Asset Pricing when Traders Sell Extreme Winners and Losers

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November 27, 2014

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, aggregated across investors, outperform others in the following month (monthly alpha = 0.5-1%, Sharpe ratio = 1.6). This supports the conjecture that these stocks experience higher selling pressure, leading to lower current prices and higher future returns. This effect cannot be explained by momentum, reversal, volatility, or other known return predictors, and it also subsumes the previously-documented capital gains overhang effect. Moreover, my findings dispute the view that the disposition effect drives momentum; by isolating the disposition effect from gains versus that from losses, I find the loss side has a return prediction opposite to momentum. Overall, this study provides new evidence that investors' tendencies can aggregate to affect equilibrium price dynamics; it also challenges the current understanding of the disposition effect and sheds light on the pattern, source, and pricing implications of this behavior.

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†I am deeply indebted to the members of my committee Patrick Bolton, Kent Daniel, Paul Tetlock and Joseph Stiglitz for many helpful discussions, guidance, and encouragement. I am also grateful for David Hirshleifer, Bob Hodrick, Gur Huberman, Bernard Salanie, Hao Zhou, Jianfeng Yu and seminar participants at various universities and research institutes for helpful comments. All remaining errors are my own. This paper was previously circulated under the title "The V-Shaped Disposition Effect".

1 Introduction

The disposition effect, first described by Shefrin and Statman (1985), refers to the investors' tendency to sell securities whose prices have increased since purchase rather than those 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 past 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 past profits: selling probability increases as the magnitude of gains or losses increases, with the gain side having a larger slope than the loss side. Figure 1 (Figure 2B in their paper) 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.

The current study investigates the pricing implications and consequent return predictability of this newly-documented refinement of the disposition effect. I refer to the asymmetric V-shaped selling schedule, which Ben-David and Hirshleifer (2012) suggest to underlie the disposition effect, as the *V-shaped disposition effect*. 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.

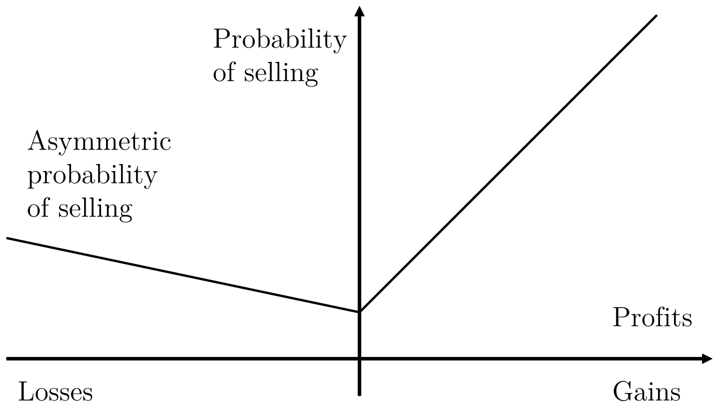
To test this hypothesis, I use stock data from 1970 to 2011 and construct stock-level measures for

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

[2]See, for example, Genesove and Mayor (2001) in housing market, Heath, Huddart, and Lang (1999) for stock options, and Camerer and Weber (1998) in 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, please see the review article by Barber and Odean (2013)

Figure 1. V-shaped Selling Propensity in Response to Profits



unrealized gains and losses. In contrast to previous studies, I isolate the effect from gains and that from losses to recognize the pronounced kink in the investors' selling schedule. The results show that stocks with larger unrealized gains as well as 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 effect generates a monthly alpha of approximately 0.5%-1%, with a Sharpe ratio as high as 1.6. This compares to the strongest evidence we have on price pressure.

To place my findings into the context of existing research, I compare a net selling propensity measure that recognizes the V-shaped disposition effect, the *V-shaped net selling propensity*, with the *capital gains overhang* variable, which assumes a monotonically increasing selling propensity in response to profits. 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 effect of capital gains overhang disappears. This suggests that the V-shaped selling schedule better depicts investors' trading pattern, and the return predictability of capital gains overhang originates from adopting the V-shaped net selling propensity.

To gain insight into the source of the V-shaped disposition effect, I conduct tests in cross-sectional subsamples based on institutional ownership, firm size, turnover ratio, and stock volatility. In more speculative subsamples (stocks with lower institutional ownership, smaller size, higher turnover, and higher volatility), the effect of unrealized gains and losses are stronger. This finding supports the conjecture that a speculative trading motive underlies the observed V. It is also consistent with Ben-David and Hirshleifer's (2012) finding that the strength of the V shape on 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, it contributes to the research on investors' trading behaviors, and more specifically how investors trade in light of past profits and what theories explanation this behavior. While 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, and the full functional form remains controversial. The V-shaped selling schedule documented by Ben-David and Hirshleifer (2012) also appears in other studies, such as Barber and Odean (2013) and Seru, Shumway, and Stoffman (2010), although it is not their focus. On the other side, Odean (2008) and Grinblatt and Keloharju (2001) show a selling pattern that appears as a monotonically increasing function of past profits. My findings at the stock level support the V-shaped selling schedule rather than the monotonic one. A concurrent study by Hartzmark (2013) finds that investors are more likely to sell extreme winning and extreme losing positions in their portfolio, and that this behavior can lead to price effects; this is generally consistent with the V-shaped selling schedule. The shape of the full trading schedule is important because it illuminates the source of this behavior. Prevalent explanations for the disposition effect, either prospect theory (Kahneman and Tversky (1979)) or realization utility (Barberis and Xiong (2009, 2012)), attribute this behavioral tendency to investors' preference. Although these models can explain the selling pattern partitioned by the sign of profits by generating a monotonic relation between selling propensity and profits, reconciling the V-shaped selling schedule in these frameworks is difficult. Instead, belief-based interpretations may come into play. Cross-sectional subsample results point to a speculative trading motive (based on investors' beliefs) as 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 have different implications for stock-level return predictability. Thus the stock-level evidence in this paper sheds further light on which mechanisms may hold promise for explaining the V-shaped disposition effect. Section 5 discusses this point in details.

Second, this study adds to the literature on the disposition effect being relevant to asset pricing. While investor tendencies and biases are of interest on their own right, they relate to asset pricing only when individual behaviors aggregate to affect equilibrium price dynamics. Grinblatt and Han (2005) develop a model in which the disposition effect 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 under-reaction 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 and 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.

Third, this paper contributes to the literature on the extent to which the disposition effect 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 (2012) disputes the causality between the disposition effect and momentum. He finds that following stock splits, which he shows to lack the disposition effect, momentum remains robustly present. 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 results present a stronger argument against this view by isolating the disposition effect from gains versus that from losses: larger unrealized losses predict higher future returns, a direction opposite to what momentum would predict. Therefore, the disposition effect is unlikely to be a source of momentum.

The rest of the paper is organized as follows. Section 2 describes the analytical framework and derives hypothesis. Section 3 describes the data and my method for constructing empirical measures. In section 4, I test the pricing implications of the V-shaped disposition effect using both portfolio sorts and the Fama-MacBeth regressions. Section 5 discusses the source of the V-shaped disposition effect and empirically tests it in cross-sectional subsamples. Section 6 discusses the relation between the disposition effect and momentum. Section 7 runs a battery of robustness checks. Finally, section 8 concludes the paper.

2 Analytical Framework and Hypothesis

2.1 Analytical Framework

How do investors' tendency to trade in light of past profits affects equilibrium prices? I adopt Grinblatt and Han (2005)'s 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 exist one single 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 is disposition-prone investors, 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 (2005)'s 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, thus they have rational demand for the stock (as potential buyers); for current stock holders, 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 only need to focus on the demand function of current stock holders, and I will empirically estimate it in the following subsection using retail investors' trading data.

2.2 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 gauging the pricing effect, I estimate the *net* selling schedule (selling - buying), which corresponds to investor's 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 start from replicating Ben-David and Hirshleifer (2012)'s results on how paper gains and losses affect selling and buying. I use the same retail investor trading data (The Odean dataset) and follow Ben-David and Hirshleifer (2012) for their data screening criteria, variable specifications, and regression design. I perform a probit regression of a selling (buying) dummy variable on investor's return since purchase and control variables. Unrealized returns are separated by their signs ($Ret^+ = Max\{Ret, 0\}$ and $Ret^- = Min\{Ret, 0\}$), and the controls include an indicator variable if return is positive, an indicator variable if return is zero, the square root of 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 previous 250 trading days) - one is equal to stock volatility when return is positive, zero otherwise; the other variable is equal to stock volatility when return is negative, 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. Please refer to Ben-David and Hirshleifer (2012) for more details.

Table 1 Panel A and Panel B report regression results for selling and buying, respectively. The estimations are almost the same as Ben-David and Hirshleifer (2012)'s findings[4](Table 4 in their paper): selling and buying probability increase with the magnitude of both paper gains and losses; for selling schedule, the gain side has a stronger effect, and for buying schedule, the loss side is stronger; both selling and buying schedule weaken as time since purchase increases, and the schedules become flat when holding period exceeds 250 trading days.

To map this trading pattern to price effects, I now introduce an alternative definition of return. Return since purchase in Ben-David and Hirshleifer (2012)'s exercises is defined as the difference 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 effect (e.g., Grinblatt and Han (2005) and Frazzini (2006)), stock-level aggregation of investors' gains and losses is all defined as a weighted sum of percentage deviation of purchase price from *current price*, $\frac{P_t - P_0}{P_t}$. I refer to the latter definition as $Ret2$ henceforth. Which definition is better?For aggregation at stock level, $Ret2$ has a unique advantage in that the weighted sum of all investors' returns can be interpreted as the return of a representative investor ($\sum_i \omega_i \frac{P_t - P_{0i}}{P_t} = \frac{P_t - \sum_i \omega_i P_{0i}}{P_t}$); on the contrary, definition of Ret does not has this convenience. On selling behavior level, there is no theoretical guidance on which form of return that investors response to; indeed, the two definitions both mean to measure the change in value since purchase, with the only difference lying in the normalizing factor. Therefore I follow the literature on pricing to employ $Ret2$ to study price effects, and I now estimate the relation between selling/buying and $Ret2$ for consistency.

I repeat the regressions in Table 1 Panel A and Panel B, but now replace Ret^+ and Ret^- with $Ret2^+$ and $Ret2^-$, where $Ret2^+ = Max\{\frac{P_t - P_0}{P_t}, 0\}$ and $Ret2^- = Min\{\frac{P_t - P_0}{P_t}, 0\}$. Table 1 Panel C

[4]These results are based on a random sample of 10000 accounts, so the numbers can not be exactly identical to those of Ben-David and Hirshleifer (2012).

and Panel D report results for selling and buying, respectively. First of all, comparing with the corresponding regression results in Panel A and B using the definition of original Ret, coefficients' t statistics and regression R squares in Panel C and D are of very similar magnitude. This suggests that $Ret2$ is no worse than Ret in capturing the relation between trading and unrealized profits.

What's the shape of investors' net selling schedule? Comparing columns (1) to (3) in Panel C with columns (1) to (3) in Panel D, we see that for the same magnitude increase in gains or losses, selling effect dominates buying effect. To illustrate, consider column (1) in both panels. For prior holding period less than 20 days, a 1% increase in $Ret2^+$ will raise selling probability by 4.75%, and will raise the probability of buying additional shares by 1.66%, thus the increase in net selling probability is 3.09%; on the loss side, a 1% increase in $Ret2^-$ will raise selling probability by 2.39%, and will raise the probability of buying additional shares by 1.86%, thus the increase in net selling probability is 0.53%. 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's the relation between net selling upon a gain and net selling upon a loss? Since trading schedule becomes flat beyond one year of holding time, I estimate this relation using results in columns (1) and (2) in Panel C and D. For prior holding period less than 20 days, we have calculated the net selling schedule and the relative magnitude between gain side and loss side is $\frac{3.05\%}{0.53\%} = 5.75$. For prior holding period between 21 and 250 days (column (2)), on the gain side, a 1% increase in $Ret2^+$ will lead to a $0.35\% - 0.11\% = 0.24\%$ increase in net selling probability; on the loss side, a 1% increase in $Ret2^-$ will lead to a $0.09\% - 0.05\% = 0.04\%$ increase in net selling probability. Thus the relation between gain side and loss side at this holding horizon is $\frac{0.24\%}{0.04\%} = 6$. Weighting this two ratio by their numbers of observations at corresponding holding periods, a proxy for their representation in the investor pool, we have the relation between the gain arm and the loss arm of the V as $5.75 \times \frac{1144228}{1144228+8106696} + 6 \times \frac{8106696}{1144228+8106696} = 5.9$[5].

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

HYPOTHESIS **1.** *The V-shaped-disposition-prone investors tend to (net) sell more when their unrealized gains and losses increase in magnitude; this effect is stronger on the gain side, as about 5.9 times the magnitude as that on the loss side. Consequently, on the stock level, stocks with larger gain overhang and larger (in absolute value) loss overhang will experience higher selling pressure,*

[5]Results in Panel C and D are robust to replacing the dependent variables, selling dummy and buying dummy, by the number of shares sold and additional shares bought. I report these results in the Appendix Table A2

resulting in lower current prices and higher future returns as future prices revert to the fundamental values. Moreover, the price effects on the gain side and that on the loss side shall be in line with the relative magnitude.

The rest of the paper will focus on testing the pricing implications, and all remaining empirical exercises will be conducted on the stock level.

3 Data and Key Variables

3.1 Stock Samples and Filters

I use daily and monthly stock data from CRSP. The sample covers all US common shares (with CRSP share codes equal to 10 and 11) listed in NYSE, AMEX, and NASDAQ from January 1970 to December 2011. To avoid the impact of the smallest and most illiquid stocks, I eliminate stocks lower than two dollars in price at the time of portfolio formation, and I require trading activity during at least 10 days in the past month. I focus on monthly frequency when assessing how gain and loss overhang affect future returns. My sample results in 1847357 stock-month combinations, which is approximately 3600 stocks per month on average.

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

3.2 Gains, Losses, and the V-shaped 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: 1. instead of aggregating all past prices, I measure gains and losses separately; 2. I use daily as opposed to weekly past prices in calculation.

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

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

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 $t-n$ without having been traded afterward.

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

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

It is known that NASDAQ volume data are subject to double counting; therefore 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 (2012) 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 investor's confusion. Later 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 is above all the historical prices within the past 5 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 less of the measuring window and the time it has been appeared 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 two reasons. First, Ben-David and Hirshleifer (2012) document the refinement of the disposition effect among individual traders and they show that the effect becomes flat beyond one year holding period (Table 4 in their paper, also Table 1 in this paper); however, the disposition effect is far from restrained to this group of investors (Frazzini (2006), Locke and Mann(2000), Shapira and Venezia (2001), Coval and Shumway (2001), among others). Taking a five-year window allows the possibility that other types of investor may have different trading horizons. Second, a five-year window provides the convenience to compare with the previous literature; note that the sum of *Gain Overhang* and *Loss Overhang* is equal to *Capital Gains Overhang* (CGO) in Grinblatt and Han (2005).

That said, I would still like to explore the direct pricing implications of individual investors' trading horizon. Therefore, based on the one year horizon, I further separate gain and loss overhang into *Recent Gain Overhang* (RG), *Distant Gain Overhang*(DG), *Recent Loss Overhang*(RL), and *Distant Loss Overhang*(DL). The recent overhangs utilize purchase prices within the past one year of portfolio formation time, while the distant overhangs use purchase prices from the previous one to five years. As before, the weight on each price is equal to the probability that the stock is last purchased on that day, and the weights are normalized so that the weights from all four parts sum up to one.

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

$$VNSP_t = Gain_t - 0.17Loss_t \tag{3}$$

The coefficient -0.17 indicates the asymmetry in the V shape in investors' net selling schedule. According to regression results in section 2.2, the slope on the the gain side of the V is about 5.9 times large as that on the loss side. Thus the coefficient in front of $Loss$ is set to be $\frac{1}{5.9} = 0.17$.

Panel A in Table 2 presents summary statistics for *Recent Gain Overhang*, *Distant Gain Overhang*, *Recent Loss Overhang*, *Distant Loss Overhang*, *Gain Overhang*, *Loss Overhang*, *Capital Gains Overhang* and *V-shaped Net Selling Propensity*. RG, DG, RL, and DL are winsorized at 1% level in each tail, while $Gain$, $Loss$, CGO and $VNSP$ are linear combinations of RG, DG, RL, and DL.

Insert Table 2 about here.

3.3 Other Control Variables

To tease out the effect of gain and loss overhang, I control for other variables known to affect future returns. By construction, gain and loss overhang utilize prices in 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 is taken to address the concern that if the momentum effect is markedly stronger on the loser side (as documented by Hong, Lim, and Stein (2000)), imposing loser and winner having the same coefficient in predicting future return will tilt the effects from gains and losses. Specifically, the loss overhang variable would have to 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 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 return, 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, Hodrick, Xing, and Zhang (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 6 months' 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 unit of millions.

Table 2 Panel B summarizes these control variables. All control variables in raw values are winsorized at 1% level in each tail. Panel C presents correlations of gain and loss variables with control variables. A somewhat surprising number is the negative correlation of -0.13 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), the value of Ret is amplified. Therefore, compared with normal definition of return, $Ret2$ has larger absolute values on the loss side than on the gain side. Indeed, Gain has a standard deviation of 0.1, while Loss has a standard deviation of 0.47; CGO has negative mean and median, and is negatively skewed. While the loss side dominates in value, the gain side has much stronger predictive power for future returns. Thats why CGO and VNSP are negatively correlated in value (through the loss side), but their predictive power are to some extent aligned (through the gain side).

4 Empirical Setup and Results

To examine how gain and loss overhang affect future returns, I present two sets of findings. First I examine returns in sorted portfolios based on 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.

4.1 Sorted Portfolios

This subsection investigates return predictability of the V-shaped disposition effect in portfolio sorts. This illustrates a simple picture of how average returns vary across different levels of the V-shaped net selling propensity.

Table 3 reports the time series average of mean returns in investment portfolios constructed on the basis of selling propensity variables.

Insert Table 3 about here.

In Panel A, I sort firms into five quintiles at the end of each month based on their V-shaped net selling propensity, with quintile 5 representing the portfolio with the largest VNSP. The left side of the table reports gross-return-weighted portfolio returns[6] while the right side shows value-weighted results. For each weighting method, I show results in portfolio raw returns, DGTW characteristics-

[6]This follows the weighting practice suggested by Asparouhova, Bessembinder, and Kalcheva (2010) to minimize confounding microstructure effects. 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.

adjusted returns[7], and Carhart four-factor alphas[8]. All specifications are examined using all months and using February to December separately[9]. For comparison, Panel B shows the same set of results for portfolio returns sorted on capital gains overhang.

In Panel A, 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, while the CGO effect is stronger in February to December than in 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 disposition effect.

A caveat that arises is that VNSP and CGO, both constructed using past prices and volumes, are correlated with other known return predictors. To better control for confounding factors, in Panels C and D, I repeat the exercises in Panels A and B, but base the sort on residual selling propensity variables, instead of the raw values. The residuals are constructed from simultaneous cross-sectional regressions of the raw selling propensity variables on past returns, size, turnover, and idiosyncratic volatility. Specifically, the residuals are calculated using the following models:

$$VNSP_{t-1} = \alpha + \beta_1 Ret_{t-1} + \beta_2 Ret_{t-12,t-2} + \beta_3 Ret_{t-36,t-13} + \beta_4 logmktcap_{t-1} + \beta_5 turnover_{t-1} + \beta_6 ivol_{t-1} + \epsilon_t$$

$$CGO_{t-1} = \alpha + \beta_1 Ret_{t-1} + \beta_2 Ret_{t-12,t-2} + \beta_3 Ret_{t-36,t-13} + \beta_4 logmktcap_{t-1} + \beta_5 turnover_{t-1} + \beta_6 ivol_{t-1} + \epsilon_t$$

Focusing on the gross-return-weighted results in Panel C, the return spread between top and bottom quintiles based on VNSP (about 0.5% per month) is of similar or larger magnitude than those in Panel A, and the t-statistics become much larger (around 6, 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 regression results in Table 6 Panel B. Note that the value-

[7] The adjusted return is defined as raw return minus DGTW benchmark return, as developed in Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004). The benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

[8] See Fama and French (1993) and Carhart (1997)

[9] Grinblatt and Han (2005) show that their capital gains overhang effect is very different in January and in other months of the year. They attribute this pattern to return reversal in January that is 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 return in January, I separately report results using February to December only.

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

4.2 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 three questions here: 1) Do gain and loss overhang predict future returns, if other known effects are controlled; 2) What is the impact of prior holding period; and 3) Can this V-shaped net selling propensity subsume previously documented capital gains overhang effect.

4.2.1 The Price Effect of Gains and Losses

I begin by testing Hypothesis 1 (in section 2.2) 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, while the *Loss Overhang* will negatively predict future return (because increased value of *Loss Overhang* means decreased 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:

$$Ret_t = \alpha + \beta_1 Gain_{t-1} + \beta_2 Loss_{t-1} + \gamma_1 X_{1t-1} + \gamma_2 X_{2t-1} + \epsilon_t \tag{4}$$

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 denote variables with information up to the end of month t. X_{1t-1} is designed to control the momentum effect and it consists of the twelve-to-two-month return separated by sign, $Ret^+_{t-12,t-2}$ and $Ret^-_{t-12,t-2}$; X_{2t-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 one year $turnover_{t-1}$ and idiosyncratic volatility $ivol_{t-1}$. Details of these variables' construction are discussed in section 3.3.

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 premium. The gross-return-weighted results reported here are almost identical to the equal-weighted results, which suggests that the liquidity bias is not a severe issue here.

Insert Table 4 about here.

Table 4 presents results from estimating equation (4) 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 and they attribute this pattern to return reversal in January that is 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 return in January, I separately report results that exclude January from the sample.

Columns (1) and (2) regress future return only on the gain and loss overhang variables; columns (3) and (4) add the past twelve-to-two month return separated by its sign as regressors; columns (5) and (6) add controls in X_2 to columns (1) and (2); and columns (7) and (8) show the marginal effects of gain and loss overhang controlling both past return variables and other standard characteristics, and these two are considered as the most proper specification. Finally, as a basis for comparison, columns (9) and (10) regress the subsequent one-month return on all control variables only.

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 1%, the future 1-month return will increase 3.3 basis points, and if the loss overhang increases 1% (the magnitude of loss decreases), the future 1-month return will decrease around 1.1 basis point. The t-statistics are 8.4 and 10.7 for *Gain* and *Loss*, respectively. Since 504 months are used in the estimation, these t-statistics translate to Sharpe ratios as high as 1.3 and 1.6 for strategies based on the gain overhang and the loss overhang, respectively. Note that the gain effect is 3 to 4 times as large as the loss effect (in all months and in February to December), which is roughly in line with the asymmetric V shape in individual trader's selling schedule (5.9 times as estimated in section 2.2). 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), 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 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 estimate would contain an upward bias because high (low) past return is known to predict high (low) future return. Moreover, the estimated coefficients on $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$ are of magnitude of difference - $Ret^{-}_{-12,-2}$ is 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[10].

The results support Hypothesis 1: stocks with larger gain and loss overhang (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 higher for stocks with large losses compared to those with small losses. This challenges the current understanding of the disposition effect that investors' selling propensity is a monotonically increasing function of past profits, 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 relevant not only on the individual level, but this behavior will also aggregate to affect equilibrium prices and generate predictable return patterns.

4.2.2 The Impact of Prior Holding Period

I then investigate how the prior holding period affects the return predictability based on the V-shaped disposition effect. Ben-David and Hirshleifer (2012) show that the V-shaped selling schedule for individuals is strongest in the short period after purchase. As the holding period becomes longer, the V becomes flatter, and the loss side eventually becomes flat after 250 trading days since purchase (Table 4 in their paper, also Table 1 of this paper). Here I decompose *Gain* and *Loss* into gains and losses within one year holding period, and those beyond one year. If we strictly follow the implications of retail investors' trading pattern, only the recent gains and losses can generate return predictability.

[10] 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) late argue that this phenomena 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 1970 to 2011, Hong, Lim, and Stein's (2000) conclusion seems to prevail.

To test this implication, I run Fama-MacBeth regressions for the following model:

$$Ret_t = \alpha + \beta_1 RG_{t-1} + \beta_2 RL_{t-1} + \beta_3 DG_{t-1} + \beta_4 DL_{t-1} + \gamma_1 X_{1t-1} + \gamma_2 X_{2t-1} + \epsilon_t \qquad (5)$$

where *Recent Gain Overhang (RG)* and *Recent Loss Overhang (RL)* are overhangs from purchase prices within the past one year, while *Distant Gain Overhang (DG)* and *Distant Loss Overhang (DL)* are overhangs from purchase prices in the past one to five years. The two sets of control variables X_1 and X_2 are the same as in equation (4).

Insert Table 5 about here.

Table 5 illustrates the results separating selling propensity variables from the recent past and those from the distant past. Again, columns (7) and (8) present estimations from the best model, and the previous columns omit certain control variables to gauge the relative importance of different effects. In columns (7) and (8), both recent and distant overhang variables exhibit return predictability, while the recent variables are much stronger than the distant ones. A 1% increase in recent gains (losses) will lead to a increase of 7.9 basis points (decrease of 1.4 basis points) in monthly return, while a 1% increase in distant gains (losses) only results in a return increase (decrease) of 2.2 basis points (0.9 basis points). The return predictability of distant gains and losses is not consistent with the horizon documented by Ben-David and Hirshleifer (2012), which is based on individual traders; however, the disposition effect is far from restrained to this group of investors (Frazzini (2006), Locke and Mann(2000), Shapira and Venezia (2001), Coval and Shumway (2001), among others). Distant gains and losses may capture the effect from other types of investors. Indeed, using mutual fund holding data, An and Argyle (2014) show that mutual fund managers also exhibit a V-shaped selling schedule, and this trading pattern lasts beyond one year of holding period. Note that the relative magnitude between gain and loss effects within one year holding period is at a multiple of $\frac{7.9}{1.4} = 5.6$, better aligned with the estimated relation in individual investors' net selling schedule; this is consistent with the conjecture that individual investors mainly contribute to price impact within one year horizon, while the distent gain and loss effects are from other investors.

4.2.3 Comparing V-shaped Net Selling Propensity with Capital Gains Overhang

Finally, I introduce a new variable *V-shaped Net Selling Propensity (VNSP)* that combines the effects from the gain side and the loss side. $VNSP = Gain - 0.17Loss$. The coefficient -0.17 resembles an average relation between the gain side and the loss side on traders' net selling schedule. I compare the V-shaped net selling propensity variable that recognizes different effects for gains and losses with the capital gains overhang variable that aggregates all purchase prices, 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.

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):

$$Ret_t = \alpha + \beta_1 CGO_{t-1} + \gamma_1 Ret_{t-1} + \gamma_2 Ret_{t-12,t-2} + \gamma_3 Ret_{t-36,t-13} + \gamma_4 logmktcap_{t-1} + \gamma_5 turnover_{t-1} + \epsilon_t \tag{6}$$

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 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* return. 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 relation between the disposition effect and momentum will be discussed in Section 6.

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 6 times as large as that of the winners, 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 will not fully capture the strong effect on the loser side; the remaining part of this "low past return predicts low future return" effect will be 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; this further dampens the effect of capital gains overhang, which even becomes negative. This arises because stocks with larger absolute loss overhang are more likely to be more volatile, which is associated with lower future returns (see Ang, Hodrick, Xing, and Zhang (2006, 2009), among others).

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

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

where the two sets of control variables X_1 and X_2 are the same as in equation (4) and (5). In columns (1) (2) (5) and (6), where I don't control the momentum effect, both variables positively predict the subsequent one-month return, while *VNSP* has 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. A 1% increase in *VNSP* raises the subsequent month return by around 4 basis points; since the average monthly difference between the 10th and 90th percentile is 23%, return spread between the top and bottom *VNSP* portfolio will roughly generate a return of 23% $\times$ 0.04% = 0.92% per month. The t-statistic for the VNSP coefficient is larger than 10; Since 504 months are used in the estimation, this t-statistic translates into a Sharpe ratio as high as 1.6 ($10.38 \div \sqrt{504} \times \sqrt{12} = 1.6$) for a hedged portfolio based on V-shaped net selling propensity. These results support that V-shaped net selling propensity dominates capital gains overhang in predicting returns.

5 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 diverge. Price-level evidence shown in the previous section will help to distinguish these potential explanations. I then examine the effect of gain and loss overhang in different cross-sectional subsamples. This evidence is consistent with the general conjecture that speculative trading motive leads to the V-shaped disposition effect.

5.1 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, prevalent explanations for the disposition effect, either loss aversion from prospect theory (Kahneman and Tversky (1979)) or realization utility (Barberis and Xiong (2009, 2012)), all attribute this behavior to the pain of realizing losses; while these theories can easily generate a monotonically increasing relation between selling propensity and profits, they are hardly compatible with the asymmetric V-shaped selling schedule with the minimum at a zero profit point. Instead, Ben-David and Hirshleifer (2012) suggest belief-based explanations underlie this observed V.

This perspective suggests that changes in beliefs, rather than features of preferences, generate the V shape. 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), thus 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 shape observed on the individual level. First, the V shape may come from investors' *limited attention*[11]. Investors may buy a stock and not re-examine 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 re-examine a position when their profits are higher. Second, the V shape may be a consequence of *rational belief-updating*. Assume that investors have private information of a stock and have bought the stock accordingly. As price rises, they may think their information has been incorporated in the market price thus want to realize the gain; as price declines, they may re-evaluate 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, the trading activities now reflect only noise.

Although all three explanations are consistent with the individual-level V shape, they have distinct price-level implications. First, the *limited attention* scenario would predict more selling for stocks with large gains and losses, but the same mechanism is likely to generate more buying for these stocks since potential buyers are attracted by the extreme returns[12], regardless of whether

[11]see Barber and Odean (2008), Seasholes and Wu (2007), among others.

[12]Barber and Odean (2008)

they currently hold the stock or not. Though we know for current stock holders, 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 would suggest trading after gains and losses reflects the process of information being absorbed into price. We would not see a predictable pattern in future returns in this case. Finally, in the third possibility, *irrational belief-updating*, selling is caused by belief changes based on misperceptions and does not draw on genuine information, thus the downward pressure on current price is temporary and future returns are predictable. Given the different implications, price-level evidence would help to distinguish the source of the V-shaped disposition effect: the return predictability shown in section 4 is consistent with the irrational belief-updating scenario, as opposed to the other two.

5.2 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 5.1, is in contrast to preference-based explanations. To assess whether speculative trading can serve as a possible source, I examine how the effect 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 effect is 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 4, 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 10 deciles according to their market capitalization; within each decile, I then equally divide firms into three groups according to the characteristic of interest (call 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% NYSE firms category, while the low group corresponds to the bottom 30%.

Insert Table 7 about here.

In each high and low subsample, I re-examine equation (4) 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 for gains and losses are indeed economically and statistically stronger than their less speculative counterpart. This finding is consistent with the investor-level evidence from Ben-David and Hirshleifer (2012), in which the strength of the V shape in an investor's selling schedule is found to be associated with his or her "speculative" characteristics such as trading frequency and gender. As more speculative investors are more likely to be prevalent in speculative stocks, the stock-level findings suggest that speculation is the source of this individual behavior.

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 return with the expected sign, and the gain effect is 2 to 6 times as large as the loss effect. This suggests that the asymmetry between gains and losses is a relatively stable relation.

There are alternative interpretations for the different strength of effect across different stock groups though. 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.

6 The Disposition Effect and Momentum

Recent research highlights the disposition effect as the driver of several return anomalies, among which price momentum is probably the most prominent one. Grinblatt and Han (2005) suggest that past returns may be noisy proxies for unrealized gains and losses, and they show that when the capital gains overhang variable is controlled in their sample, the momentum effect disappears.

Shumway and Wu (2007) subsequently use stock trading data from China to test if the disposition effect drives momentum; though they do not find momentum in their relatively short sample, they document a momentum-like phenomenon based on unrealized gains and losses and suggest that it supports the hypothesis. In contrast, Novy-Marx (2012) shows that a capital gains overhang variable constructed as in Frazzini (2006) using mutual fund holding data does not subsume momentum effect in the sample from 1980 to 2002: he instead finds that capital gains overhang has no power to predict returns after the variation in past returns in controlled for. Birru (2012) also disputes the causality between the disposition effect and momentum; he finds that following stock splits, in which he shows that the disposition effect is seen to be absent, momentum remains robustly present.

My results lend support to the second camp of research, which claims that the disposition effect cannot explain momentum. First, with regard to the original capital gains overhang variable constructed following Grinblatt and Han (2005), results shown in Table 6 Panel A columns (1) and (2) find this variable does not subsume momentum in my sample of 1970 to 2011. Moreover, allowing past winners and losers to have different strength of effect (as in columns (3) and (4)) largely reduces the coefficient for capital gains overhang. This suggests that a large portion of capital gains overhang's original predictive power comes from picking up momentum effect, when the functional form of momentum effect is misspecified in the regression.

Second, isolating the disposition effect from gains and from losses presents a stronger argument. Since the marginal effect from the loss side is negative on future returns, it runs opposite to loser stocks having lower future returns. Furthermore, Tables 4 shows the importance of controlling the momentum variable to reveal the true effect from gains and losses.

Last but not least, the asymmetry in the disposition effect and in momentum suggests the attempt to explain momentum using the disposition effect is doomed to failure. Indeed, the disposition effect mainly originates from the gain side, while momentum is mostly a loser effect. In my sample, the disposition effect from gains is about 5 times as large as that from losses; for momentum, the losers have 5 to 10 times the predictive power for future returns compared with the winners. Thus the disposition effect can hardly generate a return pattern that matches the asymmetry in momentum. There is a caveat though: Israel and Moskowitz (2013) argue that the pronounced asymmetry in momentum is sample specific; thus the explanatory power of the disposition effect for momentum might be stronger in other samples.

7 Robustness Checks

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

7.1 Alternative specifications and alternative samples

1. Adjusting prices for stock splits and dividends. In the main specification, I aggregate purchase prices without adjusting for stock splits and dividends. To make sure the results are not driven by this, I construct alternative overhang variables adjusting for sock splits and dividends and repeat the tests of equation (4) . Table 8 Columns (1) and (2) report the results. Compared with the corresponding results in Table 4 columns (7) and (8), the estimates are very similar.

2. Aggregation Frequency. Grinblatt and Han (2005) use weekly prices and volumes to measure capital gains overhang, while my study uses daily variables. To show that the findings in this paper are not artifacts due to aggregation frequency, I construct overhang variables using weekly prices and volumes. Table 8 Columns (3) and (4) show the results - the estimated coefficients are of similar magnitude as those of daily aggregated variables, shown in Table 4 columns (7) and (8).

3. Stock sample. A potential concern is that volume data from NASDAQ, even with adjustment, may create problems for my measure of gains and losses. I thus run the my best model on a sample that excludes NASDAQ stocks. The results are reported in Table 8 Columns (5) and (6). we see that gain and loss overhang still have the expected signs, and both are highly significant. The magnitude of gain overhang is smaller compared with the whole sample estimation. I interpret this difference mainly as a size effect: NYSE and AMEX firms are generally larger in size, and from Table 7 columns (5)-(8), we know that the gain effect becomes smaller as firm size increases, while the loss effect is affected to a less extent. Indeed, the change in estimated coefficients from the whole sample to NYSE AMEX sample (presumably a change in average firm size) mainly lies in the gain side.

Insert Table 8 about here.

7.2 Impact of liquidity effects

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

First, I skip 10 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) report the results for these two specifications, respectively. We see that the estimated coefficients are smaller compared with those without the lag, but all are still highly significant. The smaller magnitude is consistent with Ben-David and Hirshleifer (2012)'s finding that the V-shaped disposition effect is strong for the very recent gains and losses and the effect gradually weakens as holding period becomes longer. Indeed, skipping one month in measuring gains and losses will miss a bulk of the effect.

Third, I run value-weighted regressions to predict returns. Please note that in previous sections, all regressions are weighted by the stock's past gross return, a methodology designed to correct the liquidity bias in asset pricing test. Here the value weighting scheme is another way to make sure that the findings are not artifacts because of liquidity effects. Table 9 columns (5) and (6) report 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 firms with size comparable to the top 30% in NYSE. These firms are mega firms; though they dominate in market capitalization, they consist only 13% in number of the whole sample. Excluding these firms, Table 9 columns (7) and (8) show value-weighted results for the rest of the sample. We see that both gain and loss overhang have the expect signs and are highly significant. This suggests that the return predictability of gain and loss overhang is not likely to be driven by liquidity reasons.

Insert Table 9 about here.

7.3 Impact of short-sale constraint

Finally, I address the concern that the return predictability may be driven by binding short-sale constraints. I show that my results remain unchanged in a sample where the constraint is not likely to bind. Short-sale constraint is more likely to bind when the supply of lendable shares are low and the demand for shorting is high. I follow the literature (Asquith, Pathak and Ritter (2005), Nagel (2005), among others) to employ institutional ownership and short interest as proxies for supply and demand, respectively. Specifically, I follow Asquith, Pathak and Ritter (2005)'s definition of high demand and low supply stocks, and to be conservative, I use their most inclusive criteria to identify such stocks. The first set of criteria in their paper identify stocks who are ranked top 5% each month according to short interest divided by shares outstanding and are ranked lowest one third according to institutional ownership; the second set of criteria identify stocks who have short interest greater than or equal to 2.5% of shares outstanding and are ranked lowest one third according to institutional ownership. I repeat my pricing regressions in a sample that excludes these constraint-binding stocks. Results corresponding to criteria one and two are reported in Table 10 columns (1)-(2) and columns (3)-(4), respectively. We can see that the magnitudes of coefficients are very similar to those estimated in the whole sample. Because short interest data from Compustat have a lot of missing values before 2003 July, I repeat the exercises using only the later sample from 2003 July to 2011 December. The results are shown in columns (5)-(8). Since the number of total months drops significantly, the t-stats for all variables become much smaller, but Gain and Loss are still generally significant, and the magnitudes remain in the ball park.

Insert Table 10 about here.

Overall, my findings are robust to alternative specifications in measuring gain and loss overhang, as well as the exclusion of NASDAQ stocks and short-sale constrained stocks; moreover, they are not artifacts because of liquidity effects.

8 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 US stock data from 1970 to 2011, 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 the loss side; it's stronger for shorter prior holding period; and it is stronger among more speculative stocks. These patterns are all consistent with the individual trading tendencies documented by Ben-David and Hirshleifer (2012). These findings lend support to the V-shaped selling schedule, as opposed to the monotonically increasing relation between selling propensity and unrealized gains; they also help elucidate the pattern, source, and pricing implication of the disposition effect. In the Appendix, I also discuss the time-series variation of this return pattern induced by tax incentives; the finding further validates that the observed return patterns are indeed consequences of investors trading tendency, rather than other mechanisms.

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 this variable subsumes the previous capital gains overhang variable in capturing selling pressure and predicting subsequent returns. Regarding the extent to which it may explain return anomalies, the results from this study that isolate the disposition effect from gains and losses present a strong argument against the disposition effect as a potential source of momentum.

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Table 1. Selling and Buying in Response to Unrealized Profits

This table reports results from probit regressions of selling (buying) dummy variable on unrealized profits and a set of controls. Observations are at investor-stock-day level. In Panels A and C, the dependent variable is an indicator that equals to 1 if stock is sold on the particular investor-stock-day; in Panels B and D, the dependent variable is an indicator whether additional shares of a stock currently owned are purchased. $Ret^{+} = Max\{Ret, 0\}$, $Ret^{-} = Min\{Ret, 0\}$), $Ret2^{+} = Max\{Ret2, 0\}$ and $Ret2^{-} = Min\{Ret2, 0\}$, where $Ret = \frac{P_t - P_0}{P_0}$ while $Ret2 = \frac{P_t - P_0}{P_t}$. $I(ret = 0)$ 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 coefficients presented reflect the marginal effect on the average stock holding, and are multiplied by 100. Standard errors are clustered at the investor level. t-statistics are in square brackets. *, **, and *** denote significance levels at 10%, 5%, and 1%.

Panel A: Selling schedule with normal return definition						
	Dependent variable: I(Sell stock)x100					
	(1)	(2)	(3)	(4)	(5)	(6)
Prior holding period (days):	1 to 20	21 to 250	>250	1 to 20	21 to 250	>250
Ret^{-}	-3.46***	-0.25***	0.01	-10.15***	-0.67***	-0.03
	[-12.06]	[-8.24]	[0.59]	[-9.91]	[-5.74]	[-0.77]
Ret^{-} x sqrt(Time owned)				2.04***	0.04***	0.00
				[7.17]	[4.17]	[1.19]
Ret^{+}	3.52***	0.15***	-0.01	9.96***	0.73***	0.05***
	[13.76]	[9.66]	[-1.70]	[10.57]	[11.33]	[3.62]
Ret^{+} x sqrt(Time owned)				-1.84***	-0.05***	-0.00***
				[-8.12]	[-9.49]	[-4.32]
I(ret=0)	-0.12**	0.09***	0.02	-0.21	0.05	0.17
	[-1.98]	[3.42]	[1.20]	[-1.32]	[0.75]	[1.41]
I(ret=0) x sqrt(Time owned)				0.08	0.00	0.00
				[1.27]	[0.83]	[-1.18]
I(ret>0)	0.31***	0.05***	-0.01	0.41***	0.09***	0.06***
	[5.52]	[3.93]	[-1.31]	[2.80]	[3.03]	[3.06]
I(ret>0) x sqrt(Time owned)				-0.04	-0.01**	-0.00***
				[-0.99]	[-1.98]	[-3.78]
sqrt(Time owned)	-0.25***	-0.03***	-0.01***	-0.10**	-0.02***	-0.00***
	[-10.67]	[-26.74]	[-24.09]	[-2.10]	[-8.14]	[-5.99]
log(Buy price)	0.26***	0.04***	0.00	0.27***	0.04***	0.00
	[7.40]	[6.81]	[0.14]	[7.56]	[7.04]	[0.27]
$volatility^{-}$	9.53***	1.57***	0.12	8.88***	1.62***	0.16
	[5.23]	[5.7]	[0.69]	[4.98]	[5.93]	[0.91]
$volatility^{+}$	15.27***	6.16***	1.72***	14.24***	5.88***	1.68***
	[9.74]	[20.31]	[9.27]	[8.88]	[19.00]	[9.07]
Observations	1144228	8106696	10089805	1144228	8106696	10089805
Pseudo R^2	0.0343	0.0187	0.0135	0.0373	0.0194	0.0141

(Table 1 Continued)

Panel B: Buying schedule with normal return definition

	Dependent variable: I(Buy additional shares)x100					
	(1)	(2)	(3)	(4)	(5)	(6)
Prior holding period (days):	1 to 20	21 to 250	>250	1 to 20	21 to 250	>250
Ret^-	-2.58***	-0.14***	0.02***	-4.69***	-0.45***	-0.04
	[-9.97]	[-6.50]	[2.77]	[-7.63]	[-8.65]	[-1.63]
Ret^- x sqrt(Time owned)				0.63***	0.03***	0.00**
				[4.17]	[6.46]	[2.28]
Ret^+	1.34***	0.07***	-0.00	2.33***	0.19***	-0.00
	[6.93]	[4.79]	[-1.02]	[3.23]	[4.42]	[-0.38]
Ret^+ x sqrt(Time owned)				-0.29	-0.01***	0.00
				[-1.53]	[-3.31]	[0.09]
I(ret=0)	0.44***	-0.02	-0.01	0.0153***	0.02	-0.02
	[6.73]	[-1.13]	[-1.28]	[7.71]	[0.58]	[-0.55]
I(ret=0) x sqrt(Time owned)				-0.17***	-0.00	0.00
				[-4.69]	[-1.03]	[0.22]
I(ret>0)	-0.21***	-0.09***	-0.01***	-0.10	-0.08***	0.00
	[-6.36]	[-11.41]	[-3.56]	[-1.60]	[-4.14]	[0.13]
I(ret>0) x sqrt(Time owned)				-0.04**	-0.00	-0.00
				[-2.15]	[-0.83]	[-0.88]
sqrt(Time owned)	-0.22***	-0.01***	-0.00***	-0.17***	-0.01***	-0.00
	[-24.34]	[-16.75]	[-6.86]	[-9.66]	[-6.81]	[-1.76]
log(Buy price)	0.06**	0.00	-0.00	0.06**	0.00	-0.00
	[2.11]	[0.59]	[-1.09]	[2.11]	[0.61]	[-1.10]
$volatility^-$	9.21***	1.85***	0.30	9.39***	1.82***	0.30
	[7.84]	[6.77]	[1.68]	[7.49]	[6.54]	[1.68]
$volatility^+$	2.63	-0.03	0.09	2.58	-0.10	0.08
	[1.92]	[-0.16]	[0.78]	[1.80]	[-0.53]	[0.75]
Observations	1144228	8106693	10089796	1090375	8160546	10089796
Pseudo R^2	0.034	0.0185	0.00998	0.035	0.0196	0.0102

(Table 1 Continued)

Panel C: Selling schedule with alternative return definition

	Dependent variable: I(Sell stock)x100					
	(1)	(2)	(3)	(4)	(5)	(6)
Prior holding period (days):	1 to 20	21 to 250	>250	1 to 20	21 to 250	>250
$Ret2^-$	-2.39***	-0.09***	-0.00***	-8.08***	-0.29***	-0.00
	[-12.62]	[-8.53]	[-3.69]	[-10.38]	[-5.35]	[-0.34]
$Ret2^-$ x sqrt(Time owned)				1.67***	0.02***	0.00
				[7.89]	[4.03]	[0.15]
$Ret2^+$	4.75***	0.35***	-0.02	12.09***	1.23***	0.18***
	[13.10]	[10.68]	[-1.39]	[10.17]	[11.12]	[4.93]
$Ret2^+$ x sqrt(Time owned)				-2.15***	-0.08***	-0.01***
				[-7.53]	[-8.47]	[-5.59]
I(ret=0)	-0.16***	0.06**	0.03	-0.25	0.01	0.15
	[-2.78]	[2.58]	[1.48]	[-1.61]	[0.09]	[1.27]
I(ret=0) x sqrt(Time owned)				0.08	0.01	-0.00
				[1.35]	[1.29]	[-0.96]
I(ret>0)	0.23***	0.01	-0.00	0.30**	0.02	0.02
	[4.04]	[1.18]	[-0.73]	[2.14]	[0.66]	[1.03]
I(ret>0) x sqrt(Time owned)				-0.03	-0.00	-0.00
				[-0.75]	[-0.32]	[-1.54]
sqrt(Time owned)	-0.25***	-0.03***	-0.01***	-0.11**	-0.02***	-0.01***
	[-10.69]	[-26.92]	[-24.95]	[-2.35]	[-10.72]	[-9.68]
log(Buy price)	0.26***	0.04***	0.00	0.27***	0.04***	0.00
	[7.43]	[6.85]	[0.19]	[7.56]	[7.04]	[0.33]
$volatility^-$	9.91***	1.73***	0.06	9.01***	1.69***	0.07
	[5.56]	[6.38]	[0.36]	[5.16]	[6.23]	[0.42]
$volatility^+$	15.02***	6.04***	1.71***	14.14***	5.83***	1.70***
	[9.48]	[19.89]	[9.24]	[8.74]	[18.92]	[9.25]
Observations	1144228	8106696	10089805	1144228	8106696	10089805
Pseudo R^2	0.0344	0.0188	0.0135	0.0374	0.0195	0.0141

(Table 1 Continued)

Panel D: Buying schedule with alternative return definition

	Dependent variable: I(Buy additional shares)x100					
	(1)	(2)	(3)	(4)	(5)	(6)
Prior holding period (days):	1 to 20	21 to 250	>250	1 to 20	21 to 250	>250
$Ret2^-$	-1.86***	-0.05***	0.00***	-4.01***	-0.23***	0.00
	[-11.23]	[-6.51]	[3.05]	[-8.52]	[-9.06]	[0.05]
$Ret2^-$ x sqrt(Time owned)				0.62***	0.02***	0.00
				[5.37]	[7.62]	[0.75]
$Ret2^+$	1.66***	0.11***	-0.01	2.49***	0.24***	-0.01
	[6.26]	[3.80]	[-0.88]	[2.74]	[3.26]	[-0.70]
$Ret2^+$ x sqrt(Time owned)				-0.25	-0.01**	0.00
				[-1.03]	[-2.11]	[0.46]
I(ret=0)	0.39***	-0.03	-0.01	1.50***	0.00	-0.02
	[6.6]	[-1.95]	[-1.08]	[7.78]	[0.01]	[-0.80]
I(ret=0) x sqrt(Time owned)				-0.17***	-0.00	0,00
				[-4.89]	[-0.74]	[0.56]
I(ret>0)	-0.25***	-0.11***	-0.01***	-0.11	-0.10***	-0.00
	[-7.09]	[-13.37]	[-2.86]	[-1.77]	[-5.22]	[-0.29]
I(ret>0) x sqrt(Time owned)				-0.05**	-0.00	-0.00
				[-2.50]	[-0.14]	[-0.37]
sqrt(Time owned)	-0.22***	-0.01***	-0.00***	-0.16***	-0.01***	-0.00***
	[-24.07]	[-16.70]	[-6.91]	[-9.75]	[-9.46]	[-2.98]
log(Buy price)	0.06**	0.00	-0.00	0.06**	0.00	-0.00
	[2.08]	[0.61]	[-1.11]	[2.07]	[0.60]	[-1.11]
$volatility^-$	9.28***	1.89***	0.29	9.51***	1.89***	0.29
	[7.87]	[7.03]	[1.66]	[7.58]	[6.94]	[1.66]
$volatility^+$	2.70**	0.09	0.08	2.49	-0.07	0.08
	[2.01]	[0.46]	[0.72]	[1.77]	[-0.36]	[0.68]
Observations	1144228	8106693	10089796	1090375	8160546	10089796
Pseudo R^2	0.034	0.018	0.0101	0.0353	0.0193	0.0101

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. Recent Gain Overhang (RG) is defined as $RG_t = \sum_{n=1}^{N} \omega_{t-n} \frac{P_t - P_{t-n}}{P_t} \cdot \mathbf{1}_{\{P_{t-n} \leq P_t\}}$ using daily price P_{t-n} within one year prior to time t, and ω_{t-n} is a volumed-based weight that serves as a proxy for the fraction of stock holders at time t who bought the stock at P_{t-n}; Recent Loss Overhang (RL) is defined as $RL_t = \sum_{n=1}^{N} \omega_{t-n} \frac{P_t - P_{t-n}}{P_t} \cdot \mathbf{1}_{\{P_{t-n} > P_t\}}$ using P_{t-n} from the same period. Distant Gain Overhang (DG) and Distant Loss Overhang (DL) apply the same formula to purchase prices from five to one year prior to time t. RG, RL, DG, and DL are winsorized at 1% level in each tail. *Gain Overhang (Gain)* $= RG + DG$, while *Loss Overhang* $= RL + DL$. *Capital Gains Overhang (CGO)* $= Gain + Loss$, and *V-shaped Net Selling Propensity (VNSP)* $= Gain - 0.17Loss$. $Ret_{-12,-2}$ 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 - 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.

Panel A. Summary Stats for Net Selling Propensity Variables

	RG	RL	DG	DL	Gain	Loss	CGO	VSP
mean	0.044	-0.091	0.059	-0.201	0.104	-0.293	-0.189	0.154
p50	0.023	-0.024	0.022	-0.037	0.068	-0.112	-0.045	0.127
sd	0.056	0.189	0.081	0.396	0.108	0.468	0.522	0.104
skew	2.052	-5.738	1.748	-3.846	1.313	-3.360	-2.669	1.418
p10	0.000	-0.251	0.000	-0.598	0.002	-0.805	-0.785	0.049
p90	0.120	0.000	0.178	0.000	0.263	-0.002	0.247	0.297

Panel B. Summary Stats for Control Variables

	Ret_{-1}	$Ret_{-12,-2}$	$Ret_{-36,-13}$	logBM	logmktcap	turnover	ivol
mean	0.016	0.177	0.378	-0.519	5.344	0.005	0.029
p50	0.004	0.077	0.159	-0.444	5.212	0.003	0.024
sd	0.154	0.703	1.254	0.842	1.974	0.006	0.017
skew	4.554	9.769	14.621	-0.801	0.372	5.299	3.213
p10	-0.132	-0.378	-0.496	-1.569	2.878	0.001	0.013
p90	0.165	0.730	1.307	0.442	7.970	0.011	0.050

Panel C. Correlation Table

	Gain	Loss	CGO	VSP	Ret_{-1}	$Ret_{-12,-2}$	$Ret_{-12,-2}^{+}$	$Ret_{-12,-2}^{-}$	$Ret_{-36,-13}$	logmktcap	logBM	turnover	ivol
Gain	1.00												
Loss	0.43	1.00											
CGO	0.59	0.98	1.00										
VSP	0.72	-0.31	-0.13	1.00									
Ret_{-1}	0.32	0.18	0.22	0.20	1.00								
$Ret_{-12,-2}$	0.44	0.28	0.34	0.24	-0.01	1.00							
$Ret_{-12,-2}^{+}$	0.46	0.19	0.26	0.33	0.00	0.90	1.00						
$Ret_{-12,-2}^{-}$	0.36	0.57	0.59	-0.07	-0.05	0.49	0.32	1.00					
$Ret_{-36,-13}$	0.05	0.07	0.08	0.00	-0.03	-0.08	-0.06	-0.10	1.00				
logmktcap	0.03	-0.02	-0.01	0.05	0.02	0.05	0.02	0.14	-0.26	1.00			
logBM	0.02	0.33	0.30	-0.23	0.01	0.07	0.03	0.20	0.10	-0.28	1.00		
turnover	-0.04	0.07	0.05	-0.10	0.00	0.13	0.18	-0.13	0.18	-0.28	0.26	1.00	
ivol	0.04	-0.34	-0.30	0.31	0.11	0.12	0.21	-0.31	-0.05	-0.08	-0.46	0.24	1.00

Table 3. 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 five groups at the end of each month, with portfolio 5 contains 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, firm size, turnover, and idiosyncratic volatility. The returns are in monthly percent, t-statistics for the difference between portfolios 5 and 1 are in the square brackets, and *, **, and *** denote significance 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	0.75	0.50	-0.08	-0.11	0.20	0.10	0.83	0.72	-0.03	-0.05	0.47	0.42
2	0.79	0.52	-0.12	-0.15	0.21	0.14	0.80	0.73	-0.05	-0.05	0.41	0.42
3	0.82	0.51	-0.14	-0.19	0.19	0.11	0.89	0.83	-0.03	-0.03	0.41	0.46
4	1.04	0.71	0.03	-0.01	0.36	0.30	1.03	0.97	0.05	0.05	0.48	0.54
5	1.36	0.94	0.16	0.11	0.67	0.56	1.35	1.29	0.15	0.20	0.77	0.88
5-1	0.61	0.43	0.25***	0.22***	0.47***	0.46***	0.52	0.57*	0.18**	0.25***	0.30*	0.46***
t-stat	[1.53]	[1.10]	[3.21]	[2.82]	[3.08]	[3.03]	[1.52]	[1.66]	[1.96]	[2.60]	[1.72]	[2.64]

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	0.67	-0.04	-0.08	-0.27	0.24	-0.11	1.11	0.80	0.22	0.16	0.86	0.77
2	0.66	0.25	-0.18	-0.25	0.12	-0.01	0.93	0.78	0.03	0.00	0.61	0.62
3	0.86	0.59	-0.07	-0.09	0.24	0.19	0.89	0.76	-0.04	-0.07	0.47	0.44
4	1.10	0.93	-0.01	0.01	0.39	0.39	0.90	0.84	-0.04	-0.03	0.32	0.33
5	1.45	1.39	0.19	0.25	0.65	0.72	1.09	1.13	0.03	0.08	0.39	0.46
5-1	0.79*	1.43***	0.26**	0.52***	0.41**	0.83***	-0.02	0.33	-0.19	-0.08	-0.47***	-0.31*
t-stat	[1.82]	[3.35]	[2.40]	[5.04]	[2.50]	[5.65]	[-0.05]	[0.87]	[-1.61]	[-0.68]	[-2.96]	[-1.90]

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	0.79	0.47	-0.25	-0.30	0.19	0.12	1.08	0.97	0.06	0.04	0.64	0.67
2	0.96	0.69	-0.11	-0.15	0.37	0.31	0.97	0.89	0.05	0.05	0.56	0.58
3	0.99	0.70	-0.05	-0.11	0.35	0.28	0.82	0.69	-0.08	-0.11	0.38	0.35
4	1.16	0.88	0.08	0.04	0.47	0.40	0.93	0.90	0.02	0.03	0.43	0.44
5	1.35	1.02	0.20	0.16	0.64	0.58	1.01	1.01	0.06	0.08	0.48	0.54
5-1	0.57	0.55	0.45***	0.46***	0.45***	0.46***	-0.0701	0.04	-0.00	0.04	-0.16	-0.13
t-stat	[1.49]	[1.46]	[6.60]	[6.46]	[6.50]	[6.28]	[-0.21]	[0.12]	[-0.00]	[0.50]	[-1.39]	[-1.12]

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	1.00	0.53	-0.03	-0.16	0.44	0.24	1.03	0.99	0.13	0.14	0.64	0.66
2	0.99	0.73	-0.09	-0.12	0.35	0.30	0.93	0.87	0.00	-0.01	0.46	0.45
3	1.08	0.87	-0.04	-0.05	0.42	0.40	0.94	0.89	-0.04	-0.03	0.45	0.48
4	1.09	0.87	-0.02	-0.02	0.41	0.40	0.92	0.83	-0.08	-0.09	0.37	0.39
5	1.09	0.76	0.05	0.01	0.40	0.34	0.90	0.74	-0.06	-0.09	0.38	0.44
5-1	0.08	0.23	0.07	0.16**	-0.04	0.10	-0.13	-0.24	-0.19**	-0.22**	-0.26**	-0.22*
t-stat	[0.20]	[0.57]	[0.87]	[1.97]	[-0.43]	[1.21]	[-0.37]	[-0.65]	[-2.06]	[-2.28]	[-2.25]	[-1.73]

Table 4. Predicting Returns with Gain and Loss Overhang, 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 defined in equation (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 firm'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 defined 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 significance levels at 10%, 5%, and 1%. R-sq is the average R^2 from the cross-sectional regressions. I report coefficient estimates for all months and for February to December separately.

	(1) All	(2) Feb-Dec	(3) All	(4) Feb-Dec	(5) All	(6) Feb-Dec	(7) All	(8) Feb-Dec
Gain	0.020***	0.027***	0.000	0.008	0.049***	0.055***	0.033***	0.036***
	[3.39]	[4.73]	[0.06]	[1.60]	[10.73]	[12.70]	[8.42]	[9.29]
Loss	0.002	0.007***	-0.010***	-0.005***	-0.004***	-0.002*	-0.011***	-0.009***
	[1.23]	[4.33]	[-6.71]	[-3.92]	[-3.90]	[-1.87]	[-10.66]	[-8.82]
$Ret_{-12,-2}^{+}$			0.006***	0.005***			0.005***	0.006***
			[3.46]	[2.89]			[3.47]	[4.21]
$Ret_{-12,-2}^{-}$			0.057***	0.059***			0.033***	0.034***
			[15.01]	[14.80]			[10.56]	[10.78]
Ret_{-1}					-0.067***	-0.062***	-0.058***	-0.053***
					[-18.28]	[-16.52]	[-15.47]	[-13.83]
$Ret_{-36,-13}$					-0.003***	-0.002***	-0.001**	-0.001
					[-4.58]	[-3.11]	[-2.42]	[-0.81]
logBM					0.002***	0.002***	0.002***	0.002***
					[4.34]	[3.75]	[3.73]	[3.09]
logmktcap					-0.001***	-0.000	-0.001***	-0.001**
					[-2.66]	[-0.86]	[-4.10]	[-2.43]
ivol					-0.316***	-0.400***	-0.317***	-0.403***
					[-6.38]	[-7.95]	[-6.51]	[-8.16]
turnover					-0.079	-0.051	-0.094	-0.062
					[-0.29]	[-0.18]	[-0.36]	[-0.23]
constant	0.007***	0.005**	0.010***	0.008***	0.017***	0.015***	0.020***	0.018***
	[3.29]	[2.40]	[4.69]	[3.87]	[8.03]	[6.76]	[9.45]	[8.29]
# of Obs	1,847,357	1,693,753	1,770,492	1,623,571	1,426,862	1,306,015	1,426,496	1,305,684
R-sq	0.019	0.016	0.033	0.031	0.069	0.065	0.075	0.071
# of months	504	462	504	462	504	462	504	462

Table 5. Gain and Loss Effects in Recent Past and Distant Past, Fama-MacBeth Regressions

This table reports results for predictive Fama-MacBeth (1973) regressions of one-month return on selling propensity variables and a set of control variables, with a focus of separating gains and losses that come from the recent past and those from the distant past. The dependent variable is return in month t, and the explanatory variables are available at the end of month t-1. RG and RL are gain and loss overhang with purchase price in the past one year, while DG and DL are gain and loss overhang calculated using purchase price in the previous one to five 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 firm'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 defined 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 significance levels at 10%, 5%, and 1%. R-sq is the average R^2 from the cross-sectional regressions. I report coefficient estimates for all months and for February to December separately.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
RG	-0.042***	-0.033**	-0.075***	-0.061***	0.113***	0.129***	0.079***	0.091***
	[-2.73]	[-2.15]	[-4.73]	[-4.01]	[8.67]	[9.74]	[5.96]	[6.72]
RL	0.017***	0.021***	-0.003	-0.000	-0.004	-0.005	-0.014***	-0.016***
	[2.83]	[3.38]	[-0.65]	[-0.04]	[-1.05]	[-1.31]	[-4.18]	[-4.59]
DG	0.036***	0.041***	0.018***	0.023***	0.029***	0.032***	0.022***	0.022***
	[7.33]	[8.26]	[4.06]	[5.33]	[6.73]	[7.11]	[5.53]	[5.50]
DL	-0.001	0.004***	-0.011***	-0.006***	-0.003**	-0.000	-0.009***	-0.007***
	[-0.55]	[2.77]	[-7.20]	[-4.48]	[-2.56]	[-0.11]	[-8.05]	[-6.04]
$Ret_{-12,-2}^{+}$			0.007***	0.007***			0.003**	0.004***
			[5.13]	[4.46]			[2.21]	[2.78]
$Ret_{-12,-2}^{-}$			0.055***	0.057***			0.034***	0.036***
			[17.23]	[17.26]			[11.61]	[12.11]
Ret_{-1}					-0.071***	-0.067***	-0.060***	-0.054***
					[-20.27]	[-18.38]	[-16.88]	[-15.07]
$Ret_{-36,-13}$					-0.002***	-0.002***	-0.001**	-0.001
					[-4.09]	[-2.68]	[-2.42]	[-0.86]
logBM					0.002***	0.002***	0.002***	0.002***
					[4.30]	[3.69]	[3.75]	[3.09]
logmktcap					-0.001***	-0.000*	-0.001***	-0.001***
					[-3.52]	[-1.78]	[-4.71]	[-3.10]
ivol					-0.344***	-0.433***	-0.331***	-0.419***
					[-6.90]	[-8.56]	[-6.73]	[-8.43]
turnover					-0.512*	-0.545*	-0.430*	-0.463*
					[-1.94]	[-1.96]	[-1.67]	[-1.70]
constant	0.008***	0.006***	0.010***	0.008***	0.020***	0.017***	0.022***	0.019***
	[4.11]	[3.12]	[5.12]	[4.23]	[9.07]	[7.88]	[10.24]	[9.16]
# of Obs	1,847,357	1,693,753	1,770,492	1,623,571	1,426,862	1,306,015	1,426,496	1,305,684
R-sq	0.033	0.030	0.042	0.040	0.073	0.068	0.078	0.074
# of months	504	462	504	462	504	462	504	462

Table 6. V-shaped Net Selling Propensity and Capital Gains Overhang, Fama-MacBeth Regressions

This table compares the V-shaped net selling propensity (VNSP) effect with the original capital gains overhang (CGO) effect, 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 $VNSP = Gain - 0.17Loss$, where $Gain$ and $Loss$ are defined in equation (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 firm'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 defined 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 significance levels at 10%, 5%, and 1%. R-sq is the average R^2 from the cross-sectional regressions. I report coefficient estimates for all months and for February to December separately.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
CGO	0.004***	0.007***	-0.001	0.002**	-0.004***	-0.002***
	[3.73]	[6.74]	[-0.62]	[2.24]	[-5.20]	[-3.04]
$Ret_{-12,-2}$	0.007***	0.008***				
	[6.00]	[6.33]				
$Ret_{-12,-2}^{+}$			0.006***	0.007***	0.010***	0.011***
			[4.69]	[4.97]	[7.19]	[8.01]
$Ret_{-12,-2}^{-}$			0.038***	0.039***	0.032***	0.033***
			[11.77]	[12.10]	[10.17]	[10.43]
Ret_{-1}	-0.054***	-0.049***	-0.049***	-0.044***	-0.053***	-0.047***
	[-14.36]	[-12.96]	[-12.79]	[-11.46]	[-13.82]	[-12.32]
$Ret_{-36,-13}$	-0.002**	-0.000	-0.001	0.000	-0.001	-0.000
	[-2.49]	[-0.75]	[-1.56]	[0.27]	[-1.64]	[-0.00]
logBM					0.002***	0.001***
					[3.53]	[2.92]
logmktcap	-0.000	0.001**	-0.000	0.000	-0.001***	-0.001**
	[-0.47]	[2.09]	[-1.33]	[1.16]	[-4.27]	[-2.57]
ivol					-0.269***	-0.354***
					[-5.41]	[-7.00]
turnover	-0.978***	-1.075***	-0.729**	-0.802**	-0.211	-0.167
	[-3.19]	[-3.31]	[-2.46]	[-2.55]	[-0.81]	[-0.61]
constant	0.014***	0.008***	0.016***	0.010***	0.023***	0.021***
	[4.81]	[2.78]	[5.77]	[3.78]	[10.97]	[9.73]
# of Obs	1,576,423	1,445,034	1,576,423	1,445,034	1,426,496	1,305,684
R-sq	0.057	0.053	0.061	0.056	0.074	0.069
# of months	504	462	504	462	504	462

(Table 6 Continued)

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
CGO	0.005***	0.010***	-0.008***	-0.003***	0.003***	0.006***	-0.004***	-0.002**
	[2.98]	[7.17]	[-5.56]	[-2.59]	[2.87]	[5.78]	[-4.60]	[-2.45]
VNSP	0.016***	0.017***	0.009*	0.011**	0.046***	0.049***	0.037***	0.038***
	[2.81]	[3.13]	[1.71]	[2.43]	[11.48]	[12.59]	[10.38]	[10.61]
$Ret_{-12,-2}^{+}$			0.006***	0.005***			0.005***	0.006***
			[3.46]	[2.89]			[3.47]	[4.21]
$Ret_{-12,-2}^{-}$			0.057***	0.059***			0.033***	0.034***
			[15.01]	[14.80]			[10.56]	[10.78]
Ret_{-1}					-0.067***	-0.062***	-0.058***	-0.053***
					[-18.28]	[-16.52]	[-15.47]	[-13.83]
$Ret_{-36,-13}$					-0.003***	-0.002***	-0.001**	-0.001
					[-4.58]	[-3.11]	[-2.42]	[-0.81]
logBM					0.002***	0.002***	0.002***	0.002***
					[4.34]	[3.75]	[3.73]	[3.09]
logmktcap					-0.001***	-0.000	-0.001***	-0.001**
					[-2.66]	[-0.86]	[-4.10]	[-2.43]
ivol					-0.316***	-0.400***	-0.317***	-0.403***
					[-6.38]	[-7.95]	[-6.51]	[-8.16]
turnover					-0.079	-0.051	-0.094	-0.062
					[-0.29]	[-0.18]	[-0.36]	[-0.23]
constant	0.007***	0.005**	0.010***	0.008***	0.017***	0.015***	0.020***	0.018***
	[3.29]	[2.40]	[4.69]	[3.87]	[8.03]	[6.76]	[9.45]	[8.29]
# of Obs	1,847,357	1,693,753	1,770,492	1,623,571	1,426,862	1,306,015	1,426,496	1,305,684
R-sq	0.019	0.016	0.033	0.031	0.069	0.065	0.075	0.071
# of months	504	462	504	462	504	462	504	462

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, firm size, turnover ratio and stock volatility. Except for firm size subsamples, all other "high" groups contain the top 1/3 of firms in the whole sample ranked on the categorizing variable, while the "low" groups correspond to the bottom 1/3 of firms. As for size, "high" and "low" groups are divided by NYSE break points which correspond to the top 30% and the bottom 30% of NYSE firms. 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 defined in equation (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 firm'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 regressions are run every month, and the parameters and t-statistics (shown in square brackets) are calculated using the time series of corresponding cross-sectional regression estimates. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-sq is the average R^2 from the cross-sectional regressions. I report coefficient estimates for all months and for February to December separately.

	(1)	(2)	(3)	(4)			(5)	(6)	(7)	(8)		
	Inst Own High		Inst Own Low		High β - Low β		Mktcap High		Mktcap Low		High β - Low β	
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
Gain	0.026***	0.030***	0.035***	0.037***	-0.007	-0.007	-0.007	-0.002	0.054***	0.057***	0.061***	0.059***
	[4.67]	[5.05]	[7.31]	[7.45]	[-0.60]	[-0.42]	[-1.26]	[-0.35]	[10.33]	[10.85]	[-8.95]	[-8.74]
Loss	-0.012***	-0.010***	-0.012***	-0.010***	0.000	0.000	-0.007***	-0.008***	-0.011***	-0.009***	0.004*	0.001
	[-7.05]	[-5.75]	[-6.69]	[-5.40]	[0.09]	[0.12]	[-4.46]	[-5.01]	[-9.13]	[-7.38]	[1.85]	[0.42]
$Ret_{-12,-2}^{+}$	0.006***	0.006***	0.003**	0.003***			0.009***	0.009***	0.001	0.002*		
	[3.61]	[3.85]	[2.23]	[2.62]			[4.41]	[4.38]	[1.14]	[1.80]		
$Ret_{-12,-2}^{-}$	0.026***	0.026***	0.035***	0.038***			0.018***	0.020***	0.037***	0.037***		
	[5.85]	[5.66]	[8.10]	[8.75]			[3.22]	[3.35]	[12.04]	[11.95]		
Ret_{-1}	-0.046***	-0.041***	-0.036***	-0.034***			-0.031***	-0.025***	-0.060***	-0.056***		
	[-10.71]	[-9.37]	[-8.67]	[-7.70]			[-5.60]	[-4.41]	[-16.11]	[-14.98]		
$Ret_{-36,-13}$	-0.001**	-0.001	-0.001*	-0.000			-0.000	0.001	-0.002***	-0.001**		
	[-1.98]	[-1.24]	[-1.67]	[-0.31]			[-0.11]	[0.86]	[-3.25]	[-2.02]		
logBM	0.000	0.000	0.002***	0.002***			0.001	0.000	0.002***	0.002***		
	[0.21]	[0.21]	[3.42]	[3.52]			[0.88]	[0.07]	[3.94]	[3.71]		
logmktcap	-0.001	-0.000	-0.001**	-0.000			-0.001**	-0.001**	-0.001*	-0.000		
	[-1.51]	[-0.75]	[-2.18]	[-0.87]			[-2.29]	[-2.57]	[-1.83]	[-0.08]		
ivol	-0.139***	-0.202***	-0.257***	-0.312***			-0.254**	-0.381***	-0.268***	-0.335***		
	[-2.59]	[-3.67]	[-5.18]	[-6.14]			[-2.33]	[-3.45]	[-5.96]	[-7.27]		
turnover	0.351*	0.365*	-0.827***	-1.039***			-0.447	-0.382	-0.287	-0.261		
	[1.84]	[1.82]	[-4.07]	[-5.21]			[-1.21]	[-1.01]	[-1.17]	[-1.00]		
constant	0.012***	0.010***	0.017***	0.015***			0.019***	0.021***	0.018***	0.013***		
	[4.09]	[3.46]	[7.31]	[6.50]			[4.78]	[5.16]	[7.07]	[5.13]		
# of Obs	430,356	393,733	357,731	327,562			227,350	208,114	820,261	751,108		
R-sq	0.070	0.068	0.090	0.088			0.153	0.150	0.065	0.062		
# of months	384	352	384	352			504	462	504	462		

(Table 7 Continued)

	(9)	(10)	(11)	(12)			(13)	(14)	(15)	(16)		
	Turnover High		Turnover Low		High β - Low β		Volatility High		Volatility Low		High β - Low β	
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
Gain	0.049***	0.054***	0.019***	0.018***	0.030***	0.036***	0.051***	0.054***	0.014***	0.016***	0.037***	0.038***
	[8.40]	[9.19]	[3.99]	[3.80]	[5.05]	[5.82]	[8.55]	[8.96]	[3.79]	[4.01]	[5.82]	[6.03]
Loss	-0.017***	-0.016***	-0.007***	-0.004***	-0.010***	-0.012***	-0.012***	-0.010***	-0.007***	-0.005***	-0.005***	-0.005***
	[-10.62]	[-9.38]	[-6.18]	[-4.16]	[-6.42]	[-6.56]	[-8.75]	[-7.07]	[-5.94]	[-4.49]	[-3.97]	[-3.48]
$Ret_{-12,-2}^{+}$	0.002	0.003**	0.006***	0.007***			0.001	0.002*	0.006***	0.008***		
	[1.55]	[2.12]	[3.19]	[4.02]			[1.20]	[1.66]	[2.83]	[3.76]		
$Ret_{-12,-2}^{-}$	0.035***	0.034***	0.034***	0.037***			0.036***	0.036***	0.027***	0.030***		
	[9.36]	[9.26]	[8.24]	[8.61]			[9.14]	[9.00]	[6.85]	[7.41]		
Ret_{-1}	-0.039***	-0.035***	-0.078***	-0.071***			-0.047***	-0.043***	-0.067***	-0.059***		
	[-10.15]	[-9.04]	[-17.90]	[-16.33]			[-12.86]	[-11.68]	[-15.80]	[-13.95]		
$Ret_{-36,-13}$	-0.001**	-0.000	-0.000	0.001			-0.001*	-0.000	0.001	0.001**		
	[-2.27]	[-0.97]	[-0.50]	[1.20]			[-1.96]	[-0.40]	[1.03]	[2.25]		
logBM	0.002**	0.001*	0.002***	0.002***			0.002***	0.002***	0.002***	0.001**		
	[2.50]	[1.92]	[3.67]	[2.86]			[3.77]	[3.32]	[3.47]	[2.42]		
logmktcap	-0.001***	-0.001	-0.001**	-0.000			-0.001***	-0.001	-0.000	-0.000		
	[-2.96]	[-1.59]	[-2.49]	[-0.82]			[-2.70]	[-1.37]	[-1.52]	[-0.13]		
ivol	-0.447***	-0.525***	-0.130**	-0.210***			-0.378***	-0.433***	0.056	-0.052		
	[-8.48]	[-9.81]	[-2.53]	[-4.00]			[-7.29]	[-8.15]	[0.73]	[-0.66]		
turnover	-0.058	-0.035	2.295**	2.212**			-0.189	-0.228	0.022	-0.060		
	[-0.32]	[-0.18]	[2.06]	[1.99]			[-0.97]	[-1.11]	[0.06]	[-0.15]		
constant	0.021***	0.017***	0.014***	0.012***			0.022***	0.018***	0.011***	0.010***		
	[5.94]	[4.85]	[6.90]	[5.80]			[4.60]	[3.69]	[5.80]	[4.86]		
# of Obs	428,286	392,023	502,989	460,502			436,682	399,588	494,059	452,396		
R-sq	0.078	0.073	0.080	0.074			0.075	0.071	0.070	0.065		
# of months	504	462	504	462			504	462	504	462		

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 defined in equation (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 specifications for *Gain* and *Loss*, but the regressions are run on NYSE and AMEX stocks only. $Ret^{+}_{-12,-2}$ 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 firm'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 defined 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 significance levels at 10%, 5%, and 1%. R-sq is the average R^2 from the cross-sectional regressions. I report coefficient estimates for all months and for February to December separately.

alternative specification or sample:	(1)	(2)	(3)	(4)	(5)	(6)
	adjust prices for stock splits and dividends		aggregate prices at weekly frequency		NYSE & AMEX only	
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
Gain	0.0332***	0.0398***	0.0383***	0.0407***	0.0197***	0.0235***
	[7.44]	[9.07]	[9.69]	[10.25]	[4.49]	[5.49]
Loss	-0.0111***	-0.0080***	-0.0082***	-0.0063***	-0.0082***	-0.0062***
	[-7.75]	[-5.76]	[-8.36]	[-6.47]	[-7.23]	[-5.60]
$Ret_{-12,-2}^{+}$	-0.0595***	-0.0556***	-0.0611***	-0.0549***	0.0048***	0.0059***
	[-15.37]	[-13.90]	[-16.08]	[-14.46]	[3.23]	[3.92]
$Ret_{-12,-2}^{-}$	-0.0018***	-0.0013**	-0.0018***	-0.0008	0.0304***	0.0311***
	[-3.08]	[-2.10]	[-2.97]	[-1.37]	[8.49]	[8.45]
Ret_{-1}	0.0019***	0.0017***	0.0018***	0.0015***	-0.0520***	-0.0461***
	[4.06]	[3.62]	[3.72]	[3.05]	[-12.32]	[-10.75]
$Ret_{-36,-13}$	-0.0010***	-0.0006**	-0.0011***	-0.0007***	-0.0010	-0.0002
	[-4.01]	[-2.45]	[-4.29]	[-2.59]	[-1.57]	[-0.25]
logBM	-0.3105***	-0.3820***	-0.2987***	-0.3828***	0.0018***	0.0015***
	[-6.49]	[-7.77]	[-6.21]	[-7.84]	[3.69]	[3.08]
logmktcap	0.0043	0.0682	-0.1178	-0.0836	-0.0010***	-0.0006**
	[0.02]	[0.24]	[-0.44]	[-0.30]	[-3.69]	[-2.17]
ivol	0.0034***	0.0037***	0.0034***	0.0045***	-0.3001***	-0.3910***
	[2.61]	[2.65]	[2.65]	[3.48]	[-5.41]	[-6.90]
turnover	0.0324***	0.0317***	0.0295***	0.0311***	-0.1031	-0.0681
	[9.97]	[9.57]	[9.37]	[9.71]	[-0.38]	[-0.24]
constant	0.0195***	0.0169***	0.0199***	0.0176***	0.0195***	0.0174***
	[9.34]	[8.05]	[9.72]	[8.50]	[8.94]	[7.89]
# of Obs	1,426,496	1,305,684	1,466,316	1,341,612	823,278	754,104
R-sq	0.076	0.071	0.074	0.070	0.082	0.078
# of months	504	462	504	462	504	462

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 defined in equation (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 specifications 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 firm'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 defined 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 firms with size that are comparable to the largest 30% of NYSE firms. The parameters and t-statistics (shown in square brackets) are calculated using the time series of corresponding cross-sectional regression estimates. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-sq is the average R^2 from the cross-sectional regressions. I report coefficient 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 firms	
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
Gain	0.038***	0.039***	0.013***	0.015***	-0.003	0.001	0.019***	0.019***
	[9.59]	[9.91]	[3.75]	[4.35]	[-0.55]	[0.10]	[3.93]	[4.46]
Loss	-0.004***	-0.003**	-0.005***	-0.003***	-0.006***	-0.005***	-0.010***	-0.009***
	[-4.13]	[-2.54]	[-5.45]	[-3.49]	[-4.37]	[-4.06]	[-8.74]	[-7.38]
$Ret_{-12,-2}^{+}$	0.003***	0.005***	0.007***	0.009***	0.010***	0.011***	0.008***	0.009***
	[2.72]	[3.80]	[5.96]	[6.77]	[5.07]	[5.45]	[5.01]	[5.52]
$Ret_{-12,-2}^{-}$	0.024***	0.026***	0.029***	0.030***	0.014***	0.017***	0.020***	0.021***
	[7.84]	[8.41]	[9.41]	[9.56]	[3.20]	[3.68]	[5.46]	[5.79]
Ret_{-1}	-0.063***	-0.056***	-0.056***	-0.048***	-0.033***	-0.027***	-0.044***	-0.040***
	[-16.27]	[-14.67]	[-13.88]	[-12.21]	[-6.07]	[-4.91]	[-10.85]	[-9.43]
$Ret_{-36,-13}$	-0.002***	-0.001*	-0.001**	-0.000	0.000	0.001	-0.001	0.000
	[-3.59]	[-1.94]	[-2.29]	[-0.69]	[0.11]	[1.26]	[-1.04]	[0.57]
logBM	0.002***	0.001***	0.002***	0.001***	0.001	0.001	0.002***	0.001**
	[3.62]	[2.95]	[3.36]	[2.67]	[1.58]	[0.82]	[3.09]	[2.29]
logmktcap	-0.001***	-0.001**	-0.001***	-0.001**	-0.001***	-0.001***	-0.001**	-0.000
	[-3.89]	[-2.21]	[-4.13]	[-2.47]	[-3.25]	[-3.73]	[-2.11]	[-0.91]
ivol	-0.259***	-0.348***	-0.272***	-0.358***	-0.341***	-0.452***	-0.355***	-0.431***
	[-5.27]	[-7.04]	[-5.51]	[-7.17]	[-4.28]	[-5.62]	[-5.57]	[-6.55]
turnover	-0.214	-0.172	-0.223	-0.196	-0.557*	-0.598*	-0.106	-0.166
	[-0.82]	[-0.62]	[-0.86]	[-0.72]	[-1.70]	[-1.79]	[-0.45]	[-0.67]
constant	0.019***	0.017***	0.021***	0.019***	0.021***	0.023***	0.019***	0.017***
	[9.14]	[8.00]	[10.02]	[8.84]	[6.14]	[6.56]	[6.72]	[5.97]
# of Obs	1,425,623	1,304,873	1,404,236	1,285,340	1,426,496	1,305,684	1,199,146	1,097,570
R-sq	0.075	0.071	0.075	0.070	0.157	0.153	0.090	0.088
# of months	504	462	503	461	504	462	504	462

Table 10. Checking Impacts of Short-Sale Constraint, 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 defined in equation (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 firm'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. Columns (1)-(2) exclude stocks whose institutional ownership are ranked at the bottom 1/3 and short interest ratio areranked among the top 5%. Columns (3)-(4) exclude stocks whose institutional ownership are ranked at the bottom 1/3 and short interest ratio are greater than or equal to 2.5%. Columns (5)-(8) repeat these restrictions and conduct regressions in the subsample from 2003 Jul to 2011 Dec. Cross-sectional WLS regressions are run every month where the weights are defined as prior-period gross returns. The parameters and t-statistics (shown in square brackets) are calculated using the time series of corresponding cross-sectional regression estimates. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-sq is the average R^2 from the cross-sectional regressions. I report coefficient estimates for all months and for February to December separately.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1980 Jan - 2011 Dec				2003 Jul - 2011 Dec			
	excluding stocks IO<p33 & SI⩾p95		excluding stocks IO<p33 & SI⩾2.5%		excluding stocks IO<p33 & SI⩾p95		excluding stocks IO<p33 & SI⩾2.5%	
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
Gain	0.033***	0.036***	0.033***	0.036***	0.034***	0.039***	0.034***	0.040***
	[7.69]	[7.94]	[7.37]	[7.70]	[3.26]	[3.49]	[2.93]	[3.26]
Loss	-0.011***	-0.009***	-0.011***	-0.009***	-0.006**	-0.003	-0.005*	-0.002
	[-8.92]	[-7.27]	[-8.56]	[-6.90]	[-2.40]	[-1.21]	[-1.82]	[-0.62]
$Ret_{-12,-2}^{+}$	0.003***	0.004***	0.003***	0.004***	-0.001	-0.001	-0.001	0.000
	[3.51]	[4.34]	[3.70]	[4.58]	[-0.66]	[-0.27]	[-0.36]	[0.10]
$Ret_{-12,-2}^{-}$	0.031***	0.033***	0.031***	0.032***	0.012	0.012	0.012	0.012
	[8.83]	[8.86]	[8.82]	[8.72]	[1.41]	[1.36]	[1.46]	[1.29]
Ret_{-1}	-0.039***	-0.035***	-0.039***	-0.035***	-0.022***	-0.016*	-0.021***	-0.016*
	[-11.58]	[-10.07]	[-11.44]	[-9.99]	[-2.73]	[-1.95]	[-2.63]	[-1.90]
$Ret_{-36,-13}$	-0.001**	-0.001	-0.001**	-0.001	-0.001	-0.001	-0.002	-0.001
	[-2.29]	[-1.21]	[-2.35]	[-1.35]	[-1.15]	[-0.94]	[-1.18]	[-1.06]
logBM	0.001**	0.001**	0.001**	0.001**	0.000	0.000	-0.000	-0.000
	[2.55]	[2.47]	[2.30]	[2.18]	[0.39]	[0.42]	[-0.21]	[-0.25]
logmktcap	-0.001**	-0.000	-0.001**	-0.000	-0.000	-0.000	-0.000	-0.000
	[-2.39]	[-1.30]	[-2.40]	[-1.28]	[-0.61]	[-0.35]	[-0.73]	[-0.41]
ivol	-0.225***	-0.289***	-0.217***	-0.280***	-0.116	-0.166*	-0.082	-0.131
	[-4.98]	[-6.29]	[-4.83]	[-6.12]	[-1.37]	[-1.95]	[-0.99]	[-1.58]
turnover	-0.045	-0.107	-0.049	-0.112	0.015	0.005	0.067	0.060
	[-0.26]	[-0.60]	[-0.28]	[-0.63]	[0.12]	[0.03]	[0.50]	[0.42]
constant	0.016***	0.015***	0.016***	0.015***	0.005	0.006	0.005	0.005
	[6.84]	[6.10]	[6.74]	[5.94]	[1.31]	[1.44]	[1.14]	[1.16]
# of Obs	1,203,983	1,101,849	1,155,925	1,057,830	331,567	302,270	291,346	265,421
R-sq	0.065	0.062	0.064	0.062	0.051	0.048	0.050	0.047
# of months	384	352	384	352	102	93	102	93

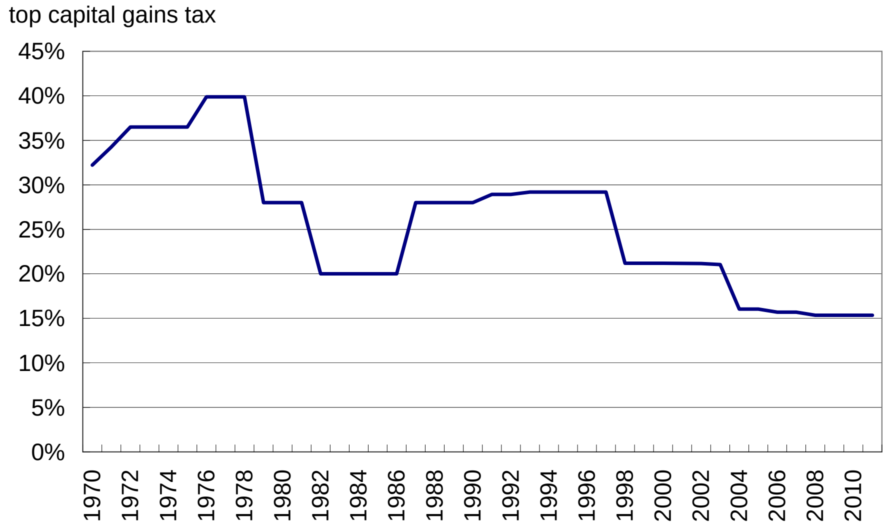
Appendix

A. Time-series Variation: the Impact of Capital Gains Tax

I here test additional pricing implications of investors' trading behavior. If the return predictability shown in section 4 really comes from investors' trading behavior rather other mechanisms, as people's trading incentives change over time, so should the aggregate gain and loss effects. I particularly examine how capital gains tax change in the 40 years of this study period lead to variation in the gain and loss effects. Capital gains tax, as shown in the literature (e.g., Odean (1998), Lakonishok and Smidt (1986), Ben-David and Hirshleifer (2012)), is not a major source of the (V-shaped) disposition effect; however, it has incremental impact on people's selling behavior. Moreover, what makes it a good test for my purpose is that tax incentive has different implications for the gain side versus the loss side. When capital gains tax is higher, investors are less willing to realize a gain since they have to pay more tax; on the loss side, they would be more willing to sell because the realized loss can offset gains earned elsewhere. Thus the price-level implication is that in high tax periods, the gain effect should be lessened, while the loss effect should be amplified. Please note that this variation is not a unique prediction of the V-shaped selling schedule - a monotonic selling schedule predicts the same pattern. This exercise does not attempt to distinguish the shape of investors' selling schedule, rather, it is designed to discriminate the source of return predictability on a more general level: whether the observed return pattern is a consequence of trading behavior in general, or it is a result of other factors, such as risk.

Capital gains tax rate in the United States depends on the holding period of the gain: if it's a short-term gain (which generally means shorter than one year), investors pay the tax rate of their ordinary income tax; if it's a long-term gain, investors pay a capital gains tax rate that is lower than their income tax. The capital gains tax rate that applies to an investor also depends on his or her ordinary income tax. Given the heterogeneity in investors' income distribution and holding period, it is hard to capture the accurate effective tax rate that applies to a representative investor. Thus, instead of employing a continuous tax rate variable, I use the maximum capital gains tax rate as an indicator to see if tax is relatively high or low in a given period. There are significant changes in tax regimes for the period of my sample (Figure 2): the top capital gains tax rate starts at 32% in 1970, increases to around 40% in 1976, then drops to 20% in the early 1980s; it then increases to 29% in 1987 but falls to below 20% and remain there since 2003. I group all months that have a tax rate higher than 25% (the median rate) into a high tax subsample, while months with a tax rate lower than 25% compose the low-tax subsample.

Figure A1. Top Capital Gains Tax Rate, 1970 - 2011



The conjecture is that, in high tax periods, compared with low tax periods, the gain effect would be weaker and the loss effect would be stronger. This is confirmed by results shown in Table A1. In these high tax and low tax subsamples, I re-examine equation (4) 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)). The coefficient of the gain overhang variable is smaller in the high tax sub-sample, and the coefficient of loss overhang variable is larger, both have the expected sign, though the difference is not statistically significant.

Table A1. Gain and Loss Effects Under Different Tax Regimes, 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 subsamples based on capital gains tax rate. The high tax sub-sample contains months where the top capital gains tax rate is higher than 25%, while the low tax sub-sample contains months where the rate is lower than 25%. 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 defined in equation (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 firm'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 defined 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 significance levels at 10%, 5%, and 1%. R-sq is the average R^2 from the cross-sectional regressions. I report coefficient estimates for all months and for February to December separately.

	(1)	(2)	(3)	(4)	(5)	(6)
	High Tax		Low Tax		|Highβ|-|Lowβ|	
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
Gain	0.030***	0.033***	0.037***	0.040***	-0.007	-0.007
	[5.44]	[6.37]	[6.63]	[6.78]	[-0.84]	[-0.84]
Loss	-0.011***	-0.010***	-0.010***	-0.008***	0.001	0.002
	[-9.09]	[-7.78]	[-6.10]	[-4.82]	[0.69]	[0.87]
$Ret_{-12,-2}^{+}$	0.006***	0.008***	0.002	0.003*		
	[3.24]	[3.78]	[1.41]	[1.95]		
$Ret_{-12,-2}^{-}$	0.039***	0.039***	0.027***	0.028***		
	[11.15]	[11.59]	[4.82]	[4.96]		
Ret_{-1}	-0.073***	-0.066***	-0.041***	-0.036***		
	[-15.21]	[-14.38]	[-7.06]	[-5.90]		
$Ret_{-36,-13}$	-0.00	0.000	-0.002**	-0.001		
	[-1.42]	[0.14]	[-2.04]	[-1.29]		
logBM	0.003***	0.002***	0.001	0.001		
	[4.06]	[2.93]	[1.14]	[1.37]		
logmktcap	-0.001***	-0.001**	-0.001**	-0.001		
	[-3.48]	[-2.06]	[-2.25]	[-1.34]		
ivol	-0.354***	-0.449***	-0.273***	-0.347***		
	[-5.51]	[-6.90]	[-3.66]	[-4.59]		
turnover	-0.092	0.031	-0.097	-0.176		
	[-0.21]	[0.07]	[-0.48]	[-0.84]		
constant	0.023***	0.019***	0.0167***	0.016***		
	[7.73]	[6.69]	[5.51]	[4.96]		
# of Obs	707,584	647,482	718,912	658,202		
R-sq	0.078	0.072	0.072	0.070		
# of months	276	253	228	209		

B. Additional Tables on Investors' Trading Schedules.

Table A2. Selling and Buying (Quantities) in Response to Unrealized Profits

This table reports results from regressions of numbers of shares sold (bought) on unrealized profits and a set of controls. Observations are at investor-stock-day level. In Panel A, the dependent variable is the number of shares sold; in Panel B, the dependent variable is additional shares bought for currently owned stocks. $Ret2^{+} = Max\{Ret2, 0\}$ 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 coefficients presented reflect the marginal effect on the average stock holding, and are multiplied by 100. Standard errors are clustered at the investor level. t-statistics are in square brackets. *, **, and *** denote significance levels at 10%, 5%, and 1%.

Panel A: Selling schedule with alternative return definition						
	Dependent variable: Shares sold					
	(1)	(2)	(3)	(4)	(5)	(6)
Prior holding period (days):	1 to 20	21 to 250	>250	1 to 20	21 to 250	>250
$Ret2^{-}$	-11.67***	-0.94	-0.42	-67.50***	-0.27	-0.65
	[-3.19]	[-1.61]	[-1.04]	[-4.52]	[-0.15]	[-0.71]
$Ret2^{-}$ x sqrt(Time owned)				16.85***	-0.03	0.01
				[4.51]	[-0.18]	[0.48]
$Ret2^{+}$	67.27***	0.80	0.68	303.11***	16.08***	3.83
	[6.25]	[1.23]	[0.67]	[6.23]	[4.13]	[1.05]
$Ret2^{+}$ x sqrt(Time owned)				-64.51***	-1.21***	-0.12
				[-5.14]	[-3.96]	[-1.16]
I(ret=0)	-0.38	0.85***	0.48	0.60	0.38	0.28
	[-0.63]	[2.71]	[1.46]	[0.39]	[0.42]	[0.45]
I(ret=0) x sqrt(Time owned)				-0.01	0.05	0.01
				[-0.03]	[0.60]	[0.48]
I(ret>0)	-2.47	-1.75***	-0.08	-0.19	-1.47	-0.01
	[-1.25]	[-3.62]	[-0.24]	[-0.05]	[-1.56]	[-0.02]
I(ret>0) x sqrt(Time owned)				-0.89	-0.04	-0.01
				[-1.26]	[-0.56]	[-0.38]
sqrt(Time owned)	-1.73***	-0.05***	-0.01	0.65	0.04	0.01
	[-5.41]	[-2.91]	[-0.94]	[1.89]	[0.81]	[1.75]
log(Buy price)	-0.63	-0.78***	-0.1492***	-0.52	-0.77***	-0.14***
	[-0.94]	[-7.43]	[-2.73]	[-0.77]	[-7.34]	[-2.65]
$volatility^{-}$	-23.50	-28.42***	-1.08	-20.46	-25.80***	-1.29
	[-0.73]	[-2.91]	[-0.10]	[-0.64]	[-2.71]	[-0.11]
$volatility^{+}$	229.58***	107.10***	18.49	198.08***	101.21***	17.97
	[3.28]	[7.02]	[1.73]	[2.94]	[6.73]	[1.70]
Constant	11.17***	4.76***	1.0336***	3.51	3.71***	0.36
	[3.78]	[8.06]	[2.78]	[1.13]	[5.29]	[1.05]
Observations	1144228	8106696	10089805	1144228	8106696	10089805
Pseudo R^2	0.047	0.013	0.02	0.047	0.013	0.02

(Table A2 Continued)

Panel B: Buying schedule with alternative return definition

	Dependent variable: Additional shares bought					
	(1)	(2)	(3)	(4)	(5)	(6)
Prior holding period (days)	1 to 20	21 to 250	>250	1 to 20	21 to 250	>250
$Ret2^-$	-17.14***	-0.66**	0.04	-25.04	-4.79***	-0.13
	[-3.55]	[-2.55]	[1.10]	[-1.55]	[-3.05]	[-1.19]
$Ret2^-$ x sqrt(Time owned)				1.89	0.32***	0.01
				[0.42]	[3.03]	[1.57]
$Ret2^+$	2.20	0.44	-0.05	23.17	2.29	0.30
	[0.42]	[0.76]	[-0.16]	[0.91]	[0.96]	[0.44]
$Ret2^+$ x sqrt(Time owned)				-7.05	-0.17	-0.01
				[-1.09]	[-1.03]	[-0.77]
I(ret=0)	5.98***	0.25	-0.18	18.42***	2.13	-0.46
	[3.60]	[0.69]	[-1.37]	[3.49]	[1.68]	[-1.45]
I(ret=0) x sqrt(Time owned)				-4.67***	-0.18	0.01
				[-3.14]	[-1.76]	[0.79]
I(ret>0)	-0.24	-0.55**	0.08	-2.67	-0.54	0.07
	[-0.16]	[-2.56]	[0.91]	[-1.22]	[-1.18]	[0.30]
I(ret>0) x sqrt(Time owned)				0.86	0.00	0.00
				[1.90]	[0.04]	[0.05]
sqrt(Time owned)	-1.84***	0.08***	-0.00	-1.80***	-0.03	0.00
	[-9.13]	[-8.51]	[-0.16]	[-4.32]	[-1.72]	[0.16]
log(Buy price)	-2.35***	0.53***	-0.32	-2.41***	0.54***	-0.32
	[-4.35]	[-5.38]	[-1.80]	[-4.20]	[-5.47]	[-1.80]
$volatility^-$	42.22	9.13	-11.91	46.96	9.21	-11.94
	[0.87]	[1.04]	[-1.50]	[0.89]	[1.06]	[-1.49]
$volatility^+$	9.21	-4.09	-2.62	11.86	-7.94	-2.99
	[0.38]	[-0.90]	[-0.50]	[0.45]	[-1.65]	[-0.57]
Constant	15.11***	3.32***	1.48**	14.96***	2.86***	1.38***
	[6.41]	[7.29]	[2.54]	[5.43]	[6.56]	[3.15]
Observations	1144228	8106693	10089796	1090375	8160546	10089796
Pseudo R^2	0.034	0.012	0.017	0.036	0.012	0.017