Essays in Investor Behavior and Asset Pricing

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ABSTRACT

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This dissertation consists of three essays on investor behavior and asset pricing.

In the first chapter, I investigate 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. Motivated by behavioral evidence found among individual traders, I focus on the pricing implications of such behavior in this chapter. 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.

The second chapter extends the study of the V-shaped disposition effect - the tendency to sell relatively big winners and big losers - to the trading behavior of mutual fund managers. We find that a 1% increase in the magnitude of unrealized gains (losses) is associated with a 4.2% (1.6%) higher probability of selling. We link this trading behavior to equilibrium

price dynamics by constructing unrealized gains and losses measures directly from mutual fund holdings. (In comparison, measures for unrealized gains and losses in chapter one are approximated by past prices and trading volumes.) We find that, consistent with the relative magnitude found in the selling behavior regressions, a 1% increase in the magnitude of gain (loss) overhang predicts a 1.4 (.9) bp increase in future one-month returns. A trading strategy based on this effect can generate a monthly return of 0.5% controlling common return predictors, and the Sharpe ratio is around 1.4. An overhang variable capturing the V-shaped disposition effect strongly dominates the monotonic capital gains overhang measure of previous literature in predictive return regressions. Funds with higher turnover, shorter holding period, higher expense ratios, and higher management fees are significantly more likely to manifest a V-shaped disposition effect.

The third chapter studies how the recourse feature of mortgage loan has impact on borrowers' strategic default incentives and on mortgage bond market. It provides a theoretical model which builds on the structural credit risk framework by Leland (1994), and explicitly analyzes borrowers' strategic default incentives under different foreclosure laws. The key results are, while possible recourse makes the payoff in strategic default less attractive, it helps deter strategic default when house price goes down. I also examine the case when cash flow problems interact with default incentives and show that recourse can help reduce default incentives, make debt value immune to liquidity shock, and has little impact on house equity value.

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Acknowledgments

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To my parents, An Muying and Xue Qinsheng

Chapter 1

Asset Pricing When Traders Sell Extreme Winners and Losers

Li An

1.1 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 usually further modeled 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 1.1 (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

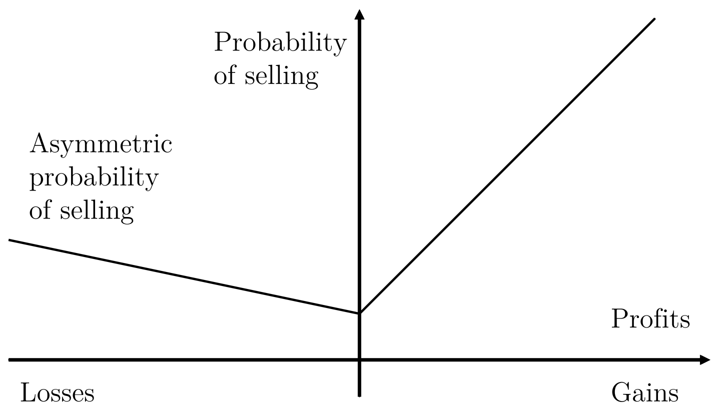
[1]See, for example, Odean (1998) and Grinblatt and Keloharju (2001) for evidence on individual investors, Locke and Mann(2000), Shapira and Venezia (2001), and Coval and Shumway (2001) for institutional investors.

[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)

studies on equilibrium prices and returns that assume a monotonically increasing relation between selling propensity and profits.

Figure 1.1: V-shaped Selling Propensity in Response to 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 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, and it is stronger for gains and losses from the recent past compared with those from the distant past - both are consistent with the trading patterns 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 selling propensity measure that recognizes the V-shaped disposition effect, the *V-shaped 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 (e.g., Goetzmann and Massa (2008); Choi, Hoyem, and Kim (2008)). A horse race between these two variables shows that once the V-shaped 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 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.

I also explore the time-series variation of return predictability based on the V-shaped disposition effect. In particular, I examine the impact of capital gains tax: if investors' selling behavior varies through time due to changes in tax, so should the return pattern based on this behavior. In a high capital gains tax environment, investors are less likely to realize their gains because they face a higher tax, but they are more likely to sell upon losses as it helps to offset capital gains earned in other stocks. Empirical results confirm this conjecture: compared with low tax periods, during high tax periods return predictability from the gain side is weaker and that from the loss effect is stronger. The tax incentive has a unique advantage as a test because it has different implications for the gain side versus the loss side. Given the horizon of forty years in my sample, many general trends, such as development of trading technology and an increase in overall trading volume, may result in the V-shaped selling propensity effects changing over time; however, few have asymmetric implications for the gain side and the loss side. This finding further validates that the observed return patterns are indeed consequences of the V-shaped disposition effect, rather than other mechanisms.

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 1.5 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 1.2 describes the data and my method for constructing empirical measures. In section 1.3, I test the pricing implications of the V-shaped disposition effect using both a portfolio approach and the Fama-MacBeth regression approach. Section 1.4 discusses the source of the V-shaped disposition effect and empirically tests it in cross-sectional subsamples. Section 1.5 examines the time-series implications of this effect from tax incentives. Section 1.6 discusses the relation between the disposition effect and momentum. Finally, section 1.7 concludes the paper.

1.2 Data and Key Variables

1.2.1 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) 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 1843236 stock-month combinations, which is approximately 3600 stocks per month on average.

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

1.2.2 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 differences: 1. instead of aggregating all past prices, I measure gains and losses separately; 2. I use daily, rather than weekly past prices in calculations; 3. To avoid confounding microstructure effects, both the current price and the purchase price are lagged by 10 trading days.

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

$$\begin{aligned} Gain_t &= \sum_{n=1}^{\infty} \omega_{t-n} gain_{t-n} \\ gain_{t-n} &= \frac{P_t - P_{t-n}}{P_t} \cdot \mathbf{1}_{\{P_{t-n} \leq P_t\}} \\ \omega_{t-n} &= \frac{1}{k} V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}] \end{aligned} \tag{1.1}$$

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:

$$\begin{aligned} Loss_t &= \sum_{n=1}^{\infty} \omega_{t-n} loss_{t-n} \\ loss_{t-n} &= \frac{P_t - P_{t-n}}{P_t} \cdot \mathbf{1}_{\{P_{t-n} > P_t\}} \\ \omega_{t-n} &= \frac{1}{k} V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}] \end{aligned} \tag{1.2}$$

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 (1.1) and (1.2), k is the normalizing constant such that $k = \sum_n V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}]$. Note that the sum of *Gain Overhang* and *Loss Overhang* is equal to *Capital Gains Overhang* (*CGO*) in Grinblatt and Han (2005).

To avoid contamination of microstructure effects, such as bid-ask bounce, I skip 10 trading days prior to the end of month t, thus $Gain_t$ and $Loss_t$ use all price information up to day

$t - 10$. This choice of length should be sufficient to avoid most of the bid-ask bounce effect, but not so long as to miss the V-shaped disposition effect, which is presumably strongest in the short-term period [4].

To explore the impact of prior holding period on the V-shaped disposition effect, 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 Selling Propensity* (VSP):

$$VSP_t = Gain_t - 0.2Loss_t \tag{1.3}$$

The coefficient -0.2 indicates the asymmetry in the V shape in investors' selling schedule. According to Ben-David and Hirshleifer (2012), investors' selling propensity increases more sharply with the magnitude of gains compared with losses, and this is qualitatively illustrated in Figure 1 in their paper. The relative strength of the gain side and the loss side varies across different prior holding periods, but the gain side is always steeper. I take the number 0.2 (assuming the gain effect is 5 times as strong as the loss effect), which resembles an average relation between gains and losses on the individual level; my price-level estimation in section 1.3.2 suggests a similar magnitude.

[4]Ben-David and Hirshleifer (2012) shows evidence that the V of selling probability in relation to profits is strongest for a short prior holding period, and I will test the price-level implication of this point later in section 1.3.2.

[INSERT TABLE 1.1 HERE]

Panel A in Table 1.1 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 Selling Propensity*. RG, DG, RL, and DL are winsorized at 1% level in each tail, while $Gain$, $Loss$, CGO and VSP are linear combinations of RG, DG, RL, and DL.

1.2.3 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 effect from loser stocks that is incompletely captured by the model specification when 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.

In Table 1.1, Panel B summarizes these control variables, and Panel C presents correlations of gain and loss variables with control variables. All control variables in raw values are winsorized at 1% level in each tail.

1.3 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 selling propensity. I then employ Fama and MacBeth (1973) regressions to better control for other known characteristics that may affect future returns.

1.3.1 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 selling propensity.

Table 1.2 reports the time series average of mean returns in investment portfolios constructed on the basis of residual selling propensity variables. The residuals are constructed from simultaneous cross-sectional regressions of the raw selling propensity variables on past returns, size, turnover, and idiosyncratic volatility. This approach addresses the concern that these regressors, which are known to affect returns and are also largely correlate with gains and losses (as shown in Table 1.1 Panel C), may mask or reverse the V-shaped disposition effect without proper control. Specifically, the residuals are constructed using the following models:

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

[INSERT TABLE 1.2 HERE]

In Panel A, I sort firms into five quintiles at the end of each month based on their residual V-shaped selling propensity, with quintile 5 representing the portfolio with the largest residual selling propensity. The left side of the table reports gross-return-weighted portfolio returns[5] while the right side shows value-weighted results. For each weighting method, I show results in portfolio raw returns, DGTW characteristics-adjusted returns[6], and Carhart four-factor alphas[7]. All specifications are examined using all months and using February to December separately[8]. For comparison, Panel B shows the same set of results for portfolio returns sorted on the capital gains overhang variable in Grinblatt and Han (2005).

Focusing on the gross-return-weighted results in panel A, portfolio returns increase monotonically with their VSP quintile. The return difference between quintiles 5 and 1 is about 0.5% per month. Since the sorting variable is the residual that is orthogonal to size and past returns (by construction), each portfolio has similar characteristics and risk factor loadings (the loadings on market and value are also similar across quintiles). Thus, though the raw return spread and the adjusted return spread (or the alpha spread) have similar magnitudes, the latter has a much higher t-statistic (around 7) because the characteristic return benchmarks (or factor model) remove impacts from unrelated return generators.

Panel B confirms Grinblatt and Han's (2005) finding that equal-weighted portfolio returns increase with the capital gains overhang variable. However, a comparison of the left sides of Panel A and Panel B shows that the effect from VSP is 2 to 3 times as large as the

[5]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.

[6]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

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

[8]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.

effect from CGO, and the t-statistics are much higher. Moreover, the VSP effect shows little seasonality, while the CGO effect is stronger in February to December than in all months. This pattern occurs because VSP accounts for the negative impact from the loss side which permits the January reversal caused by tax-loss selling to be captured.

Note that the value-weighted portfolios in Panels A and B 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 1.4 in which I examine results in subsamples, the V-shaped 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.

To enhance the comparison between VSP and CGO, double sorts are used in Panel C to show the effect of one variable, while the other is kept (almost) constant. On the left side, stocks are first sorted on CGO residuals into five groups. Within each of these CGO quintiles, they are further sorted into five VSP groups (VSP1 - VSP5). The right side of the panel reverses the sorting order. To save space I focus on gross-return-weighted characteristic-adjusted returns in all months in this exercise, and the results for alpha are very similar. On the left, within each CGO group, return increases as VSP quintile increases, and the difference between quintiles 5 and 1 is generally significant. In contrast, the right side shows that once VSP is kept on a similar level, variation in CGO does not generally generate significant return spread between quitiles 5 and 1 .

This suggests that the asymmetric V-shaped relation between selling probability and past profits underlies the disposition effect, as opposed to a monotonic relation. Moreover, the V-shaped selling propensity is a more precise stock-level measure for this effect that better predicts future returns.

1.3.2 Fama-Macbeth Regression Analysis

This subsection explores the pricing implications of the V-shaped disposition effect in Fama-MacBeth regressions. While the results using the portfolio approach suggest a strong relation between the V-shaped 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 selling propensity subsume previously documented capital gains overhang effect.

The Price Effect of Gains and Losses

I begin by testing the hypothesis that the V-shaped selling schedule on the individual level will have aggregate pricing implications.

HYPOTHESIS **1.** *The V-shaped-disposition-prone investors tend to sell more when their unrealized gains and losses increase in magnitude; this effect is stronger on the gain side versus 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, resulting in lower current prices and higher future returns as future prices revert to the fundamental values.*

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:

$$Ret_t = \alpha + \beta_1 Gain_{t-1} + \beta_2 Loss_{t-1} + \gamma_1 X_{1t-1} + \gamma_2 X_{2t-1} + \epsilon_t \tag{1.4}$$

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 1.2.3.

I perform the Fama-MacBeth procedure using weighted least square regressions with the weights equal to the previous one-month gross return to avoid microstructure noise contamination. This follows the methodology developed by Asparouhova, Bessembinder, and Kalcheva (2010) to correct the bias from microstructure noise in estimating cross-sectional return 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 1.3 HERE]

Table 1.3 presents results from estimating equation (1.4) 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 3.6 basis points, and if the loss overhang increases 1% (the magnitude of loss decreases), the future 1-month return will decrease around 1 basis point. The t-statistics are 8.8 and 10 for *Gain* and *Loss*, respectively. Since 504 months are used in the estimation, these t-statistics translate to Sharpe ratios as high as 1.4 and 1.5 for strategies based on the gain overhang and the loss overhang, respectively. Note that the gain effect is 4 or 5 times as large as the loss effect (in all months and in February to December), which is consistent with the asymmetric V shape in individual selling schedule as shown by Ben-David and Hirshleifer (2012). 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.

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.

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 days since purchase (in their Table 1.4, Panel A). Here I test if the length of the prior holding period affects the relation between the gain and loss overhang and future returns. I run Fama-MacBeth regressions for the following model:

$$Ret_t = \alpha + \beta_1 RG_{t-1} + \beta_2 RL_{t-1} + \beta_3 DG_{t-1} + \beta_4 DL_{t-1} + \gamma_1 X_{1t-1} + \gamma_2 X_{2t-1} + \epsilon_t \qquad (1.5)$$

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 (1.4).

[INSERT TABLE 1.4 HERE]

Table 1.4 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), gain and loss overhang variables exhibit the expected signs, while the recent variables are much stronger than the distant ones. A 1% increase in recent gains (losses) will lead to a increase of 9.1 basis points (decrease of 1.5 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 (0.8 basis points). The recent effects are about 2 to 4 times as large as the distant effects. These findings support the conjecture that the strength of the V-shaped disposition effect depends on the length of prior holding - the sooner, the stronger.

Comparing V-shaped Selling Propensity with Capital Gains Overhang

Finally, I introduce a new variable *V-shaped Selling Propensity (VSP)* that combines the effects from the gain side and the loss side. $VSP = Gain - 0.2Loss$. The coefficient -0.2 resembles an average relation between the gain side and the loss side on the individual level. I compare the V-shaped 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 (e.g., Goetzmann and Massa (2008); Choi, Hoyem, and Kim (2008)), actually originates from this V-shaped disposition effect.

HYPOTHESIS **2.** *Investors' selling probability in response to past profits is an asymmetric V-shaped function, for which the minimum locates at a zero-profit point, and the loss side of V is flatter than the gain side. Capital gains overhang, a variable that aggregates investors' selling pressure with the assumption of a monotonically increasing selling propensity in response to profits, is a misspecification for the true relation. However, it still correlates with the proper variable and exhibits predictive return relation when run on its own. Once the proper selling propensity variable is added, capital gains overhang will have no predictive power for future returns, while the V-shaped selling propensity will pick up the 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 1.5 HERE]

Columns (1) and (2) in Table 1.5 Panel A report Fama-MacBeth regression results from the following equation (taken from Grinblatt and Han (2005) Table 3 Panel C):

$$Ret_t = \alpha + \beta_1 CGO_{t-1} + \gamma_1 Ret_{t-1} + \gamma_2 Ret_{t-12,t-2} + \gamma_3 Ret_{t-36,t-13} + \gamma_4 logmktcap_{t-1} + \gamma_5 turnover_{t-1} + \epsilon_t \tag{1.6}$$

Focusing on the all-month estimation in column (1), a 1% increase in CGO will lead to a 0.5 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 1.6.

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 5 times larger than that of the winners, with a much larger t-statistic[9]. 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, which further dampens the effect of capital gains overhang. 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 1.5 Panel B compares the effects of *CGO* and *VSP*, by estimating models that take the following form:

$$Ret_t = \alpha + \beta_1 CGO_{t-1} + \beta_2 VSP_{t-1} + \gamma_1 X_{1t-1} + \gamma_2 X_{2t-1} + \epsilon_t \tag{1.7}$$

where the two sets of control variables X_1 and X_2 are the same as in equation (1.4)

[9]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.

and (1.5). In columns (1) (2) (5) and (6), where I don't control the momentum effect, both variables significantly predict the subsequent one-month return, while *VSP* has much larger economic and statistical significance. Moving to columns (7) and (8) which include momentum and the whole set of control variables, CGO loses its predictive power, while *VSP* remains highly significant. A 1% increase in *VSP* 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 quintiles sorted on *VSP* will roughly generate a return of $23\% \times 0.04\% = 0.92\%$ per month. The t-statistic for the VSP 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 ($10.54 \div \sqrt{504} \times \sqrt{12} = 1.6$) for a portfolio based on the V-shaped selling propensity. This supports *hypothesis 2* that the *V-shaped selling propensity* subsumes the original *capital gains overhang* effect.

Recall that the V-shaped selling propensity variable is constructed by setting the loss effect as 0.2 times the size of the gain effect (see equation (1.3)). If I change the this number to 0.1 (0.3, 0.5), the estimated coefficient for VSP in column (7) becomes 0.041 (0.035, 0.031) with the t-statistic equal to 10.54 (10.54, 10.54). This suggests the estimation is not very sensitive to the pre-specified relation between gains and losses.

1.4 The Source of the V-shaped Disposition Effect and Cross-sectional Analysis

This section is devoted to obtaining deeper understanding of the source of the V-shaped disposition effect. I first discuss several possible mechanisms that may generate the observed V shape on the individual level; however, the pricing implications of these interpretations 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.

1.4.1 The Source of the V-shaped Disposition Effect

An important insight from Ben-David and Hirshleifer (2012) is that investors' higher propensity to sell upon gains over losses is not necessarily driven by a preference for realizing gains over losses per se. Indeed, 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*[10]. Investors may buy a stock and not re-examine

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

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 as well since potential buyers are attracted by the extreme returns[11] (regardless of whether they currently hold the stock or not). Thus, how selling and buying attracted by salient price movements would generate return predictability is ambiguous. 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 mispercep-

[11] Barber and Odean (2008)

tions 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 1.3 is consistent with the irrational belief-updating scenario, as opposed to the other two.

1.4.2 Subsample Analysis: the Impact of Speculativeness

In this subsection, I test the broad conjecture that speculative trading incurs the V-shaped disposition effect. This conjecture, encompassing all three possibilities discussed in section 1.4.1, 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 1.3, is the average daily turnover ratio within one year; and volatility is calculated as daily stock return volatility in the past one year. Since institutional ownership, turnover, and volatility are all largely correlated with firm size, sorting based on the raw variables may end up testing the role of size in all exercises. To avoid this situation, I base subsamples on size-adjusted characteristics. Specifically, I first sort all firms into 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%.

In each high and low subsample, I re-examine equation (1.4) 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 1.2 columns (7) and (8)). Table 1.6 presents the results.

[INSERT TABLE 1.6 HERE]

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 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 3 to 6 times as large as the loss effect. This suggests that the asymmetry between gains and losses is a relatively stable relation.

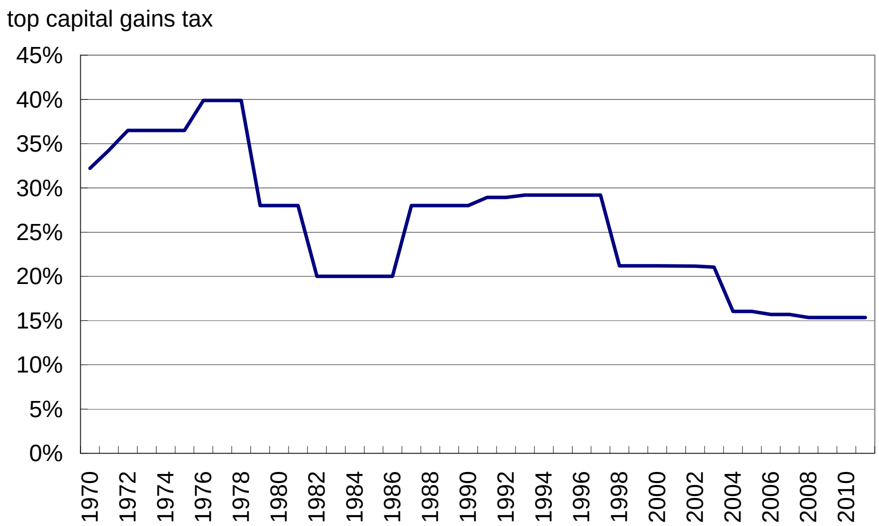
There are alternative interpretations for the different strength of effect across different stock groups though. One possibility is that the V-shaped selling propensity effect is stronger among stocks for which there is a high limit to arbitrage. Low institutional ownership may reflect less presence 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.

1.5 Time-series Variation: the Impact of Capital Gains Tax

This section explores the time series variation of the V-shaped disposition effect. If the return predictability shown in section 1.3 really comes from gain and loss overhang rather other mechanisms, as people's selling 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), 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.

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

Figure 1.2: Top Capital Gains Tax Rate, 1970 - 2011



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 1.2): 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.

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 1.7. In these high tax and low tax subsamples, I re-examine equation (1.4) 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 1.2 columns (7) and (8)). As predicted, the coefficient of the gain overhang variable is smaller in the high tax sub-sample, and the coefficient of loss overhang variable is larger. If we compare the relative importance of the two sides of the V, the gain side is 3 times as large as the loss side in high tax periods, and ratio increases to 5 to 7 times in low tax periods.

[INSERT TABLE 1.7 HERE]

1.6 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 1.4 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 1.2 and 1.3 show the importance of controlling the momentum variable to reveal the true effect from gains and losses; in contrast, adding selling propensity variables has little effect on either the strength or the asymmetry in momentum. This is illustrated in Table 1.8, in which I compare the momentum effect with and without controlling the gain and loss overhang variables. This evidence argues that momentum and the disposition effect are two separate phenomena, and momentum is stronger and more robust.

[INSERT TABLE 1.8 HERE]

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.

1.7 Conclusions

This study provides new evidence that investors' selling tendency in response to past 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). The time-series variation of this effect also occurs exactly as predicted by tax incentives. These findings lend support to the V-shaped selling schedule, as opposed to the monotonically increasing relation between selling propensity and profits. The findings also help elucidate the pattern, source, and pricing implication of this behavior.

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.

Table 1.1: Summary Statistics of 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} from one year to ten trading days 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 Selling Propensity (VSP)* $=$ *Gain* $- 0.2$*Loss*. $Ret_{-12,-2}$ is the previous twelve-to-two-month cumulative return, $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$ are the positive part and the negative part of $Ret_{-12,-2}$, Ret_{-1} is the past one-month return, $Ret_{-36,-13}$ is the past three-to-one-year cumulative return, *logBM* is the logarithm of book-to-market ratio, *logmktcap* is the logarithm of a firm's market capitalization, *turnover* is the average daily turnover ratio in the past one year, and finally, *ivol* is the idiosyncratic volatility - 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 Selling Propensity Variables

	RG	RL	DG	DL	Gain	Loss	CGO	VSP
Mean	0.046	-0.092	0.051	-0.167	0.095	-0.264	-0.162	0.149
Median	0.025	-0.026	0.015	-0.025	0.062	-0.098	-0.037	0.124
St. Dev.	0.057	0.174	0.073	0.351	0.100	0.449	0.466	0.100
Skew	1.877	-4.547	1.884	-4.400	1.313	-4.376	-2.765	1.623
P10	0.001	-0.256	0.000	-0.495	0.001	-0.711	-0.687	0.049
P90	0.126	0.000	0.157	0.000	0.242	-0.001	0.229	0.284

Panel B. Summary Stats for Control Variables

	Ret(-1)	Ret(-12,-2)	Ret(-36,-13)	logBM	logmktcap	turnover	ivol
Mean	0.016	0.175	0.372	-0.552	5.164	0.005	0.030
Median	0.003	0.070	0.153	-0.475	4.997	0.003	0.026
St. Dev.	0.164	0.732	1.251	0.855	1.933	0.007	0.018
Skew	4.635	12.416	14.213	-0.782	0.444	5.473	3.295
P10	-0.140	-0.401	-0.505	-1.620	2.784	0.001	0.013
P90	0.173	0.751	1.305	0.423	7.757	0.012	0.052

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	0.41	1.00											
CGO	0.57	0.98	1.00										
VSP	0.62	-0.46	-0.29	1.00									
Ret_{-1}	0.33	0.18	0.23	0.16	1.00								
$Ret_{-12,-2}$	0.39	0.26	0.32	0.15	-0.01	1.00							
$Ret_{-12,-2}^{+}$	0.34	0.15	0.20	0.20	0.00	0.97	1.00						
$Ret_{-12,-2}^{-}$	0.34	0.52	0.54	-0.12	-0.05	0.49	0.26	1.00					
$Ret_{-36,-13}$	0.03	0.07	0.07	-0.04	-0.03	-0.08	-0.06	-0.10	1.00				
logmktcap	0.02	0.32	0.29	-0.26	0.01	0.07	0.02	0.20	0.10	1.00			
logBM	0.08	-0.04	-0.02	0.10	0.02	0.05	0.02	0.13	-0.26	-0.28	1.00		
turnover	-0.10	0.11	0.08	-0.20	0.00	0.13	0.18	-0.13	0.18	0.26	-0.28	1.00	
ivol	0.03	-0.28	-0.25	0.27	0.11	0.12	0.22	-0.31	-0.05	-0.46	-0.08	0.24	1.00

Table 1.2: Portfolio Sorts on V-shaped Selling Propensity and Capital Gains Overhang

This table reports returns in portfolios constructed based on residual selling propensity variables. In Panel A, stocks are sorted by their *V-Shaped Selling Propensity (VSP) residual* into five groups at the end of each month, with portfolio 5 contains stocks with the highest *VSP residual*. 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) residual* instead. Finally, Panel C reports portfolio returns in double sorts, focusing on gross-return-weighted, characteristic-adjusted portfolio returns in all months. On the left side, stocks are first sorted on CGO residual into five groups; within each of these CGO quintiles, they are further sorted into five VSP groups (VSP1 - VSP5). The right side of the panel reverses the sorting order. Each portfolio is to be held for the following one month, and the time series average of gross-return weighted portfolio returns is reported. In all panels, Residuals are constructed by regressing raw selling propensity variables (*VSP* or *CGO*) on past returns, firm size, turnover, and idiosyncratic volatility. The returns are in monthly percent, t-statistics for the difference between portfolios 5 and 1 are in the square brackets, and *, **, and *** denote significance levels at 10%, 5%, and 1%.

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

VSP	Gross-Return Weighted						Value Weighted					
	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	0.78	0.46	-0.27	-0.31	0.18	0.10	1.14	1.03	0.11	0.10	0.67	0.71
2	0.99	0.71	-0.07	-0.12	0.39	0.33	0.90	0.81	-0.01	-0.01	0.50	0.51
3	1.01	0.73	-0.04	-0.09	0.37	0.30	0.87	0.74	-0.04	-0.07	0.45	0.40
4	1.12	0.84	0.04	0.00	0.44	0.38	0.89	0.85	-0.01	-0.01	0.39	0.40
5	1.36	1.04	0.21	0.17	0.66	0.59	1.04	1.04	0.08	0.10	0.50	0.55
5-1	0.58	0.58	0.47***	0.48***	0.48***	0.49***	-0.10	0.02	-0.03	0.00	-0.17	-0.16
t-stat	[1.54]	[1.54]	[7.01]	[6.78]	[7.56]	[7.26]	[-0.30]	[0.05]	[-0.45]	[-0.05]	[-1.52]	[-1.39]

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

CGO	Gross-Return Weighted						Value Weighted					
	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	0.98	0.53	-0.06	-0.18	0.41	0.23	1.03	0.98	0.12	0.12	0.64	0.65
2	0.97	0.70	-0.10	-0.14	0.34	0.27	0.90	0.83	-0.03	-0.05	0.45	0.44
3	1.04	0.82	-0.07	-0.09	0.38	0.37	0.95	0.90	-0.01	0.00	0.46	0.50
4	1.11	0.89	0.00	0.00	0.43	0.42	0.94	0.87	-0.06	-0.05	0.37	0.42
5	1.16	0.83	0.10	0.06	0.48	0.40	0.97	0.82	-0.03	-0.05	0.43	0.48
5-1	0.18	0.30	0.17**	0.24***	0.07	0.17**	-0.06	-0.16	-0.14*	-0.17*	-0.21*	-0.17
t-stat	[0.45]	[0.74]	[2.05]	[2.95]	[0.93]	[2.19]	[-0.18]	[-0.44]	[-1.75]	[-1.95]	[-1.95]	[-1.46]

(Table 1.2 Continued)

Panel C: gross-return-weighted portfolio adjusted return for all months, double sorts

	first sort on CGO						first sort on VSP				
	1	2	3	4	5		1	2	3	4	5
VSP1	-0.29	-0.24	-0.19	-0.22	-0.27	CGO1	-0.36	0.00	-0.10	-0.14	-0.05
VSP2	-0.05	-0.10	-0.11	-0.13	-0.01	CGO2	-0.15	-0.07	-0.13	0.01	0.25
VSP3	-0.07	-0.06	-0.07	0.01	0.19	CGO3	-0.22	-0.11	-0.04	0.04	0.35
VSP4	0.15	-0.16	-0.02	0.07	0.31	CGO4	-0.27	-0.10	-0.06	0.11	0.28
VSP5	-0.02	0.06	0.03	0.23	0.28	CGO5	-0.32	-0.06	0.13	0.18	0.19
5-1	0.27	0.29***	0.22**	0.45***	0.55***	5-1	0.04	-0.06	0.22**	0.32***	0.24
t-stat	[1.59]	[3.00]	[2.21]	[3.99]	[4.28]	t-stat	[0.28]	[-0.58]	[2.09]	[2.73]	[1.46]

Table 1.3: 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 (1.1) and (1.2). $Ret^{+}_{-12,-2}$ 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)	(7)	(8)	(9)	(10)
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
Gain	0.026***	0.034***	0.003	0.012**	0.053***	0.059***	0.036***	0.039***		
	[4.12]	[5.89]	[0.48]	[2.26]	[11.20]	[13.35]	[8.77]	[9.62]		
Loss	0.002	0.006***	-0.009***	-0.005***	-0.004***	-0.002*	-0.010***	-0.008***		
	[0.91]	[4.07]	[-7.05]	[-4.36]	[-3.72]	[-1.72]	[-10.02]	[-8.20]		
$Ret_{-12,-2}^{+}$			0.006***	0.005***			0.005***	0.006***	0.009***	0.010***
			[3.47]	[2.88]			[3.60]	[4.40]	[6.46]	[7.63]
$Ret_{-12,-2}^{-}$			0.056***	0.058***			0.032***	0.033***	0.025***	0.029***
			[13.88]	[13.98]			[10.07]	[10.41]	[7.63]	[8.90]
Ret_{-1}					-0.068***	-0.063***	-0.060***	-0.054***	-0.057***	-0.049***
					[-18.54]	[-16.76]	[-15.86]	[-14.19]	[-14.07]	[-12.49]
$Ret_{-36,-13}$					-0.003***	-0.002***	-0.002**	-0.001	-0.002**	-0.000
					[-4.44]	[-2.94]	[-2.54]	[-0.90]	[-2.56]	[-0.68]
logBM					0.002***	0.002***	0.002***	0.002***	0.002***	0.001***
					[4.14]	[3.55]	[3.61]	[2.96]	[3.42]	[2.78]
logmktcap					-0.001***	-0.000	-0.001***	-0.001***	-0.001***	-0.001**
					[-2.98]	[-1.14]	[-4.28]	[-2.59]	[-3.97]	[-2.27]
ivol					-0.312***	-0.398***	-0.301***	-0.389***	-0.214***	-0.322***
					[-6.14]	[-7.74]	[-6.07]	[-7.75]	[-4.07]	[-6.14]
turnover					-0.009	0.019	-0.046	-0.016	-0.353	-0.249
					[-0.03]	[0.07]	[-0.17]	[-0.06]	[-1.34]	[-0.90]
constant	0.007***	0.005*	0.009***	0.008***	0.018***	0.015***	0.020***	0.017***	0.022***	0.020***
	[2.94]	[1.96]	[4.54]	[3.65]	[8.12]	[6.82]	[9.44]	[8.27]	[10.53]	[9.31]
# of Obs	1,836,046	1,683,375	1,761,306	1,615,142	1,423,570	1,302,995	1,423,239	1,302,698	1,423,239	1,302,698
R-sq	0.017	0.015	0.033	0.030	0.069	0.064	0.075	0.071	0.072	0.068
# of months	504	462	504	462	504	462	504	462	504	462

Table 1.4: 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	-0.030**	-0.019	-0.064***	-0.049***	0.125***	0.141***	0.091***	0.102***
	[-2.00]	[-1.31]	[-4.17]	[-3.41]	[9.13]	[10.05]	[6.86]	[7.47]
RL	0.013**	0.018***	-0.005	-0.002	-0.006*	-0.006*	-0.015***	-0.015***
	[2.35]	[3.08]	[-1.16]	[-0.41]	[-1.73]	[-1.71]	[-4.72]	[-4.86]
DG	0.038***	0.044***	0.020***	0.025***	0.029***	0.031***	0.022***	0.023***
	[5.78]	[6.53]	[3.45]	[4.49]	[5.89]	[6.37]	[4.76]	[4.82]
DL	-0.001	0.003**	-0.010***	-0.006***	-0.002**	0.000	-0.008***	-0.005***
	[-0.62]	[2.22]	[-6.67]	[-4.21]	[-1.99]	[0.31]	[-6.94]	[-5.01]
$Ret_{-12,-2}^{+}$			0.007***	0.006***			0.003**	0.004***
			[4.93]	[4.25]			[2.19]	[2.86]
$Ret_{-12,-2}^{-}$			0.054***	0.057***			0.033***	0.035***
			[16.03]	[16.36]			[11.20]	[11.74]
Ret_{-1}					-0.072***	-0.068***	-0.062***	-0.056***
					[-20.55]	[-18.66]	[-17.34]	[-15.52]
$Ret_{-36,-13}$					-0.001***	-0.001*	-0.001***	-0.001***
					[-3.66]	[-1.84]	[-4.79]	[-3.13]
logBM					0.002***	0.002***	0.002***	0.002***
					[4.27]	[3.67]	[3.77]	[3.11]
logmktcap					-0.002***	-0.001**	-0.002**	-0.001
					[-3.94]	[-2.47]	[-2.51]	[-0.90]
ivol					-0.347***	-0.437***	-0.322***	-0.413***
					[-6.84]	[-8.49]	[-6.49]	[-8.19]
turnover					-0.470*	-0.490*	-0.406	-0.426
					[-1.78]	[-1.76]	[-1.57]	[-1.56]
constant	0.008***	0.006***	0.010***	0.008***	0.020***	0.017***	0.021***	0.019***
	[3.66]	[2.60]	[4.90]	[3.96]	[9.08]	[7.81]	[10.20]	[9.06]
# of Obs	1,836,046	1,683,375	1,761,306	1,615,142	1,423,570	1,302,995	1,423,239	1,302,698
R-sq	0.031	0.028	0.041	0.039	0.073	0.068	0.078	0.074
# of months	504	462	504	462	504	462	504	462

Table 1.5: V-shaped Selling Propensity and Capital Gains Overhang, Fama-MacBeth Regressions

This table compares the V-shaped selling propensity (VSP) 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 *VSP*. 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 $VSP = Gain - 0.2Loss$, where *Gain* and *Loss* are defined in equation (1.1) and (1.2). $Ret_{-12,-2}$ 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: Tests in Grinblatt and Han (2005) and impacts of additional controls						
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
CGO	0.005***	0.007***	0.000	0.003***	-0.000	0.002**
	[4.35]	[7.21]	[0.36]	[3.13]	[-0.06]	[2.05]
$Ret_{-12,-2}$	0.007***	0.008***				
	[6.02]	[6.48]				
$Ret_{-12,-2}^{+}$			0.006***	0.007***	0.009***	0.011***
			[4.71]	[5.08]	[7.08]	[7.97]
$Ret_{-12,-2}^{-}$			0.037***	0.039***	0.030***	0.032***
			[11.37]	[11.90]	[9.85]	[10.24]
Ret_{-1}	-0.054***	-0.049***	-0.050***	-0.044***	-0.053***	-0.047***
	[-14.42]	[-12.98]	[-12.98]	[-11.60]	[-14.10]	[-12.55]
$Ret_{-36,-13}$	-0.002**	-0.000	-0.001*	0.000	-0.001*	-0.000
	[-2.38]	[-0.58]	[-1.67]	[0.22]	[-1.82]	[-0.14]
logBM					0.002***	0.001***
					[3.53]	[2.91]
logmktcap	-0.000	0.001**	-0.001	0.000	-0.001***	-0.001**
	[-0.53]	[2.09]	[-1.44]	[1.10]	[-4.25]	[-2.55]
ivol					-0.257***	-0.345***
					[-5.11]	[-6.74]
turnover	-0.990***	-1.095***	-0.727**	-0.806**	-0.209	-0.166
	[-3.22]	[-3.36]	[-2.45]	[-2.56]	[-0.80]	[-0.60]
constant	0.014***	0.008***	0.016***	0.010***	0.023***	0.020***
	[4.80]	[2.74]	[5.83]	[3.82]	[10.89]	[9.65]
# of Obs	1,572,385	1,441,332	1,572,385	1,441,332	1,423,239	1,302,698
R-sq	0.057	0.053	0.060	0.056	0.074	0.069
# of months	504	462	504	462	504	462

(Table 1.5 Continued)

Panel B: Horse rase of VSP and CGO								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
CGO	0.006***	0.011***	-0.007***	-0.002*	0.005***	0.008***	-0.002**	0.000
	[3.16]	[7.11]	[-4.68]	[-1.79]	[4.21]	[7.21]	[-2.10]	[0.04]
VSP	0.020***	0.023***	0.010**	0.014***	0.047***	0.051***	0.038***	0.039***
	[3.81]	[4.59]	[2.07]	[3.18]	[12.03]	[13.40]	[10.54]	[10.83]
$Ret_{-12,-2}^{+}$			0.006***	0.005***			0.005***	0.006***
			[3.47]	[2.88]			[3.60]	[4.40]
$Ret_{-12,-2}^{-}$			0.056***	0.058***			0.032***	0.033***
			[13.88]	[13.98]			[10.07]	[10.41]
Ret_{-1}					-0.068***	-0.063***	-0.060***	-0.054***
					[-18.54]	[-16.76]	[-15.86]	[-14.19]
$Ret_{-36,-13}$					-0.003***	-0.002***	-0.002**	-0.001
					[-4.44]	[-2.94]	[-2.54]	[-0.90]
logBM					0.002***	0.002***	0.002***	0.002***
					[4.14]	[3.55]	[3.61]	[2.96]
logmktcap					-0.001***	-0.000	-0.001***	-0.001***
					[-2.98]	[-1.14]	[-4.28]	[-2.59]
ivol					-0.312***	-0.398***	-0.301***	-0.390***
					[-6.14]	[-7.74]	[-6.07]	[-7.75]
turnover					-0.009	0.019	-0.046	-0.016
					[-0.03]	[0.07]	[-0.17]	[-0.06]
constant	0.007***	0.005*	0.009***	0.008***	0.0175***	0.0147***	0.020***	0.017***
	[2.94]	[1.96]	[4.54]	[3.65]	[8.12]	[6.82]	[9.44]	[8.27]
# of Obs	1,836,046	1,683,375	1,761,306	1,615,142	1,423,570	1,302,995	1,423,239	1,302,698
R-sq	0.017	0.015	0.033	0.030	0.069	0.064	0.075	0.071
# of months	504	462	504	462	504	462	504	462

Table 1.6: 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 (1.1) and (1.2). $Ret^{+}_{-12,-2}$ 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.

	Inst Own High		Inst Own Low		Mktcap High		Mktcap Low		Turnover High		Turnover Low		Volatility High		Volatility Low	
	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec	All	Feb-Dec
Gain	0.029***	0.032***	0.039***	0.042***	-0.008	-0.003	0.057***	0.060***	0.057***	0.062***	0.019***	0.019***	0.051***	0.055***	0.017***	0.019***
	[5.01]	[5.15]	[8.81]	[8.90]	[-1.45]	[-0.52]	[10.69]	[11.40]	[8.74]	[9.51]	[3.95]	[3.86]	[8.29]	[8.83]	[4.29]	[4.48]
Loss	-0.011***	-0.009***	-0.011***	-0.010***	-0.008***	-0.008***	-0.010***	-0.008***	-0.016***	-0.015***	-0.006***	-0.004***	-0.011***	-0.010***	-0.006***	-0.005***
	[-6.06]	[-5.00]	[-6.96]	[-6.08]	[-4.72]	[-5.05]	[-8.38]	[-6.80]	[-8.82]	[-7.99]	[-6.20]	[-4.23]	[-7.76]	[-6.51]	[-5.57]	[-4.29]
$Ret_{-12,-2}+$	0.007***	0.008***	0.004**	0.005***	0.009***	0.009***	0.003*	0.004**	0.003**	0.004**	0.006***	0.008***	0.004**	0.005**	0.005**	0.007***
	[4.33]	[4.64]	[2.28]	[2.82]	[4.21]	[4.15]	[1.69]	[2.42]	[2.04]	[2.48]	[2.88]	[3.69]	[2.01]	[2.37]	[2.58]	[3.45]
$Ret_{-12,-2}-$	0.024***	0.025***	0.033***	0.037***	0.017***	0.019***	0.035***	0.036***	0.032***	0.032***	0.034***	0.038***	0.035***	0.035***	0.025***	0.029***
	[5.48]	[5.44]	[8.05]	[9.07]	[2.97]	[3.14]	[11.02]	[11.19]	[8.34]	[8.45]	[8.03]	[8.59]	[8.33]	[8.46]	[6.19]	[6.81]
Ret_{-1}	-0.052***	-0.046***	-0.039***	-0.036***	-0.032***	-0.025***	-0.070***	-0.065***	-0.045***	-0.040***	-0.083***	-0.075***	-0.054***	-0.050***	-0.068***	-0.060***
	[-11.50]	[-10.02]	[-8.39]	[-7.26]	[-5.61]	[-4.39]	[-17.47]	[-16.05]	[-10.90]	[-9.62]	[-18.71]	[-17.06]	[-13.35]	[-11.94]	[-15.90]	[-14.04]
$Ret_{-36,-13}$	-0.001**	-0.001	-0.002**	-0.001	-0.000	0.001	-0.002***	-0.002***	-0.002***	-0.001	-0.001	0.001	-0.002**	-0.001	0.001	0.001**
	[-1.99]	[-1.11]	[-2.36]	[-0.98]	[-0.03]	[0.96]	[-4.00]	[-2.63]	[-2.66]	[-1.36]	[-0.71]	[1.02]	[-2.49]	[-0.95]	[0.86]	[2.25]
logBM	0.000	0.000	0.002***	0.002***	0.001	0.000	0.002***	0.002***	0.001**	0.001	0.002***	0.001***	0.002***	0.002***	0.002***	0.001**
	[0.17]	[0.11]	[2.82]	[2.88]	[0.99]	[0.24]	[3.68]	[3.41]	[2.11]	[1.53]	[3.57]	[2.75]	[3.41]	[3.05]	[3.43]	[2.40]
logmktcap	-0.001**	-0.000	-0.001***	-0.001	-0.001**	-0.001***	-0.001**	-0.000	-0.001***	-0.001***	-0.001***	-0.000	-0.002***	-0.001***	-0.000	-0.000
	[-2.07]	[-1.21]	[-2.63]	[-1.60]	[-2.38]	[-2.63]	[-2.14]	[-0.45]	[-4.06]	[-2.82]	[-2.75]	[-1.07]	[-4.22]	[-3.03]	[-1.52]	[-0.10]
ivol	-0.143**	-0.207***	-0.329***	-0.398***	-0.301***	-0.417***	-0.288***	-0.366***	-0.505***	-0.597***	-0.145***	-0.228***	-0.481***	-0.548***	0.064	-0.049
	[-2.52]	[-3.54]	[-5.45]	[-6.44]	[-2.87]	[-3.93]	[-5.69]	[-7.11]	[-8.51]	[-9.94]	[-2.74]	[-4.20]	[-7.86]	[-8.69]	[0.83]	[-0.63]
turnover	0.476**	0.479**	-0.705***	-0.907***	-0.422	-0.386	-0.250	-0.180	-0.033	0.082	2.516**	2.426**	-0.184	-0.173	-0.011	-0.077
	[2.39]	[2.30]	[-3.23]	[-4.23]	[-1.03]	[-0.92]	[-0.87]	[-0.59]	[-0.14]	[0.33]	[2.27]	[2.20]	[-0.72]	[-0.65]	[-0.03]	[-0.18]
constant	0.012***	0.011***	0.019***	0.018***	0.020***	0.021***	0.019***	0.014***	0.024***	0.021***	0.015***	0.013***	0.029***	0.025***	0.011***	0.009***
	[4.40]	[3.67]	[7.99]	[7.32]	[5.02]	[5.37]	[7.55]	[5.69]	[7.06]	[6.02]	[7.24]	[6.12]	[5.98]	[5.14]	[5.70]	[4.75]
# of Obs	433,668	396,757	356,808	326,641	227,313	208,082	817,191	748,294	433,196	396,534	505,625	462,887	442,729	405,106	495,725	453,922
R-sq	0.070	0.068	0.090	0.088	0.153	0.150	0.064	0.061	0.077	0.073	0.078	0.072	0.074	0.070	0.070	0.065
# of Months	384	352	384	352	504	462	504	462	504	462	504	462	504	462	504	462

Table 1.7: 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 (1.1) and (1.2). $Ret^{+}_{-12,-2}$ 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.

	High Tax		Low Tax	
	All	Feb-Dec	All	Feb-Dec
Gain	0.030***	0.033***	0.043***	0.047***
	[5.45]	[6.37]	[7.08]	[7.26]
Loss	-0.010***	-0.009***	-0.009***	-0.007***
	[-9.11]	[-7.74]	[-5.40]	[-4.18]
$Ret_{-12,-2}^{+}$	0.006***	0.008***	0.003	0.004**
	[3.26]	[3.83]	[1.63]	[2.19]
$Ret_{-12,-2}^{-}$	0.038***	0.038***	0.024***	0.026***
	[10.79]	[11.27]	[4.45]	[4.68]
Ret_{-1}	-0.073***	-0.067***	-0.043***	-0.038***
	[-15.38]	[-14.53]	[-7.42]	[-6.23]
$Ret_{-36,-13}$	-0.001	0.000	-0.002**	-0.001
	[-1.51]	[0.07]	[-2.12]	[-1.34]
logBM	0.003***	0.002***	0.001	0.001
	[3.99]	[2.87]	[1.04]	[1.26]
logmktcap	-0.001***	-0.001**	-0.001**	-0.001
	[-3.57]	[-2.16]	[-2.42]	[-1.47]
ivol	-0.342***	-0.440***	-0.252***	-0.329***
	[-5.27]	[-6.69]	[-3.29]	[-4.24]
turnover	-0.036	0.088	-0.058	-0.142
	[-0.08]	[0.19]	[-0.29]	[-0.68]
constant	0.023***	0.019***	0.016***	0.015***
	[7.74]	[6.71]	[5.49]	[4.90]
# of Obs	706,440	646,432	716,799	656,266
R-sq	0.078	0.072	0.072	0.070
# of months	276	253	228	209

Table 1.8: The V-shaped Disposition Effect and Momentum, Fama-MacBeth Regressions

This table reports results for predictive Fama-MacBeth (1973) regressions of one-month return on lagged momentum variables, with and without controlling gain and loss effects. The dependent variable is return in month t, and the explanatory variables are available at the end of month t-1. $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$ are the positive part and the negative part of the previous twelve-to-two-month return. *Gain* and *Loss* are gain overhang and loss overhang defined in equation (1.1) and (1.2). 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)
	All	Feb-Dec	All	Feb-Dec
$Ret_{-12,-2}^{+}$	0.005***	0.006***	0.006***	0.005***
	[2.97]	[3.16]	[3.47]	[2.88]
$Ret_{-12,-2}^{-}$	0.046***	0.055***	0.056***	0.058***
	[9.68]	[11.61]	[13.88]	[13.98]
Gain			0.003	0.012**
			[0.48]	[2.26]
Loss			-0.009***	-0.005***
			[-7.05]	[-4.36]
constant	0.012***	0.010***	0.009***	0.008***
	[5.65]	[4.69]	[4.54]	[3.65]
# of Obs	1,761,306	1,615,142	1,761,306	1,615,142
R-sq	0.024	0.024	0.033	0.030
# of months	504	462	504	462

Chapter 2

V-Shaped Disposition: Mutual Fund Trading Behavior and Price Effects

Li An, Bronson Argyle

2.1 Introduction

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

In this paper, we study how mutual fund managers' trading behaviors affect stock prices. We present two main findings: first, we document a behavioral pattern characterized by mutual fund managers being more likely to sell stocks with relatively large gains and losses, rather than those with small gains and losses; second, we construct stock-level variables to capture the price pressure from such selling behavior, and we show that these variables strongly predict stock returns in the cross section. By investigating the holdings data of mutual funds, we have the advantage of observing fund managers' trading behaviors and are able to directly test the ensuing pricing implications. In our sample, we find price pattern dynamics that are robustly consistent with the cross-sectional variations of the documented selling behavior.

This research bears on the most recent studies of the disposition effect. First introduced to the finance literature by Shefrin and Statman (1985), the disposition effect refers to investors' tendency to sell their winning securities more readily than their losers. Since then, this trading behavior has been widely documented using evidence from both individual and institutional investors[1], across different asset markets[2], and around the world[3]. Previous research mostly focuses on the difference in selling propensity when investors experience a gain versus a loss, rather than the full functional form of how investors trade in response to past profits. In a recent study, Ben-David and Hirshleifer (2012) take a close look at individual trading account data (as in Odean (1998)) and document a refinement of the disposition effect: counterintuitively, individual investors do not increase their selling probability monotonically from the extreme losers to the extreme winners; instead, they have a V-shaped selling schedule in response to past profit. Moreover, the gain side of the V is steeper than the loss side of the V, thus the average propensity to sell following a gain is higher than the average propensity to sell following a loss.

We examine the selling schedule of mutual fund managers in response to unrealized profits. While studying individual traders is interesting in order to understand investors' trading behavior, mutual fund managers tend to represent more capital, resemble more of a representative investor, and are more important in deciding the market price. We find that mutual fund managers, like individual traders, exhibit a V-shaped selling schedule, i.e. the probability that managers sell a particular security increases with the magnitude of the unrealized gain or loss of that security.

We argue that such trading behavior can generate price pressure and subsequent return predictability in the cross section. As mutual fund managers are more likely to sell stocks

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

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

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

with large gains and losses (compared with stocks with modestly unrealized gains and losses), it increases the supply of such stocks and in turn presses the equilibrium price down from its fundamental value. As future price reverts back to the fundamental value, stocks with large gains and losses will outperform others in the subsequent periods.

To test this hypothesis, we construct price pressure variables directly from mutual fund holdings data. We follow the methodology developed by Frazzini (2006) to measure the aggregate cost base for a particular stock using the time series of net purchases across the mutual fund universe. Taking into account investors' V-shaped selling schedule, we separate unrealized gains from unrealized losses. Empirical results confirm our hypothesis: stocks with large gain overhang and large loss overhang indeed outperform in the next month, and the price effect is both economically and statistically significant: a 1 percentage point increase in the aggregate unrealized gains (losses) for a stock predicts a 1.5 (0.8) basis point increase in the next month return. A trading strategy based on this effect can generate a Sharpe ratio of 1.4. These result are consistent with price effects documented by An (2014), where investors' aggregate cost base is approximated based on trading volume.

To better establish the link between investors' trading behavior and the price pattern, we conduct a series of tests to explore the cross-sectional variation in mutual funds' trading behaviors, and we test if the return predictability mostly comes from the positions of those who exhibit the strongest V-shaped selling schedule. For example, we find that more speculative mutual fund managers, characterized by having a shorter average holding period of stocks and having a higher turnover ratio, tend to have a steeper V-shaped selling schedule; we then decompose our overhang variables into unrealized gains and losses from speculative funds and those from "nonspeculative" funds. We find the former overhang variables are stronger in predicting future returns. Our dataset and our chosen way to measure selling pressure allow us to pin down the source of return predictability. These tests closely tie the variation in price pattern to the variation in investor behavior, and it is a unique contribution of our paper.

We contribute to the literature on the disposition effect in two ways. First, on top of the empirical regularity that investors sell more winners than losers, we document the full functional form of how investors trade in response to past profit. The evidence of a V-shaped selling schedule among mutual fund managers corroborates the findings by Ben-David and Hirshleifer (2012) for individual traders. The V shape in investors' selling schedule is important for two reasons. First, it refutes the common presumption that investors' selling propensity monotonically increases with their past profit, upon which much empirical work has been based. Moreover, it calls into question commonly offered explanations for the disposition effect. Prevalent theories, either prospect theory (Kahneman and Tversky (1979)) that states investors are loss-averse, or the realization utility developed by Barberis and Xiong (2009, 2012), all rely on the point that investors derive a higher utility by realizing gains rather than losses; however, while these preference-based interpretations can generate a monotonic selling schedule, they can hardly reconcile the V shape in investors selling schedule.

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

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

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

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

explores various robustness checks of the main finding. Section 7 concludes.

2.2 Data description

Data are collected from three datasets. Mutual funds holding data are taken from the Thomson Reuters Mutual Fund and Institutional Holdings databases from the S12 and S34 Master Files. The data span the time series from January 1980 to December 2012, inclusively. These data are crosschecked at the fund-date level against the CRSP Mutual Fund Summary database as discussed below. The CRSP Mutual Fund Summary database is also used to construct some of the fund-date level control variables. Security price and accounting information are taken from the CRSP Security File. We include all common shares of domestic securities corresponding to a share code of 10 or 11 which excludes ADRs, ATCs, REIT, and closed-end funds. Similar to previous literature, we employ the following filters:

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

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

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

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

Applying these filters results in roughly 20M valid fund-quarter-holding combinations for which price data exists from CRSP. We assume that holdings are constant during the quarter and that all trading takes place at the end of the reporting quarter. Numerous work has discussed and demonstrated the reality of intraquarterly trading[5], but given that the ratio of the size of trading to Total Net Assets is relatively small, we abstract away from these realities to focus on the capital overhang effects. At best, daily trading simply adds noise to our estimation, and at worst it biases against our results. Further, as discussed in the CRSP/Compustat manual, fund numbers (variable "*fundno*") are often reused for unrelated funds; we assume that a gap of more than 2 years between reporting dates implies the cessation of the previous fund and the outset of a new fund.

[INSERT TABLE 2.1 HERE]

2.3 Specification

2.3.1 Trading Behavior

To identify the v-shaped disposition effect directly in the trading behavior of fund managers, we construct two sets of two measures of the holding period overhang. Our primary measure of the holding period overhang for a given security in the portfolio of fund f in period t, is given by

$$hp\_overhang_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{p_t - p_{t-n}}{p_t} \right] \tag{2.1}$$

where $V_{f,t,t-n}$ is the number of shares purchased of the security at time period $t-n$ that are still held in the fund at time period t, and p_t is the price of the security at time period t.

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

Intuitively, the overhang variable is capturing the average deviation of the current price from the purchase price $(p_t - p_{t-n})$ as a percentage of the current period's price (p_t), weighted by the number of shares purchased in a given period that are still currently held $(V_{f,t,t-n})$. We follow the argument laid out in Frazzini (2006) and employ a First In First Out (FIFO) assumption to populate $V_{f,t,t-n}$ - the mental accounting of fund managers. When part (or all) of a position is sold, shares are sold in the order that they were purchased. For example, if in time period 0, the fund manager of a given fund purchases 500 shares of a security, and in time period 1 she adds another 1000 shares, then the fund manager now owns 1500 shares, and the net positions for the fund are given by $V_{f,1,0} = 500$ and $V_{f,1,1} = 1000$. If the fund manager decides to sell 700 shares in time period 2, then we would assume that the shares that were purchased first are sold first, such that $V_{f,2,0} = 0$, $V_{f,2,1} = 800$, and $V_{f,2,2} = 0$.

To be consistent with the construction of the capital overhang variables (discussed below), the denominator of the unweighted component of $hp\_overhang_t$ is the current price (as opposed to the purchase price). In this way, $hp\_overhang_t$ is simply the capital overhang at the fund-holding level. We will also examine an alternative measure normalized by the purchase price.

In order to examine a V-shaped disposition effect, we further separate the holding period overhang into unrealized gains and losses for a given security in the portfolio of fund f at time t:

$$hp\_gain_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} \leq p_t}}{p_t} \right] \tag{2.2}$$

and

$$hp\_loss_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} > p_t}}{p_t} \right], \tag{2.3}$$

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

$$hp\_time_{ft} = \sum_{n=0}^{t} \frac{V_{f,t,t-n}}{\sum_{n=0}^{t} V_{f,t,t-n}} \left[t-n\right]. \tag{2.4}$$

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

$$\begin{aligned} \mathbb{I}(selling)_{fit} \quad = \quad & \alpha + \beta^{+} hp\_gain_{fit} + \beta^{-} hp\_loss_{fit} + \\ & \zeta^{+} hp\_gain_{fit} * \sqrt{hp\_time_{fit}} + \zeta^{-} hp\_loss_{fit} * \sqrt{hp\_time_{fit}} \\ & + \zeta \sqrt{hp\_time_{fit}} + \text{Controls}_{fit} \boldsymbol{\gamma} + \epsilon_{fit} \end{aligned} \tag{2.5}$$

where Controls_{fit} is a vector of fund-level and security-level control variables and $\boldsymbol{\gamma}$ is a vector of corresponding coefficients. We exclude all months that are not reporting months for the fund; we do this to address potential concerns that our observed effect is mechanically influenced by our assumption that holdings are constant between reporting months. We also exclude outlier funds whose Total Net Assets is in either .5% tail. As an exploration of robustness, we use fund-level flow at various horizons (when data permit) and daily security-level volatility calculated over the previous year as controls.

2.3.2 Price Effect

In our primary analysis of the pricing implications of a V-shaped disposition effect, the capital gains overhang for a given security at time t is calculated at a monthly horizon and is defined analogously:

$$overhang_t = \frac{p_t - rp_t}{p_t}, \tag{2.6}$$

where p_t is the single share price of the given security at time t, and rp_t is the corresponding reference price. The reference price (rp_t) is defined as:

$$rp_t = \frac{\sum_{n=0}^{t} V_{t,t-n} p_{t-n}}{\sum_{n=0}^{t} V_{t,t-n}}, \tag{2.7}$$

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

$$V_{t,t-n} = \sum_{f=1}^{F} V_{f,t,t-n}, \tag{2.8}$$

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

$$gain\_overhang_t = \sum_{n=0}^{t} \frac{V_{t,t-n}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} \leq p_t}}{p_t} \right] \tag{2.9}$$

and

$$loss\_overhang_t = \sum_{n=0}^{t} \frac{V_{t,t-n}}{\sum_{n=0}^{t} V_{t,t-n}} \left[\frac{(p_t - p_{t-n})\, \mathbb{I}_{p_{t-n} > p_t}}{p_t} \right] \tag{2.10}$$

In order to examine the pricing implications of a V-shaped disposition effect, we consider two empirical models. The first model estimates how gain overhang and loss overhang predict future returns separately :

$$Ret_{i,t} = \alpha + \beta_1 gain\_overhang_{i,t-1} + \beta_2 loss\_overhang_{i,t-1} + \gamma_1 Ctrl1_{i,t-1} + \gamma_2 Ctrl2_{i,t-1} + \epsilon_{i,t}, \tag{2.11}$$

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

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

$$Ret_{i,t} = \alpha + \beta_1 CGO_{i,t-1} + \beta_2 VSP_{i,t-1} + \gamma_1 Ctrl1_{i,t-1} + \gamma_2 Ctrl2_{i,t-1} + \epsilon_{i,t}, \tag{2.12}$$

Our results from the selling behavior regressions (expressed in equation 2.5) suggest that mutual fund managers are twice as likely to sell a gain as to sell a loss with the same magnitude, thus we expect a gain overhang to result in twice the selling pressure as a similarly sized loss overhang. We take ϕ equal to 0.5.

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

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

We conduct predictive Fama-MacBeth regressions. To avoid the liquidity bias in estimations, we follow the suggestion by Asparouhova, Bessembinder, and Kalcheva (2010) and run weighted least square (WLS) regressions with the weight equal to past one-month gross return. OLS results (omitted to save space) are qualitatively the same, suggesting that liquidity bias is not a severe issue in our exercises. We follow An (2014) and run tests using all

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

months as well as excluding January, to demonstrate that our results are not driven by the January effect[7].

Finally, it is important to discuss the timing of information availability. Holdings data that are reported by Thomson Reuters stipulate both the effective date of holdings data (variable *"rdate"*) as well as the date that these holdings were filed with the SEC (variable *"fdate"*). It is not uncommon, especially in the early sample, for the difference between when the information is relevant (*rdate*) and when it is reported (*fdate*) to be severe (up to 24 months in extreme cases). This is seemingly less common in the latter portion of the data. Though the selling behavior can and should be identified using the data as of the corresponding *rdate*, the correct course of action is less clear when examining the price effect regressions (equations 2.11 and 2.12). While using the holdings data as of the *rdate* is justifiable to identify a pure price effect, these results would not speak to a viable trading strategy. To this end, for the selling behavior regressions, we use the data as of the corresponding *rdate*, but for the price effect regressions we estimate holdings based on the most recent filing date (with at least a 1 month lag). This is identical to the argument formulated in Frazzini (2006) and ensures that overhang data are publicly available.

2.3.3 Alternative Measures

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

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

alternative holding period overhang is thus calculated as:

$$hp\_overhang\_alt_{ft} = \frac{\sum_{n=0}^{t} V_{f,t,t-n}\left(p_t - p_{t-n}\right)}{\sum_{n=0}^{t} V_{f,t,t-n} p_{t-n}}, \tag{2.13}$$

and the alternative fund-security overhang variables are constructed accordingly:

$$hp\_gain\_alt_{ft} = \frac{\sum_{n=0}^{t} V_{f,t,t-n}\left(p_t - p_{t-n}\right) \mathbb{I}_{p_{t-n} \leq p_t}}{\sum_{n=0}^{t} V_{f,t,t-n} p_{t-n}} \tag{2.14}$$

and

$$hp\_loss\_alt_{ft} = \frac{\sum_{n=0}^{t} V_{f,t,t-n}\left(p_t - p_{t-n}\right) \mathbb{I}_{p_{t-n} > p_t}}{\sum_{n=0}^{t} V_{f,t,t-n} p_{t-n}}. \tag{2.15}$$

Similarly, this implies that the alternative pricing effect overhang is defined as

$$overhang\_alt_t = \frac{p_t - rp_t}{rp_t}, \tag{2.16}$$

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

$$gain\_overhang\_alt_t = \frac{\sum_{n=0}^{t} V_{t,t-n}\left(p_t - p_{t-n}\right) \mathbb{I}_{p_{t-n} \leq p_t}}{\sum_{n=0}^{t} V_{t,t-n} p_{t-n}} \tag{2.17}$$

and

$$loss\_overhang\_alt_t = \frac{\sum_{n=0}^{t} V_{t,t-n}\left(p_t - p_{t-n}\right) \mathbb{I}_{p_{t-n} > p_t}}{\sum_{n=0}^{t} V_{t,t-n} p_{t-n}}. \tag{2.18}$$

We argue that the measures normalized by current price (p_t) are preferred, because the overhang variables are then weighted averages of the deviations from the purchase prices. The alternative measure offers no such intuitive interpretation, though it is consistent with the usual definition of holding period returns.

2.4 Results

2.4.1 Trading Behavior

Results from the selling behavior regressions are shown in Table 2.2. All errors are clustered at the fund level except regression 6, where the errors are two-way clustered at the fund-time level. The results from regression (1) shows a strong overhang effect. We see that both the hp_gain_{fit} (4.10) and hp_loss_{fit} (-1.64) coefficients are strongly significant with t-stats of 43.4 and -38.1, respectively. The magnitude of these coefficients implies that a 1% increase in the holding period gain implies a 4.1% higher probability that some or all of the security will be sold this period. A 1% more extreme holding period loss implies a 1.6% higher probability of being sold. These results confirm the V-shaped disposition effect, and the relatively magnitude ($\frac{1.64}{4.10} = .4$) further suggests an asymmetric V-shaped effect. Regressions (2) and (3) repeat this regression, but separate the sample based on "short" holding period $\left(\sqrt{hp\_time} \leq 3.5\right)$ and "long" holding period $\left(\sqrt{hp\_time} > 3.5\right)$. Both subsamples manifest a strongly V-shaped disposition effect - the ratio of loss to gain coefficients $\left(\left|\frac{hp_loss}{hp_gain}\right|\right)$is equal to .32 for short holding periods and .51 for long holding periods. However, the magnitude of the coefficients and the corresponding t-stats are bigger for shorter holding periods.

Regressions (4) and (5) split the data into a "past" subsample spanning 1980 to 2001 and a "recent" subsample spanning 2002-2012. We see that coefficient estimates are qualitatively identical to the original regression with t-stats above 30, though the magnitude of the results in the recent sample is slightly smaller. Regression (6) uses the logit2 code written by Jingling Guan and Mitchell Petersen (2008) to perform logit regressions using two-way clustering at the fund-quarter level. T-stats are reduced (as expected), but remain highly statistically significant. Finally, regression (7) is a further robustness check including an outflow dummy equal to 1 if the monthly flow of the fund is less than zero and an interaction between outflow and the holding period overhang. The usage of the flow data reduces the sample to only those funds in the CRSP universe for which flow data can be calculated (reducing the number of observations from roughly 20.4 million to 7.4 million). The resulting coefficient estimates have slightly smaller magnitudes (3.64 for the holding period gains and -1.37 for the holding period losses), but are very close to the original estimates. We also explore various windows for the measurement of the fund flows, at 3 month and 12 months horizons, without notable change in the coefficient estimates (results omitted). We conclude that the observed V-shaped disposition effect is orthogonal to fund flow effects[8]

[INSERT TABLE 2.2 HERE]

2.4.2 Pricing Effect

In this section, we discuss the empirical pricing implications of mutual fund managers' V-shaped selling schedules. We first estimate how gain overhang and loss overhang predict future return separately. Then, using the selling behavior regressions as our guide, we combine the gain and loss overhang estimates in order to capture the V-shaped disposition effect in a single variable. We pit this variable against the capital gains overhang variable found in previous literature.

Table 2.3 presents results from estimating equation 2.11 using Fama-MacBeth regressions. In these regressions, we expect gain overhang and loss overhang, the variables of our main interest, to have a positive coefficient and a negative coefficient, respectively. Note that by construction, all values of the loss overhang variable are negative, so an increase in loss overhang means a decrease in the magnitude of loss. Regressions (7) and (8) are the full model regressions with all proper controls. Regressions (1) through (6) omit various sets

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

of control variables to gauge the relative importance of different price effects. In columns (1) and (2), we regress future one-month return onto gain overhang and loss overhang only, and we see that the coefficients on loss overhang (0.002 in all months, and 0.004 in Feb to Dec) have opposite signs than expected. This is due to the fact that stocks with large unrealized losses tend to be momentum losers, and failing to properly control for momentum masks the true marginal effect of the overhang variables. Indeed, adding the two legs of momentum, $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$, we see in regressions (3) and (4) that the gain and loss overhang variables have the expected sign. Notably, the coefficient for $Ret^{-}_{-12,-2}$ is roughly an order of magnitude larger than the coefficient for $Ret^{+}_{-12,-2}$. This suggests that the loser leg of momentum is indeed markedly stronger than the winner leg and that it is important to separate the momentum return by sign to capture the true price effect. In regressions (5) and (6), we omit momentum controls and add other common return predictors ($Ctrl2$). Finally, regressions (7) and (8) add all relevant controls and present our best estimations. In these two regressions, gain overhang positively predict future return and loss overhang negatively predict future return, both as expected; focusing on the all-month estimation, the coefficients suggest that a 1 percentage point increase in gain (loss) overhang would cause a 1.4 (0.9) basis point increase (decrease) in the next month return. The t-statistics (6.02 and -8.65) are very large - given 391 months are used in the estimation, these numbers imply that a trading portfolio based on gain (loss) overhang with zero loading on other control variables would have a Sharpe ratio of $\left(6.02\sqrt{\frac{12}{391}}\right) = 1.05$ and $\left(8.6\sqrt{\frac{12}{391}}\right) = 1.51$, respectively.

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

We also draw attention to the relationship between idiosyncratic volatility and the overhang effects. It has been documented that high idiosyncratic volatility stocks are associated with low future returns[9], and perhaps unsurprisingly, stocks with large gain and loss overhang tend to be those with high idiosyncratic volatility. This result actually biases against our results since our model predicts the opposite direction than what *ivol* would: stocks with large gain and loss overhang will outperform in the next month as prices return to fundamentals. Indeed, controlling for idiosyncratic volatility strengthens the predictive power of our overhang variables - note the change in overhang coefficient estimates from columns (1) & (2) to columns (5) & (6) and the change from columns (3) & (4) to columns (7) & (8).

[INSERT TABLE 2.3 HERE]

[To be added: subsample results (1980-2001, 2002-2012) of pricing effects]

To compare and contract with previous literature, we first construct a single V-shaped selling pressure variable, *V-shaped Selling Pressure (VSP)*, equal to $(gain\_overhang + \phi|loss\_overhang|)$ with $\phi = .5$. We conduct a horse race between *VSP* and the linear Capital Gains Overhang (CGO) variable as in Frazzini (2006). Table2.4 presents the results. We see that with control variables included, CGO loses all of its predictive power, while VSP remains highly significant. The coefficient of 0.016 in the all-month estimation suggests that a 1 percentage point increase in *VSP* would lead to 1.6 basis point increase in future one-month return; given that the average 10th and 90th percentile of monthly *VSP* sample is 0.04 and 0.36, a port-

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

folio that longs the top *VSP* quintile and shorts the bottom *VSP* quintile would generate a monthly return spread of approximately $(36 - 4) \times 1.6 = 51.2$ basis points. The t-statistic $= 8.44$, which implies that the Sharpe ratio is around $8.44/\sqrt{391} \times \sqrt{12} = 1.47$.

[INSERT TABLE 2.4 HERE]

2.4.3 Alternative Measures

We explore the alternative measure of holding period overhang which is normalized by purchase price instead of current price. This definition is more consistent with the usual formulation of holding period return. Previous literature has focused solely on the original measure of overhang (normalized by current price) and has failed to explore this interesting alternative. Selling behavior results are shown in Table 2.5. Many of the observations drawn using the original measures are maintained. We see highly significant overhang coefficients that persist throughout a number of subsample and error-clustering specifications. Also, results are much more prevalent for shorter holding periods (regression (2)) than for longer holding periods (regression (3)) which is consistent with the findings presented earlier. The most interesting observation from these results is that the overhang coefficients are still very statistically and economically significant, but the relative magnitude between holding period gain and loss is opposite the original measure. From regression (1), we see that the ratio of coefficients $\left|\frac{hp\_loss}{hp\_gain}\right| = 1.71$. This relationship is consistent across all of the selling behavior regressions for the alternative measures.

[INSERT TABLE 2.5 HERE]

We examine the pricing effects of the alternative measure in Table 2.6. Interestingly, we see when using the alternative measures, the relative impact of the gain overhang and the loss overhang have reversed from the previous results - consistent with the selling behavior regressions using the alternative measures. In the fully controlled regressions (7) and (8), the significant gain and loss coefficients (t-stats are greater than 7) are .0115 and -.0225, respectively, in the all-months case.

[INSERT TABLE 2.6 HERE]

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

2.5 Exploring the link: how heterogeneity in mutual funds' behavior affects price patterns

As a further exploration of the source of the V-shaped disposition effect, we repeat the selling behavior regressions on subsamples of the fund universe, splitting the data based on fund characteristics designed to capture inefficiencies and speculation in the fund manager. These characteristic variables are the expense ratio, the management fee, the turnover, and the average holding period within a portfolio. The expense ratio is the ratio of operating expenses to total investment. Management fee is the ratio of fees, as reported in the Statement of Operations, to the Average Net Assets($). The turnover is the ratio of aggregated purchases ($) divided by the average 12-month Total Net Assets. Fund characteristics data are only available for the subset of funds that are in the CRSP Mutual Fund database, and the universe is reduced to roughly 7.4 million fund-holding-period observations.

A given portfolio that is included in the CRSP database will have almost always (at most) a single corresponding fund in the Thomson Reuters data. However, the same portfolio may correspond to several separate share classes (varying fee structures, eligibility requirements, etc.) in the CRSP database. Treating these share classes as separate portfolios would bias the results towards funds with more share classes. To address this bias, we instead construct weighted averages of the characteristic variables based on the Total Net Assets of the various share classes. For example, consider a single portfolio with two share classes: Fund A with Total Net Assets of $400M and Fund B with Total Net Assets of $200M. Both of these funds represent exposure to the same portfolio (and trading behavior), but they may have very different characteristics. For instance, assume that the expense ratio of Fund A is 2% and the expense ratio of Fund B is 5%. We thus calculate the weighted average expense ratio: $\frac{400}{600}.02 + \frac{200}{600}.05 = .03$ for the portfolio. This procedure allows us to parsimonously determine the overall average expense ratio (in the case of our example) of the fund.

Though this procedure is not without alternatives, our primary goal is simply to categorize the fund, and this procedure allows us to computationally parse the characteristics of varied share classes in an intuitive manner. We thus obtain weighted averages of the fund expense ratio, management fee, and turnover. Summary statistics for the weighted versions of these variables are shown in Table 2.1 labeled as *wt_exp_ratio*, *wt_mgmt_ratio*, *wt_turn_ratio*, respectively. We form the average holding period directly from the holdings data using *hp_time*.

[INSERT TABLE 2.7 HERE]

Selling behavior results splitting funds based on the two fee structure variables (expense ratio and management fee) are shown in Table 2.7. In both instances, we see that funds with higher expense ratios and management fees manifest a much more significant V-shaped disposition effect - the coefficient for holding period gain (*hp_gain*) for funds in the top third by expense ratio is a highly significant 4.27, whereas the corresponding coefficient for funds in the bottom third by expense ratio is 2.34. The difference is statistically significant, and we see a similar difference in the coefficients for holding period loss (*hp_loss*). Funds sorted by management fees, a subset of the operational costs included in the expense ratio, produces qualitatively consistent results. To the extent that higher fees proxy for management efficiency, these results suggest that the V-shaped disposition effect may be the manifestation of inefficient management.

[INSERT TABLE 2.8 HERE]

Selling behavior results splitting funds based on the two speculation variables (turnover and average holding period) are shown in Table 2.8. Though these two variables are related, they capture different aspects, and high turnover does not necessarily imply low average holding period. We find that the V-shaped disposition effect is much more severe amongst funds with higher trading turnover and short average holding period: the gain and loss coefficients for high turnover funds (5.1 and -2.1, respectively) are roughly twice the size of the gain and loss coefficients for funds with low relative turnover (2.43 and -0.93, respectively). Similarly, funds with the shortest average holding period have coefficients almost twice the magnitude of funds with the longest average holding period. These results suggest that relatively active managers are more prone to evince a V-shaped disposition effect.

2.6 Robustness checks

2.6.1 Extreme Rank Dependency

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

$$best\_dummy_{fit} = \begin{cases} 1 & \text{if security } i \text{has the highest } hp\_overhang \\ & \text{in the portfolio of fund } f \text{in period } t \\ 0 & \text{otherwise} \end{cases} \tag{2.19}$$

and

$$worst\_dummy_{fit} = \begin{cases} 1 & \text{if security } i \text{has the lowest } hp\_overhang \\ & \text{in the portfolio of fund } f \text{in period } t \\ 0 & \text{otherwise} \end{cases} . \tag{2.20}$$

We also control for the universe-of-funds-wide versions of the Hartzmark dummies in the pricing effect regressions, constructed according to:

$$best\_dummy_{i,t} = \begin{cases} 1 & \text{if security } i \text{has the highest } hp\_overhang \\ & \text{in the portfolio of at least one fund in period } t \\ 0 & \text{otherwise} \end{cases} \tag{2.21}$$

and

$$worst\_dummy_{i,t} = \begin{cases} 1 & \text{if security } i \text{has the lowest } hp\_overhang \\ & \text{in the portfolio of at least one fund in period } t\ . \\ 0 & \text{otherwise} \end{cases} \tag{2.22}$$

[INSERT TABLE 2.9 HERE]

Selling behavior regressions using both the original and alternative measures that include these dummies are shown in Table 2.9. Regression 1 repeats the main regression without subsample splits. Both the coefficient estimates and the resulting ratio of gain and loss coefficients are practically unchanged from the regressions omitting these extreme rank dummies. Regression 2 substitutes the alternatives measures and finds similar results. Those these dummies do not effect our overhang findings, the corresponding coefficient are persistently significant even when controlling for fund flow variables at 1 month, 3 month, and 12 month horizons (results omitted). The standardized coefficents for the *best_dummy* is equal to $.0938\frac{.497}{.494} = .0944$ whereas the standardized coefficient of the *hp_gain* variable is equal to $3.9974\frac{.128}{.494} = 1.04$. Also, the R^2 improvement from adding these rank dummies is minimal (.0129 versus .0112).

We also find that including the similar security-level dummies in the pricing equations has virtually no qualitative effect on the overhang coefficient estimates. These results are shown in Table 2.10.

[INSERT TABLE 2.10 HERE]

2.6.2 Simple Measures

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

$$hp\_overhang\_simple_{ft} = \frac{p_t - p_{t-n^*}}{p_t}, \tag{2.23}$$

and

$$hp\_overhang\_alt\_simple_{ft} = \frac{p_t - p_{t-n^*}}{p_{t-n^*}}, \tag{2.24}$$

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

$$hp\_gain\_simple_{ft} = \frac{[p_t - p_{t-n^*}]\, \mathbb{I}_{p_{t-n} \le p_t}}{p_t} \tag{2.25}$$

and

$$hp\_loss\_simple_{ft} = \frac{[p_t - p_{t-n^*}]\, \mathbb{I}_{p_{t-n} > p_t}}{p_t}. \tag{2.26}$$

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

We similarly construct the simpler measures of the holding period :

$$hp\_time\_simple_{ft} = t - n^*. \tag{2.27}$$

We examine the same logit selling regression as before (equation 2.5) but use the simple measures of holding period overhang (based on the "oldest" surviving holding of a security according to a FIFO assumption). Results are shown in Table 2.11. We see that for both the main and alternative measures, the coefficients of the simple versions are within an order of magnitude of the original weighted measures. Though the t-stats are still highly significant (above 7), they are much lower than the original measures. This suggests that fund managers are much more inclined to process overhang that is based on the average of the purchase prices as opposed to simply the original price. We interpret this as justification for the original, V-weighted versions of the overhang measures. The relative magnitude, however, of $\left|\frac{hp\_loss\_alt}{hp\_gain\_alt}\right| = .55$ is very similar and suggests and similar v-shaped disposition structure. Further, if we include a flow variable directly (regression (2)), we see that though the number of observations is nearly cut in half due to data constraints, the magnitude and statistical significance of the overhang coefficients are qualitatively unchanged.

[INSERT TABLE 2.11 HERE]

2.6.3 Placebo Test

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

[INSERT TABLE 2.12 HERE]

Results from the selling behavior regressions, using on this subset of mutual funds are shown in Table 2.12.

2.7 Conclusions

This paper has sought to robustly establish two contributions to the current literature. First, we have shown that mutual fund managers, like the individual retail investors of previous research, also exhibit a V-shaped disposition effect - they are more likely to sell both their past relative winners and losers. We found that the slope of the selling schedule for past winners is roughly twice the magnitude of the slope of the selling schedule for past losers, and we established this results using both a weighted measure of holding period overhang which took into account the net purchases of a funds' holdings as well as a simple measure focusing solely on the purchase price. This discovery and these results are in contrast to the assumption of a monotonic selling schedule proposed elsewhere in the literature. Further, we have shown that this behavior is much more prevalent among managers whose other observable behaviors would be considered speculative (short holding periods and high turnover relative to other mutual fund managers). These results imply that speculation may be an underlying motive that leads to the disposition effect. All of our results were orthogonal to a string of fund flow variables and volatility.

The second major contribution of this research has been to demonstrate that this observed behavior, aggregated across fund managers, has observable price impacts on equilibrium prices. When properly controlling for momentum, we found that a 1 percentage point increase in the magnitude of the gain (loss) overhang implied a 1.4 (.9) basis point increase in future one-month returns. The relative magnitude of these effects $\left(\frac{.9}{1.44}\right) = .625$ and $\left(\frac{.85}{1.54}\right) = .55$ are completely in line with the estimates of the relative impact of holding period gain and loss on the selling behavior of indivual mutual fund managers. With these results in hand, we are able to directly pit a monotonic capital gains overhang measure (used in the literature) against a V-Shaped capital gains overhang measure. Properly controlling for momentum and short- and long-term reversal, we conducted a horse rase between the two measures. The monotonic measure loses all of its predictive power (point estimate of -.0012 with a t-stat of 1.28) against the V-shaped measure (point estimate of .0156 with a t-stat of 8.44). The results are qualitatively unchanged if we address the January effect (the tendency of investors to harvest losses to offset capital gains at the end of the tax year) by excluding January observations.

We thus document both the fund manager level V-shaped disposition effect and the accompanying price effects. We submit this result to a battery of robustness checks and alterations, most significantly of which is an alternative overhang measure. We construct an alternative overhang measure that normalizes price deviations by purchase price (instead of current price). Selling behavior regression using these alternative measures of overhang produce surprising results: though the holding period gain and loss variables continue to be both economically and statistically significant, the relative magnitudes of their slopes is reversed - it is now the loss overhang whose magnitude is roughly twice that of the gain overhang. However, aggregating these measures to the security-level analogs and running predictive pricing regressions shows that the loss overhang impact is almost twice as big as that of the gain overhang where a 1 percentage point increase in the magnitude of the loss (gain) overhang results in a 2.25 (1.15) basis point increase in next month returns. The ratio of these magnitudes, $\left(\frac{1.15}{2.25}\right) = .51$ is again completely consistent with the selling behavior regressions using the alternative measure.

Finally, we expand on these findings by dividing funds on the basis of various fund characteristics. Repeating both the selling behavior and pricing regressions, we find evidence that the V-shaped disposition effect is more prevalent for fund managers with characteristics associated with speculation (shorter holding period and higher turnover) and inefficiency (higher expense ratios and management fees). Splitting the sample into thirds on the basis of these characteristics, we found that the gain and loss coefficients were nearly twice as extreme for high speculation, inefficient funds relative to low speculation, efficient funds.

Table 2.1: Summary Statistics.

Panel A describes the data used to examine selling behavior. *hp_overhang* is the measure of overhang expressed in equation 2.1. *hp_overhang_* is the alternative measure of overhang expressed in equation 2.13. $\mathbb{I}(selling)$ is a fund-security-period dummy equal to 1 if the part or all of the security was sold in a given period. *assets* are the Total Net Assets of the fund expressed in thousands ($). $flow1m$, $flow3m$, and $flow12m$ are the 1 month, 3 month, and 12 month fund flow, respectively. $fret1m$, $fret3m$, and $fret12m$ are the 1 month, 3 month, and 12 month fund return, respectively. *ivol* is the average daily residual from a 3 factor Fama-French model over the previous year. *best_dummy* is a dummy equal to 1 for the highest ranked security according to *hp_overhang* in the portfolio of the fund in a given period. *worst_dummy* is a dummy equal to 1 for the lowest ranked security according to *hp_overhang* in the portfolio of the fund in a given period. *wt_exp_ratio*, *wt_mgmt_ratio*, *wt_turn_ratio* are the weighted-average expense ratio, management fee, and turnover ratio for the fund, respectively. *outflow_dummy* is equal to 1 if the $flow1m < 0$. *hp_gain* is the holding period gain defined in equation 2.2. *hp_loss* is the holding period loss defined in equation 2.3. *hp_gain_alt* and *hp_loss_alt* are the alternative holding period gain and loss as defined in equations 2.14 and 2.15, respectively. *hp_time* is the net purchase-weighted holding period at the fund-security-period level. *hp_time_alt* is the corresponding alternative holding period measure. *shares* is the number of shares held at the fund-security-period level.

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

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

Table 2.1: Summary Statistics (Continued). Panels B & C describes the data used to examine pricing effects. *gain_overhang* and *loss_overhang* are the security level overhang variables expressed in equations 2.9 and 2.10, respectively. *CGO* is the monotonic disposition effect overhang documented in Frazzini (2006). *VSP* is the V-shaped disposition effect overhang as is defined as $VSP = gain\_overhang + .5\,|loss\_overhang|$. *Ret* is the one-month security return. $Ret_{-36,-13}$ is the lagged 24-month return. $Ret_{-12,-2}$ is the lagged 11-month cumulative return, and $Ret^{+}_{i,t-12,t-2} = Max\{0, Ret_{i,t-12,t-2}\}$, and $Ret^{-}_{i,t-12,t-2} = Min\{0, Ret_{i,t-12,t-2}\}$. *logBM* is the logarithm of the book-to-market ratio. *logMktcap* is the logarithm of market capitalization. *turnover* is the average daily turnover ratio $\left(\frac{trading\_volume}{shares\_outstanding}\right)$ over the past year.

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

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

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

	gain_overhang	*loss_overhang*	*CGO*	*VSP*	Ret_{-1}	$Ret^{+}_{-12,-2}$	$Ret^{-}_{-12,-2}$	$Ret_{-12,-2}$	$Ret_{-36,-13}$	*logBM*	*logMktcap*	*ivol*	*turnover*
gain_overhang	1												
loss_overhang	0.36	1											
CGO	0.58	0.93	1										
VSP	0.69	-0.39	-0.19	1									
Ret	0.28	0.19	0.25	0.12	1								
$Ret^{+}_{-12,-2}$	0.49	0.18	0.28	0.33	0.01	1							
$Ret^{-}_{-12,-2}$	0.39	0.59	0.65	-0.11	-0.03	0.34	1						
$Ret_{-12,-2}$	0.54	0.34	0.45	0.25	0.00	0.95	0.61	1					
$Ret_{-36,-13}$	0.06	0.03	0.04	0.04	-0.02	-0.05	-0.11	-0.08	1				
logBM	0.01	0.03	0.03	-0.01	0.02	0.01	0.11	0.04	-0.30	1			
logMktcap	0.13	0.19	0.21	-0.02	0.04	0.04	0.19	0.10	0.09	-0.29	1		
ivol	-0.09	-0.39	-0.39	0.24	0.02	0.14	-0.38	0.00	-0.02	-0.08	-0.47	1	
turnover	0.05	-0.14	-0.12	0.17	-0.01	0.14	-0.17	0.07	0.17	-0.29	0.30	0.24	1

Table 2.2: Selling Behavior Regressions.

For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. hp_gain and hp_loss represent the holding period gain and holding period loss as defined in equations 2.2 and 2.3, respectively. hp_time is equal to the weighted average holding period. $flow1m$ is the one month flow calculated for the subset of funds in the CRSP Mutual Fund Holdings database. $outflow\_dummy$ is equal to one if $flow1m < 0$. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. With the exception of regression 6 (which calculates two-way clustered errors at the fund-time level), all errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

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

Table 2.3: Pricing effect Fama-Macbeth regressions.

For ease of notation, subscripts have been omitted. Cross-sectional WLS regressions are run for each month with the weight equal to the previous month gross return, and coefficient estimates and t-statistics (shown in square brackets) are calculated using the time series of cross-sectional estimations. The dependent variable is return in month t, and the explanatory variables are all available at the end of month t-1. *gain_overhang* and *loss_overhang* are stock-level unrealized gains and loss aggregated across all mutual funds, as defined in equation 2.9 and 2.10. $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$are the positive part and the negative part of cumulative return from month $t-12$ to $t-2$; Ret_{-1} is return in month $t-1$; $Ret_{-36,-13}$ is cumulative return from past three year to past one year. $logBM$ and $logMktcap$ are the logarithm of a firm's book-to-market ratio and market capitalizatio, respectively. *ivol* is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. *turnover* is the avergage daily turnover ratio in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-squared is the average R^2 from the cross-sectional regressions.

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

Table 2.4: Horse race between CGO and VSP, Fama-Macbeth regressions.

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

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

Table 2.5: Selling Behavior Regressions - Alternative Measure.

For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. The alternative measures (hp_gain_alt and hp_loss_alt) are normalized by the purchase price instead of the current price as defined in equations 2.14 and 2.15, respectively. hp_time is equal to the weighted average holding period. $best\_dummy$ is a dummy identifying that the security is the best performing security (ranked by $hp\_overhang$) in the portfolio in a given period; $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. With the exception of regression 7 (which calculates two-way clustered errors at the fund-time level), all errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

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

Table 2.6: Pricing effect Fama-Macbeth regressions - alternative overhang measures.

For ease of notation, subscripts have been omitted. Cross-sectional WLS regressions are run for each month with the weight equal to the previous month gross return, and coefficient estimates and t-statistics (shown in square brackets) are calculated using the time series of cross-sectional estimations. The dependent variable is return in month t, and the explanatory variables are all available at the end of month t-1. *gain_overhan_alt* and *loss_overhang_alt* are stock-level unrealized gains and loss aggregated across all mutual funds, as defined in equation 2.17 and 2.18. $Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$are the positive part and the negative part of cumulative return from month $t-12$ to $t-2$; Ret_{-1} is return in month $t-1$; $Ret_{-36,-13}$ is cumulative return from past three year to past one year. $logBM$ and $logMktcap$ are the logarithm of a firm's book-to-market ratio and market capitalizatio, respectively. *ivol* is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. *turnover* is the avergage daily turnover ratio in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-squared is the average R^2 from the cross-sectional regressions.

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

Table 2.7: Selling Behavior Regressions - Characteristic Splits - Fee Variables.

For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. hp_gain and hp_loss represent the holding period gain and holding period loss as defined in equations 2.2 and 2.3, respectively. hp_time is equal to the weighted average holding period. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. All errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

Sort Variable	wt_exp_ratio			wt_mgmt_ratio		
	LOW	MED	HIGH	LOW	MED	HIGH
hp_gain	2.3397***	4.0877***	4.2756***	2.7382***	3.5296***	4.3809***
	[10.72]	[17.77]	[29.72]	[13.92]	[14.77]	[31.11]
hp_loss	-1.0893***	-1.6555***	-1.7360***	-1.2805***	-1.3588***	-1.8572***
	[-13.54]	[-13.74]	[-25.69]	[-16.24]	[-12.53]	[-29.06]
$hp\_gain * \sqrt{hp\_time}$	-0.3174***	-0.7252***	-0.8255***	-0.3917***	-0.6038***	-0.8335***
	[-7.82]	[-13.26]	[-22.99]	[-9.57]	[-11.32]	[-26.07]
$hp\_loss * \sqrt{hp\_time}$	0.1643***	0.2837***	0.3187***	0.1959***	0.2241***	0.3483***
	[9.18]	[9.39]	[18.18]	[11.28]	[8.50]	[21.42]
$\sqrt{hp\_time}$	0.0921***	0.1494***	0.1763***	0.1141***	0.1312***	0.1588***
	[4.98]	[7.88]	[11.47]	[5.69]	[8.09]	[10.60]
$ivol$	-5.5498***	1.2129	2.3758***	-2.5944	-0.8712	1.6852**
	[-3.30]	[0.61]	[3.31]	[-1.38]	[-0.68]	[2.06]
$Constant$	-0.9374***	-1.1684***	-0.9789***	-1.1837***	-0.9433***	-0.9425***
	[-13.06]	[-15.74]	[-20.93]	[-17.30]	[-15.97]	[-19.44]
Error Cluster Level	Fund	Fund	Fund	Fund	Fund	Fund
Observations	2,714,916	2,587,554	2,651,133	2,652,694	2,652,542	2,648,367
Pseudo R-squared	0.0015	0.0037	0.0029	0.0092	0.0103	0.0146

Table 2.8: Selling Behavior Regressions - Characteristic Splits - Speculation.

For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. hp_gain and hp_loss represent the holding period gain and holding period loss as defined in equations 2.2 and 2.3, respectively. hp_time is equal to the weighted average holding period. $ivol$ is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. All errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

Sort Variable	wt_turn_ratio			$\overline{hp\_time}$		
	LOW	MED	HIGH	LOW	MED	HIGH
hp_gain	2.4399***	4.0515***	5.0958***	6.0897***	5.0477***	3.0321***
	[11.74]	[24.91]	[32.56]	[59.69]	[68.07]	[22.35]
hp_loss	-0.9251***	-1.7351***	-2.1249***	-2.0529***	-1.6560***	-1.1091***
	[-13.65]	[-16.31]	[-31.85]	[-39.73]	[-53.81]	[-20.65]
$hp\_gain * \sqrt{hp\_time}$	-0.3196***	-0.7428***	-1.1590***	-1.7042***	-1.0423***	-0.4459***
	[-8.75]	[-19.16]	[-25.44]	[-53.67]	[-56.11]	[-18.59]
$hp\_loss * \sqrt{hp\_time}$	0.1264***	0.3049***	0.4507***	0.4867***	0.3120***	0.1586***
	[9.51]	[11.23]	[24.02]	[31.98]	[40.41]	[15.53]
$\sqrt{hp\_time}$	0.1123***	0.1831***	0.3496***	0.6540***	0.3169***	0.1106***
	[7.24]	[11.21]	[20.50]	[76.28]	[49.78]	[13.60]
$ivol$	-6.5675***	0.5258	1.3721*	-2.5944	-0.8712	1.6852**
	[-3.84]	[0.31]	[1.81]	[-1.38]	[-0.68]	[2.06]
$Constant$	-1.0975***	-1.4076***	-1.2299***	-1.1837***	-0.9433***	-0.9425***
	[-16.69]	[-20.75]	[-25.39]	[-17.30]	[-15.97]	[-19.44]
Error Cluster Level	Fund	Fund	Fund	Fund	Fund	Fund
Observations	2,657,904	2,648,345	2,647,354	2,652,694	2,652,542	2,648,367
Pseudo R-squared	0.00883	0.0147	0.0262	0.0092	0.0103	0.0146

Table 2.9: Selling Behavior Regressions - Extreme Rank Dependency.

For ease of notation, subscripts have been omitted. All regressions are pooled logit regressions. The dependent variable is $\mathbb{I}(selling)$, a dummy that is equal to 1 if fund f sold part or all of its position in security i in time period t. *hp_gain* and *hp_loss* represent the holding period gain and holding period loss as defined in equations 2.2 and 2.3, respectively. The alternative measures (*hp_gain_alt* and *hp_loss_alt*) are normalized by the purchase price instead of the current price as defined in equations 2.14 and 2.15, respectively. *hp_time* is equal to the weighted average holding period. *best_dummy* is a dummy identifying that the security is the best performing security (ranked by *hp_overhang*) in the portfolio in a given period; *worst_dummy* is a dummy identifying that the security is the worst performing security (again ranked by *hp_overhang*) in the portfolio in a given period. *ivol* is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. All errors are clustered at the fund level. *, **, and *** denote significance levels at 10%, 5%, and 1%

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

Table 2.10: Pricing effect Fama-Macbeth regressions - Extreme Rank Dependency.

For ease of notation, subscripts have been omitted. Cross-sectional WLS regressions are run for each month with the weight equal to the previous month gross return, and coefficient estimates and t-statistics (shown in square brackets) are calculated using the time series of cross-sectional estimations. The dependent variable is return in month t, and the explanatory variables are all available at the end of month t-1. *gain_overhang* and *loss_overhang* are stock-level unrealized gains and loss aggregated across all mutual funds, as defined in equation 2.9 and 2.10. The alternative measures (*gain_overhang_alt* and *loss_overhang_alt*) are normalized by the purchase price instead of the current price as defined in equations 2.17 and 2.18, respectively. *best_dummy* (*worst_dummy*) is a dummy variable that equals to 1 if the security is the best-performing (worst-performaing) security in at least one fund's portfolio at the end of month t-1 (according to publicly available information), 0 otherwise.$Ret^{+}_{-12,-2}$ and $Ret^{-}_{-12,-2}$are the positive part and the negative part of cumulative return from month $t-12$ to $t-2$; Ret_{-1} is return in month $t-1$; $Ret_{-36,-13}$ is cumulative return from past three year to past one year. $logBM$ and $logMktcap$ are the logarithm of a firm's book-to-market ratio and market capitalizatio, respectively. *ivol* is the idiosyncratic volatility calculated using the daily return residual from a Fama-French three factor model in the past one year. *turnover* is the avergage daily turnover ratio in the past one year. *, **, and *** denote significance levels at 10%, 5%, and 1%. R-squared is the average R^2 from the cross-sectional regressions.

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

Table 2.11: Selling Behavior Regressions - Simple Measures.

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

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

Table 2.12: Selling Behavior Regressions - Placebo Test With Index Funds.

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

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

Chapter 3

Mortgage Debt, Recourse, and Strategic Default

Li An

3.1 Introduction

The most recent housing market downturn, which started in 2006, is one of the worst housing crises in history. House prices plunged and defaults zoomed to historical highs around the United States. In California, for example, the total number of strategic defaults was 68 times higher in 2008 than it was in 2005; in Florida, it was 46 times higher. In most other parts of the country, defaults were about nine times higher in 2008 than in 2005[1]. This crisis is notable in that house prices have fallen by 40 to 50 percent during the last few years in some areas, yet many home-owners owe more on their home mortgages than their houses are worth because they put very little or nothing down when they bought their houses in the expansion. Home-owners with a negative home equity have an incentive to strategically default on their mortgage debt - render their houses to the bank and walk away, which the Wall Street Journal calls "American dream 2: default, then rent"[2]. Thus to reduce costly default, it is important to understand the home-owners' strategic default decision.

This paper explores how foreclosure legal arrangements have impacts on mortgage default incentives and the mortgage market. In the literature, the lender's claim in a mortgage default is usually limited to the collateral, the house value, ever since Asay's seminal effort in 1978, which first applies the Black-Scholes (Black and Scholes 1972) option pricing model to price mortgage. However, in many states in the United States, if the lender forecloses

[1] See Experian-Oliver Wyman, Market Intelligence Report, Understanding Strategic Default in Mortgages (2009)

[2] Wall Street Journal, 2009 December 16. "American Dream 2: Default, Then Rent". http://online.wsj.com/article/SB126040517376983621.html

and sells the house for less than the amount owed, the lender still has a recourse for the difference. While this recourse decreases the payoff of strategic default, it raises debt value ex ante, not only because it gives the creditor a greater claim in the state of default, but also because it lowers the incentive for a strategic default. Indeed, in the past few years, the default rate increased the most drastically in states,like California, where mortgage debt is non-recourse and in states, like Florida, where legal restrictions and costs make the lender very unlikely to collect on a deficiency judgement although foreclosure law allows recourse.

This paper provides a theoretical model that explicitly analyzes the strategic default incentives under different foreclosure laws. I build the model based on the structural credit risk framework by Leland (1994), who uses the option-based valuation technique to analyze the problem of corporate bonds with endogenous default incentives. The relatively simple framework allows me to reach a tractable closed-form solution.

In the baseline model, I discuss the situation in which a home-owner does not have any cash flow problems, and strategic default is the only source of default. In the full model, I include a liquidity shock to the home-owner who may have to default for cash flow reasons, although he or she otherwise wants to keep serving the debt out of his or her financial interest. The key results are that possible recourse makes the payoff in strategic default less attractive, and it deters strategic default when the house price goes down. The full model illustrates that liquidity shocks not only incur liquidity default, which is obvious by definition, but they also exacerbate the strategic default problem since they lower the continuation value:continue to severe the debt now involves a potential loss of value due to possible liquidity default in the future. Recourse could help reduce default incentives and make debt value immune to liquidity shock, and it has little impact on house equity value in the presence of the interaction between cash flow problems and strategic default incentives. The deterrent role of recourse is consistent with the empirical evidence found by Ghent and Kudlyak (2009).

This paper also relates to the discussion on why "so few" home-owners with negative equity actually default, which contradicts the predictions of standard option-based default models. Recent empirical evidence of the low numbers of defaults is reported by Guiso, Sapienza, and Zingales(2009), Foote, Gerardi, and Willen (2008), and Experian and Oliver Wyman (2009), while early theoretical and empirical results are summarized by Vandell (1995). In light of this model, if there is recourse for the mortgage debt, the default boundary of equity value is actually not zero, but rather a negative value that equals the value of the obligation potentially in default. In an extreme case of full-recourse, this value could be as low as -100% of the initial home equity, which suggests that a large difference may exist between what is predicted by theory and what is measured empirically.

The paper is organized as follows. Section 3.2 provides a brief overview of the foreclosure law across the states. Section 3.3 presents the baseline model. Section 3.4 presents the full model with liquidity shock. Section 3.5 discusses the policy implications and concludes the paper.

3.2 Foreclosure Law across the States

In the case of a mortgage default, if selling the house garners less than the amount of debt owned by the borrower, the lender may or may not have recourse for the shortfall according to foreclosure law. It is actually a unique phenomenon in the United States that mortgage loans can be non-recourse in some states. Across states, the foreclosure laws vary a lot.

Some states explicitly classify mortgage loans as non-recourse, for instance, Arizona, California, and Oregon, while most states allow deficiency judgment. Among the states that allow the lender to pursue recourse, several aspects of recourse vary. First, different restrictions exist on how the fair market value is determined. In some states, a single appraiser determines the fair market value, while in other states a fair market value must be determined by a jury; legal costs and time required in such a process also differ because restrictions vary. Second, state foreclosure laws differ on whether a time-consuming judicial foreclosure process is required to obtain the deficiency judgment. Third, the personal property or wages that can be exempted from collection differs by state. The onerous time and legal costs can make it impractical to pursue deficiency judgment, although it is legally allowed. Ghent and Kudlyaky (2009) discuss foreclosure arrangements in details and they also include a summary of foreclosure law by state in their appendix.

Even when deficiency judgment is obtained, the borrower still has the option to claim personal bankruptcy. The claim on the shortfall is noncollateral and can be discharged in bankruptcy.

3.3 The Baseline Model: Borrower without Cash Flow Problems

3.3.1 Model Set-up

Assume the house price follows a continuous diffusion process with drift $\mu(V,t)$ and constant proportional volatility σ,

$$\frac{dV}{V} = \mu(V,t)\ dt + \sigma dZ$$

where dZ is an increment of standard Brownian motion.

A borrower (home-buyer) who wants to purchase a house at day zero, but is wealth-constrained, must obtain funds from a bank. Assume the mortgage market is competitive, banks are risk neutral, and the risk-free rate is r. The initial loan-to-value ratio a is determined by the initial financial condition of the borrower as well as his or her credit-worthiness which limits the amount he or she can borrow; here I take a as given. In general, owning a house has consumption value, the utility of living in the house, as well as asset value, the gain (loss) from potential appreciation (depreciation) of the house price. The consumption value could be achieved by renting a house with the money that would otherwise used in house purchase or mortgage repayment; thus for simplicity, a home-owner in this model only cares about the asset value, or to be more specific, the equity value of the house.

A mortgage contract between the borrower and the bank specifies:

A) Maturity T. In this model, I assume $T = \infty$.

B) The principal M, which equals to loan-to-value ratio a times initial house value; that is, $M = aV$

C) A fix-rate repayment schedule C. Fair price of initial mortgage rate would set the value of newly made mortgage debt equal to the principal ($D = M$).

The payoffs to both parties in the case of mortgage default are governed by state foreclosure law. In default, the house would be sold to repay the balance. In a fire sale or costly foreclosure, only a fraction of current house value can typically be recovered; let α denotes this fraction. As discussed in section 3.2, whether the lender has recourse in case of default varies across states; in states that allow deficiency judgement, costs and restrictions differ and affect the ease of obtaining recourse. I model the variation in legal arrangement with a parameter $\beta \in [0, 1]$, which denotes the probability of obtaining recourse. Finally, the borrower also has the option to file personal bankruptcy after default on a mortgage, which can discharge the claim over the shortfall. I denote the probability of bankruptcy after deficiency judgement with $1 - p$; that is, there are chances that the borrower actually pays back the difference.

In the baseline model, I assume the borrower does not have any cash flow problems - he or she can keep serving the mortgage debt as long as he or she wants. The only case in which default happens is when the house value drops too low and continuing to serve the debt is worse than defaulting and facing a possible obligation on the shortfall. Of course, in practice, besides the *strategic default* already mentioned, cases also exist in which the borrower wants to serve the debt because it is best for his or her financial interest, but he or she has cash flow problems and cannot meet the payment. I call the second kind *liquidity default*, and I 'll discuss the full model, taking both types into account, in section 4.

The overall expected payoff of the lender when the borrower defaults on mortgage is

$$\alpha V + \beta p(M - \alpha V)$$

Symmetrically, the boundary payoff for the borrower in default is

$$-\beta p(M - \alpha V)$$

3.3.2 Valuation and Endogenous Default Boundary

Debt Value and Equity Value

As standard in Leland's (1994) framework, when the house value V drops to a boundary V_B, the equity value drops to the continuation value, which equals the payoff in default. The borrower would then declare default on the mortgage. We take this boundary as given for now and will find the endogenous default boundary later.

We consider the value of this mortgage debt, $D(V; V_B)$, which depends on current house price V and the default boundary V_B,. Since the maturity is infinity, debt value is time-independent. As in Leland (1994), the debt value satisfies the following partial derivative equation:

$$rD = rVD_V + \frac{1}{2}\sigma^2 V^2 D_{VV} + C \tag{3.1}$$

where D_V and D_{VV} are the first and second partial derivative of D with respect to V.

The left side of the equation is the required instantaneous return of the bond in a risk-neutral world. And the right side is the instantaneous change of debt value due to the change of the house value V (the first two terms), plus a coupon payment per unit of time.

We know PDE of this form has a general solution in the form of

$$\begin{aligned} D &= A_0 + A_1 V + A_2 V^{-X} \\ X &= \frac{2r}{\sigma^2} \end{aligned} \tag{3.2}$$

Two boundary conditions:

$$\begin{aligned} D(V_B) &= \alpha V + \beta p(M - \alpha V) \\ D(\infty) &= \frac{C}{r} \end{aligned}$$

set the debt value equal to the lender's payoff in default when V hits the default boundary V_B , and equal to the value of the riskless perpetuity with coupon C as V goes toward infinity.

We solve for the coefficients in (2) by plugging in the two boundary conditions and get

$$D(V; V_B) = \frac{C}{r} + [(1 - \beta p)\alpha V_B + \beta p M - \frac{C}{r})(\frac{V}{V_B})^{-X}$$

Consider a claim that pays $(1-\alpha)V$ only in default. Such a claim has the same value as value loss in default, or the bankruptcy cost. The present value of such bankruptcy cost $BC(V;V_B)$ also satisfies equation (1) and has boundary conditions:

$$\begin{aligned} BC(V_B) &= (1-\alpha)V \\ BC(\infty) &= 0 \end{aligned}$$

Thus

$$BC(V;V_B) = (1-\alpha)V_B(\frac{V}{V_B})^{-X}$$

The equity value of the homeowner at any point of time is the current house value minus the bankruptcy cost associated with borrowing, then minus the current value of the mortgage debt. That is

$$\begin{aligned} E(V;V_B) &= V - BC(V;V_B) - D(V;V_B) \\ &= V - \frac{C}{r} + [\frac{C}{r} - (1-\beta p\alpha)V_B - \beta pM](\frac{V}{V_B})^{-X} \end{aligned}$$

Endogenous Default Boundary

Consider the home-buyer's problem. Since he or she cannot commit to not strategically default, and his or her equity value depends on the fair mortgage rate, which in turn depends on the lender's expectation of the home-buyer's default choice. Therefore, in equilibrium, the home-buyer would choose the default boundary that maximizes his or her equity value; this is also fairly expected by the lender.

The first order condition is:

$$\frac{\partial E(V;V_B)}{\partial V_B} = 0$$

we solve for the default boundary V_B :

$$V_B = \frac{X}{(1-\beta p\alpha)(1+X)}(\frac{C}{r} - \beta pM)$$

which does not depend on V.

Plug V_B back into $D(V;V_B)$ and $E(V;V_B)$, and we have the following:

$$\begin{aligned} D(V) &= \frac{C}{r} - (1-\beta p\alpha + X - \alpha X)[\frac{(\frac{C}{r} - \beta pM)}{(1-\beta p\alpha)(1+X)}]^{X+1}(\frac{V}{X})^{-X} \\ E(V) &= V - C/r + (1-\beta p\alpha)[\frac{(\frac{C}{r} - \beta pM)}{(1-\beta p\alpha)(1+X)}]^{X+1}(\frac{V}{X})^{-X} \end{aligned}$$

3.3.3 Results: Recourse, Strategic Default and Mortgage Market

To answer the question of what effect the legal environment has on mortgage default and mortgage market, I first show that the probability of obtaining recourse affects debt value, not only by increasing the lender's or debt holders' payoff in default, but also by influencing strategic default incentives. I then discuss the effect on the mortgage debt market.

The discussion is made under the following set of baseline parameters:

$$\begin{aligned} r &= 3\% \\ \sigma &= 5\% \\ \alpha &= 0.7 \\ p &= 0.5 \\ a &= 80\% \\ V_0 &= 100 \end{aligned}$$

I set the annual risk-free rate r to be 3%, and the annual volatility of house prices σ to be 5%, which is consistent with empirical facts. Proportion of value recovered in fire sale or foreclosure α is set as 0.7; this is consistent with the estimation made by Campbell, Giglio and Pathak (2009), who find foreclosure reduces the value of the home by approximately 28%. I let the probability of personal bankruptcy after deficiency judgment p to be 0.5, initial loan to value ratio a to be 80%, and initial value of a house V_0 to be 100. Thus the initial mortgage loan balance M is 80 and the book value of equity is 20.

Fix-rate coupon C is such that the initial debt value is at par. I choose the smallest positive real root of equation $D(V_0; C) = M$ to be C. Initial mortgage rate, the one in the mortgage contract, is calculated as $R = \frac{C}{M}$; mortgage yield, the bond yield in the second market, is calculated as $y = \frac{C}{D(V)}$, which changes with the house value.

Negative Equity, Strategic Default, and Foreclosure Law

The recent housing crisis has attracted the attention of many economists trying to understand home-owners' mortgage default decisions. Among other works, Guiso, Sapienza, and Zingales (2009) study survey data and find that no household would default if the equity shortfall is less than 10% of the house value; 17% of households would default, even if the home-owners can afford to pay their mortgage, if the equity shortfall reaches 50% of their house value. Many people are puzzled by so few home-owners defaulting when the value of their house is less than the mortgage balance because it contradicts the economic rationale. Guiso, Sapienza and Zingales (2009) explain this outcome as arising from moral and social constraints. I argue that transaction costs, which include moving costs, sentimental attachment to the house, reputation issues, and moral concerns, and so forth, are important in practice; however, it may not be necessary to turn to transaction costs to explain the low number of defaults on negative equity houses. Several points exist that may give more power to the "ruthless" economic theory.

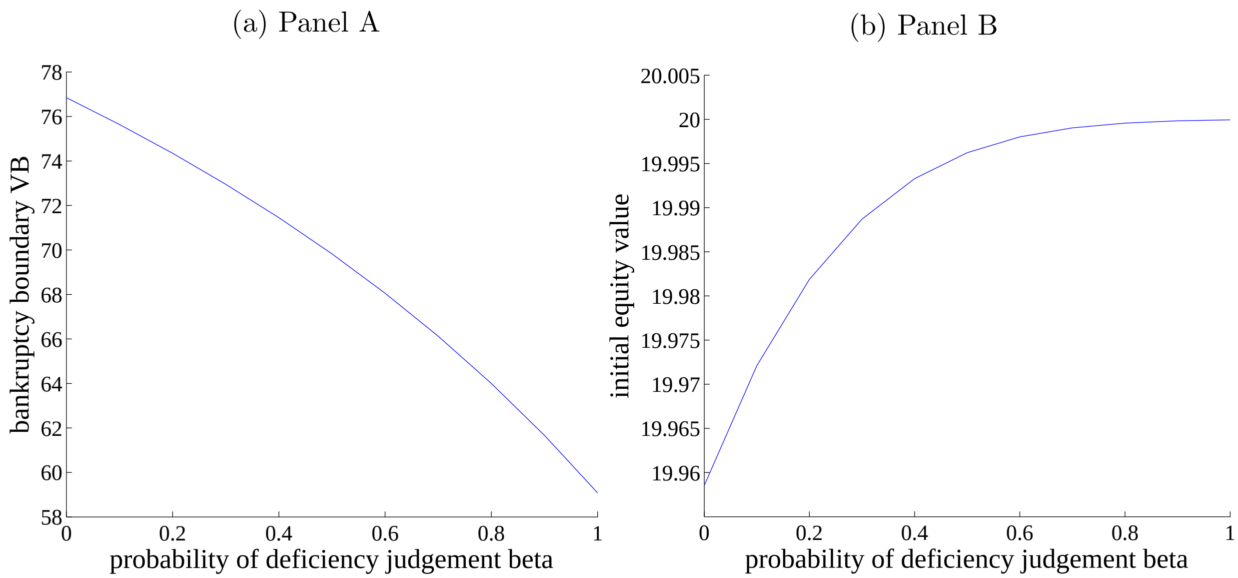
First, the economic value of equity may disagree with the book value of equity, which is typically used in empirical works. Economic value of equity is larger than book value, since it contains the option value of default later. Or from another perspective, equity value equals house value less debt value and the present value of bankruptcy cost; when house price falls, debt value would be significantly reduced from par value. Thus, when the book value of house equity drops to zero, economic value could still be positive. Similar arguments are made by Foote, Gerardi, Paul, and Willen (2008).

Second, when a lender could possibly obtain recourse over the difference between debt balance and proceeding, the alternative value of default is the probability of obtaining recourse times the shortfall of the amount owned, which is no longer zero. In other words, violation of limited obligation makes the alternative choice of default worse; thus, the equity value at which the borrower would choose to default falls accordingly. The greater the probability that deficiency judgment will be achieved, the worse the payoff to borrower in default, and thus the more effective deterrent role that foreclosure law plays.

Figure 3.1 illustrates the effect of legal environment on a borrower's default incentive. Panel A shows the default boundary falling from 77, which is close to the book value of 80, to 59, as the probability of obtaining a deficiency judgment increases from 0 to 1. Panel B plots the initial value of equity when house value V=100; when the probability of obtaining a deficiency judgment is high (close to 1), the house equity is almost equal to the book value, and there is almost no loss of value due to potential bankruptcy. This is consistent with the empirical results of Ghent and Kudlyak (2009) who find that at the mean value of the default option at the time of default, the probability of default is 20% higher in non-recourse states than in recourse states.

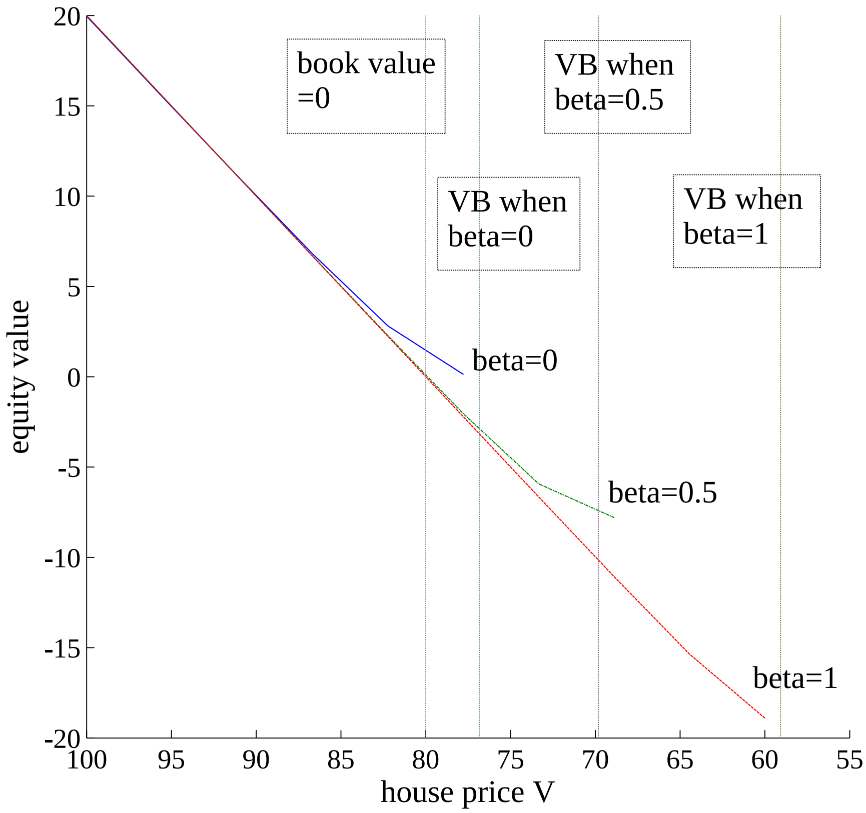
The relationship between house equity value and strategic default is more clearly illustrated in Figure 3.2. As the house price falls from 100 to 60, the house equity value falls

Figure 3.1: Default Boundary, House Equity Value and Recourse.



accordingly. The four vertical lines plot the default boundary when the book value of equity and the economic value are considered, while the probability of obtaining a deficiency judgment β equals 0, 0.5 and 1, respectively. First, when the book value of equity drops to zero (i.e. $V = 80$), the value of equity is above zero when $\beta = 0$, although the difference is not large, which suggests that book value of equity is not a bad proxy when mortgage debt is non-recourse. However, when the probability of obtaining a deficiency judgment increases to 0.5 and 1, the equity values at which default happens are about -40% and -100% of book equity. This may help to explain why many people keep serving the debt while (the book value of) house equity is significantly negative, without turning to transaction costs.

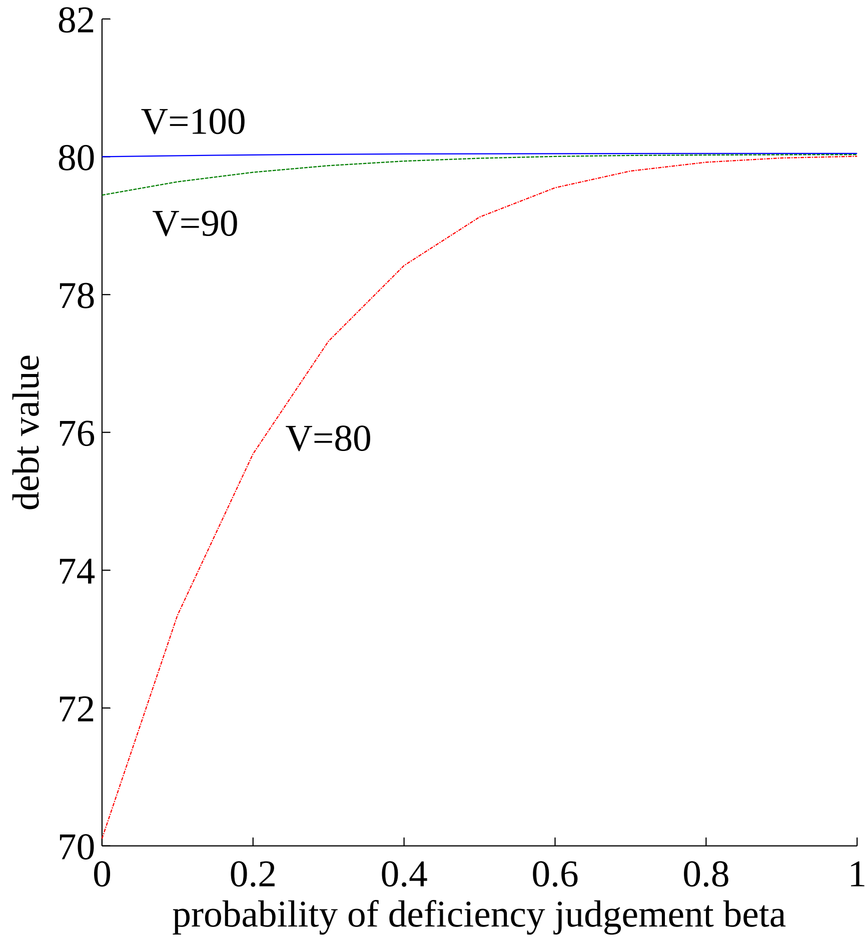
Figure 3.2: House Equity Value When House Price Falls



Mortgage Debt Market and Foreclosure Law

Home-owners' default decisions directly affect the mortgage debt market, which is in turn closely related to foreclosure law. Figure 3.3 shows how debt value changes under a different legal environment when a house price falls. On the left side, where mortgage debt is non-recourse, debt value is sensitive to changes in house price - debt value decreases 12.5% in response to a 20% drop in house price, when initial loan-to-value ratio(LTV) is 80% as specified above. In contrast, on the right side, where mortgage debt has full recourse, debt value is almost unaffected by the fluctuation in house price.

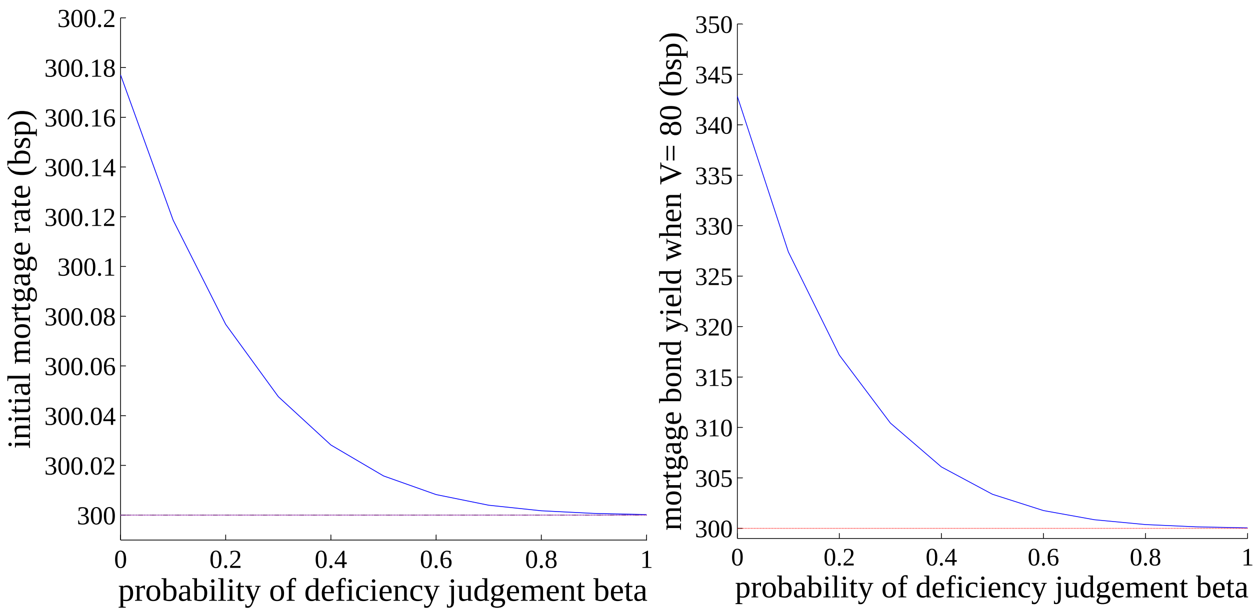
Figure 3.3: Debt Value When House Price Falls.



Foreclosure law affects payoffs and strategic default incentives ex post, as well as the expectation of default ex ante. Figure 3.4 plots the ex ante mortgage rate, which sets the initial debt value to book value, and the ex post mortgage yield when V=80 against β. Note that the spread over risk-free rate is small in both cases. This is because the model assumes infinite maturity, thus the present value is very sensitive to change in discount rate. A very slight change in mortgage rate would result in a large variation of debt value. Nevertheless, mortgage rate and mortgage yield are qualitatively more volatile when mortgage debt is non-recourse.

Figure 3.4: Initial Mortgage Rate, Mortgage Yield, and Recourse.

(a) Panel A (b) Panel B



3.4 Full Model: Borrower with Cash Flow Problems

3.4.1 Model Modification and Valuation

The weakness of the baseline model is that it cannot explain heterogeneity in mortgage default when the legal environment is the same. It is also not very realistic that the only source of default is strategic: many defaults occur when the borrowers experience adverse events that cause cash flow problems, such as divorce, unemployment, or illness. Thus I introduce an exogenous liquidity shock in this full model. This shock addresses the other kind of default, liquidity default, in which the borrower wants to continue serving the debt in his or her financial interest, but has to default because he or she cannot meet the payment for cash flow reasons. This liquidity shock can be interpreted as reflecting heterogeneous characteristics of the borrower because it depends on personal income, creditability, and so forth. It can also be interpreted on an aggregate level as changes in the economic situation.

I model this liquidity shock with parameter $l \in [0, 1]$, the arrival rate of the liquidity shock that causes the borrower fail to keep making mortgage payment. All other conditions are as specified in the model set-up in section 3.3. I solve the equity value directly by solving

$$rE = rVE_V + \frac{1}{2}\sigma^2 V^2 E_{VV} - C - l[E - \max(\alpha V - M, 0) - \beta p \max(M - \alpha V, 0)]$$

The left side is the required instantaneous return of the equity in a risk-neutral world. On the right side, the first two terms are the instantaneous change of equity value due to the change of house value V, the third term is coupon payment per unit of time, and the fourth term is the instantaneous expected value loss to a home-owner due to liquidity shock. When the liquidation value αV is greater than balance M, the payoff to the home owner in liquidity default is $\alpha V - M$; when the liquidation value αV is less than balance M, the payoff to the home owner is the possible claim over the shortfall $\beta p(M - \alpha V)$; and the expected loss is the difference between the current equity value and the terminal payoff times the arrival rate l.

Boundary conditions are:

$$
\begin{aligned}
E(V_B;V_B) &= -\beta p(M-\alpha V) \\
E(V;V_B)\,|_{V\to\infty} &= V-\frac{C}{r} \\
\text{where } V_B &= \arg\max_{V_b} E(V;V_b)
\end{aligned}
$$

Symmetrically, debt value satisfies the equation:

$$
rD = rVD_V + \frac{1}{2}\sigma^2 V^2 D_{VV} + C - l[D - \min(M, \alpha V + \beta p \max(M-\alpha V, 0)]
$$

The last term on the right side indicates that the expected loss due to liquidity shock is l times the difference between current debt value D and the the terminal payoff in liquidity default; that is M when $M < \alpha V$, and $\alpha V + \beta p(M-\alpha V)$ when $M > \alpha V$. Boundary conditions are

$$
\begin{aligned}
D(V_B) &= \alpha V + \beta p(M-\alpha V) \\
D(\infty) &= \frac{C}{r}
\end{aligned}
$$

I solve this model numerically, under the baseline parameter values as previously specified.

3.4.2 Results: Recourse, Liquidity Shock and Mortgage Default

In this section I discuss the effect of a liquidity shock on mortgage default incentive and mortgage market under different legal environments. The unexpected feature means the liquidity shock is not priced in the coupon payment, and it captures an unexpected change in the home-owner's financial condition. Several interpretations are possible. First, a liquidity shock can be interpreted as an unexpected deterioration of an individual's situation, which is independent across borrowers. As emphasized in Capozza, Kazarian, and Thomson (1997), adverse events such as divorce, illness, and unemployment play important roles in mortgage default. Second, a liquidity shock can also be interpreted as an unexpected economic downturn, such as the current financial crisis, in which unemployment rate surges, asset prices plunge, and the current and expected future cash flows of all individuals in the economy are adversely affected.

Figure 3.5 plots the relationship between default boundary V_B and probability of deficiency judgment β under different arrival rates of liquidity shock l. The plot clearly shows that liquidity shock increases mortgage default rate, not only because it affects borrowers' ability to pay, but less evidently, because it also affects borrowers' incentive to pay. As the arrival rate increases, it is less attractive for a borrower to keep serving the debt. Since the continuation value decreases, it is more likely in the future that a liquidity shock would occur in which case the borrower has to bear the loss in liquidity default. He or she would thus default at a house value at which she would not have before. And this strategic default incentive is exacerbated by lack of recourse - the lower the probability of obtaining a deficiency judgment, the higher the default boundary.

Figure 3.5: Default Boundary in Presence of Liquidity Shock.

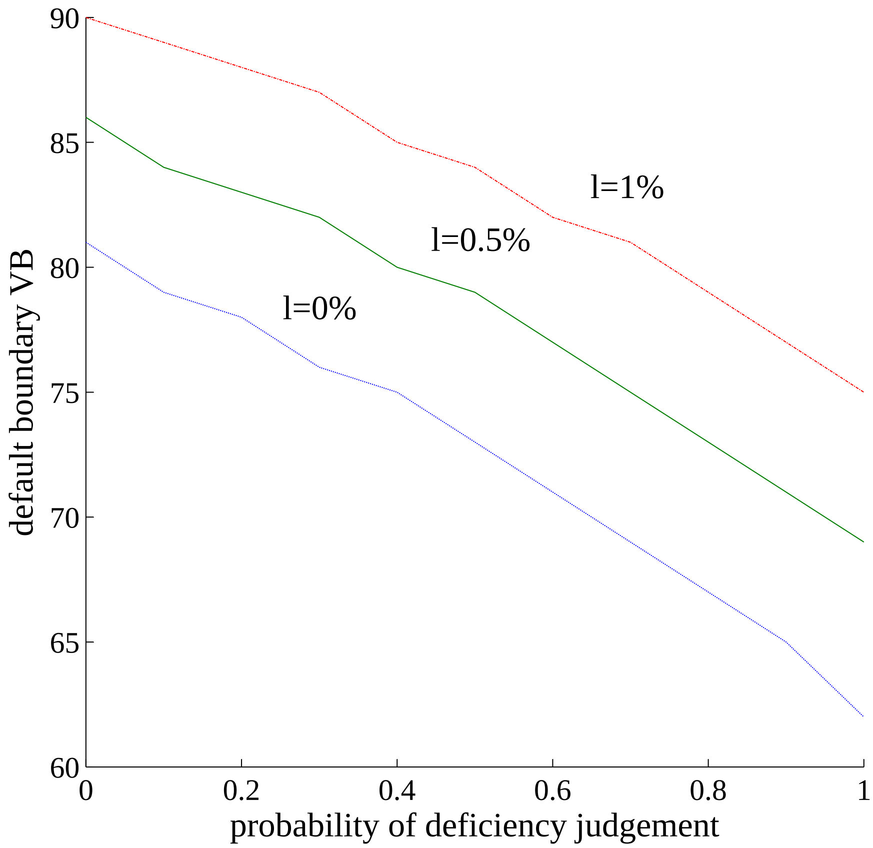
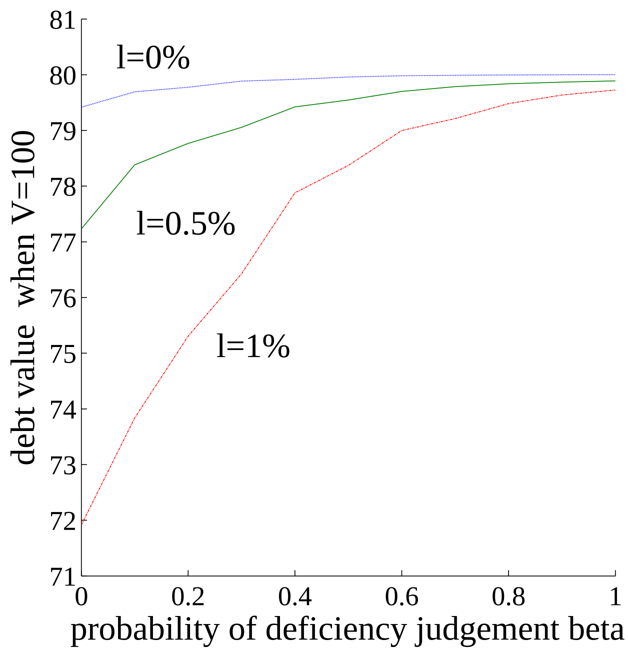


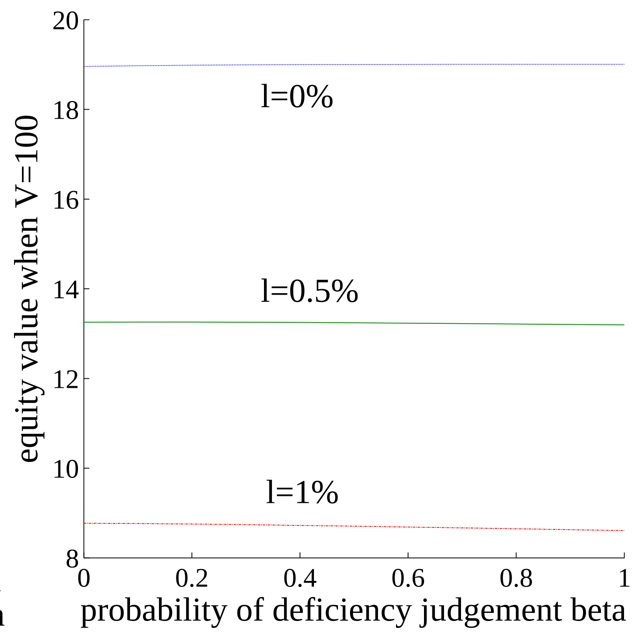
Figure 3.6 plots the debt and equity value when V=100. Panel A shows that debt value is very sensitive to liquidity shock when β is small, while it is almost unaffected when β is large. In contrast, as shown in panel B, β has little impact on equity value under any of the three scenarios. This suggests that greater recourse could help increase debt value by deterring strategic default and avoiding bankruptcy cost, while also not decreasing a home-owner's value too much.

Figure 3.6: Debt Value and Equity Value in Presence of Liquidity Shock When V=100.

(a) Panel A

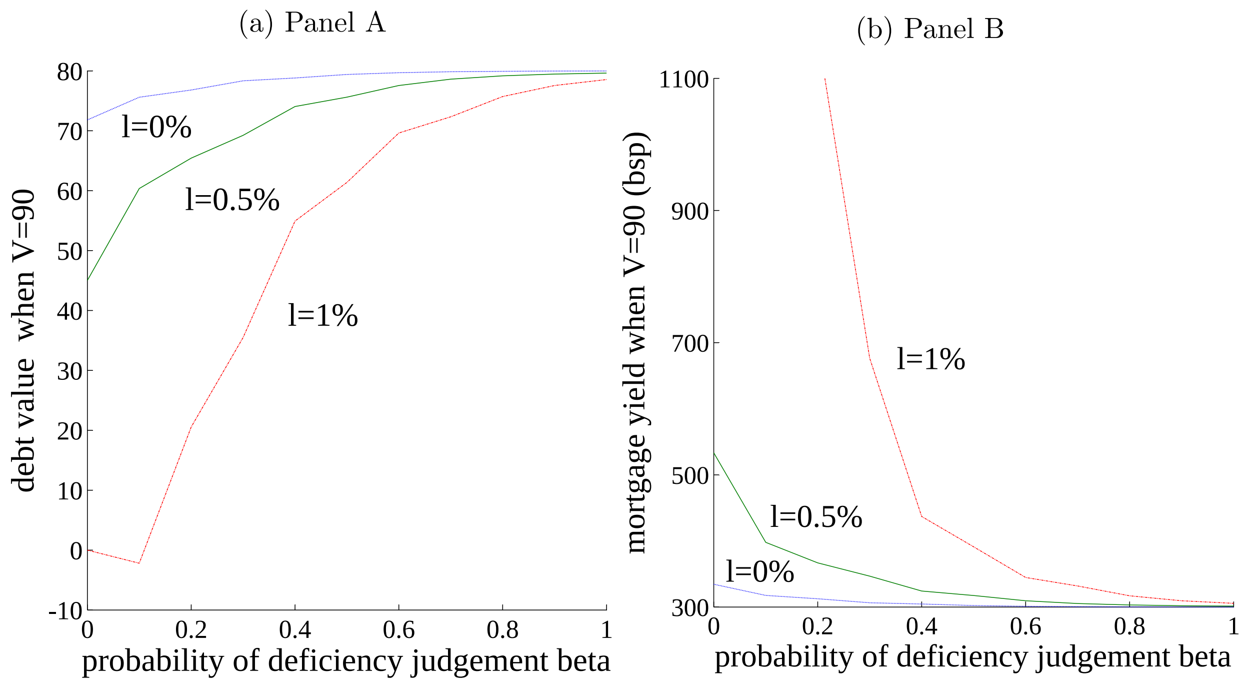


(b) Panel B



Mortgage bond values are adversely affected in recessions in which people have more cash flow problems, and the mortgage bond spread widens. The 2008 financial crisis showed the mortgage spread surged to a historical high. Figure 3.7 plots the debt value and mortgage bond yield when $V = 90$, a 10% drop in house price. When mortgage debt is non-recourse, debt value could be largely affected by changes in the house price, in the presence of liquidity shock, and mortgage bond market could be very volatile. In contrast, full recourse makes debt value immune to changes in the house price even when liquidity shock is relatively high.

Figure 3.7: Debt Value and Mortgage Yield in Presence of Liquidity Shock When V=90.



3.5 Policy Implications and Conclusions

One important policy question in the most recent housing crisis is how to reduce foreclosure. As reported in many recent empirical studies, strategic default has become a severe problem because house prices have fallen in the last few years by 40 to 50 percent in some areas. Many borrowers had put very little down when they bought their houses, which is historically a rare case. Thus a policy that aims at alleviating the situation should effectively address the default incentive issues.

The two common loss mitigation policies are modification and forbearance. Modification involves permanent changes in the original terms on the loan, while forbearance allows the lender to temporarily forebear the low payment or late payment, without changing the initial terms. Under the framework of this model, the modification may help those who are experiencing cash flow problems, but it does not work for strategic defaults because it does not affect default incentives. This explain the concern of Adelino, Gerardi and Willen (2009) about re-default issues. On the other hand, forbearance would mitigate the situation becuase it reduces liquidity defaults. More importantly, however, it can increase the continuation value of serving the debt by decreasing the probability that a liquidity shock occurs and the borrower has to default; thus strategic default boundary should fall as well.

This paper analyzes the strategic default problem using an option-based model, and shows that recourse can play an effective role in deterring default when a house price falls or the economic situation goes bad. It reduces strategic default by diminishing the payoff in default, thus it makes continuing to serve the debt the more economical choice. In addition to popular policies, this paper suggests that recourse might be another possible solution to the default problem. The caveat is that, deterring defaults will adversely affect the welfare of home-buyers who are in really bad situations; to make a feasible policy, home-buyers need to be compensated through other channels, which needs further studies in the future.

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