorts on gain and loss

This table reports returns in double-sorted portfolios based on the residual values of gain and loss. The residuals are constructed by regressing *Gain* and *Loss* on past returns, rm size, turnover, and idiosyncratic volatility. At the end of each month, stocks are independently sorted by the residual gain and the negative value of residual loss into ten groups, respectively. Stocks in a portfolio are weighted by their gross returns in the previous month. Each portfolio is to be held for the following one month, and the time-series average of portfolio returns is reported. Panel A presents raw returns, and Panel B presents DGTW characteristic-adjusted returns. The returns are in monthly percent, *t*-statistics for the di erence between portfolios 10 and 1 are in the square brackets, and *, **, and *** denote signi cance levels at 10%, 5%, and 1%.

Panel A: Double sorts on residual gain and loss, raw return

	Small gain	G2	G3	G4	G5	G6	G7	G8	G9	Big gain	10{1	*t*-stat
Small loss	{1.46	{0.41	{0.02	0.01	0.35	0.39	0.42	0.65	0.53	0.80	2.26***	[4.13]
L2	{0.22	0.49	0.44	0.65	0.84	0.96	1.04	1.31	1.42	1.52	1.75***	[3.87]
L3	0.16	0.53	0.82	0.90	1.05	1.07	1.25	1.47	1.47	1.67	1.50***	[3.59]
L4	0.74	0.92	0.88	1.06	1.02	1.29	1.24	1.39	1.62	1.56	0.82**	[2.21]
L5	0.47	0.88	0.99	1.13	1.02	1.21	1.26	1.42	1.40	1.68	1.21***	[3.56]
L6	0.72	1.02	1.00	1.04	1.17	1.10	1.42	1.31	1.56	1.58	0.87***	[2.62]
L7	0.99	1.03	1.18	1.11	1.17	1.17	1.31	1.35	1.45	1.42	0.44	[1.31]
L8	0.86	1.06	1.07	0.91	1.09	1.06	1.19	1.35	1.67	1.63	0.76**	[2.09]
L9	1.08	1.03	1.05	0.97	1.05	1.18	0.80	1.15	0.96	1.97	0.89**	[2.13]
Big loss	0.84	0.94	1.20	1.15	1.11	1.04	0.96	0.91	1.10	2.56	1.72**	[2.29]
10{1	2.29***	1.35***	1.22***	1.14***	0.76*	0.66	0.54	0.26	0.57	1.75***		
t-stat	[4.39]	[3.09]	[3.13]	[2.70]	[1.73]	[1.42]	[1.12]	[0.49]	[1.00]	[2.28]		

Panel B: Double sorts on residual gain and loss, characteristic-adjusted return

	Small gain	G2	G3	G4	G5	G6	G7	G8	G9	Big gain	10{1	*t*-stat
Small loss	{1.35	{0.78	{0.85	{0.64	{0.45	{0.39	{0.44	{0.06	{0.19	{0.22	1.13***	[2.75]
L2	{0.96	{0.57	{0.46	{0.39	{0.15	{0.09	{0.04	0.15	0.28	0.35	1.31***	[3.75]
L3	{0.82	{0.37	{0.26	{0.19	{0.13	{0.13	0.01	0.29	0.17	0.39	1.21***	[4.02]
L4	{0.14	{0.07	{0.11	0.01	{0.12	0.12	0.02	0.18	0.37	0.26	0.40*	[1.68]
L5	{0.20	{0.12	{0.17	0.06	{0.06	0.07	0.00	0.13	0.18	0.37	0.57***	[3.01]
L6	{0.24	{0.05	{0.07	{0.16	0.02	{0.06	0.09	0.04	0.15	0.19	0.43**	[2.42]
L7	0.02	{0.04	0.17	{0.04	{0.10	0.01	0.08	0.14	0.07	0.06	0.05	[0.25]
L8	{0.24	{0.10	0.01	{0.29	{0.12	{0.12	{0.04	{0.02	0.48	0.28	0.52***	[2.82]
L9	{0.07	{0.11	0.03	{0.07	0.06	0.31	{0.33	{0.13	{0.31	0.60	0.66**	[2.54]
Big loss	{0.25	{0.11	0.09	0.17	0.22	0.30	0.10	0.19	{0.30	1.38	1.63***	[2.61]
10{1	1.10***	0.67**	0.94***	0.81***	0.68***	0.69***	0.54**	0.25	{0.10	1.60**		
t-stat	[2.72]	[2.08]	[4.04]	[3.75]	[2.87]	[2.79]	[2.13]	[0.84]	[{0.29]	[2.54]		

Table 4

Portfolio sorts on V-shaped net selling propensity and capital gains overhang

This table reports returns in portfolios constructed based on net selling propensity variables. In Panel A, stocks are sorted by their *V-Shaped Net Selling Propensity (VNSP)* into ve groups at the end of each month, with portfolio 5 containing stocks with the highest *VNSP*. 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, I show raw portfolio returns, DGTW characteristic-adjusted returns, and Carhart (1997) four-factor alphas, and results in all months and in February to December are reported separately. 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 *VNSP* and residual *CGO*. The residuals are constructed by regressing raw net selling propensity variables (*VNSP* or *CGO*) on past returns, rm size, turnover, and idiosyncratic volatility. The returns are in monthly percent, *t*-statistics for the di erence between portfolios 5 and 1 are in the square brackets, and *, **, and *** denote signi cance levels at 10%, 5%, and 1%.

Panel A: Portfolio return, sorted on V-shaped net selling propensity (VNSP)

	Gross-return weighted						Value weighted					
VNSP	Raw return		Adjusted return		Alpha		Raw return		Adjusted return		Alpha	
	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.
1	0.82	0.59	{0.10	{0.12	0.21	0.12	0.82	0.73	{0.06	{0.09	0.43	0.38
2	0.87	0.63	{0.13	{0.15	0.19	0.15	0.86	0.80	{0.01	{0.01	0.43	0.43
3	0.93	0.64	{0.13	{0.17	0.19	0.13	0.85	0.82	{0.04	{0.01	0.31	0.39
4	1.16	0.85	0.04	0.00	0.37	0.32	1.07	1.02	0.11	0.13	0.49	0.55
5	1.38	0.94	0.14	0.06	0.61	0.46	1.41	1.27	0.17	0.17	0.89	0.93
5{1	0.56	0.35	0.24***	0.19**	0.40***	0.34***	0.59*	0.54*	0.23**	0.26**	0.46***	0.55***
t-stat	[1.61]	[1.00]	[3.07]	[2.31]	[3.07]	[2.62]	[1.89]	[1.71]	[2.15]	[2.36]	[2.86]	[3.43]

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

	Gross-return weighted						Value weighted					
CGO	Raw return		Adjusted return		Alpha		Raw return		Adjusted return		Alpha	
	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.
1	0.75	0.10	{0.08	{0.29	0.24	{0.07	1.04	0.78	0.23	0.17	0.79	0.72
2	0.75	0.35	{0.18	{0.26	0.12	0.00	0.90	0.77	0.03	{0.01	0.55	0.57
3	0.95	0.68	{0.07	{0.10	0.24	0.18	0.90	0.78	{0.04	{0.07	0.44	0.41
4	1.16	1.00	{0.02	0.00	0.35	0.36	0.89	0.84	{0.04	{0.03	0.28	0.28
5	1.54	1.46	0.18	0.25	0.62	0.68	1.11	1.15	0.03	0.09	0.36	0.42
5{1	0.78**	1.36***	0.26**	0.54***	0.38***	0.76***	0.07	0.37	{0.20*	{0.08	{0.43***	{0.3**
t-stat	[2.08]	[3.68]	[2.43]	[5.26]	[2.76]	[6.03]	[0.20]	[1.12]	[{1.72]	[{0.68]	[{3.11]	[{2.14]

Panel C: Portfolio return, sorted on V-shaped net selling propensity (VNSP) residual

	Gross-return weighted						Value weighted					
res VNSP	Raw return		Adjusted return		Alpha		Raw return		Adjusted return		Alpha	
	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.
1	0.66	0.33	{0.32	{0.38	0.02	{0.07	0.98	0.84	0.01	{0.02	0.62	0.66
2	1.00	0.72	{0.09	{0.12	0.35	0.29	0.98	0.87	0.06	0.03	0.60	0.58
3	1.09	0.80	{0.04	{0.09	0.35	0.26	0.87	0.78	{0.05	{0.08	0.41	0.41
4	1.24	0.96	0.08	0.04	0.45	0.38	0.88	0.86	{0.02	0.00	0.37	0.39
5	1.41	1.10	0.19	0.16	0.64	0.57	1.03	1.04	0.07	0.10	0.47	0.54
5{1	0.75**	0.76**	0.52***	0.54***	0.62***	0.64***	0.05	0.19	0.06	0.13	{0.15	{0.12
t-stat	[2.23]	[2.27]	[7.96]	[8.18]	[9.84]	[9.75]	[0.17]	[0.65]	[0.67]	[1.39]	[{1.30]	[{1.03]

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

	Gross-return weighted						Value weighted					
res CGO	Raw return		Adjusted return		Alpha		Raw return		Adjusted return		Alpha	
	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.
1	0.66	0.66	0.01	{0.11	0.44	0.24	0.95	0.91	0.09	0.09	0.60	0.61
2	0.79	0.79	{0.08	{0.12	0.33	0.27	0.93	0.87	0.00	0.01	0.45	0.47
3	0.91	0.91	{0.04	{0.04	0.39	0.38	0.88	0.82	{0.07	{0.07	0.37	0.41
4	0.93	0.93	0.00	{0.01	0.42	0.38	1.00	0.93	0.04	0.03	0.59	0.58
5	0.63	0.63	{0.07	{0.11	0.22	0.15	0.86	0.68	{0.12	{0.18	0.33	0.33
5{1	{0.03	{0.03	{0.08	0.00	{0.22***	{0.09	{0.10	{0.23	{0.21**	{0.27***	{0.27**	{0.28**
t-stat	[{0.45]	[{0.09]	[{1.08]	[{0.03]	[{3.11]	[{1.30]	[{0.31]	[{0.71]	[{2.29]	[{2.90]	[{2.25]	[{2.26]

Table 5
Predicting returns with gain and loss overhangs, Fama-MacBeth regressions

This table reports results for predictive Fama-MacBeth (1973) regressions of one-month return on lagged gain and loss overhang variables and a set of control variables. The dependent variable is return in month t, and the explanatory variables are available at the end of month $t-1$. $Gain$ and $Loss$ are gain overhang and loss overhang de ned in Equations (1) and (2). $Ret_{12,\ 2}$ is the previous twelve- to two-month cumulative return, while $Ret^{+}_{12,\ 2}$ and $Ret_{12,\ 2}$ are the positive part and the negative part of it, respectively. Ret_{1} is the past one-month return, $Ret_{36,\ 13}$ is the past three- to one-year cumulative return, *logBM* is the logarithm of book-to-market ratio, *logmktcap* is the logarithm of a rm's market capitalization, *turnover* is the average daily turnover ratio in the past one year, and *ivol* is idiosyncratic volatility, the daily volatility of return residuals with respect to Fama-French three-factor model in the past one year. Cross-sectional WLS regressions are run every month with weights de ned as prior-period gross returns, and the parameters and t-statistics (shown in square brackets) are calculated using the time series of corresponding cross-sectional regression estimates. *, **, and *** denote signi cance levels at 10%, 5%, and 1%. R^2 is the average R^2 from the cross-sectional regressions. I report coe cient estimates for all months and for February to December separately.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.
Gain	0.023***	0.029***	0.003	0.010**	0.051***	0.056***	0.032***	0.035***	0.030***	0.032***
	[4.52]	[5.90]	[0.64]	[2.42]	[12.44]	[14.29]	[9.06]	[9.69]	[8.73]	[9.10]
Loss	0.001	0.006***	{0.010***	{0.006***	{0.004***	{0.002**	{0.010***	{0.008***	{0.006***	{0.004***
	[0.73]	[3.96]	[{7.81]	[{5.10]	[{3.90]	[{2.02]	[{10.02]	[{8.34]	[{6.28]	[{4.52]
$\text{Ret}^{+}_{12,\ 2}$			0.007***	0.006***			0.005	0.006		
			[4.57]	[3.94]			[1.53]	[1.64]		
$\text{Ret}_{12,\ 2}$			0.053***	0.056***			0.029***	0.031***		
			[15.47]	[15.83]			[9.42]	[9.57]		
$\text{Ret}_{12,\ 2}$									0.009***	0.011***
									[6.46]	[7.15]
Ret_{1}					{0.065***	{0.061***	{0.056***	{0.050***	{0.058***	{0.052***
					[{18.29]	[{16.62]	[{15.81]	[{14.26]	[{15.89]	[{14.28]
$\text{Ret}_{36,\ 13}$					{0.003***	{0.002***	{0.002***	{0.001	{0.002***	{0.001*
					[{5.17]	[{3.68]	[{3.05]	[{1.50]	[{3.35]	[{1.75]
logBM					0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
					[4.71]	[4.00]	[4.13]	[3.38]	[4.36]	[3.59]
logmktcap					{0.001***	{0.000	{0.001***	{0.001***	{0.001***	{0.001***
					[{3.56]	[{1.50]	[{5.13]	[{3.21]	[{4.99]	[{3.07]
ivol					{0.208***	{0.289***	{0.220***	{0.301***	{0.246***	{0.329***
					[{4.03]	[{5.45]	[{4.30]	[{5.74]	[{4.75]	[{6.18]
turnover					{0.248	{0.192	{0.394	{0.338	{0.551*	{0.505*
					[{0.85]	[{0.63]	[{1.39]	[{1.14]	[{1.96]	[{1.73]
Constant	0.008***	0.006***	0.010***	0.008***	0.017***	0.014***	0.020***	0.017***	0.020***	0.017***
	[4.00]	[2.99]	[5.39]	[4.40]	[8.67]	[7.13]	[10.48]	[9.07]	[10.57]	[9.17]
Avg. monthly obs.	3,438	3,440	3,415	3,417	2,726	2,721	2,726	2,721	2,726	2,721
R^2	0.018	0.015	0.031	0.029	0.074	0.071	0.082	0.078	0.079	0.075
# of months	611	561	611	561	611	561	611	561	611	561

Table 6
V-shaped net selling propensity and capital gains overhang, Fama-MacBeth regressions

This table compares the V-shaped net selling propensity (VNSP) e ect with the original capital gains overhang (CGO) e ect, with the latter being documented in Grinblatt and Han (2005). Panel A re-runs the best model in Grinblatt and Han (2005) in columns (1) and (2), while columns (3){(6) show the impact to the original results of adding additional controls that I employ in this study. Panel B runs a horse race between CGO and $VNSP$. Both panels employ predictive Fama-MacBeth (1973) regressions of one-month return on selling propensity variables, as well as a set of control variables. The dependent variable is return in month t, and explanatory variables are available at the end of month $t-1$. $CGO = Gain + Loss$, while $VNSP = Gain - 0{:}23 Loss$, where $Gain$ and $Loss$ are de ned in Equations (1) and (2). $Ret_{12,\ 2}$ is the previous twelve- to two-month cumulative return, $Ret^{+}_{12,\ 2}$ and $Ret_{12,\ 2}$ are the positive part and the negative part of $Ret_{12,\ 2}$, Ret_{1} is the past one-month return, $Ret_{36,\ 13}$ is the past three- to one-year cumulative return, $logBM$ is the logarithm of book-to-market ratio, $logmktcap$ is the logarithm of a rm's market capitalization, $turnover$ is the average daily turnover ratio in the past one year, and $ivol$ is idiosyncratic volatility, the daily volatility of return residuals with respect to Fama-French three-factor model in the past one year. Cross-sectional WLS regressions are run every month with weights de ned as prior-period gross returns, and the parameters and t-statistics (shown in square brackets) are calculated using the time series of corresponding cross-sectional regression estimates. *, **, and *** denote signi cance levels at 10%, 5%, and 1%. R^2 is the average R^2 from the cross-sectional regressions. I report coe cient estimates for all months and for February to December separately.

Panel A						
	(1) All	(2) Feb.{Dec.	(3) All	(4) Feb.{Dec.	(5) All	(6) Feb.{Dec.
CGO	0.004***	0.007***	{0.000	0.002**	{0.003***	{0.002*
	[4.56]	[7.71]	[{0.53]	[2.35]	[{3.99]	[{1.95]
$\text{Ret}_{12,\ 2}$	0.009***	0.009***				
	[8.02]	[8.61]				
$\text{Ret}^{+}_{12,\ 2}$			0.008***	0.008***	0.010***	0.011***
			[6.66]	[6.86]	[3.08]	[3.13]
$\text{Ret}_{12,\ 2}$			0.038***	0.040***	0.028***	0.029***
			[13.07]	[13.86]	[9.08]	[9.24]
Ret_{1}	{0.051***	{0.046***	{0.046***	{0.041***	{0.050***	{0.045***
	[{15.38]	[{13.90]	[{13.57]	[{12.15]	[{14.22]	[{12.74]
$\text{Ret}_{36,\ 13}$	{0.002***	{0.001	{0.001**	{0.000	{0.001**	{0.000
	[{3.06]	[{1.18]	[{1.98]	[{0.01]	[{2.10]	[{0.50]
logBM					0.002***	0.001***
					[3.91]	[3.18]
logmktcap	{0.001	0.000	{0.001**	0.000	{0.001***	{0.001***
	[{1.60]	[1.23]	[{2.54]	[0.18]	[{5.29]	[{3.36]
ivol					{0.174***	{0.256***
					[{3.35]	[{4.78]
turnover	{1.027***	{1.091***	{0.794***	{0.819***	{0.537*	{0.473
	[{3.70]	[{3.75]	[{2.97]	[{2.93]	[{1.91]	[{1.61]
Constant	0.016***	0.009***	0.018***	0.012***	0.023***	0.020***
	[6.01]	[3.71]	[7.12]	[4.88]	[12.06]	[10.60]
Avg. monthly obs.	3,165	3,166	3,165	3,166	2,726	2,721
R^2	0.057	0.052	0.060	0.055	0.080	0.076
# of months	611	561	611	561	611	561

(Table 6 Continued)

Panel B

	(1) All	(2) Feb.{Dec.	(3) All	(4) Feb.{Dec.	(5) All	(6) Feb.{Dec.	(7) All	(8) Feb.{Dec.	(9) All	(10) Feb.{Dec.
CGO	0.005***	0.010***	{0.007***	{0.003**	0.006***	0.009***	{0.002**	{0.000	0.001	0.003***
	[3.64]	[8.11]	[{5.52]	[{2.55]	[5.55]	[8.54]	[{2.10]	[{0.08]	[0.79]	[2.84]
VNSP	0.018***	0.019***	0.010***	0.013***	0.044***	0.047***	0.034***	0.035***	0.029***	0.030***
	[3.96]	[4.24]	[2.60]	[3.51]	[12.94]	[13.92]	[10.76]	[10.77]	[9.59]	[9.38]
$\text{Ret}^{+}_{12,\ 2}$			0.007***	0.006***			0.005	0.006		
			[4.57]	[3.94]			[1.53]	[1.64]		
$\text{Ret}_{12,\ 2}$			0.053***	0.056***			0.029***	0.031***		
			[15.47]	[15.83]			[9.42]	[9.57]		
$\text{Ret}_{12,\ 2}$									0.009***	0.011***
									[6.46]	[7.15]
Ret_{1}					{0.065***	{0.061***	{0.056***	{0.050***	{0.058***	{0.052***
					[{18.29]	[{16.62]	[{15.81]	[{14.26]	[{15.89]	[{14.28]
$\text{Ret}_{36,\ 13}$					{0.003***	{0.002***	{0.002***	{0.001	{0.002***	{0.001*
					[{5.17]	[{3.68]	[{3.05]	[{1.50]	[{3.35]	[{1.75]
logBM					0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
					[4.71]	[4.00]	[4.13]	[3.38]	[4.36]	[3.59]
logmktcap					{0.001***	{0.000	{0.001***	{0.001***	{0.001***	{0.001***
					[{3.56]	[{1.50]	[{5.13]	[{3.21]	[{4.99]	[{3.07]
ivol					{0.208***	{0.289***	{0.220***	{0.301***	{0.246***	{0.329***
					[{4.03]	[{5.45]	[{4.30]	[{5.74]	[{4.75]	[{6.18]
turnover					{0.248	{0.192	{0.394	{0.338	{0.551*	{0.505*
					[{0.85]	[{0.63]	[{1.39]	[{1.14]	[{1.96]	[{1.73]
Constant	0.008***	0.006***	0.010***	0.008***	0.017***	0.014***	0.020***	0.017***	0.020***	0.017***
	[4.00]	[2.99]	[5.39]	[4.40]	[8.67]	[7.13]	[10.48]	[9.07]	[10.57]	[9.17]
Avg. monthly obs.	3,438	3,440	3,415	3,417	2,726	2,721	2,726	2,721	2,726	2,721
R^2	0.018	0.015	0.031	0.029	0.074	0.071	0.082	0.078	0.079	0.075
# of months	611	561	611	561	611	561	611	561	611	561

Table 7
Gain and loss effects in subsamples, Fama-MacBeth regressions

This table reports results for predictive Fama-MacBeth (1973) regressions of one-month return on lagged gain and loss overhang variables and a set of control variables in cross-sectional subsamples . The subsamples are constructed based on institutional ownership, rm size, turnover ratio, and stock volatility. Except for rm size subsamples, all other \high" groups contain the top 1/3 of rms in the whole sample ranked on the categorizing variable, while the \low" groups correspond to the bottom 1/3 of rms. As for size, \high" and \low" groups are divided by NYSE break points that correspond to the top 30% and the bottom 30% of NYSE rms. The dependent variable is return in month *t*, and the explanatory variables are available at the end of month $t - 1$. $Gain$ and $Loss$ are gain overhang and loss overhang de ned in Equations (1) and (2). $Ret^{+}_{12, \ 2}$ and $Ret_{12, \ 2}$ are the positive part and the negative part of the previous twelve- to two-month cumulative return, Ret_{1} is the past one-month return, $Ret_{36, \ 13}$ is the past three- to one-year cumulative return, *logBM* is the logarithm of book-to-market ratio, *logmktcap* is the logarithm of a rm's market capitalization, *turnover* is the average daily turnover ratio in the past one year, and *ivol* is

(Table 7 Continued)

Table 8
Alternative specifications and alternative samples, Fama-MacBeth regressions

This table reports results for predictive Fama-MacBeth (1973) regressions of one-month return on lagged gain and loss overhang variables and a set of control variables. The dependent variable is return in month *t*, and the explanatory variables are available at the end of month $t-1$. *Gain* and *Loss* are gain overhang and loss overhang de ned in Equations (1) and (2). In columns (1) and (2), *Gain* and *Loss* are constructed using prices adjusted for stock splits and dividends. In columns (3) and (4), *Gain* and *Loss* are constructed using weekly prices and volumes. In columns (5) and (6), I apply the main speci cations for *Gain* and *Loss*, but the regressions are run on NYSE and AMEX stocks only. In columns (7) and (8), *Gain* and *Loss* are measured at the one-year horizon, instead of ve years. $Ret^{+}_{12,\ 2}$ and $Ret_{12,\ 2}$ are the positive part and the negative part of the previous twelve- to two-month cumulative return, Ret_{1} is the past one-month return, $Ret_{36,\ 13}$ is the past three- to one-year cumulative return, *logBM* is the logarithm of book-to-market ratio, *logmktcap* is the logarithm of a rm's market capitalization, *turnover* is the average daily turnover ratio in the past one year, and *ivol* is idiosyncratic volatility, the daily volatility of return residuals with respect to Fama-French three-factor model in the past one year. Cross-sectional WLS regressions are run every month with weights de ned as prior-period gross returns, and the parameters and *t*-statistics (shown in square brackets) are calculated using the time series of corresponding cross-sectional regression estimates. *, **, and *** denote signi cance levels at 10%, 5%, and 1%. R^2 is the average R^2 from the cross-sectional regressions. I report coe cient estimates for all months and for February to December separately.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alternative speci cation or sample	Adjust prices for stock splits and dividends		Aggregate prices at weekly frequency		NYSE & AMEX only		Measure *Gain* and *Loss* at 1-year horizon	
	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.
Gain	0.030***	0.036***	0.036***	0.038***	0.020***	0.023***	0.046***	0.051***
	[7.93]	[9.58]	[10.04]	[10.54]	[5.34]	[6.11]	[8.73]	[9.60]
Loss	{0.010***	{0.008***	{0.006***	{0.005***	{0.007***	{0.006***	{0.009***	{0.008***
	[{6.24]	[{4.57]	[{7.68]	[{6.05]	[{6.54]	[{5.10]	[{4.16]	[{3.67]
$Ret^{+}_{12,\ 2}$	0.006**	0.006**	0.004	0.005	0.005	0.006*	0.008*	0.009*
	[2.45]	[2.35]	[1.28]	[1.42]	[1.53]	[1.65]	[1.84]	[1.94]
$Ret_{12,\ 2}$	0.028***	0.028***	0.025***	0.027***	0.027***	0.028***	0.026***	0.028***
	[8.98]	[8.55]	[8.23]	[8.52]	[7.88]	[7.96]	[8.49]	[9.13]
Ret_{1}	{0.057***	{0.053***	{0.059***	{0.053***	{0.051***	{0.045***	{0.058***	{0.053***
	[{15.92]	[{14.59]	[{16.49]	[{14.97]	[{13.08]	[{11.54]	[{17.04]	[{15.32]
$Ret_{36,\ 13}$								

Table 9
Checking liquidity effects, Fama-MacBeth regressions

This table reports results for predictive Fama-MacBeth (1973) regressions of one-month return on lagged gain and loss overhang variables and a set of control variables. The dependent variable is return in month t, and the explanatory variables are available at the end of month $t-1$. $Gain$ and $Loss$ are gain overhang and loss overhang de ned in Equations (1) and (2). In columns (1) and (2), $Gain$ and $Loss$ are lagged by ten days from the end of month $t-1$. In columns (3) and (4), $Gain$ and $Loss$ are lagged by one month. For columns (5){(8), I apply the main speci cations for $Gain$ and $Loss$. $Ret^{+}_{12,\ 2}$ and $Ret_{12,\ 2}$ are the positive part and the negative part of the previous twelve- to two-month cumulative return, Ret_{1} is the past one-month return, $Ret_{36,\ 13}$ is the past three- to one-year cumulative return, *logBM* is the logarithm of book-to-market ratio, *logmktcap* is the logarithm of a rm's market capitalization, *turnover* is the average daily turnover ratio in the past one year, and *ivol* is idiosyncratic volatility, the daily volatility of return residuals with respect to Fama-French three-factor model in the past one year. Cross-sectional WLS regressions are run every month. In columns (1){(4), the weight is de ned as prior-period gross return, and in columns (5){(8), the weight is market capitalization of a stock. Columns (1){(6) utilize the whole sample, while columns (7){(8) exclude rms with size in the top quintile for each month. The parameters and t-statistics (shown in square brackets) are calculated using the time series of corresponding cross-sectional regression estimates. *, **, and *** denote signi cance levels at 10%, 5%, and 1%. R^2 is the average R^2 from the cross-sectional regressions. I report coe cient estimates for all months and for February to December separately.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Lag *Gain* & *Loss* by 10 days		Lag *Gain* & *Loss* by 1 month		Value weighted		Value weighted, excluding mega-sized rms	
	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.	All	Feb.{Dec.
Gain	0.037***	0.038***	0.014***	0.016***	{0.002	0.000	0.026***	0.027***
	[10.75]	[10.92]	[4.56]	[5.13]	[{0.50]	[0.10]	[4.53]	[4.45]
Loss	{0.003***	{0.002**	{0.005***	{0.003***	{0.005***	{0.005***	{0.009***	{0.008***
	[{3.38]	[{2.08]	[{5.18]	[{3.43]	[{3.87]	[{3.61]	[{6.90]	[{5.57]
$Ret^{+}_{12,\ 2}$	0.004	0.005	0.010***	0.011***	0.011***	0.012***	{0.002	{0.001
	[1.11]	[1.30]	[5.35]	[5.57]	[3.66]	[3.72]	[{0.23]	[{0.16]
$Ret_{12,\ 2}$	0.021***	0.023***	0.025***	0.026***	0.012***	0.015***	0.022***	0.023***
	[6.76]	[7.27]	[8.21]	[8.30]	[2.75]	[3.25]	[4.22]	[4.13]
Ret_{1}	{0.060***	{0.053***	{0.053***	{0.045***	{0.033***	{0.028***	{0.050***	{0.046***
	[{16.46]	[{14.91]	[{14.09]	[{12.46]	[{6.92]	[{5.66]	[{10.32]	[{8.91]
$Ret_{36,\ 13}$	{0.002***	{0.001***	{0.001***	{0.001	{0.000	0.000	{0.002**	{0.001
	[{4.22]	[{2.62]	[{2.80]	[{1.24]	[{0.62]	[0.51]	[{2.44]	[{1.08]
logBM	0.002***	0.001***	0.002***	0.001***	0.001	0.000	0.003***	0.003***
	[4.03]	[3.25]	[3.81]	[3.03]	[0.93]	[0.12]	[3.07]	[2.59]
logmktcap	{0.001***	{0.001***	{0.001***	{0.001***	{0.001***	{0.001***	{0.001	0.000
	[{4.96]	[{3.01]	[{4.93]	[{2.98]	[{4.03]	[{4.20]	[{1.35]	[0.34]
ivol	{0.166***	{0.252***	{0.180***	{0.262***	{0.285***	{0.367***	{0.220**	{0.283***
	[{3.24]	[{4.80]	[{3.57]	[{5.10]	[{3.79]	[{4.79]	[{2.34]	[{2.83]
turnover	{0.498*	{0.432	{0.462*	{0.403	{0.517	{0.530	{0.184	{0.186
	[{1.76]	[{1.46]	[{1.67]	[{1.40]	[{1.43]	[{1.42]	[{0.55]	[{0.53]
Constant	0.019***	0.017***	0.020***	0.018***	0.021***	0.022***	0.018***	0.014***
	[10.25]	[8.82]	[10.99]	[9.52]	[6.91]	[7.06]	[6.57]	[5.14]
Avg. monthly obs.	2,725	2,721	2,704	2,700	2,726	2,721	2,100	2,096
R^2	0.082	0.078	0.081	0.077	0.161	0.158	0.094	0.092
# of months	611	561	610	560	611	561	611	561