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Essays on the Disposition Effect and Asset Prices

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ABSTRACT

This dissertation is comprised of two essays that focus on the role of disposition effect to market reactions in seasoned equity offerings and the importance of considering the dynamics of reference price in disposition effect.

The first essay investigates the association between the disposition effect and the stock price reaction to announcements of seasoned equity offers (SEOs). I find that SEO issuing firms in which investors have greater unrealized capital gains exhibit a more severe SEO announcement reaction. This result is consistent with the well-known disposition effect, whereby investors tend to sell stocks in which they have unrealized capital gains and hold stocks with unrealized losses. I also find supporting evidence that investors' behavioral biases contribute more to SEO announcement reactions for firms with lower institutional ownership. The results suggest that the disposition effect can influence SEO announcement reactions.

In the second essay I study the disposition effect using highest price as a reference point. Recent literature shows that investors' selling propensity is V-shaped with respect to unrealized profits, challenging the predicted monotonic relationship. I find that such monotonic relationship exists between the selling propensity and the perceived return when gains and losses are measured relative to a new reference point: the highest price experienced by the investor since purchase. I find consistent evidence when using the highest price in the past 52 weeks as a reference point. Further evidence shows that stocks with higher perceived returns subsequently underperform. Overall, my findings suggest that accounting for the dynamics of the reference point in measuring perceived trading profits is crucial for understanding the disposition effect, and that the highest-price-based disposition effect may be driven by informed trading.

CHAPTER 1

CAN THE DISPOSITION EFFECT EXPLAIN THE MARKET REACTION TO SEO ANNOUNCEMENTS?

1.1 Introduction

Investors are often quick to sell stocks for a profit but are reluctant to sell shares at a loss. This behavioral tendency to sell winning investments too early and hold losing investments too long is referred to as the "disposition effect," first described by Shefrin and Statman (1985) and developed from the foundation set by Kahneman and Tversky's (1979) prospect theory and Thaler's (1985) work on mental accounting. Empirical support is offered by Odean (1998), who studies brokerage trading accounts and reports investors' preference for realizing winners as opposed to losers.

This study investigates whether the disposition effect impacts the stock price reaction to announcements of seasoned equity offers (SEOs). I argue that SEO firms in which investors have a high degree of unrealized capital gains will tend to sell off more sharply around the SEO announcement, as investors try to lock in gains on their winners before a further stock price correction. As a result I should observe more negative SEO announcement reactions for stocks with high unrealized capital gains. In contrast, SEO firms associated with unrealized capital losses are less likely to sell off as strongly as investors in these stocks are more willing to hold their losing positions, resulting in less negative announcement reactions. I expect that this disposition-induced SEO announcement is stronger among firms with greater retail ownership as these investors are more prone to the disposition effect.

I test whether the disposition effect influences SEO announcement reactions by constructing a variable that measures unrealized capital gains. In particular, I estimate Grinblatt and Han's (2005) measure of capital gains overhang (CGO). Across all CRSP firms during my sample period, 85% of SEO announcing firms have unrealized capital gains (positive CGO), while about 55% of all CRSP firms have unrealized capital gains. This evidence makes sense given the often favorable stock performance leading up to SEOs.

I find evidence that the disposition effect influences the market reaction to SEO announcements. In multivariate estimations that explain the SEO announcement effect, defined as the three-day cumulative abnormal return centered on the announcement date, I find that the variable CGO has a negative and significant coefficient indicating more negative SEO reactions for stocks with more unrealized capital gains. After controlling for a host of variables including prior stock performance (which is related to but different than CGO), a one standard deviation increase in the value of CGO is associated with a 0.20 percentage point decrease in the announcement effect. This represents over 6% of the unconditional average SEO announcement reaction. This effect is primarily driven by positive CGO values suggesting that it is driven by the tendency for investors to sell their winners. Moreover, in the presence of high institutional ownership, the variable CGO has no influence on SEO reactions indicating that more retail-oriented stocks drive the effect.

Next, I consider recent evidence that investors also sell extreme winners and losers. Ben-David and Hirshleifer (2012), Hartzmark (2015), and An (2015) find that investors with extreme unrealized capital gains or losses tend to sell their stocks sooner, thus exhibiting a v-shaped disposition effect. If there is strong evidence of extreme behavior in the disposition effect in SEO stocks, investors will sell stocks with extreme unrealized capital gains *and* losses and I would expect to observe a more negative SEO announcement reaction at either extreme. In this case, investors with extreme unrealized capital gains or losses would be under a high selling pressure upon the announcement. Thus, there would be excessively negative reactions to the SEO announcement. I find no evidence that extreme losers experience more negative announcement reactions.

Finally, I test for a post-announcement reversal, and are particularly interested in high CGO firms, given that these firms are the ones that sell off more sharply. I indeed find that the more severe selloff at the announcement precedes a significantly positive stock price effect in the week after the SEO announcement, all else equal. This supports the idea that the larger SEO announcement effect for high CGO firms is a disposition-induced overreaction, and leads to a subsequent correction.

This study is one of few that focuses on the connection between the disposition effect and the market reaction to corporate events. Kaustia (2004) finds that when a stock trades below its IPO price, turnover is significantly lower and increases on the day it trades above the IPO price for the first time. Frazzini (2006) finds evidence that the disposition effect drives an underreaction to news and results in post earnings announcement drift. He finds that negative earnings news leads to stronger negative post-announcement drift when investors have greater capital losses. Choi, Hoyem, and Kim (2010) argue that the disposition effect is associated with high returns for stocks that experience abnormally high trading volume around earnings announcements. Marciukaityte and Szewczyk (2012) find evidence of greater discounting in pure secondary offerings, and argue that the results suggest that the increased supply of winning stocks due to disposition behavior depresses the stock price.

My analysis differs from the prior literature by examining the influence of the disposition effect on market reaction to seasoned equity offering announcements. While numerous studies over the past several decades examine the determinants of SEO announcement effects, no study has examined the disposition effect as a factor that could influence the SEO announcement effect. Although the negative reaction to SEO announcements is well-known (e.g. Asquith and Mullins 1986), only recently have studies began to consider the effect of behavioral biases on announcement reactions. My findings contribute to the SEO announcement literature by showing that behavior biases can influence the reactions to this news.

1.2 Sample and Variables

The sample consists of seasoned equity offers from the Securities Data Company (SDC) Global New Issues database that were announced in January 1970–January 2017. I obtain firm stock information from the CRSP daily stock database and firm accounting information from the COMPUSTAT North America annual database. I compute CGO from the CRSP daily stock data.

1.2.1 SEO sample and descriptive statistics

Following earlier studies, I collect the sample of U.S. common stock offerings that are announced during January 1970 – January 2017, excluding initial public offerings, rights offers, units offers, private placements, and offerings by non-U.S. firms. I exclude units and non-U.S. offers by restricting sample firms be common stocks (CRSP share codes of 10 and 11). I also exclude offers by financials (SIC codes 6000 – 6999) and utilities (SIC codes 4910 – 4940), and those that are not listed on the NYSE, AMEX, or Nasdaq.[1] This results in a sample of 11,683 offers.

To be included in the sample, a firm must issue some primary shares, have at least 30 trading days of prior volume and return data available on CRSP from the offer date, have offer prices of at least $5.00 and less than $400.00, and have no stock split occurred during the 11-day window around the offer date. These restrictions eliminate 2523, 26, 1151, and 85 offers, respectively. Next, I exclude firms that do not have enough CRSP data to estimate the measure of unrealized capital gains (Section 1.2.3 provides details). This results in a final sample of 7,224 seasoned equity offers.

My final sample includes both accelerated offers and marketed offers. I flag shelf-registered, accelerated, and overnight offers. There are 1,718 shelf-registered offers reported in the SDC database, 1,781 accelerated offers, and 545 overnight offers. Accelerated offers are offers where the announcement date and issue date are separated by two or fewer days. Overnight offers are a subset of accelerated offers in which the announcement date is the same as issue date. I define the announcement date as the date on which the firm publicly announces its upcoming offer. For both non-shelf and shelf offers, I follow prior literature and use the SDC launch date as the announcement date.[2]

To correctly identify the SEO offer date, following Safieddine and Wilhelm (1996) and others, I apply a volume-based offer date correction. If trading volume on the day following the SDC offer date is (1) more than twice the trading volume on the SDC offer date and (2) more

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[1] SIC codes are obtained from CRSP. I delete sample offers if SIC codes, stock price, and shares outstanding on the offer date are missing.

[2] Bortolotti, Megginson, and Smart (2008) find that dates on Lexis/Nexis almost always fall within one or two days of the SDC launch date and conclude that a narrow window (-1,+1) centered at launch date accurately captures the announcement date.

than twice the average daily volume over the prior 250 trading days, then the day following the SDC offer date is assigned as the offer date. This correction results in an offer-date change for 42.8% of the initial sample offers collected from SDC.

Table 1 reports descriptive statistics for firm and offer characteristics. Detailed explanations on variables are provided in the Appendix. The average sample issuer has a market value of $1.2 billion before the announcement, a market-to-book ratio of 2.48, and a residual stock volatility of 4%. The average offer raises about $98.5 million in proceeds and the ratio of shares offered to shares outstanding before the announcement equals 0.19. The average leverage equals 0.27, and the average issuer exhibits a buy-and-hold return of 71% in the 12 months before the SEO announcement. Consistent with previous literature (e.g. Asquith and Mullins 1986; Jung, Kim, and Stulz 1996), I observe that firms experience a significant stock price run-up before the SEO announcement. About one-seventh of the shares offered in the sample offer are sold by existing shareholders.

Table 2 presents the correlations between the main variables. The capital gains overhang variable and prior 12 month buy-and-hold abnormal return (prior-1year BHAR) are positively correlated; the market value of the firm (Mktcap) is highly positively correlated with offer proceeds and negatively correlated with the relative offer size; the market-to-book ratio is positively correlated with the residual volatility and negatively correlated with the leverage.

1.2.2 SEO announcement effect

I measure cumulative abnormal returns (CARs) around the announcement date over the 3-day-window, days (–1, +1). I use a market model approach with the CRSP value-weighted index returns as a proxy for market return. The estimation period is from –180 to –11 trading days before the SEO announcement date, where the launch date from the SDC database equals the announcement date. The cumulative abnormal return is the excess return of the estimated alpha and beta times the market return. Descriptive statistics on three-day CAR are presented in Table 1 and the mean value of a CAR is -3.16%, statistically significant. I also compute two-day CAR, days (0, +1) and the mean value is -2.91%. These average CAR values are similar to -2% to -3% often reported for U.S. SEOs in previous research.[3]

1.2.3 Capital gains overhang (CGO)

1.2.3.1 CGO variable construction

For each stock, I measure the aggregate unrealized gains at each month end following Grinblatt and Han (2005), and several others (An 2015; Bhootra and Hur 2015).[4] I refer to the measure of the aggregate unrealized gains as CGO. It is the percentage deviation of reference price from its current price, where reference price is a volume-weighted average of past stock price.

I compute the CGO variable and reference price RP_t at the end of each month from December 1969 to December 2016 as follows:

$$CGO_t = (P_t - RP_t)/P_t \tag{1}$$

$$RP_t = \frac{1}{k}\sum_{n=1}^{T}\left(V_{t-n}\prod_{i=1}^{n-1}[1 - V_{t-n+i}]\right)P_{t-n} \tag{2}$$

[3] For a two-day window, days (0, +1), Asquith and Mullins (1986) find an abnormal return for primary stock issues for industrial firms of -3% and Jung, Kim, and Stulz (1996) find an abnormal return for primary stock issues of -2.7%. Kim and Purnanandam (2014) find an abnormal return of -1.97% and Ferreira and Laux (2016) find an abnormal return of -1.8%.

[4] Grinblatt and Han (2005) estimate CGO on a weekly basis; An (2015) estimates gain and loss overhangs separately using daily data on a monthly basis; Bhootra and Hur (2015) estimate CGO using daily data on a monthly basis.

where V_{t-n} is the stock turnover ratio at time t – n and P_{t-n} is the stock price at time t – n. The term in parentheses multiplying P_{t-n} is a weight. The weight on P_{t-n} is the probability of stock purchased at day t – n and not traded since then.

Following Grinblatt and Han (2005), I limit my estimation period to three years and rescale the weights of all trading days to sum to one.[5] In equation (1) and (2), k is a constant that normalizes the weights such that $k = \sum_{n=1}^{T} V_{t-n} \prod_{i=1}^{n-1} [1 - V_{t-n+i}]$, where T is the number of trading days in the past three years. If data are available for less than three years, I use the data during the period available. I adjust for stock splits and dividends in my computation.

In my analysis I define t as the end of the month when the SEO announcement occurs for the next month period. My final SEO sample includes the CGO variable measured at the month-end prior to the SEO announcement. Descriptive statistics for CGO are presented in Table 1. The average sample firm has an unrealized capital gain of 16%. There are 6197 offers with unrealized capital gains, in which CGO is positive, and 1027 offers with unrealized losses, in which CGO is negative, in the month-end prior to SEO announcement.

1.2.3.2. CGO and stock performance before the SEO announcement

Prior work has well described that SEO firms tend to have a stock price run-up before the announcement. I examine stock performance before the announcement for seasoned equity offers. I find that both past 12 month buy-and-hold abnormal returns and buy-and-hold stock returns are significantly positive. SEO firms tend to perform well before they make an announcement, implying that the majority SEO firms are past winners. If most of SEO firms are

[5] Grinblatt and Han (2005) define reference price over an infinite horizon period; however, they find robust results using three, five, or seven years of data in the estimation period. Prior literature uses either a three- or five-year period for estimation and finds robust results using vice-versa.

past winners, then I may expect most of SEO firms to have unrealized capital gains. I compare the percentage of offers with positive CGO estimated at the end of month prior to the announcement in my SEO sample and for all CRSP firms during my sample period. I find that 85% of the SEO firms have unrealized capital gains (positive CGO) and for all CRSP firms, about 55% have unrealized capital gains, which is less than in the SEO sample. If investors holding stocks of SEO firms exhibit the behavior of the disposition effect, I expect to observe a more negative SEO announcement reaction for firms with higher CGO.

1.2.4 Control variables

Previous research has documented the causes of negative market reactions to SEO announcements. The main causes to consider can be classified into two broad categories: information asymmetry leading to adverse selection problem and firm characteristics leading to the agency problem.[6] I follow earlier studies and select control variables to proxy for these two categories.

To proxy for asymmetric information, I include firm size (Mktcap) measured by the stock market value on the day before the announcement, and stock residual volatility (Volatility). Large firms generally are more likely to be followed by analysts and have more media attention, resulting in less information asymmetry. Thus, I expect the firm size to be positively related to announcement returns. Investors face high uncertainty when firm stocks are more volatile. The stock residual volatility (Volatility) has been used as a measure of firm-specific information asymmetry (e.g. Bhagat, Marr, and Thompson 1985; Kim and Purnanandam 2014). To compute

[6] Myers and Majluf (1984) argue that seasoned equity offerings are considered as the negative signal due to information asymmetry among managers and investors and could lead to an adverse selection problem. Jung, Kim, and Stulz (1996) and Kim and Prananandum (2014) argue that investors may react negatively due to the agency problem.

this measure, I regress daily stock return on the CRSP value-weighted market index return over 250 trading days ending two trading days before the SEO announcement. I take the standard deviation of the residuals as a proxy for information asymmetry. I expect a negative relation between residual volatility and announcement returns. I also estimate the residual volatility using returns over 250 trading days ending 20 trading days before the announcement as in Jung et al. (1996) and find similar results.

Proxies for investment opportunities and agency problems include the market-to-book ratio (MTB), past excess return (prior-1year BHAR), and financial leverage (leverage). The market-to-book ratio (MTB) is widely used as a proxy for growth opportunities (e.g. Denis 1994; Jung, Kim, and Stulz 1996; Kim and Purnanandam 2014). Jung, Kim, and Stulz (1996) argue that firms with high-growth opportunities are less likely to waste proceeds from SEO in negative NPV projects. Thus, I expect to have a positive relation between market-to-book ratio and market reaction to the SEO announcement. Lucas and McDonald (1990) and Jung et al. (1996) use firms' past excess returns as a proxy for the availability of good projects. I measure buy-and-hold abnormal returns (prior-1year BHAR) as in Asquith and Mullins (1986) and Jung et al. over 12 months (instead of 11 months) to 20 trading days before the SEO announcement. Financial leverage is the sum of long- and short-term debt divided by the book value of total assets. Jensen (1986) and Stulz (1990) argue that leverage limits management's discretion and reduces the agency problem, implying that managers of highly levered firms are less likely to misuse raised funds.

I also control for offer characteristics: offer size (proceeds and relative offer size), and secondary shares (secondary). Offer size measures an economy of scale effect (Smith 1977), implying a positive relation between offer size and excess returns. However, there have been mixed results in prior empirical literature (Asquith and Mullins 1986; Mikkelson and Partch 1985). I use both relative offer size and an offer size filed in the SDC as proceeds in millions in my empirical tests. Relative offer size is defined as the ratio of number of shares offered to number of shares outstanding on the day before the announcement. Offer size is reported as proceeds in million $ in the SDC, and I use the natural log of proceeds in my empirical tests. Insiders making secondary offers in SEOs may be selling on private information, and any adverse selection effect may be exaggerated (Brav, Gezcy, and Gompers 2000). Other authors, such as Kim and Purnanandam (2014), reason that secondary offerings are indicative of agency costs. Following prior work, I add the proportion of secondary shares offered relative to total shares offered (Secondary) as a control variable.

1.3 Main Results

In this section, I present the main results. My tests focus on the association between the disposition effect and the market reaction to SEO announcements, the impact of disposition effect in the presence of high institutional ownership, and a post-announcement reversal.

1.3.1 Disposition effect and reaction to SEO announcements

1.3.1.1 Univariate results

In this section, I examine whether market reactions to SEO announcements can be explained by CGO. Table 3 presents the mean and median around SEO announcements across deciles of CGO. We measure the value of CGO in the month prior to the SEO announcement month. Reactions tend to be more negative for the high CGO deciles consistent with my hypothesis that SEO firms in which investors have larger unrealized capital gains experience more negative announcement reactions to SEOs.

1.3.1.2 Multivariate results

I further investigate the association between CGO and market reactions to SEO announcements by specifying ordinary least-squares (OLS) estimations that explain SEO announcement reactions. The regression is specified as

$$\mathrm{CAR}(-1,+1)_i = \alpha + \beta \mathrm{CGO}_i + \gamma \mathbf{Z}_i + \theta \mathrm{Year}_t + \zeta \mathrm{Industry}_j + \varepsilon \qquad (3)$$

where CAR(-1,+1) is a 3-day CAR centered on the SEO announcement date and *i* represents each SEO issuance. My variable of interest is the CGO and the vector Z represents several control variables that are well-known determinants of SEO announcement reactions. I also control for year and industry fixed effects where *t* represents the announcement year and *j* represents the Fama–French 48 industry classification.

Table 4 presents estimations to examine the impact of capital gains overhang on the announcement reaction with the inclusion of control variables. Each model displays robust standard errors (in parentheses) clustered by industry. In Model (1), the key explanatory variable is the CGO, the aggregate unrealized capital gains. In Model (2) I replace the CGO with two variables: Positive CGO and Negative CGO. The Positive CGO equals the CGO if it is positive and is zero otherwise. The Negative CGO equals the CGO if it is negative and is zero otherwise. The coefficient estimates separate the influences of positive and negative CGO values on the SEO announcement effect.

In Model (1), consistent with my hypothesis, I find a significant negative association between the CGO and SEO announcement reactions indicating that SEOs by firms in which investors have more unrealized capital gains are associated with more negative SEO reactions. In economic terms, a one-standard-deviation increase in the value of CGO decreases the SEO announcement effect by 0.20 percentage points (which represents over 6% of the average announcement reaction). In Model (2), I observe that the negative association to SEO announcement reactions is predominantly driven by Positive CGO, which implies that the effect we capture is due primarily to investors' tendency to sell the winners early. For example, a one standard deviation increase in the value of Positive CGO is in association with a 0.24 percentage points decrease in the announcement effect. This represents over 7% of unconditional average SEO announcement reaction.

The coefficients of control variables remain similar and consistent to prior literature across the specified models in Table 4. I observe that the offer size (proceeds) and leverage are positively related to the SEO announcement reaction and that the firm size (mktcap), residual volatility (volatility), relative offer size, and proportion of secondary shares offered (secondary) are all negatively related to the SEO announcement reaction.[7] The prior 12-month buy-and-hold abnormal return (prior 1-year BHAR) remains insignificant as it correlates with the CGO.

After controlling for firm and offer characteristics, I find that the disposition effect significantly explains the negative reaction to the SEO announcement. This effect is primarily driven by the investor-tendency to sell winner stocks early.[8]

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[7] For firm size, I observe the opposite relation to the SEO announcement reaction than what I expected because the two variables are highly correlated with one another. When I control for offer size and firm size separately in the regression, which are not reported, I observe that each variable is positively related to the SEO announcement returns as expected.

[8] I also estimate multivariate regressions using a 2-day window CAR(0,+1) around the announcement date and find similar results.

Recent studies in the disposition effect find conflicting evidence that investors holding extreme winners or losers are likely to sell their stocks sooner, thus pointing to a V-shaped disposition effect. If an extreme disposition behavior exists in SEO stocks, then I would expect to observe a more negative SEO announcement reaction at either extreme; i.e. large unrealized capital gains or large unrealized losses. Motivated by the non-linear univariate association between CGO values and SEO announcement effect, in Model (3), I replace CGO with two binary indicators for highest and lowest CGO Quintiles (CGO_Quintile1 (top 20%) and CGO_Quintile5). Each of these variables takes the value of one for SEOs in the particular quintile and zero otherwise. The coefficient estimates compare the SEO announcement reaction for the specified quintile to the announcement reaction for the middle 60% of CGO.

I observe that the announcement reaction is significantly lower for the portfolio with the highest CGO stocks, indicating that extreme winners experience more negative announcement reactions. In Model (3), which controls for other factors, SEO announcement return is 0.4 percentage points lower for firm stocks in the highest quintile of CGO compared to SEO firm stocks in the middle 60%. This difference represents over 12% of the unconditional mean announcement reaction of 3.16%. I, however, find no evidence that extreme losers also experience more negative announcement reactions.

To summarize, in Table 4, there appears to be a nonlinear relationship between the disposition effect and SEO announcement reactions with a particularly strong effect for stocks with the highest values of CGO.

1.3.2 Institutional ownership and disposition effect on SEO announcements

In this section, I investigate whether the CGO effect on SEO announcement reactions becomes significantly stronger among equity issuing firms with lower institutional ownership. I add institutional ownership information to my final SEO sample for each firm based on the quarter prior to the announcement date of equity issuance. Institutional ownership data is obtained from the Thomson Reuters Institutional Holdings (13F) database, which contains quarterly information on the institutional ownership of stocks listed on the NYSE, AMEX, and NASDAQ and is available from the first quarter of 1980 (March 1980).

I define institutional ownership as the number of shares owned by institutional investors at the end of the quarter prior to the announcement as a ratio of the total number of shares outstanding in the same quarter. There are 5,383 seasoned equity offers available with institutional ownership and the announcement dates range from June 1980 to January 2017. On average, institutional investors hold about 46.8% of shares of a firm in a quarter before the SEO announcement date and there are about 76 institutional investors holding shares for a SEO issuing firm.

1.3.2.1 Portfolio sorts on institutional ownership and CGO

To investigate whether the relationship between the disposition effect and the reaction to SEO announcements is attributable to lower institutional ownership, I form quintiles of institutional ownership. Since institutional ownership has increased drastically over the years, going from 24% in 1980 to 71% in 2016, I first split the sample of SEOs into seven five year periods, and within each I sort SEOs into quintiles and combine each quintile group in each subsample. Table 5 contains the average 3-day announcement reaction (CAR) across 25 double-sorted portfolios based on institutional ownership and CGO.

Within each CGO quintile, the average CAR is negative and monotonically decreasing as institutional ownership decreases. The difference in average CARs (High – Low) between the high and low institutional ownership groups are about 60% larger and more statistically significant among higher CGO groups. In the high CGO group, the difference of average CARs (High – Low) is about 2.6% and statistically significant at the 1% level. Among the low CGO group, the difference of average CARs (High – Low) is about 1.6% and statistically significant at the 5% level.[9] Table 5 suggests that the impact of the disposition effect on the market reaction to SEO announcements is stronger when SEO issuing firms have lower institutional ownership, supporting my hypothesis. In other words, when SEO issuers have more shares held by retail investors, the disposition effect has a larger effect on announcement reactions to such issuing firms.

Next, I empirically investigate whether the impact of the disposition effect on the SEO announcement effect is dominant among equity issuing firms with lower institutional stock ownership after controlling for firm and offer characteristics.

1.3.2.2 Multivariate results

In this section, I estimate multivariate regression models to further examine whether investors' behavioral trading biases that affect the market reaction to the SEO announcement are stronger among equity issuing firms without high institutional stock ownership.

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[9] The average CAR difference between high and low institutional ownership groups across the full sample is 0.6% with significance at 5% level, which is unreported. The CAR difference for the highest CGO quintile group is significantly larger than that across full sample by 2%.

I specify OLS estimations to explain the SEO announcement reactions and the regression is specified as:

$$\text{CAR}(-1,+1)_i = \alpha + \beta_1\text{CGO}_i + \beta_2\text{CGO}_i\text{xHigh (Low) INST}_i + \gamma\mathbf{Z}_i + \theta\text{Year}_t + \zeta\text{Industry}_j + \varepsilon \tag{4}$$

where CAR(-1,+1) is a 3-day CAR centered on the SEO announcement date and *i* represents each SEO issuance. I include an interaction term that captures both the CGO and high (low) institutional ownership effect, CGO x High (Low) INST. A dummy variable, High (Low) INST is equal to one if the SEO is in the top (bottom) quintile portfolio for institutional ownership and zero otherwise. The vector **Z** represents several control variables that are well-known determinants of the SEO announcement reactions. I also control for the year and industry fixed effects, where *t* represents the announcement year and *j* represents the Fama-French 48 industry classification.

Table 6 reports the estimation results of the specified models with control variables. Each model displays robust standard errors (in parentheses) clustered by industry. Model (1) contains CGO and the control variables, Model (2) adds an interaction term with a high institutional ownership dummy variable, and Model (3) adds an interaction term with low institutional ownership dummy variable.

My variables of interest are the CGO and an interaction term, CGO x High (Low) INST. In Model (1), the estimation result is economically consistent with Table 4. The CGO has a significantly negative impact on the SEO announcement reactions after controlling for firm and offer characteristics. In Model (2), both coefficients of the main variables are statistically significant. The coefficient of CGO is -1.7% and is statistically significant at the 10% level. The coefficient of the interaction term CGO x High INST is 2.0% and is statistically significant at the 10% level. However, both coefficients of the main variables are insignificant in Model (3).

In economic terms, one standard deviation increase in the CGO causes decreases in the average announcement reactions by 0.28 percentage points for SEOs, excluding issuers with the prior highest institutional ownership of stocks. This represents over 8% of the unconditional average SEO announcement reaction. Meanwhile, the average announcement reactions increase by 0.05 percentage points at one standard deviation increase in the CGO for SEOs with issuers that had the highest institutional ownership of stocks in the previous quarter.

Thus, the CGO is more strongly and negatively associated with the announcement effect for SEOs, in which the issuer had lower institutional ownership in the prior quarter. There is no negative association between the CGO and SEO announcement effect in the presence of high institutional ownership. This implies that the influence of disposition effect on SEO announcement reaction is mainly driven by SEO issuing firms with lower prior institutional ownership of stocks, supporting my hypothesis. Therefore, I find supporting evidence that the investors' biased behavior in trading can contribute in explaining the negative SEO announcement market reactions, especially for issuers with retail-oriented stocks before the announcement.

1.3.3 Disposition effect and post-announcement stock performances

In this section, I investigate post-announcement stock performances for SEOs. Since SEO announcements are regarded as negative signals, if there is an overly strong negative reaction at the announcement due to the disposition effect, I expect to observe a reversal in stock price after the announcement. In the previous section, I observed that high CGO firms are the ones experiencing a severe selloff at the announcement resulting more negative SEO announcement reactions. Thus, I expect to observe a positive stock price effect during the week after the SEO announcement for high CGO firms.

I restrict my sample to have more than 6 days between the announcement date and the offer date, for robustness. There are 4,998 seasoned equity offers available after the restriction, with 88.3% of the sample (4,415 offers) having positive CGO and 11.7% of the sample (583 offers) having negative CGO. I define the post-SEO announcement effect as CARs after the SEO announcement date over the 5-day-window, days (+2, +6). To estimate this measure, I use a market model approach with the CRSP value-weighted index returns as a proxy for market return. The estimation period is from -180 to -11 trading days before the SEO announcement date, where the launch date from the SDC database equals the announcement date. The cumulative abnormal return is the excess return of the estimated alpha and beta times the market return. The average post-SEO announcement effect is -0.7%.

To test for post-announcement reversal, I perform multivariate regression estimations. I specify OLS estimations that explain post-SEO announcement reactions. The regression is specified as

$$\mathrm{CAR}(+2,+6)_i = \alpha + \beta \mathrm{CGO}_i + \gamma \mathbf{Z}_i + \theta \mathrm{Year}_t + \zeta \mathrm{Industry}_j + \varepsilon \qquad (5)$$

where CAR(+2,+6) is a 5-day CAR beginning 2 days after the day of the announcement, *i* represents each SEO issuance. My variable of interest is the CGO and the vector **Z** represents several control variables that are well-known determinants of SEO announcement reactions, including 3-day CAR centered at the SEO announcement. I also control for year and industry fixed-effects, where *t* represents announcement year and *j* represents Fama-French 48 industry classification.

Similar to main regression estimations, I use two different proxies for the CGO: a proxy for linear and non-linear effect (CGO; Positive CGO and Negative CGO), and a proxy for extreme effect (CGO_Q1 (top 25%) and Q4). Table 7 presents model estimations including control variables, with each model displaying robust standard errors (in parentheses) clustered by industry. In Model (1) the key explanatory variable is CGO, the aggregate unrealized capital gains. In Model (2) I replace CGO with two variables: Positive CGO, which equals CGO if it is positive and zero otherwise, and Negative CGO, which equals CGO if it is negative and zero otherwise. In Models (3), to examine extreme effect of CGO on the post-SEO announcement return, I replace CGO with dummy variables for the top (CGO_Q1) and bottom (CGO_Q4) quartiles of CGO.

In Model (1), the coefficient of the CGO is not statistically significant. In Model (2), the coefficient of the positive CGO remains statistically insignificant, whereas the coefficient of the negative CGO is -5.6% and significant at a level of 5%. In economic terms, a one standard deviation decrease in the negative domain of the CGO causes an increase in the post-SEO announcement CAR by 0.32 percentage points. In other words, SEO firms in which investors have unrealized capital losses experience a positive post-announcement 5-day CARs.

In Model (3) the coefficient of CGO_Q1 is 0.6% and statistically significant at a level of 10%. When compared with middle 50% group of CGO, an SEO firm with a value of CGO in the top 25% experience about 0.6 percentage point higher post-announcement reaction. In other words, firms with the highest unrealized capital gains experience reversals in post-announcement abnormal returns.

After controlling for firm and offer characteristics, I find that firms with highest quartile of CGO experience reversals in post-SEO announcement abnormal returns, estimated over a 5-

day window before the issuance. The results from multivariate analyses support my expectation that SEO firms with high unrealized capital gains experience a reversal in post-SEO announcement market reactions.

1.4 Conclusion

This study is the first work to investigate the association between the disposition effect and the SEO announcement effect. I find that firms with more unrealized capital gains have stronger negative SEO announcement reactions, after controlling for firm and offer characteristics. This is consistent with the implication of the traditional disposition effect (Grinblatt and Han 2005; Odean 1998). Further, I find evidence that the association between the disposition effect and SEO announcement reactions mainly exists among the equity issuing firms with lower institutional ownership in the quarter prior to the announcement. This is consistent with the idea that retail investors are more subject to this behavioral bias, whereas institutional investors are less subject to the disposition effect.

Furthermore, I find that firms with extreme positive CGOs experience reversals in post-announcement returns, as the more severe reaction at the announcement is corrected with a positive stock price effect over the following week. In summary, investors' disposition to sell their winning stocks and hold their losers influences the reaction to SEO announcements.

CHAPTER 2

REVIVING THE DISPOSITION EFFECT: HIGHEST PRICE AS THE REFERENCE POINT

2.1 Introduction

The disposition effect is among the most well-known and most studied investor behaviors. Investors exhibiting the disposition effect tend to hold losing stocks too long and sell winning stocks too soon. Shefrin and Statman (1985) were the first to discover this effect and propose possible explanations based on prospect theory (Kahneman and Tversky 1979), metal accounting (Thaler 1980), realization utility (Gross 1982), and others. Odean (1998) was the first to directly test the disposition effect using a large brokerage account dataset and shows that the probability of selling stocks with unrealized gains is significantly higher than that of stocks with unrealized losses.

However, recent studies suggest that the relationship between the propensity to sell and unrealized trading profits is not monotonic. Ben-David and Hirshleifer (BH 2012) document an asymmetric V-shaped selling pattern with respect to unrealized profits, indicating that selling propensity increases with the size of both unrealized gains and losses, although the gain region has a steeper slope than the loss region. BH refers to this pattern as the V-shaped disposition effect. Hartzmark (2015) finds a similar V-shaped selling schedule using the ranking of trading profit within a portfolio as opposed to using the actual size of the profit. The V-shaped selling schedule presents a puzzle in understanding investors’ selling behavior as a function of profit as neither prospect theory nor realization utility predicts a V-shaped selling propensity as a function of trading profits. Instead, both theories predict that selling propensity is a monotonic, increasing function of unrealized profits.

In this paper, I suggest that it is crucial to understand the dynamics of the reference point used to measure trading profits when identifying the disposition effect. Specifically, I hypothesize that the highest stock price experienced by an investor since purchasing a stock is an important reference point for the investor to measure trading profits. Using the highest stock price as the reference price, I show that stocks held for intermediate (above one month) or long periods (above one year) are subject to a monotonic, increasing selling schedule with respect to the perceived trading profits measured by this reference point.

Why is the highest price observed since purchase an important reference point? I draw my hypothesis based on prior literature on psychology and experimental economics. From the time investors purchase a stock, they observe many prices with which to measure gains and losses when deciding whether to sell the stock. In the finance literature, traditionally, the weighted purchase price is used as a proxy for the reference price to measure trading profits (Odean 1998; Ben-David and Hirshleifer 2012). However, a reference point solely based on purchase prices ignores the dynamics and path dependence of the reference point. Much experimental research shows that reference points generally move from the initial purchase price as the stock price changes, usually in the direction of prior trading profits, and more readily so after gains than after losses (e.g., Gneezy 2005; Arkes et. al. 2008, 2010; Baucells et al. 2011; Grosshans and Zeisberger 2016). Moreover, Grinblatt and Keloharju (2001) and Kaustia (2004) observe the relative importance of the highest and lowest stock prices over the previous month as reference points in studying the disposition effect. As a result, all else being equal, investors will put more weight on the highest price than the lowest price observed since purchase, and more extreme past prices may lead to greater deviation of the reference point from the purchase price. Therefore, I hypothesize that the observed historical peak since purchase is an important reference point.

Using a large individual brokerage dataset from 1991 to 1996, similar to the dataset used by Odean (1998) and the same dataset used by Ben-David and Hirshleifer (2012), I show that there is a monotonic disposition effect for stocks held over one month to one year and over one year when I use the "historical maximum price since purchase" as a reference point. I define the new measure of perceived trading profit as: Ret (RP=max $_{t-1}$) = (Price – Maximum Price)/Maximum Price, where the maximum price is the highest price experienced by an investor since purchasing the stock and before fully closing the long position. For stocks held less than one month, I continue to observe a V-shaped selling schedule with respect to this perceived trading profit. This finding is consistent with the hypothesis of Ben-David and Hirshleifer (2012) that the V-shaped selling schedule is driven by investors' speculative trading.

To illustrate key findings, Figures 1, 2, and 3 provide selling schedules over different holding periods for perceived gains and losses based on Ret (RP=max $_{t-1}$). In Figure 1, for holding periods less than 21 trading days, I observe an asymmetric V-shaped selling schedule as shown by Ben-David and Hirshleifer (2012). The slopes of selling probability in the perceived loss and gain regions are asymmetric: the right branch is steeper than the left branch.

In Figures 2 and 3, I observe a monotonic selling schedule with a kink at zero-perceived return and a steeper slope of selling probability in the perceived gain region. This implies that investors are more prone to sell a stock at a higher probability as the perceived gain increases or the perceived loss decreases. A possible explanation for the larger slope in the perceived gain region is that people pay more attention when the stock price exceeds the maximum price since purchase. As investors pay more attention on the highest price, they are more likely to sell a stock as its price exceeds the historical maximum price observed since purchase (sell winners) and they are less likely to sell a stock as its price falls below the maximum price since purchase (reluctant to sell losers). I further show that a simple sorting by the perceived returns, Ret (RP=max $_{t-1}$), confirms the V-shaped selling schedule for shorter holding periods. However, for holding periods above one month or one year, the propensity to sell monotonically increases as when I move from the lowest to the highest Ret (RP=max $_{t-1}$) decile.

More importantly, I show that the selling schedule based on Ret (RP=max $_{t-1}$) is robust to controls for the unrealized profits based on the purchase price and other standard variables employed by Ben-David and Hirshleifer (2012). For holding periods less than 21 trading days (1 to 20 days), there is a strong V-shaped pattern in the selling propensity with both perceived return, Ret (RP=max $_{t-1}$), and unrealized return based on purchase prices. For holding periods over 20 days, I observe a strong monotonic pattern in the selling propensity with perceived return, with all the controls. This monotonic pattern still exists for holding periods after 250 days. Once more, I observe a steeper slope for the perceived gain than the perceived loss region.

After establishing that the selling schedule with respect to Ret (RP=max $_{t-1}$) is robust and incremental to variables in previous research, I then test whether such selling schedules are beneficial or detrimental to investors' portfolios. To determine whether these investors are making the right decisions in selling stocks, I compute cumulative abnormal returns (CAR) for the subsequent 20, 42, and 126 trading days since the sale. If investors are more likely to sell stocks with higher perceived returns based on Ret (RP=max $_{t-1}$), and such selling propensities are not supported by correct return expectations, I expect those stocks to subsequently outperform stocks with lower Ret (RP=max $_{t-1}$). By contrast, if such selling propensities are driven by informed trades, those stocks are expected to subsequently underperform. To test these hypotheses, I look at the difference of CAR for stocks with the highest and lowest perceived returns. My results show that, on average, the subsequent high-minus-low return spread is significantly negative, suggesting that investors more often make wise decisions to sell stocks with high Ret ($RP=max_{t-1}$).

I also test whether there is a rank effect based on Ret ($RP=max_{t-1}$) following Hartzmark (2015). Hartzmark suggests that the V-shaped propensity to sell is better understood as a propensity to realize extreme-ranked positions. He shows that individuals are more likely to sell the extreme winning and extreme losing positions in their portfolio ("the rank effect"). I apply the same control variables from Ben-David and Hirshleifer (2012) and Hartzmark (2015) and find that there exists a similar rank effect that is V-shaped when I rank stocks within a portfolio based on Ret ($RP=max_{t-1}$). In other words, while investors are more likely to sell stocks with higher perceived returns in general, more specifically, they are more likely to sell stocks with extreme returns as ranked within their own portfolio. This is consistent with the attention story proposed by Hartzmark, stating that investors tend to focus on extreme performers in their portfolio when choosing stocks to sell. This rank effect, in my setting, is distinct from the monotonic, increasing selling propensity with respect to the perceived profit, or the monotonic disposition effect.

Lastly, as a robustness check, I examine the disposition effect using another reference point, the widely used 52-week high price since purchase. The recent 52-week high price is a salient price and easy to remember as it is widely available through media. Thus the 52-week high price can be used as a reference point by investors given attention and memory constraints. Baker, Pan and Wurgler (2012) find that the recent highs of stock prices are used as reference points during mergers and acquisitions, with the 52-week high price as one of the recent peaks for stock prices.

Similarly, I find that the selling schedule based on Ret (RP=52-week-max$_{t-23}$) is robust to controls for the unrealized profits deviated from the purchase price and other variables used in Ben-David and Hirshleifer (2012). For holding periods less than 21 trading days, I observe a decreasing pattern in selling propensity as there are more losses or gains from perceived returns based on Ret (RP=52-week-max$_{t-23}$), but a strong V-shaped pattern remains in the propensity to sell with unrealized returns based on purchase prices. I find robust results for holding periods over 20 days and after 250 days. There remains a strong monotonic pattern in selling propensity with perceived return using all the controls. Once more, I observe a steeper slope for the perceived gain region than the perceived loss region.

In summary, my study applies the idea of reference point adaptation and uses a new reference point, the maximum price since purchase, to analyze the disposition effect. I demonstrate and provide evidence of the V-shaped disposition effect for holding periods from 1 to 20 days and a monotonic disposition effect for holding periods over 20 days. Further evidence suggests that such selling behaviors are likely to be beneficial for investors' portfolio performance. A possible explanation of my findings is that investors place more weight on the historical maximum price since purchase when forming reference points to measure trading profits. My findings contribute to the literature on disposition effect (Odean 1998; Ben-David and Hirshleifer 2012; An 2015) by reviving the monotonic disposition effect when I account for the dynamics of the reference point.

The remainder of the paper is organized as follows. Section 2.2 describes my sample and variables. Section 2.3 discusses the testing of investor trading in response to perceived gains and perceived losses and re-establishes the disposition effect. Section 2.4 provides the future return performance after the sale transaction. Section 2.5 discusses the testing of the rank effect. Section 2.6 reports robust analyses of investor trading in response to perceived returns using three other reference points (52-week high, minimum since purchase, 1-month high prices). Section 2.7 provides the conclusion and implications.

2.2 Data and Variables

2.2.1 Sample of investors' transaction data

I use the same retail investor trading data as in Ben-David and Hirshleifer (2012), introduced by Barber and Odean (2000) and similar to the one used by Odean (1998). The data set consists of trading activities for 78,000 households with accounts at a large discount broker. It includes stock transactions from 77,037 unique accounts over the period from January 1991 through December 1996. I select a random sample of 50,000 accounts. For accuracy of results, this study uses a larger sample than previous studies. Ben-David and Hirshleifer (2012) use a sample of 10,000 accounts from 1991 to 1996.

To clean and prepare the data, I restrict that all investor-stock transactions (stocks are identified by an 8-character CUSIP) be observed in CRSP on all transaction dates. This study uses only common stocks and removes investors' stocks if one of the transactions has negative commissions. To diminish microstructure frictions, this study removes all observations of stocks that has at least one day with no active trading during the previous 250 trading days. I do not adjust for stock splits and dividends when computing returns[10]. Birru (2015) proposes that investors may naively calculate their gains and losses based on their nominal purchase price,

[10] Birru (2015) shows that the disposition effect does not exist after stock splits. An (2015) also does not adjust for stock splits and dividends.

without adjusting for stock splits and dividends. He shows that the disposition effect is absent after stock splits and attributes this observation to investors' confusion. Lastly, I remove investor-stocks that have short-sale transactions or positions opened before 1991[11].

Next, I merge CRSP data and the investor transaction data set. For each investor-stock, I tag the days when shares of the stock are initially or additionally purchased (a position is opened or an existing position is increased), or when shares are sold (including a partial sale). I compute holding period as the number of trading days between current stock holding day and weighted average of purchase day, with the quantity purchased as a weight. In addition, I record purchase and selling prices from the transaction data set and closing prices from CRSP. I also record maximum price since purchase (opening position). I winsorize independent variables at the 1st and the 99th return percentiles within each holding period to remove outliers. I remove the purchase day from the sample. After removing these observations, I have 113.8 million observations. I then divide the sample into three different holding period groups (since purchase), namely, from 1 to 20 days, 21 to 250 days, and over 250 days.

2.2.2 Return based on a new reference point (maximum price) and control variables

I compute two different returns, specifically, the return based on weighted average purchase price, as in Ben-David and Hirshleifer (2012), and the perceived return, noted as Ret (RP=max $_{t-1}$), based on the historical maximum price since purchase. Ret (RP=max $_{t-1}$) equals (price – maximum price)/maximum price, where "maximum price" is the maximum price since

[11] For each investor, I accumulate stock shares over time. If the cumulative number of a stock's shares becomes negative (when purchased before 1991 and account closed during the sample period; or a short sale), I remove the investor-stock observations from the sample.

purchase. I use the same return variables and control variables as in Ben-David and Hirshleifer (2012). Variables are defined as follows:

Return since purchase (Ret- and Ret+); indicators if return is positive or zero (I(ret >0) and I(ret=0)); the square root of the time since purchase (Sqrt(Time owned)), measured in holding days; the logged purchase price (log(Buy price)) and two stock return volatility variables (Volatility+ and Volatility-), computed on the 250 trading days preceding the purchase. Volatility+ is equal to the volatility if the observation is a gain, and is equal to zero otherwise; Volatility- is equal to the volatility if the observation is a loss, and is equal to zero otherwise. The variables for stock return volatility indicate the possibility that investors trade more actively in stocks that are more speculative.[12]

Table 8 provides descriptive statistics of the return and control variables used in this study for different holding periods.

2.2.3 Constructing rank variables

Following Hartzmark (2015), I construct rank variables using the two return variables in this analysis. The two return variables (return since purchase and perceived return) are ranked into deciles. A stock is ranked best (worst) if it has the highest (lowest) return in a portfolio. I construct rank variables (Best, 2nd Best, 2nd Worst, and Worst) for each return variable. Each of the rank variables is an indicator of its rank. For example, Best is a dummy variable equal to one if the stock has the highest return since purchase in a portfolio. Worst (RP=$\max_{t-1}$) is an

[12] "In the absence of a volatility interaction term, a V-shape pattern could arise as an artifact of changes in the composition of the sample as a function of the gain or loss. Highly volatile stocks will tend to be more heavily represented among extreme gains and losses. If the probability of selling a more volatile stock is unconditionally higher, a spurious V could result" (Ben-David and Hirshleifer 2012).

indicator if the stock is ranked worst (has the lowest return) in a portfolio. Variable definitions are listed in the Appendix.

2.3. Tests of Investor Trading in Response to Perceived Gains and Perceived Losses

2.3.1 Univariate analysis

Table 9 provides the propensity to sell stocks with the highest and lowest perceived returns across different holding periods. Stocks are sorted by perceived return (Ret (RP=max_{t-1})), as the lowest decile being 1 to the highest decile being 10. High – Low is the difference between the high and low rows and table 9 is the t-statistic testing a null hypothesis that the high and low rows are equal. The t-statistics are clustered by investor-day level. For all investors, a position with the highest perceived return is 42.4% more likely to be sold than a position with the lowest perceived return. Specifically, a position with the highest perceived return is more likely to be sold than a position with the lowest perceived return by 63% for a holding period of 1 to 20 days, by 40% 21 to 250 days, by 10% over 250 days. I observe that the difference in selling probability decreases but remain significant as he holding period increases and becomes flat when holding period exceeds 250 days. For a short holding period, there is a V-shape in propensity to sell as the decile moves from the lowest to the highest. However, after a 20-day holding period, the propensity to sell monotonically increases as the decile moves from the lowest to the highest. This provides evidence of the monotonic disposition effect in the relationship between selling probability and perceived profits.

For holding periods from 1 to 20 days, I observe a V-shaped disposition effect, as seen in Ben-David and Hirshleifer (2012). However, after 21 days, I observe a monotonic disposition effect. This implies that investors are less likely to sell the stocks with higher perceived losses and more likely to sell the stocks with perceived gains (or lower perceived losses). The last column indicates that the monotonic disposition effect is generally dominant when investors use perceived gains and losses in making decisions.

2.3.2 Regression analysis

I run probit regressions of a sale dummy variable (Sell), equal to one if a stock is sold and zero otherwise, on investor's perceived return, return since purchase, and control variables from Ben-David and Hirshleifer (2012) as in Equation (6) below:

$$\begin{aligned} Sell = {} & \alpha + \beta_1 \text{ Ret } (RP=\max_{t-1}) + \beta_2 \text{ Ret- } (RP=\max_{t-1}) + \beta_3 \text{ Ret+ } (RP=\max_{t-1}) \\ & + \beta_4 \text{ I}(\text{ret } (RP=\max_{t-1}) > 0) + \beta_5 (\text{Ret-}) + \beta_6 \text{ Ret-} \times \text{sqrt(Time owned)} \\ & + \beta_7 (\text{Ret+}) + \beta_8 \text{ Ret+} \times \text{sqrt(Time owned)} \\ & + \beta_9 \text{ I}(\text{ret} = 0) + \beta_{10} \text{ I}(\text{ret} = 0) \times \text{sqrt(Time owned)} \\ & + \beta_{11} \text{ I}(\text{ret} > 0) + \beta_{12} \text{ I}(\text{ret} > 0) \times \text{sqrt(Time owned)} + \beta_{13} \text{ sqrt(Time owned)} \\ & + \beta_{14} \log(\text{Buy price}) + \beta_{15} (\text{Volatility-}) + \beta_{16} (\text{Volatility+}) + \varepsilon \qquad (6) \end{aligned}$$

Ret($RP=\max_{t-1}$) is the perceived return (return calculated based on the maximum price since purchase). Ret− ($RP=\max_{t-1}$) is defined as the minimum between the perceived return and zero. Ret+ ($RP=\max_{t-1}$) is defined as the maximum between the perceived return and zero. These return variables separately capture a linear relationship between the probability of selling in the positive and negative regions of perceived returns. Ret− is defined as the minimum between the return since purchase and zero. Ret+ is defined as the maximum between the return since purchase and zero. I also add other control variables, namely, indicators for return since purchase (and perceived return), logged purchase price, and two stock return volatilities. The control variables are described in Section 2.2.2 and are also defined in the Appendix.

Table 10 reports both univariate and multivariate regression results on the propensity to sell for different holding periods. Columns (1) and (2) examine the relation between the perceived return and selling propensity, while Columns (3) to (5) examine the effect of perceived return with additional controls. I explain the results focusing on Columns (2) and (5). Specifically, Panel A shows that the probability of selling has an asymmetric V-shape around the perceived returns up to 20 days from purchase; in the perceived loss region, the probability of selling increases with the magnitude of perceived losses, while in the perceived gain region, the propensity to sell increases more sharply with the magnitude of perceived gains. To illustrate, consider Column (2). An increase of one standard deviation in profits (1.1% from Table 1, Panel A) increases the probability of selling by about 0.208% (= 18.94 * 0.011). An increase of one standard deviation in losses increases the probability of selling by about 0.078%.

According to Ben-David and Hirshleifer (2012), one possible explanation for the V-shaped selling schedule for short holding period (up to 20 days) is that speculative traders with limited attention tend to reevaluate their portfolios after substantial gains and losses. A little change in price after the purchase date does not grab investor's attention; however, a substantial gain or loss seizes investors' attention. Consequently, investors reevaluate their positions and sell the stocks.

Panels B and C show that after 20 days from purchase, the probability of selling monotonically increases as perceived returns increase (or as perceived losses decrease) with asymmetric increases subsequent to the sign of perceived returns. To illustrate, consider Panel B, Column (5). An increase of one standard deviation in profits (losses) increases (decreases) the probability of selling by about 0.012% (0.031%). For holding periods of over 250 days in Panel

C, Column (5), the effect is similar. An increase of one standard deviation in profits (losses) increases (decreases) the probability of selling by about 0.003% (0.039%).

Thus, I consistently observe a V-shaped disposition effect for holding periods within 1 to 20 days, as observed in Ben-David and Hirshleifer (2012). However, after 21 days, I observe a monotonic disposition effect. This means that investors are less likely to sell the stocks with higher perceived losses and more likely to sell the stocks with more perceived gains (or lower perceived losses).

2.4. Future Performance of Stocks after Selling

I observe a V-shaped selling schedule with respect to Ret (RP=max $_{t-1}$) for short holding periods and a monotonic-increasing selling schedule with respect to Ret (RP=max $_{t-1}$) when investors consider perceived gains and losses. This leads to the question of whether these investors are making the right decisions. If investors are more likely to sell stocks with higher perceived returns based on Ret (RP=max $_{t-1}$), and such selling propensities are not supported by correct return expectations, I expect those stocks to subsequently outperform the stocks with lower Ret (RP=max $_{t-1}$). By contrast, if such selling propensities are driven by informed trades, those stocks are expected to subsequently underperform. To test these hypotheses, I look at the difference of cumulative abnormal returns (CAR) for stocks with the highest and lowest perceived returns.

Table 11 reports future abnormal returns (market-adjusted) after the sale, averaged across investor-stock for different holding periods. I keep only the stocks that are sold and compute the CAR for the following 20, 42, and 126 (trading) days after the stock is sold. For robustness, I try different sorting methods on perceived returns when stocks are sold and adjust for stock splits and dividends. Panel A uses the decile sorting used in Table 9. Panel B re-sorts the stocks (only those that are sold) into deciles based on perceived returns. Panel C removes the observations (holding samples) that went through stock splits first and then sorts the stocks into deciles based on perceived returns. I discuss the results mainly on Panel A in this paper.

Table 11 demonstrates that investors generally make the right decision. According to previous literature on the disposition effect, stocks that are sold more are expected to outperform in the future, indicating that investors make wrong decisions in selling stocks. Thus my result could be surprising, but my finding may imply that the selling schedule observed in Section 2.3 in relation to high-perceived return could be driven by informed trading.

The high-minus-low return spread is not significant in Panel A, but it is significant and negative in Panels B and C. I also observe a reverse V-shaped pattern in CAR, which is expected from the V-shaped selling propensity of stocks purchased less than 20 days. For stocks purchased less than 20 days, those with extreme perceived returns (gain/loss) make comparably large losses. It is wise to sell those stocks earlier than the other stocks (in the middle deciles). Thus, Table 11 provides evidence that investors make wise decisions to sell stocks and confirms the asymmetric V-shaped disposition effect. Specifically, this indicates that investors sell stocks with the lowest and highest perceived returns earlier and that the propensity to sell extreme winners is higher than the propensity to sell extreme losers in terms of perceived returns.

For stocks purchased more than 21 days, the high-minus-low return spreads are negative and statistically significant. This implies that when investors sell stocks with higher perceived returns and keep stocks with lower perceived returns, they are actually making the right decision since the stocks with the highest perceived returns underperform stocks with the lowest perceived returns.

2.5. Rank Effect

Hartzmark (2015) suggests that the propensity to sell positions at larger gains and losses observed in Ben-David and Hirshleifer (2012) is better understood as a propensity to realize extreme-ranked positions. Individuals are more likely to sell the extreme winning and losing positions in their portfolio ("the rank effect"). Following Hartzmark (2015), I perform logit regressions for a dummy variable, Sell (equal to one if a stock is sold and zero otherwise), on variables for rank and a number of controls from Ben-David and Hirshleifer (2012) and Hartzmark (2015) as in Equation (7) below:

$$\begin{aligned} \text{Sell} = {} & \alpha + \gamma\,(\text{Rank Variables}) + \beta_1\,(\text{Ret-}) + \beta_2\,(\text{Ret+}) + \beta_3\,\text{I(ret} > 0) \\ & + \beta_4\,\text{Ret+} \times \text{sqrt(Time owned)} + \beta_5\,\text{Ret-} \times \text{sqrt(Time owned)} \\ & + \beta_6\,\text{sqrt(Time owned)} + \beta_7\,(\text{Volatility-}) + \beta_8\,(\text{Volatility+}) + \varepsilon \end{aligned} \tag{7}$$

Rank Variables represents the different measures of the rank effect. The variable definitions for rank variables and control variables are described in Section 2.2 and are also defined in the Appendix.

Table 12 reports the rank effect using logit regressions with different rank variables. Column (1) presents the regression for individual investors with no rank variables. Columns (2) to (4) add rank variables to examine the rank effect for individual investors. Column (2) adds rank variables from Hartzmark (2015) based on return since purchase within each portfolio. Column (3) adds rank variables based on perceived returns within each portfolio. Column (4) adds all rank variables, controlling for Hartzmark's (2015) variables. All results are presented as marginal effects multiplied by 100.

In Column (1), I observe an asymmetric V-shape as in Ben-David and Hirshleifer (2012). Without controlling for rank, consistent with Hartzmark (2015) and Ben-David and Hirshleifer (2012), there is a V-shaped disposition effect.

In Column (2), similar to Hartzmark (2015), I observe the rank effect. The rank variables are positive and statistically significant. This rank effect is "V-shaped," indicating that the most-extreme-ranked stock within portfolios (best/worst) is more likely to be sold than the less-extreme-ranked stock within portfolios (2nd best/worst). The best-ranked stock (Best) is 10.98% more likely to be sold, while the 2nd best-ranked stock (2nd Best) is 7.4% more likely to be sold. The worst-ranked stock (Worst) is 7.4% more likely to be sold, while the 2nd worst-ranked stock (2nd Worst) is 5.0% more likely to be sold.

Using perceived returns to construct rank variables, in Columns (3) and (4), once again, I observe statistically significant rank variables and confirm the V-shaped rank effect. For example, in Column (3), the best-ranked stock within a portfolio (or stock with highest perceived return in a portfolio) is 8.9% more likely to be sold, while the 2nd best-ranked stock within a portfolio is 5.0% more likely to be sold. In Column (4), the best-ranked stock (Best) is 6.7% more likely to be sold, while the 2nd best-ranked stock (2nd Best) is 3.5% more likely to be sold.

2.6 Robustness Tests of Investor Trading in Response to Perceived Returns based on Three Other Reference Points

2.6.1 52-week high as a reference point

In this section I use a different reference point, the 52-week high price. The 52-week high price is widely available to investors as it is often reported and discussed in financial media and newspapers. Baker, Pan, and Wurgler (2012) find that the recent highs of stock prices are used as reference points during mergers and acquisitions. They use the 52-week high price as one of recent peaks for stock prices. Thus, the 52-week high price can also be considered as a reference point used by investors.

I define the perceived return based on the 52-week high price as Ret (RP=52-week-max $_{t-23}$) = (price$_t$ – maximum price)/maximum price, where the maximum price is the 52-week maximum price measured on 23 trading days prior to selling the stock.

I run probit regressions of a sale dummy variable (Sell), equal to one if a stock is sold and zero otherwise, on investor's perceived return, return since pappAppeappurchase, and control variables from Ben-David and Hirshleifer (2012) as in Equation (8) below:

$$\begin{aligned}\text{Sell} = {} & \alpha + \beta_1 \text{ Ret (RP=52-week-max}_{t-23}) + \beta_2 \text{ Ret- (RP=52-week-max}_{t-23}) \\ & + \beta_3 \text{ Ret+ (RP=52-week-max}_{t-23}) + \beta_4 \text{ I(ret (RP=52-week-max}_{t-23}) > 0) \\ & + \beta_5 \text{ (Ret-)} + \beta_6 \text{ Ret-} \times \text{sqrt(Time owned)} + \beta_7 \text{ (Ret+)} \\ & + \beta_8 \text{ Ret+} \times \text{sqrt(Time owned)} + \beta_9 \text{ I(ret = 0)} + \beta_{10} \text{ I(ret = 0)} \times \text{sqrt(Time owned)} \\ & + \beta_{11} \text{ I(ret > 0)} + \beta_{12} \text{ I(ret > 0)} \times \text{sqrt(Time owned)} + \beta_{13} \text{ sqrt(Time owned)} \\ & + \beta_{14} \text{ log(Buy price)} + \beta_{15} \text{ (Volatility-)} + \beta_{16} \text{ (Volatility+)} + \varepsilon \end{aligned} \tag{8}$$

Ret(RP=52-week-max $_{t-23}$) is the perceived return (return calculated based on the 52-week high price measured on 23 trading days prior to selling the stock). Ret− (RP=52-week-max $_{t-23}$) is defined as the minimum between the perceived return and zero. Ret+ (RP=52-week-max $_{t-23}$) is defined as the maximum between the perceived return and zero. These return variables separately capture a linear relationship between the probability of selling in the positive and negative regions of perceived returns. Ret− is defined as the minimum between the return since purchase and zero. Ret+ is defined as the maximum between the return since purchase and zero. I also add other control variables: indicators for return since purchase (and perceived return), logged purchase price, and two stock return volatilities. The control variables are described in Section 2.2.2 and are also defined in the Appendix.

Table 13 Panel A reports multivariate regression results on the propensity to sell with controls and for different holding periods. Table 13 Panel B presents univariate decile sorts on the propensity to sell with the new perceived return using the 52-week high price across different holding periods. Table 13 Panel A, Columns (1) and (2) show the relation between the perceived return and the selling propensity for holding periods less than 21 trading days. Columns (3) and (4) report the effect of the perceived return for holding periods over 20 trading days and less than 251 trading days, while the last two columns display results for holding period over 250 trading days.

For holding period less than 21 days, Column (1) in Table 6 presents a positive association between the propensity to sell and the perceived return with additional controls. However, in Column (2), the probability of selling has an asymmetric reverse V-shape around the perceived return; the probability of selling decreases at a similar rate of 0.2% with the magnitude of perceived losses and gains. To illustrate, in Column (2), an increase of one standard deviation in profits (losses) decreases the probability of selling by about 0.010% (0.051%).

For holding periods over 20 days and less than 251 days, Columns (3) and (4) in Table 6 present a positive association between the propensity to sell and the perceived return with additional controls. Column (4) shows that the probability of selling increases at a larger rate as perceived return increases among stocks that have positive perceived returns. To illustrate, an increase of one standard deviation in profits (losses) increases (decreases) the probability of selling by about 0.015% (0.027%). For holding periods over 250 days, the effect is similar.

Column (6) shows that an increase of one standard deviation in profits (losses) increases (decreases) the probability of selling by about 0.011% (0.017%).

In summary, from Table 13 Panel A, I observe a reverse V-shaped disposition effect for holding periods from 1 to 20 days, which is different from prior literature. However, after 21 days, I observe a monotonic disposition effect. This implies that investors are less likely to sell the stocks with higher perceived losses and more likely to sell the stocks with more perceived gains (or lower perceived losses).

Table 13 Panel B shows univariate decile sorts on the selling probability by sorting the sample based on deciles of Ret(RP=52-week-max $_{t-23}$) and the perceived return computed based on the 52-week high price 23 days prior to selling the stock. In this panel, I find a similar pattern as seen in Table 9 (which displays a table of univariate decile sorts on the selling probability based on the perceived return using the maximum price since purchase). For holding periods less than 21 days, there is a V or U-shaped pattern in the selling probability. The probability of selling the stock decreases sharply at the lowest decile group and slowly decreases as it moves toward the higher decile group, increasing sharply at the highest decile group for the perceived return, Ret(RP=52-week-max $_{t-23}$). For holding periods over 20 days and over 250 days, the selling probability increases monotonically as it moves toward the higher decile group for the perceived return, Ret(RP=52-week-max $_{t-23}$).

Thus, overall results provide evidence of a monotonic disposition effect for holding periods longer than 21 days even when using the 52-week high price measured 23 days prior to selling the stock. This result is robust to what I find earlier in Section 2.3 using the historical maximum price since purchase (measured one day prior to selling the stock).

2.6.2 Two other reference points: minimum price and 1-month high

In this section, I use two other reference points (minimum price since purchase and 1-month-high price measured on the day prior to selling the stock) in computing perceived returns and examine associations between each perceived return and the propensity to sell.

Three perceived returns are used, namely, Ret (RP=min $_{t-1}$) and Ret (RP=1-month-max $_{t-1}$). Ret (RP=min $_{t-1}$) equals (price – minimum price)/minimum price, where the minimum price is the historical minimum price since purchase measured on the day prior to selling the stock. Ret (RP=1-month-max $_{t-1}$) equals (price – maximum price)/maximum price, where the maximum price is the recent 1-month maximum price measured on the day prior to selling the stock.

Consistent with previous literature, Ben-David and Hirshleifer (2012), I observe a strong V-shape in the propensity to sell with perceived return based on the minimum price since purchase as a reference point. This implies that an investor is more likely to sell when the magnitude of perceived profit or loss increases. When using the recent 1-month high price as a reference point, I find that, within a short holding period of one month, investors exhibit a disposition behavior characterized by a linear propensity to sell their stocks. However, with longer holding periods, investors exhibit a disposition behavior characterized by a V-shaped propensity to sell as observed in Ben-David and Hirshleifer (2012). One explanation to this is that one-month high prices explain the short-term momentum. An investor is likely to chase the recent 1-month-high price and thus sell the stock if the price is above the recent 1-month high price.

I run probit regressions of a sale dummy variable (Sell), equal to one if a stock is sold and zero otherwise, on investor's perceived return (noted as Ret (RP)), return since purchase, and control variables from Ben-David and Hirshleifer (2012) as in Equation (9) below:

$$\begin{aligned}\text{Sell} = \alpha &+ \beta_1 \text{ Ret (RP)} + \beta_2 \text{ Ret- (RP)} + \beta_3 \text{ Ret+ (RP)} + \beta_4 \text{ I(ret (RP)} > 0) \\ &+ \beta_5 \text{ (Ret-)} + \beta_6 \text{ Ret-} \times \text{sqrt(Time owned)} + \beta_7 \text{ (Ret+)} \\ &+ \beta_8 \text{ Ret+} \times \text{sqrt(Time owned)} + \beta_9 \text{ I(ret} = 0) + \beta_{10} \text{ I(ret} = 0) \times \text{sqrt(Time owned)} \\ &+ \beta_{11} \text{ I(ret} > 0) + \beta_{12} \text{ I(ret} > 0) \times \text{sqrt(Time owned)} + \beta_{13} \text{ sqrt(Time owned)} \\ &+ \beta_{14} \text{ log(Buy price)} + \beta_{15} \text{ (Volatility-)} + \beta_{16} \text{ (Volatility+)} + \varepsilon \qquad (9)\end{aligned}$$

Ret− (RP) is defined as the minimum between the perceived return and zero. Ret+ (RP) is defined as the maximum between the perceived return and zero. These return variables separately capture a linear relationship between the probability of selling in the positive and negative regions of perceived returns. Ret− is defined as the minimum between the return since purchase and zero. Ret+ is defined as the maximum between the return since purchase and zero. I also add other control variables: indicators for return since purchase (and perceived return), logged purchase price, and two stock return volatilities. The control variables are described in Section 2.2.2 and are also defined in the Appendix.

I estimate multivariate regressions using three different perceived returns, listed as Ret (RP=min $_{t-1}$) and Ret (RP=1-month-max $_{t-1}$). Thus, for each regression in Equation (9), RP is replaced by RP=min $_{t-1}$ and RP=1-month-max $_{t-1}$. Table 14 reports multivariate regression results on the propensity to sell after adding controls across different holding periods. Panel A and B displays estimations with Ret (RP=min $_{t-1}$) and Ret (RP=1-month-max $_{t-1}$) for perceived returns based on the minimum price since purchase and recent 1-month maximum price, respectively. Perceived returns are constructed using reference points measured on the day prior to selling the stock. In each panel, Columns (1) and (2) show the relation between the perceived return and the selling propensity for holding periods less than 21 trading days, while Columns (3) and (4) report the effect of perceived return for holding periods over 20 trading days and less than 251 trading days. The last two columns display results for holding periods over 250 trading days.

Specifically, when the minimum price since purchase is used as a reference point, I observe results consistent with those of Ben-David and Hirshleifer (2012) as seen in Panel A of Table 10. For holding periods less than one month and less than one year, Columns (2) and (4) show a strong V-shape pattern for the selling propensity with respect to perceived return. For example, in Column (2), an increase of one standard deviation in profits (losses) increases the probability of selling by about 0.133% (0.107%). For holding periods over one year, although the size is small, the probability of selling increases monotonically as perceived return increases (or perceived loss decreases). To illustrate, consider Column (6). An increase of one standard deviation in profits increases the probability of selling by about 0.014%.

Moving to Panel B, when the 1-month maximum price is used as a reference point, a monotonic, increasing pattern is observed in the propensity to sell as perceived return increases (or perceived loss decreases) with asymmetric increases subsequent to the sign of perceived profits for the holding period less than 21 days. To illustrate, Column (2) shows that an increase of one standard deviation in profits (losses) increases (decreases) the probability of selling by about 0.017% (0.019%). However, for holding periods over 20 days and over 250 days, a strong V-shaped pattern is observed in the propensity to sell with respect to perceived return. To illustrate, consider Column (4). An increase of one standard deviation in profits (losses) increases the probability of selling by about 0.038% (0.048%). Similarly, in Column (6), an increase of one standard deviation in profits (losses) increases the probability of selling by about 0.009% (0.017%).

In summary, when using the highest price within a month or the lowest price since purchase, I observe a V-shaped selling propensity with respect to perceived return, especially for stocks that are held more than one month or over one year. However, when using the highest price over a holding period longer than one month (for example, recent peak in one year or peak price since purchase), I observe a monotonic, increasing pattern in the probability to sell as perceived return increases (or perceived loss decreases), especially for stocks that are held more than one month or over one year.

2.7 Conclusion

The disposition effect is among the most well known and most studied investor behaviors. Investors exhibiting the disposition effect tend to hold losing stocks too long and sell winning stocks too soon. Odean (1998) was the first to test the disposition effect directly using a large brokerage account dataset and show the monotonic disposition effect that the probability of selling stock with unrealized gains is significantly higher than that of stocks with unrealized losses.

However, recent studies suggest that the relationship between the propensity to sell and the unrealized trading profit is not monotonic. Ben-David and Hirshleifer (2012) document an asymmetric V-shaped selling schedule with respect to unrealized profits indicating that selling propensity increases with the size of the unrealized gains and losses, although the gain region has a steeper slope than the loss region. They refer to this pattern as the V-shaped disposition effect. However, the V-shaped selling schedule presents a puzzle in understanding investors' selling behavior as a function of profit as neither the prospect theory nor the realization utility predicts a

V-shaped selling propensity as a function of trading profits. Instead, both theories predict that selling propensity is a monotonic and increasing function of unrealized profits.

This study verifies that it is crucial to understand the dynamics of the reference point used to measure trading profits when identifying the disposition effect. Therefore, I apply the idea of reference point adaptation and use a new reference point, the maximum price since purchase, to analyze the disposition effect. I demonstrate and provide evidence of the V-shaped disposition effect for holding periods from 1 to 20 days and a monotonic disposition effect for holding periods over 20 days. In addition, I apply another reference point, the 52-week high price, as a robustness check and confirm a monotonic disposition effect for holding periods over 20 days. This further evidence suggests that such selling behaviors are likely to be beneficial for investors' portfolio performance. This study mainly contributes with its finding that the V-shape selling schedule appears on stocks held for short periods and that the monotonic, increasing selling schedule appears on stocks held for longer periods when I account for the historical maximum price since purchase as the reference point to measure trading profits.

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APPENDIX A

VARIABLE DEFINITIONS FOR "CAN THE DISPOSITION EFFECT EXPLAIN THE MARKET REACTION TO SEO ANNOUNCEMENTS?"

Announcement CARs

CAR(-1,+1): The 3-day CARs centered at the SEO announcement date. The abnormal returns are estimated using a market model over -180 days to -11 days from the day of SEO announcement
CAR(+2,+6): The 5-day CARs starting from 2 days after the SEO announcement date. The abnormal returns are estimated using a market model over -180 days to -11 days from the day of SEO announcement.

Variables for CGO

CGO: The capital gains overhang measured at of a given month prior to the SEO announcement month. It is estimated for each month-end using daily stock data over 3years.
Positive CGO: It is equal to CGO if positive, otherwise zero.
Negative CGO: It is equal to CGO if negative, otherwise zero.
CGO_Quintile1: A dummy variable equal to one if the offering firm is in the top quintile of CGO, otherwise zero.
CGO_Quintile2: A dummy variable equal to one if the offering firm is in the 2nd top quintile of CGO, otherwise zero.
CGO_Quintile4: A dummy variable equal to one if the offering firm is in the 2nd bottom quintile of CGO, otherwise zero.
CGO_Quintile5: A dummy variable equal to one if the offering firm is in the bottom quintile of CGO, otherwise zero.
CGO_Q1: A dummy variable equal to one if the offering firm is in the top quartile of CGO, otherwise zero.
CGO_Q4: A dummy variable equal to one if the offering firm is in the bottom quartile of CGO, otherwise zero.

Institutional ownership

INST: the number of shares owned by institution investors at the end of the quarter prior to the equity issue announcement date as a ratio of the total number of shares outstanding in the same quarter.
High INST: A dummy variable equal to one if the offering firm is in the highest quintile of institutional ownership, otherwise zero.
Low INST: A dummy variable equal to one if the offering firm is in the lowest quintile of institutional ownership, otherwise zero.

Control variables

Proceeds: The proceeds of the offer reported in the SDC database (unit: million $)
Mktcap: The stock price multiplied by number of shares outstanding on the day prior to the SEO announcement
Volatility: The residual standard deviation estimated using a market model over 250 trading days from 2 trading days prior to SEO announcement
MTB: The market-to-book ratio, defined as book value of total assets minus book value of equity plus market capitalization divided by book value of total assets, measured at the fiscal year prior to the SEO announcement year
Leverage: The sum of short-term and long-term debt divided by book value of total assets, measured at the fiscal year prior to the SEO announcement year
Relative offer size: The number of shares offered divided by number of common shares outstanding on the day before the SEO announcement.
Secondary: The proportion secondary shares offered relative to total shares offered, which is equal to the number of secondary offers divided by the number of shares offered
Prior 1-year BHAR: The buy-and-hold stock return minus buy-and-hold value-weighted market return estimated over the 12 months (250 trading days) ending 20 trading days before the SEO announcement

All continuous variables are winsorized at 1% and 99% level to mitigate the influence of outliers.

APPENDIX B

TABLES FOR "CAN THE DISPOSITION EFFECT EXPLAIN THE MARKET REACTION TO SEO ANNOUNCEMENTS?"

Table 1. Summary Statistics

This table displays descriptive statistics on main variables and firm and offer characteristics for all SEOs. The sample includes SEOs announced from January 1970 – January 2017. The 3-day CAR(-1, +1) is defined as the 3-day CARs centered at the SEO announcement date. CGO is defined Grinblatt and Han's (2005) measure of unrealized capital gains and is defined in Equations (1)–(2) in Section 1.2.3. Proceeds equal the net proceeds of the offer, in millions. Mktcap equals shares outstanding (in millions) multiplied by stock price on the day prior to announcement. Volatility equals the residual standard deviation from the market model estimated over the year ending two days prior to announcement. MTB equals the market value of equity on the day prior to announcement plus the book value of equity at the end of the prior fiscal year minus shareholders' equity at the end of the prior fiscal year, all scaled by total book assets at the end of the prior fiscal year. Leverage equals long-term debt plus short-term debt as a ratio of total book assets. Relative offer size equals the number of shares offered divided by total shares outstanding. Secondary equals the secondary component of the offer, defined as the percentage of offered shares that are being sold by existing shareholders. Prior 1-year BHAR equals the stock return over the one year ending one month prior to the SEO announcement, net of the return on the CRSP value-weighted index over the same period. Offer characteristics are from the SDC database and firm characteristics are from the Compustat Annual database. To be included in the final sample, an SEO firm must have enough information from the CRSP database. All continuous variables are winsorized at 1% and 99% levels.

	N	Mean	StdDev	P1	P25	Median	P75	P99
CAR (-1, +1)	7224	-0.032	0.068	-0.231	-0.068	-0.029	0.005	0.177
CGO	7224	0.163	0.169	-0.42	0.074	0.18	0.273	0.516
Proceeds ($ millions)	7224	98.521	145.041	2.9	23.4	52.8	108	943
Mktcap ($ millions)	7224	1176.61	2656.93	16.62	146.96	384.78	982.74	19296.52
Ln(proceeds)	7224	3.924	1.163	1.065	3.153	3.967	4.682	6.849
Ln(mktcap)	7224	5.982	1.425	2.811	4.99	5.953	6.89	9.868
Volatility	7224	0.036	0.017	0.011	0.024	0.032	0.043	0.101
MTB	6138	2.478	2.096	0.756	1.21	1.717	2.917	12.93
Leverage	7167	0.267	0.249	0	0.049	0.233	0.404	1.24
Relative offer size	7224	0.188	0.142	0.005	0.091	0.158	0.249	0.769
Secondary	7224	0.137	0.238	0	0	0	0.199	0.911
Prior 1-year BHAR	7224	0.706	1.135	-0.582	0.056	0.388	0.952	6.585

Table 2. Correlation Table

This table displays pair-wise correlation of main variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8	9	10
1 CAR(-1, +1)	1.000									
2 CGO	-0.016	1.000								
3 Ln(proceeds)	-0.002	0.007	1.000							
4 Ln(mktcap)	0.010	-0.011	0.752***	1.000						
5 Volatility	-0.134***	-0.085***	-0.038***	-0.050***	1.000					
6 MTB	-0.001	-0.125***	0.043***	0.133***	0.255***	1.000				
7 Leverage	0.043***	0.016	0.083***	0.054***	-0.092***	-0.288***	1.000			
8 Relative offer size	-0.047***	0.024**	-0.031***	-0.567***	0.065***	-0.151	0.065***	1.000		
9 Secondary	-0.052***	0.124***	0.038***	-0.071***	0.057***	0.054	-0.034***	0.149***	1.000	
10 Prior 1-year BHAR	-0.042***	0.336***	0.014	0.022*	0.345***	0.047***	-0.037***	0.001	0.038***	1.000

Table 3. SEO Announcement Reactions Sorted by CGO

This table presents average and median levels of 3-day CARs across deciles sorted by capital gains overhang (CGO) defined in Equations (1)–(2) in Section 1.2.3. The 3-day CAR(-1, +1) is defined as the 3-day CARs centered at the SEO announcement date.

		CGO		CAR(-1, +1)	
	N	Mean	Median	Mean	Median
High	722	0.424	0.411	-0.035	-0.034
2	722	0.326	0.325	-0.036	-0.033
3	723	0.274	0.273	-0.033	-0.031
4	722	0.234	0.234	-0.029	-0.030
5	723	0.198	0.197	-0.028	-0.026
6	722	0.162	0.162	-0.032	-0.030
7	723	0.121	0.121	-0.028	-0.026
8	722	0.073	0.074	-0.028	-0.026
9	723	0.004	0.006	-0.032	-0.028
Low	722	-0.180	-0.140	-0.035	-0.032

Table 4. CGO and SEO Announcement Reactions

This table displays OLS estimations that explain the association between CGO and SEO announcement reactions. The 3-day CAR(-1, +1) is defined as the 3-day CARs centered at the SEO announcement date. The key explanatory variables are CGO; Positive / Negative CGO; and CGO_Quintile1 and CGO_Quintile5. CGO is defined in Equations (1)–(2) in Section 1.2.3. Positive CGO equals the CGO if positive and zero if negative. Negative CGO equals the CGO is negative and zero if positive. The latter two variables are binary indicators that equals one if the stock is in the fifth and first quintile of CGO. Control variable definitions are in Appendix. All regressions contain year and industry fixed effects. I present coefficient estimates and robust t-statistics (in parentheses) from standard errors that are clustered by industry. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: CAR(-1,+1)		
	(1)	(2)	(3)
CGO	-0.012**		
	(0.005)		
Positive CGO		-0.018***	
		(0.007)	
Negative CGO		0.003	
		(0.013)	
CGO_Quintile1 (top 20%)			-0.004**
			(0.001)
CGO_Quintile5 (bottom 20%)			0.002
			(0.002)
Ln(proceeds)	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)
Ln(mktcap)	-0.005***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)
Volatility	-0.325***	-0.320***	-0.312***
	(0.100)	(0.099)	(0.101)
MTB	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Leverage	0.011**	0.011**	0.011**
	(0.005)	(0.005)	(0.005)
Relative offer size	-0.059***	-0.059***	-0.059***
	(0.013)	(0.013)	(0.013)
Secondary	-0.011***	-0.011***	-0.012***
	(0.004)	(0.004)	(0.004)
Pre-1year BHAR	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Constant	0.012	0.014	0.011
	(0.010)	(0.010)	(0.010)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	6,123	6,123	6,123
R-squared	0.054	0.054	0.054

Table 5. SEO Announcement Reactions Sorted by CGO and Institutional Ownership

This table reports 3-day announcement reactions of SEOs across 25 double-sorted portfolios. SEO issuing firms are sorted into quintiles based on CGO then within each quintile of CGO, for every five years, firms are assigned into five groups based on the level of institutional ownership. The High – Low is the average difference in the 3-day announcement returns (CARs) of SEOs between the highest and lowest quintile of institutional ownership. Institutional ownership equals the number of shares owned by institutions at the end of the quarter prior to announcement as a ratio of total shares outstanding in the same quarter. CGO is defined in Equations (1)–(2) in Section 1.2.3. P-values reported in brackets are based on t-tests, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

		CGO				
		High	2	3	4	Low
Institutional Ownership	High	-0.022	-0.021	-0.026	-0.017	-0.024
	2	-0.032	-0.028	-0.024	-0.028	-0.029
	3	-0.036	-0.026	-0.031	-0.035	-0.031
	4	-0.041	-0.036	-0.033	-0.035	-0.042
	Low	-0.048	-0.046	-0.034	-0.034	-0.039
	High – Low	0.026***	0.025***	0.008	0.016**	0.015**
	p-value	[0.000]	[0.000]	[0.218]	[0.012]	[0.036]

Table 6. CGO and SEO Announcement Reactions with High / Low Institutional Ownership

This table displays OLS estimations that explain the association between CGO and SEO announcement reactions for a different level of institutional ownership of SEO issuers. The 3-day CAR(-1, +1) is defined as the 3-day CARs centered at the SEO announcement date. The key explanatory variables are CGO and an interaction term between CGO and High / Low INST. CGO is defined in Equations (1)–(2) in Section 1.2.3. High INST and Low INST are binary indicators that equal one if the SEO issuer is assigned in the fifth quintile and first quintile of institutional ownership, respectively. Column (1) includes CGO and an interaction term of CGO and High INST. Column (2) includes CGO and an interaction term of CGO and Low INST. Control variable definitions are in Appendix. All regressions contain year and industry fixed effects. I present coefficient estimates and robust t-statistics (in parentheses) from standard errors that are clustered by industry (Fama-French 48 industry classification). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: CAR(-1, +1)		
	(1)	(2)	(3)
CGO	-0.014*	-0.017*	-0.010
	(0.008)	(0.009)	(0.009)
CGO x High INST		0.020*	
		(0.011)	
CGO x Low INST			-0.014
			(0.013)
Ln(proceeds)	0.008***	0.008***	0.007***
	(0.002)	(0.002)	(0.002)
Ln(mktcap)	-0.005**	-0.006***	-0.005**
	(0.002)	(0.002)	(0.002)
Volatility	-0.327***	-0.319***	-0.323***
	(0.114)	(0.116)	(0.112)
MTB	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Leverage	0.011*	0.012*	0.012*
	(0.006)	(0.006)	(0.006)
Relative offer size	-0.067***	-0.067***	-0.066***
	(0.015)	(0.015)	(0.015)
Secondary	-0.011***	-0.011**	-0.011***
	(0.004)	(0.004)	(0.004)
Prior 1-year BHAR	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Constant	0.001	0.001	0.003
	(0.012)	(0.012)	(0.012)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	4,541	4,541	4,541
R-squared	0.057	0.058	0.057

Table 7. CGO and Post-announcement Stock Performance before the Stock Offer

This table displays OLS estimations that explain post announcement stock performance before stocks are offered. The 5-day CAR(+2, +6) is defined as the 5-day CARs estimated from 2 days after the SEO announcement date and before the offer date. The key explanatory variables are CGO; Positive / Negative CGO; and CGO_Q4 and CGO_Q1. CGO is defined in Equations (1)–(2) in Section 1.2.3. Positive CGO is defined as CGO if positive and zero if negative. Negative CGO equals CGO if negative and zero if positive. CGO_Q1 and CGO_Q4 are binary indicators that equals one if the stock is in the fourth and first quartile of CGO. Control variable definitions are in Appendix. All regressions contain year and industry fixed effects. I present coefficient estimates and robust t-statistics (in parentheses) from standard errors that are clustered by industry. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: CAR(+2, +6)		
	(1)	(2)	(3)
CGO	-0.002		
	(0.009)		
Positive CGO		0.015	
		(0.014)	
Negative CGO		-0.056**	
		(0.025)	
CGO_Q1 (top 25%)			0.006**
			(0.003)
CGO_Q4 (bottom 25%)			0.005
			(0.004)
CAR(-1, +1)	-0.080**	-0.079**	-0.080**
	(0.031)	(0.032)	(0.032)
Ln(Proceeds)	0.025***	0.025***	0.025***
	(0.003)	(0.003)	(0.003)
Ln(Mktcap)	-0.021***	-0.021***	-0.021***
	(0.003)	(0.003)	(0.003)
Volatility	-0.263**	-0.287**	-0.269**
	(0.113)	(0.111)	(0.120)
MTB	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Leverage	-0.004	-0.004	-0.004
	(0.007)	(0.007)	(0.007)
Relative offer size	-0.091***	-0.091***	-0.091***
	(0.018)	(0.018)	(0.018)
Secondary	-0.012*	-0.012*	-0.013*
	(0.007)	(0.007)	(0.007)
Prior 1-year BHAR	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.002)
Constant	0.169***	0.160***	0.160***
	(0.012)	(0.012)	(0.010)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	4,015	4,015	4,015
R-squared	0.062	0.064	0.064

APPENDIX C

VARIABLE DEFINITIONS FOR "REVIVING THE DISPOSITION EFFECT: HIGHEST PRICE AS THE REFERENCE POINT"

Variable	Definition
Ret (RP=max $_{t-1}$)	The return based on the past maximum price since purchase, prior to sell
Ret+ (RP=max $_{t-1}$)	The perceived return, Ret (RP=max $_{t-1}$), if positive, zero otherwise.
Ret- (RP=max $_{t-1}$)	The perceived return, Ret (RP=max $_{t-1}$), if negative, zero otherwise.
I(ret (RP=max $_{t-1}$) > 0)	An indicator if the perceived return, Ret (RP=max $_{t-1}$), is positive.
Ret- (Ret+)	The return since purchase if the return since purchase is negative (positive), zero otherwise.
I(ret = 0)	An indicator for whether the return since purchase is zero.
I(ret > 0)	An indicator for whether the return since purchase is positive.
I(ret < 0)	An indicator for whether the return since purchase is negative.
sqrt(Time owned)	The square root of the number of days since purchase.
log(Buy price)	The logged purchase price (in dollars).
Volatility- (Volatility+)	The stock volatility calculated using daily returns using the 250 days prior to the purchase if the return since purchase is negative (positive), zero otherwise.
Best (RP=max $_{t-1}$)	A dummy variable equal to 1 if the stock has the highest perceived return (Ret(RP=max $_{t-1}$)) in the portfolio when sorted into deciles.
2nd Best (RP=max $_{t-1}$)	A dummy variable equal to 1 if the stock has the 2nd highest perceived return (Ret(RP=max $_{t-1}$)) in the portfolio when sorted into deciles.
Worst (RP=max $_{t-1}$)	A dummy variable equal to 1 if the stock has the lowest perceived return (Ret(RP=max $_{t-1}$)) in the portfolio when sorted into deciles.
2nd Worst (RP=max $_{t-1}$)	A dummy variable equal to 1 if the stock has the 2nd lowest perceived return (Ret(RP=max $_{t-1}$)) in the portfolio when sorted into deciles.
Best	A dummy variable equal to 1 if the stock has the highest return since purchase in the portfolio when sorted into deciles.

Variable	Definition
2nd Best	A dummy variable equal to 1 if the stock has the 2nd highest return since purchase in the portfolio when sorted into deciles.
Worst	A dummy variable equal to 1 if the stock has the lowest return since purchase in the portfolio when sorted into deciles.
2nd Worst	A dummy variable equal to 1 if the stock has the 2nd lowest return since purchase in the portfolio when sorted into deciles.
Ret (RP=52-week-max $_{t-23}$)	The return based on the past 52-week maximum price measured on 23 days prior to sell
Ret+ (RP=52-week-max $_{t-23}$)	The perceived return, Ret (RP=52-week-max $_{t-23}$), if positive, zero otherwise.
Ret- (RP=52-week-max $_{t-23}$)	The perceived return, Ret (RP=52-week-max $_{t-23}$), if negative, zero otherwise.
I(ret (RP=52-week-max $_{t-23}$) > 0)	An indicator if the perceived return, Ret (RP=52-week-max $_{t-23}$), is positive.
Ret (RP=min $_{t-1}$)	The return based on the past minimum price since purchase, prior to sell
Ret+ (RP=min $_{t-1}$)	The perceived return, Ret (RP=min $_{t-1}$), if positive, zero otherwise.
Ret- (RP=min $_{t-1}$)	The perceived return, Ret (RP=min $_{t-1}$), if negative, zero otherwise.
I(ret (RP=min $_{t-1}$) > 0)	An indicator if the perceived return, Ret (RP=min $_{t-1}$), is positive.
Ret (RP=1-month-max $_{t-1}$)	The return based on the past 1-month maximum price since purchase, prior to sell
Ret+ (RP=1-month-max $_{t-1}$)	The perceived return, Ret (RP=1-month-max $_{t-1}$), if positive, zero otherwise.
Ret- (RP=1-month-max $_{t-1}$)	The perceived return, Ret (RP=1-month-max $_{t-1}$), if negative, zero otherwise.
I(ret (RP=1-month-max $_{t-1}$) > 0)	An indicator if the perceived return, Ret (RP=1-month-max $_{t-1}$), is positive.

APPENDIX D

TABLES FOR "REVIVING THE DISPOSITION EFFECT: HIGHEST PRICE AS THE REFERENCE POINT"

Table 8. Summary Statistics of Independent Variables

Panel A, B, and C report summary statistics for independent variables including control variables across three different prior holding periods, respectively. Ret (RP=max $_{t-1}$) is defined as Ret (RP=max $_{t-1}$) = (price – maximum price)/maximum price, where maximum price is defined as past maximum price since purchase on one day prior to sell, for investor-stock level. Ret+ (RP=max $_{t-1}$) is Max{Ret (RP=max $_{t-1}$), 0} and Ret- (RP=max $_{t-1}$) is Min{Ret (RP=max $_{t-1}$), 0} and I(ret (RP=max $_{t-1}$) > 0) is an indicator if Ret (RP=max $_{t-1}$) > 0. Ret+ is Max{Ret, 0} and Ret- is Min{Ret, 0} and I(ret = 0) is an indicator if return is zero. I(ret > 0) is an indicator if return is positive. Sqrt (Time owned) is the square root of prior holding period measured in holding days, log(Buy price) is the logarithm of purchase price, Volatility- (Volatility+) is equal to volatility if return is negative (positive) and zero otherwise.

Panel A: Prior holding period 1 to 20 days (6.6 million)

	Mean	Std. Dev.	Minimum	p25	Median	p75	Maximum
Ret (RP=max $_{t-1}$)	-0.051	0.072	-0.375	-0.073	-0.031	-0.006	0.068
Ret- (RP=max $_{t-1}$)	-0.054	0.069	-0.375	-0.073	-0.031	-0.006	0.000
Ret+ (RP=max $_{t-1}$)	0.003	0.011	0.000	0.000	0.000	0.000	0.068
I(ret (RP=max $_{t-1}$) > 0)	0.154	0.361	0	0	0	0	1
Ret-	-0.034	0.060	-0.324	-0.045	0	0	0
Ret+	0.031	0.056	0	0	0	0.040	0.304
I(ret = 0)	0.045	0.207	0	0	0	0	1
I(ret > 0)	0.461	0.498	0	0	0	1	1
I(ret < 0)	0.494	0.500	0	0	0	1	1
sqrt(Time owned)	3.719	1.249	1	2.828	3.873	4.796	5.477
log(Buy price)	3.097	0.886	0.272	2.621	3.229	3.735	4.648
Volatility-	0.015	0.018	0	0	0	0.026	0.077
Volatility+	0.012	0.016	0	0	0	0.022	0.066

Panel B: Prior holding period 21 to 250 days (46.9 million)

	Mean	Std. Dev.	Minimum	p25	Median	p75	Maximum
Ret (RP=max $_{t-1}$)	-0.175	0.172	-0.740	-0.256	-0.120	-0.045	0.026
Ret- (RP=max $_{t-1}$)	-0.176	0.172	-0.740	-0.256	-0.120	-0.045	0.000
Ret+ (RP=max $_{t-1}$)	0.001	0.003	0.000	0.000	0.000	0.000	0.026
I(ret (RP=max $_{t-1}$) > 0)	0.043	0.203	0	0	0	0	1
Ret-	-0.102	0.156	-0.672	-0.154	-0.009	0	0
Ret+	0.094	0.177	0	0	0	0.120	1.048
I(ret = 0)	0.013	0.112	0	0	0	0	1
I(ret > 0)	0.474	0.499	0	0	0	1	1
I(ret < 0)	0.513	0.500	0	0	1	1	1
sqrt(Time owned)	12.783	3.788	5.745	9.644	12.961	16.031	19
log(Buy price)	3.095	0.899	0.266	2.616	3.244	3.741	4.632
Volatility-	0.015	0.018	0	0	0.010	0.026	0.079
Volatility+	0.012	0.015	0	0	0	0.020	0.063

Table 8 – continued

Panel C: Prior holding period > 250 days (60.8 million)

	Mean	Std. Dev.	Minimum	p25	Median	p75	Maximum
Ret (RP=max $_{t-1}$)	-0.285	0.232	-0.882	-0.449	-0.231	-0.086	0.013
Ret- (RP=max $_{t-1}$)	-0.286	0.232	-0.882	-0.449	-0.231	-0.086	0.000
Ret+ (RP=max $_{t-1}$)	0.000	0.002	0.000	0.000	0.000	0.000	0.013
I(ret (RP=max $_{t-1}$) > 0)	0.026	0.158	0	0	0	0	1
Ret-	-0.156	0.221	-0.845	-0.271	0	0	0
Ret+	0.299	0.711	0	0	0	0.304	4.925
I(ret = 0)	0.005	0.073	0	0	0	0	1
I(ret > 0)	0.497	0.500	0	0	0	1	1
I(ret < 0)	0.497	0.500	0	0	0	1	1
sqrt(Time owned)	29.049	6.642	19.287	23.388	28.160	33.975	44.249
log(Buy price)	3.123	0.920	0.258	2.621	3.291	3.774	4.685
Volatility-	0.013	0.016	0	0	0	0.021	0.068
Volatility+	0.012	0.015	0	0	0	0.019	0.067

Table 9. Proportions of Stocks Sold by Decile Sorts (RP = Max)

This table reports selling probability (multiplied by 100) with decile sorts based on the perceived return (Ret ($RP=max_{t-1}$)) for four different horizons: prior holding periods up to 20 trading days since purchase, between 21 to 250 trading days since purchase, over 250 trading days since purchase, and all observations. The last two rows present the difference between the indicated groups with a t-statistic on the null hypothesis that the difference is 0.

	1 to 20	21 to 250	> 250	All
All ranks ($RP=max_{t-1}$)	0.72	0.28	0.08	0.20
Low (1)	0.89	0.18	0.06	0.08
2	0.71	0.22	0.05	0.10
3	0.58	0.23	0.06	0.13
4	0.53	0.24	0.07	0.15
5	0.50	0.26	0.07	0.17
6	0.51	0.26	0.08	0.20
7	0.53	0.26	0.09	0.21
8	0.57	0.28	0.10	0.23
9	0.78	0.31	0.10	0.25
High (10)	1.53	0.58	0.15	0.49
High – Low	0.63	0.40	0.10	0.41
t-statistics	[33.23]	[100.63]	[52.25]	[185.82]
Observations	6.6 mil.	46.9 mil.	60.4 mil.	114.3mil.

Table 10. Probability of Selling Stock

This table reports marginal effect (multiplied by 100) from probit regressions for selling and a set of control variables. The analysis is based on 50,000 random accounts among 77,037 retail accounts from a brokerage firm from 1991 to 1996. Observations are at an investor-stock-day level. Panel A, B, and C report regression estimations on selling propensity across different prior holding periods, respectively. Columns (1) and (2) present simple regressions, columns (3) to (5) present multivariate regressions using return since purchase and perceived return with additional controls. Ret (RP=max $_{t-1}$) = (price – max price)/max price, where max price is past maximum price since purchase on a day prior to sell. Ret+ (RP=max $_{t-1}$) = Max{Ret (RP=max $_{t-1}$), 0}, Ret- (RP=max $_{t-1}$) = Min{Ret (RP=max $_{t-1}$), 0}, Ret+ = Max{Ret, 0}, Ret- = Min{Ret, 0}. I(ret (RP=max $_{t-1}$) > 0) is an indicator if Ret(RP=max $_{t-1}$) > 0. I(ret = 0) (I(ret > 0)) is an indicator if return is zero (positive). Sqrt (Time owned) is the square root of prior holding period measured in holding days and log(Buy price) is the logarithm of purchase price. Volatility- (Volatility+) is the volatility if the return is negative (positive). The top number is the marginal effect multiplied by 100, and the lower number in square brackets is the t-statistics. Standard errors are clustered by date and account for the investors.

Table 10 – continued

Panel A: Prior holding period 1 to 20 trading days

	Dependent variable: I(Sell stock) × 100				
Prior holding period (days):	1 to 20				
	(1)	(2)	(3)	(4)	(5)
Ret (RP=max $_{t-1}$)	0.54			-0.72	
	[4.11]			[-4.52]	
Ret- (RP=max $_{t-1}$)		-1.13			-2.40
		[-11.68]			[-16.79]
Ret+ (RP=max $_{t-1}$)		18.94			1.65
		[50.62]			[4.08]
I(ret (RP=max $_{t-1}$) > 0)					0.20
					[10.26]
Ret-			-6.53	-5.79	-4.06
			[-24.56]	[-18.26]	[-13.52]
Ret- × sqrt(Time owned)			1.02	1.01	0.99
			[16.90]	[16.82]	[16.60]
Ret+			7.81	8.02	7.49
			[29.79]	[30.35]	[27.00]
Ret+ × sqrt(Time owned)			-0.96	-0.99	-0.95
			[-17.10]	[-17.52]	[-16.22]
I(ret = 0)			0.74	0.73	0.70
			[10.28]	[10.16]	[9.83]
I(ret = 0) × sqrt(Time owned)			-0.04	-0.04	-0.05
			[-2.11]	[-2.2]	[-2.42]
I(ret > 0)			0.31	0.33	0.09
			[5.99]	[6.48]	[2.01]
I(ret > 0) × sqrt(Time owned)			-0.03	-0.03	0.01
			[-2.91]	[-3.15]	[1.25]
sqrt(Time owned)			-0.08	-0.08	-0.10
			[-7.58]	[-8.08]	[-9.91]
log(Buy price)			0.33	0.33	0.33
			[27.55]	[27.65]	[27.37]
Volatility-			18.42	18.17	17.24
			[24.35]	[24.09]	[22.83]
Volatility+			23.06	22.44	21.59
			[27.96]	[27.20]	[26.16]
Intercept	-4.84	-4.98	-6.48	-6.46	-6.39
	[-255.89]	[-260.86]	[-86.70]	[-86.22]	[-86.76]
Observations	6.6 mil.	6.6 mil.	6.6 mil.	6.6 mil.	6.6 mil.
Pseudo R^2	0.0000	0.0010	0.0033	0.0033	0.0035

Table 10 – continued

Panel B: Prior holding period 21 to 250 trading days

	Dependent variable: I(Sell stock) × 100				
Prior holding period (days):	21 to 250				
	(1)	(2)	(3)	(4)	(5)
Ret (RP=max $_{t-1}$)	0.5112			0.38	
	[3.74]			[17.58]	
Ret- (RP=max $_{t-1}$)		-1.21			0.18
		[-12.15]			[8.95]
Ret+ (RP=max $_{t-1}$)		19.25			3.91
		[50.17]			[11.82]
I(ret (RP=max $_{t-1}$) > 0)					0.12
					[18.97]
Ret-			-0.08	-0.45	-0.26
			[2.42]	[-11.03]	[-6.50]
Ret- × sqrt(Time owned)			0.01	0.01	0.01
			[4.59]	[5.67]	[5.17]
Ret+			0.49	0.44	0.36
			[24.28]	[21.78]	[17.19]
Ret+ × sqrt(Time owned)			-0.02	-0.02	-0.02
			[-16.95]	[-16.11]	[-13.52]
I(ret = 0)			0.14	0.15	0.14
			[5.50]	[6.25]	[5.61]
I(ret = 0) × sqrt(Time owned)			0.01	0.01	0.01
			[3.04]	[3.01]	[3.05]
I(ret > 0)			0.07	0.06	0.02
			[6.27]	[5.18]	[1.61]
I(ret > 0) × sqrt(Time owned)			0.00	0.00	0.00
			[-2.85]	[-3.54]	[-0.63]
sqrt(Time owned)			-0.02	-0.02	-0.02
			[-26.06]	[-20.72]	[-23.00]
log(Buy price)			0.07	0.06	0.06
			[29.76]	[28.63]	[27.46]
Volatility-			5.26	5.72	5.31
			[37.47]	[41.05]	[38.31]
Volatility+			8.74	9.79	9.48
			[55.76]	[60.72]	[59.34]
Intercept			-2.54	-2.54	-2.52
			[-179.71]	[-179.67]	[-179.55]
Observations	6.6 mil.	6.6 mil.	46.9 mil.	46.9 mil.	46.9 mil.
Pseudo R^2	0.0000	0.0010	0.0009	0.0009	0.001

Table 10 – continued

Panel C: Prior holding period over 250 trading days

	Dependent variable: I(Sell stock) × 100				
Prior holding period (days):	> 250				
	(1)	(2)	(3)	(4)	(5)
Ret (RP=max $_{t-1}$)	0.5112			0.19	
	[3.74]			[37.46]	
Ret- (RP=max $_{t-1}$)		-1.21			0.17
		[-12.15]			[33.28]
Ret+ (RP=max $_{t-1}$)		19.25			1.33
		[50.17]			[3.26]
I(ret (RP=max $_{t-1}$) > 0)					0.04
					[9.88]
Ret-			0.08	-0.09	-0.07
			[5.86]	[-6.44]	[-4.84]
Ret- × sqrt(Time owned)			0.00	0.00	0.00
			[-2.64]	[-1.05]	[-1.25]
Ret+			0.00	0.00	-0.01
			[0.30]	[-1.05]	[-1.99]
Ret+ × sqrt(Time owned)			0.00	0.00	0.00
			[-1.60]	[-2.44]	[-1.88]
I(ret = 0)			0.05	0.06	0.06
			[2.30]	[2.82]	[2.67]
I(ret = 0) × sqrt(Time owned)			0.00	0.00	0.00
			[0.44]	[0.31]	[0.34]
I(ret > 0)			0.03	0.01	0.01
			[4.92]	[1.67]	[0.86]
I(ret > 0) × sqrt(Time owned)			0.00	0.00	0.00
			[-0.63]	[-1.07]	[-0.68]
sqrt(Time owned)			-0.01	-0.01	-0.01
			[-32.63]	[-27.43]	[-28.05]
log(Buy price)			0.01	0.01	0.01
			[17.84]	[15.38]	[14.33]
Volatility-			1.65	1.96	1.87
			[27.61]	[32.57]	[31.12]
Volatility+			1.93	2.77	2.71
			[31.90]	[42.93]	[42.01]
Intercept			-0.81	-0.80	-0.79
			[-128.41]	[-127.35]	[-126.97]
Observations	6.6 mil.	6.6 mil.	60.8 mil.	60.8 mil.	60.8 mil.
Pseudo R^2	0.0000	0.0010	0.0003	0.0003	0.0003

Table 11. Future Return Performance Following Sales (Rank: RP=Max)

This table reports cumulative average returns (in percent) in excess of the market return for 20, 42, and 126 trading days following sales. The data is sorted based on the perceived return, Ret (RP=max $_{t-1}$), defined as return based on the past maximum price since purchase on a day prior to sell. The last four rows present the difference between the indicated groups with a t-statistic on the null hypothesis that the difference is 0. Panel A uses rank deciles used in Table 9, Panel B re-sorts the data (selling transactions) based on the perceived return, and Panel C removes the observations that went through stock splits and then re-sorts the data (selling transactions) based on the perceived return.

Panel A: Ranks by Ret (RP=max $_{t-1}$) as in Table 9

	1 to 20			21 to 250			> 250		
Prior holding period (days):	20 days later	42 days later	126 days later	20 days later	42 days later	126 days later	20 days later	42 days later	126 days later
All ranks (RP=max $_{t-1}$)	-0.28	-0.73	-2.09	0.33	0.31	0.18	0.44	0.54	1.78
Low (0)	-0.96	-2.07	-4.92	2.28	2.70	4.49	2.98	4.31	11.08
1	-0.09	-0.89	-3.00	-0.18	-0.30	-1.30	0.26	0.15	1.89
2	0.04	-0.08	-1.96	-0.52	-0.76	-1.07	0.16	-0.50	0.69
3	-0.11	-0.73	-1.78	-0.21	-0.21	-0.51	-0.19	-0.81	-0.81
4	-0.16	-0.44	-1.28	0.26	0.07	-0.10	-0.14	-0.21	-0.30
5	0.01	-0.19	-1.18	0.12	0.06	-0.07	-0.02	-0.06	0.10
6	-0.29	-0.40	-1.64	0.39	0.44	0.32	0.04	0.31	0.77
7	0.19	-0.24	-0.69	0.65	0.66	0.11	0.41	0.75	0.77
8	-0.22	-0.37	-0.66	0.50	0.40	0.09	0.77	1.03	1.93
High (9)	-1.14	-1.91	-3.73	0.01	0.05	-0.19	0.17	0.44	1.71
High – Low	-0.19	0.17	1.18	-2.27	-2.65	-4.68	-2.81	-3.87	-9.37
t-statistics	[-0.67]	[0.41]	[1.78]	[-8.68]	[-7.59]	[-8.49]	[-6.92]	[-7.11]	[-10.50]
(9 - 1)	-1.05	-1.02	-0.73	0.19	0.35	1.11	-0.09	0.29	-0.18
t-statistics	[-3.90]	[-2.65]	[-1.14]	[1.15]	[1.48]	[2.77]	[-0.34]	[0.81]	[0.29]
Observations	48,071	48,071	48,071	134,918	134,918	134,918	50,086	50,086	50,086

Panel B: Ranks by Ret (RP=max $_{t-1}$) within stocks that are sold

	1 to 20			21 to 250			> 250		
Prior holding period (days):	20 days later	42 days later	126 days later	20 days later	42 days later	126 days later	20 days later	42 days later	126 days later
All ranks (RP=max $_{t-1}$)	-0.44	-0.97	-2.44	0.27	0.24	0.048	0.38	0.51	1.57
Low (0)	-1.06	-2.20	-4.86	1.42	1.67	2.56	2.16	2.84	7.95
1	-0.27	-1.19	-3.71	-0.43	-0.69	-1.40	0.19	-0.08	1.40
2	0.03	-0.16	-2.17	-0.27	-0.27	-0.56	-0.24	-0.79	-0.59
3	-0.01	-0.67	-1.90	0.22	0.03	-0.17	-0.15	-0.27	-0.46
4	-0.22	-0.40	-0.87	0.10	0.04	-0.04	0.05	0.12	0.13
5	-0.18	-0.26	-1.64	0.46	0.49	0.19	0.01	0.25	0.79
6	0.17	-0.05	-0.58	0.68	0.67	0.10	0.60	1.06	1.06
7	-0.48	-0.85	-1.08	0.44	0.33	0.15	0.81	1.00	1.84
8	-0.52	-1.15	-2.21	0.08	0.23	0.15	0.32	0.62	1.82
High (9)	-1.86	-2.76	-5.39	-0.05	-0.12	-0.51	0.03	0.29	1.78
High – Low	-0.81	-0.56	-0.53	-1.47	-1.79	-3.06	-2.13	-2.55	-6.17
t-statistics	[-2.17]	[-1.06]	[-0.61]	[-7.03]	[-6.26]	[-6.52]	[-6.55]	[-5.80]	[-8.46]
(9 - 1)	-1.60	-1.57	-1.68	0.38	0.57	0.89	-0.15	0.37	0.39
t-statistics	[-4.16]	[-3.20]	[-2.08]	[2.27]	[2.34]	[2.12]	[-0.70]	[1.18]	[0.73]
Observations	48,071	48,071	48,071	134,918	134,918	134,918	50,086	50,086	50,086

Table 11 – continued

Panel C: Ranks by Ret (RP=max $_{t-1}$) within stocks that are sold with adjustment in stock splits

Prior holding period (days):	1 to 20			21 to 250			> 250		
	20 days later	42 days later	126 days later	20 days later	42 days later	126 days later	20 days later	42 days later	126 days later
All ranks (RP=max $_{t-1}$)	-0.45	-1.06	-3.03	0.42	0.28	-0.44	0.87	1.16	2.31
Low (0)	-1.29	-2.66	-5.21	2.21	2.63	4.09	4.66	6.87	15.05
1	-0.54	-1.18	-3.89	-0.18	-0.64	-2.68	0.62	0.34	0.91
2	0.08	-0.27	-2.91	-0.91	-1.48	-1.53	0.37	0.10	1.61
3	0.13	-0.37	-1.84	-0.02	0.08	-0.96	0.67	-0.27	-1.61
4	-0.24	-0.64	-1.72	0.33	-0.06	-0.95	-0.58	-0.93	-1.14
5	-0.02	-0.11	-2.17	0.27	0.10	-0.76	-0.13	0.04	0.95
6	0.35	-0.08	-1.34	1.07	0.92	-0.39	0.72	1.51	2.17
7	-0.18	-0.67	-1.40	0.89	0.85	0.35	1.24	1.53	0.59
8	-0.68	-1.11	-3.06	0.40	0.41	-0.71	1.17	1.63	2.33
High (9)	-2.14	-3.54	-6.78	0.09	-0.04	-0.90	-0.08	0.80	2.18
High - Low	-0.85	-0.88	-1.57	-2.12	-2.66	-4.99	-4.75	-6.08	-12.87
t-statistics	[-1.91]	[-1.39]	[-1.50]	[-6.23]	[-5.79]	[-6.66]	[-6.06]	[-5.93]	[-7.70]
(9 - 1)	-1.60	-2.36	-2.88	0.27	0.60	1.78	-0.71	0.46	1.27
t-statistics	[-3.81]	[-3.93]	[-2.94]	[1.00]	[1.60]	[2.71]	[-1.26]	[0.58]	[-0.96]
Observations	36,186	36,186	36,186	70,658	70,658	70,658	15,522	15,522	15,522

Table 12. Rank Effect with Controls for Past Performance

This table presents marginal effect (multiplied by 100) from logistic regression. The dependent variable is a dummy variable equal to 1 if a stock is sold. Best (RP=max $_{t-1}$) (Worst (RP=max $_{t-1}$)) is an indicator equal to 1 if the stock has the highest (lowest) perceived return (Ret (RP=max $_{t-1}$)) in the portfolio. 2nd Best (RP=max $_{t-1}$) (2nd Worst (RP=max $_{t-1}$)) is an indicator for the second highest (lowest) perceived return (Ret (RP=max $_{t-1}$)). Best (Worst) is an indicator equal to 1 if the stock has the highest (lowest) return since purchase in the portfolio and 2nd Best (2nd Worst) is an indicator for the second highest (lowest) return since purchase. Ret+ is Max{Ret, 0} and Ret- is Min{Ret, 0}, where Ret is return since purchase. I(ret > 0) is an indicator if return since purchase is positive. Volatility- (Volatility+) takes the value of volatility when the return since purchase is negative (positive) and zero otherwise. The top number is the marginal effect, and the lower number in square bracket is the t-statistics. Standard errors are clustered by date and account for the investors.

	Dependent variable: Sell x100			
	(1)	(2)	(3)	(4)
Best (RP=max $_{t-1}$)			8.969	6.694
			[72.98]	[53.63]
Worst (RP=max $_{t-1}$)			5.88	2.946
			[35.99]	[15.13]
2nd Best (RP=max $_{t-1}$)			4.919	3.344
			[37.43]	[25.28]
2nd Worst (RP=max $_{t-1}$)			4.849	2.908
			[33.13]	[18.2]
Best		11.203		9.267
		[81.8]		[67.24]
Worst		7.245		5.412
		[41.25]		[25.69]
2nd Best		7.432		5.905
		[57.78]		[45.33]
2nd Worst		4.909		3.845
		[31.97]		[23.04]
Ret+	8.73	1.717	7.903	2.271
	[27.32]	[5.23]	[25.2]	[7.03]
Ret-	-14.172	-4.115	-11.391	-5.946
	[-18.62]	[-5.29]	[-14.84]	[-7.62]
I(ret > 0)	1.779	0.896	-0.023	-0.329
	[10]	[5.03]	[-0.13]	[-1.85]
Ret+ × sqrt(Time owned)	-0.354	-0.267	-0.352	-0.278
	[-25.39]	[-18.72]	[-25.84]	[-19.93]
Ret- × sqrt(Time owned)	0.57	0.475	0.744	0.628
	[16.73]	[14.45]	[21.78]	[18.81]
sqrt(Time owned)	-0.153	-0.15	-0.081	-0.096
	[-25.59]	[-25.01]	[-13.81]	[-16.01]
Volatility-	-24.369	-17.47	-21.648	-16.738
	[-5.54]	[-4.11]	[-5.08]	[-3.98]
Volatility+	101.069	82.892	105.63	92.551
	[26.14]	[21.88]	[27.7]	[24.44]
Constant	-20.56	-21.281	-22.418	-22.438
	[-134.61]	[-137.77]	[-142.97]	[-141.71]
Observations	661,499	661,499	661,499	661,499
Pseudo R^2	0.0138	0.0289	0.0252	0.034

Table 13. Robustness Test: Probability of Selling Stock (RP = 52-week High)

This table reports multivariate and univariate test results for perceived return, Ret (RP=52-week-max $_{t-23}$), estimated with the 52-week maximum price on 23 days prior to sell. The analysis is based on 50,000 random accounts among 77,037 retail accounts from a brokerage firm from 1991 to 1996. Observations are at an investor-stock-day level. Panel A presents marginal effects (multiplied by 100) from probit regressions for selling with a set of control variables. Each column presents multivariate estimation on selling propensity with perceived return, return since purchase, and additional controls. Columns (1) and (2) are for holding period less than 21 days. Columns (3) and (4) are for holding period over 20 days and less than 250 days. Columns (5) and (6) are for holding period over 250 days. The perceived return, Ret (RP=52-week-max $_{t-23}$), equals (price – 52-week-max)/52-week-max, where 52-week-max is defined as past 52-week maximum price since purchase on 23 days prior to sell, for investor-stock level. Ret+ (RP=52-week-max $_{t-23}$) (Ret- (RP=52-week-max $_{t-23}$)) takes the value of Ret (RP=52-week-max $_{t-23}$) if positive (negative) and zero otherwise. I(ret(RP=52-week-max $_{t-23}$) > 0) is an indicator equal to one if Ret (RP=52-week-max $_{t-23}$) is positive. Ret+ (Ret-) takes the value of the return since purchase if positive (negative) and zero otherwise. I(ret > 0) an indicator if return since purchase is positive. Sqrt (Time owned) is the square root of prior holding period measured in holding days and log (Buy price) is the logarithm of purchase price. Volatility- (Volatility+) takes the value of volatility when the return since purchase is negative (positive) and zero otherwise. The top number is the marginal effect multiplied by 100, and the lower number in square brackets is the t-statistics. Standard errors are clustered by date and account for the investors. Panel B displays selling probability (multiplied by 100) with decile sorts based on the perceived return, Ret (RP=52-week-max $_{t-23}$), for four different horizons: prior holding periods up to 20 trading days since purchase, between 21 to 250 trading days since purchase, over 250 trading days since purchase, and all observations. The last two rows present the difference between the indicated groups with a t-statistic on the null hypothesis that the difference is 0.

Table 13 – continued

Panel A: Multivariate regression

	Dependent variable: I(Sell stock) × 100					
Prior holding period (days):	1 to 20		21 to 250		>250	
	(1)	(2)	(3)	(4)	(5)	(6)
Ret (RP=52-week-max $_{t-23}$)	0.13		0.15		0.15	
	[5.46]		[19.19]		[39.51]	
Ret- (RP=52-week-max $_{t-23}$)		0.22		0.12		0.09
		[6.92]		[14.32]		[21.78]
Ret+ (RP=52-week-max $_{t-23}$)		-0.20		0.66		0.44
		[-1.84]		[11.57]		[21.99]
I(ret (RP=52-week-max $_{t-23}$) > 0)		-0.02		-0.01		0.01
		[-0.79]		[-2.69]		[4.79]
Ret-	-6.58	-6.63	-0.19	-0.18	-0.09	-0.02
	[-22.73]	[-22.87]	[-4.99]	[-4.58]	[-5.42]	[-1.29]
Ret- × sqrt(Time owned)	1.03	1.04	0.01	0.01	0.00	0.00
	[15.65]	[15.69]	[4.63]	[4.65]	[3.49]	[0.73]
Ret+	7.74	7.81	0.42	0.37	-0.01	-0.01
	[28.57]	[28.67]	[18.81]	[16.51]	[-1.90]	[-4.19]
Ret+ × sqrt(Time owned)	-0.96	-0.96	-0.02	-0.02	0.00	0.00
	[-16.21]	[-16.22]	[-14.29]	[-13.19]	[-1.24]	[0.60]
I(ret = 0)	0.83	0.84	0.17	0.17	0.04	0.03
	[10.42]	[10.61]	[6.37]	[6.26]	[1.50]	[1.11]
I(ret = 0) × sqrt(Time owned)	-0.06	-0.06	0.00	0.00	0.00	0.00
	[-2.48]	[-2.46]	[2.14]	[2.15]	[1.53]	[1.58]
I(ret > 0)	0.36	0.35	0.06	0.06	0.00	0.00
	[6.37]	[6.32]	[4.70]	[4.82]	[0.45]	[0.09]
I(ret > 0) × sqrt(Time owned)	-0.04	-0.04	0.00	0.00	0.00	0.00
	[-3.38]	[-3.4]	[-2.96]	[-2.77]	[2.29]	[2.27]
sqrt(Time owned)	-0.07	-0.07	-0.02	-0.02	-0.01	-0.01
	[-6.79]	[-6.92]	[-24.74]	[-24.46]	[-29.86]	[-30.77]
log(Buy price)	0.32	0.32	0.06	0.06	0.01	0.01
	[25.83]	[25.93]	[28.10]	[27.79]	[13.14]	[11.99]
Volatility-	18.63	19.18	5.69	5.59	1.95	1.71
	[24.09]	[24.92]	[38.44]	[37.73]	[30.02]	[26.16]
Volatility+	22.83	23.51	9.66	9.54	2.42	2.17
	[27.31]	[28.04]	[57.85]	[57.00]	[36.28]	[32.47]
Constant	-6.40	-6.39	-2.51	-2.52	-0.78	-0.78
	[-80.09]	[-79.76]	[-164.82]	[-164.18]	[-109.50]	[-110.46]
Observations	5.1 mil.	5.1 mil.	36.8 mil.	36.8 mil.	47.7 mil.	47.7 mil.
Pseudo R^2	0.0034	0.0034	0.0009	0.0009	0.0003	0.0003

Table 13 – continued

Panel B: Proportions of stocks sold by decile sorts

	1 to 20	21 to 250	> 250	All
All ranks (RP=52-week-max $_{t-23}$)	0.71	0.28	0.08	0.08
Low (0)	0.78	0.24	0.06	0.06
1	0.68	0.23	0.07	0.07
2	0.67	0.25	0.08	0.08
3	0.68	0.26	0.07	0.07
4	0.68	0.27	0.07	0.07
5	0.66	0.27	0.07	0.07
6	0.64	0.29	0.08	0.08
7	0.65	0.28	0.08	0.08
8	0.64	0.29	0.10	0.10
High (9)	1.05	0.43	0.15	0.15
High – Low	0.27	0.19	0.09	0.42
t-statistics	[14.57]	[43.78]	[42.31]	[187.96]
Observations	5.1 mil.	36.8 mil.	47.6 mil.	113.8mil.

Table 14. Robustness Test: Probability of Selling Stock (RP = Min, RP = 1-month High)

This table reports marginal effect (multiplied by 100) from probit regressions for selling and a set of control variables. The analysis is based on 50,000 random accounts among 77,037 retail accounts from a brokerage firm from 1991 to 1996. Observations are at an investor-stock-day level. Panel A and B present regression estimations on selling propensity with respect to Ret (RP=min $_{t-1}$) and Ret (RP=1-month-max $_{t-1}$). Ret (RP=min $_{t-1}$) = (price – min price)/min price, where min price is the past minimum price since purchase on a day prior to sell. Panel B presents marginal effect for selling with respect to Ret (RP=1-month-max $_{t-1}$) = (price – 1-month-max)/ 1-month-max, where 1-month-max is the past 1-month maximum price since purchase on a day prior to sell. Each column presents multivariate estimation on selling propensity with perceived return, return since purchase, and additional controls. Columns (1) and (2) are for holding period less than 21 days; Columns (3) and (4) are for holding period over 20 days and less than 251 days; Columns (5) and (6) are for holding period over 250 days. Ret+ (RP=min $_{t-1}$) (Ret- (RP=min $_{t-1}$)) takes the value of Ret (RP=min $_{t-1}$) if positive (negative) and zero otherwise. I(ret(RP=min $_{t-1}$) > 0) is an indicator if Ret (RP=min $_{t-1}$) is positive. Ret+ (RP=1-month-max $_{t-1}$) (Ret- (RP=1-month-max $_{t-1}$)) takes the value of Ret (RP=1-month-max $_{t-1}$) if positive (negative) and zero otherwise. I(ret(RP=1-month-max $_{t-1}$) > 0) is an indicator if Ret (RP=1-month-max $_{t-1}$) is positive. Ret+ (Ret-) takes the value of return since purchase if positive (negative) and zero otherwise. I(ret = 0) is an indicator if return is zero. I(ret > 0) is an indicator if return is positive. Sqrt (Time owned) is the square root of prior holding period measured in holding days and log (Buy price) is the logarithm of purchase price. Volatility- (Volatility+) is the volatility when negative (positive) return. The top number is the marginal effect multiplied by 100, and the lower number in square brackets is the t-statistics. Standard errors are clustered by date and account for the investors.

Table 14 – continued

Panel A Probability of selling stock (RP = min)

	Dependent variable: I(Sell stock) × 100					
Prior holding period (days):	1 to 20		21 to250		> 250	
	(1)	(2)	(3)	(4)	(5)	(6)
Ret (RP=min $_{t-1}$)	-0.60		0.12		0.01	
	[-4.33]		[17.55]		[12.66]	
Ret- (RP=min $_{t-1}$)		-8.91		-6.16		0.81
		[-20.49]		[-25.85]		[1.31]
Ret+ (RP=min $_{t-1}$)		1.82		0.19		0.01
		[16.29]		[28.81]		[13.57]
I(ret (RP=min $_{t-1}$) > 0)		-0.41		-0.14		-0.05
		[-25.57]		[-28.44]		[-12.52]
Ret-	-6.38	-4.67	-0.11	0.15	0.07	0.09
	[-23.95]	[-16.87]	[-3.18]	[4.36]	[5.29]	[6.71]
Ret- × sqrt(Time owned)	1.00	0.90	0.01	0.00	0.00	0.00
	[16.48]	[14.44]	[4.84]	[0.64]	[-2.23]	[-3.01]
Ret+	8.38	6.10	0.37	0.32	-0.01	-0.01
	[26.93]	[21.14]	[17.10]	[14.68]	[-2.83]	[-2.99]
Ret+ × sqrt(Time owned)	-0.96	-0.97	-0.02	-0.03	0.00	0.00
	[-17.01]	[-17.46]	[-18.09]	[-18.63]	[-2.21]	[-2.26]
I(ret = 0)	0.76	0.92	0.12	0.16	0.05	0.05
	[10.62]	[13.09]	[4.81]	[6.67]	[2.19]	[2.24]
I(ret = 0) × sqrt(Time owned)	-0.04	-0.08	0.01	0.00	0.00	0.00
	[-2.14]	[-3.89]	[3.04]	[1.64]	[0.44]	[0.41]
I(ret > 0)	0.31	0.95	0.08	0.14	0.03	0.03
	[6.07]	[18.34]	[6.90]	[12.87]	[5.64]	[5.79]
I(ret > 0) × sqrt(Time owned)	-0.03	-0.14	0.00	-0.01	0.00	0.00
	[-3.10]	[-13.70]	[-2.62]	[-7.16]	[-0.75]	[-0.88]
sqrt(Time owned)	-0.07	0.02	-0.02	-0.02	-0.01	-0.01
	[-6.60]	[1.61]	[-28.38]	[-25.22]	[-33.31]	[-33.41]
log(Buy price)	0.33	0.34	0.06	0.07	0.01	0.01
	[27.54]	[28.58]	[29.72]	[31.35]	[18.05]	[18.80]
Volatility-	18.88	18.02	4.70	4.83	1.55	1.58
	[25.26]	[23.82]	[33.23]	[34.21]	[25.90]	[26.39]
Volatility+	23.73	21.20	7.88	7.56	1.72	1.74
	[29.05]	[26.02]	[49.88]	[48.13]	[27.74]	[27.94]
Constant	-6.51	-6.64	-2.51	-2.43	-0.81	-0.76
	[-87.47]	[-87.55]	[-178.80]	[-167.17]	[-128.50]	[-107.22]
Observations	6.6 mil.	6.6 mil.	46.9 mil.	46.9 mil.	60.8 mil.	60.8 mil.
Pseudo R^2	0.0033	0.0039	0.0009	0.001	0.0003	0.0003

Table 14 – continued

Panel B. Probability of selling stock (RP = 1-month high)

	Dependent variable: I(Sell stock) × 100					
Prior holding period (days):	1 to 20		21 to 250		>250	
	(1)	(2)	(3)	(4)	(5)	(6)
Ret (RP=1-month-max $_{t-1}$)	0.25		0.11		0.11	
	[-4.11]		[3.81]		[10.53]	
Ret- (RP=1-month-max $_{t-1}$)		0.16		-0.60		-0.07
		[2.48]		[-26.17]		[-7.97]
Ret+ (RP=1-month-max $_{t-1}$)		1.42		3.79		1.01
		[3.32]		[35.29]		[17.26]
I(ret (RP=1-month-max $_{t-1}$) > 0)		0.02		0.12		0.03
		[1.22]		[24.08]		[17.56]
Ret-	-6.75	-6.66	-0.16	0.27	0.06	0.08
	[-22.88]	[-22.62]	[-3.93]	[6.87]	[4.24]	[5.67]
Ret- × sqrt(Time owned)	1.04	1.04	0.02	0.00	0.00	0.00
	[15.73]	[15.78]	[5.65]	[-1.58]	[-2.30]	[-2.92]
Ret+	7.66	7.38	0.47	0.34	0.00	0.00
	[28.32]	[26.14]	[21.69]	[15.21]	[-0.01]	[-0.79]
Ret+ × sqrt(Time owned)	-0.94	-0.91	-0.02	-0.02	0.00	0.00
	[-16.09]	[-15.26]	[-15.16]	][-10.57[	[-1.68]	[-0.98]
I(ret = 0)	0.82	0.82	0.16	0.12	0.04	0.02
	[10.42]	[10.36]	[6.00]	[4.43]	[1.50]	[0.95]
I(ret = 0) × sqrt(Time owned)	-0.05	-0.05	0.01	0.00	0.00	0.00
	[-2.30]	[-2.30]	[2.25]	[2.15]	[1.35]	[1.47]
I(ret > 0)	0.35	0.34	0.07	0.04	0.03	0.02
	[6.27]	[6.20]	[5.70]	[3.82]	[4.13]	[3.67]
I(ret > 0) × sqrt(Time owned)	-0.04	-0.04	0.00	0.00	0.00	0.00
	[-3.23]	[-3.12]	[-2.51]	[-1.22]	[-0.07]	[-0.12]
sqrt(Time owned)	-0.08	-0.08	-0.02	-0.02	-0.01	-0.01
	[-7.23]	[-7.09]	[-24.06]	[-25.70]	[-29.18]	[-29.38]
log(Buy price)	0.33	0.33	0.07	0.06	0.01	0.01
	[26.33]	[26.24]	[28.01]	[26.66]	[16.12]	[14.84]
Volatility-	18.83	18.66	5.40	4.21	1.83	1.47
	[24.53]	[24.40]	[35.84]	[27.97]	[27.66]	[21.94]
Volatility+	23.14	23.08	8.99	7.62	2.11	1.79
	[27.69]	[27.61]	[52.81]	[45.30]	[31.64]	[26.82]
Constant	-6.45	-6.46	-2.55	-2.54	-0.82	-0.82
	[-81.59]	[-81.67]	[-171.70]	[-171.73]	[-115.76]	[-117.17]
Observations	5.2 mil.	5.2 mil.	36.8 mil.	36.8 mil.	47.7 mil.	47.7 mil.
Pseudo R^2	0.0034	0.0034	0.0009	0.0012	0.0003	0.0003

APPENDIX E

FIGURES FOR "REVIVING THE DISPOSITION EFFECT: HIGHEST PRICE AS THE REFERENCE POINT"

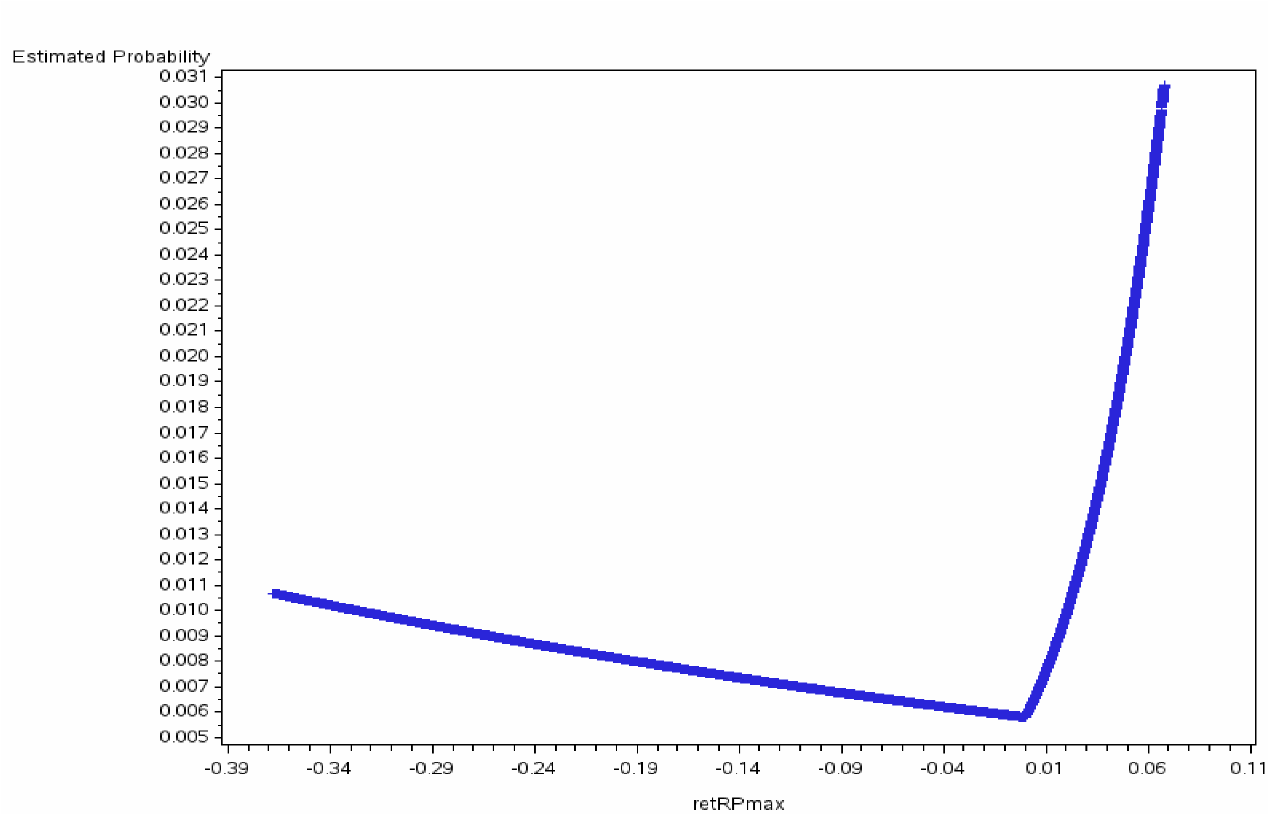

Figure 1. Probability of Selling Schedule across Holding Periods between 1 and 20 Days since Purchase

The probability of selling schedule is increasing with the magnitude of profits with asymmetric slopes in the perceived gain and loss regions. The estimated probability is calculated based on simple logistic regression of Sell indicator on loss and gain side for Ret(RP=max $_{t-1}$), which are defined as Ret- (RP=max $_{t-1}$) and Ret+ (RP=max $_{t-1}$). The variable definitions are listed in the Appendix.

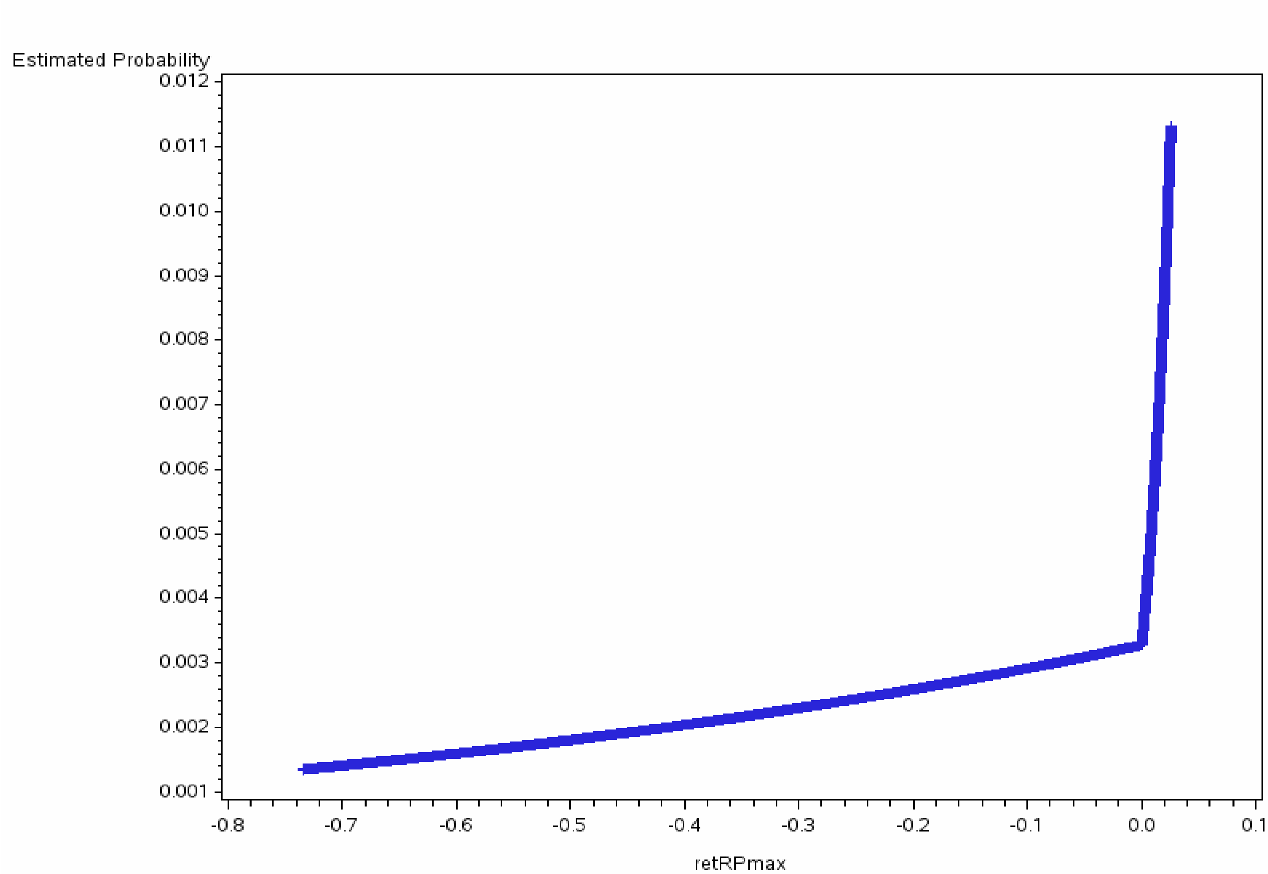

Figure 2. Probability of Selling Schedule across Holding Periods between 21 and 250 Days since Purchase

The probability of selling schedule is monotonically increasing from perceived loss region to perceived gain region. There is a kink at zero perceived return and the probability of selling increases dramatically high with magnitude of perceived profits in perceived gain region. The estimated probability is calculated based on a simple logistic regression of Sell indicator on loss and gain side for Ret(RP=max $_{t-1}$), which are defined as Ret- (RP=max $_{t-1}$) and Ret+ (RP=max $_{t-1}$). The variable definitions are listed in the Appendix.

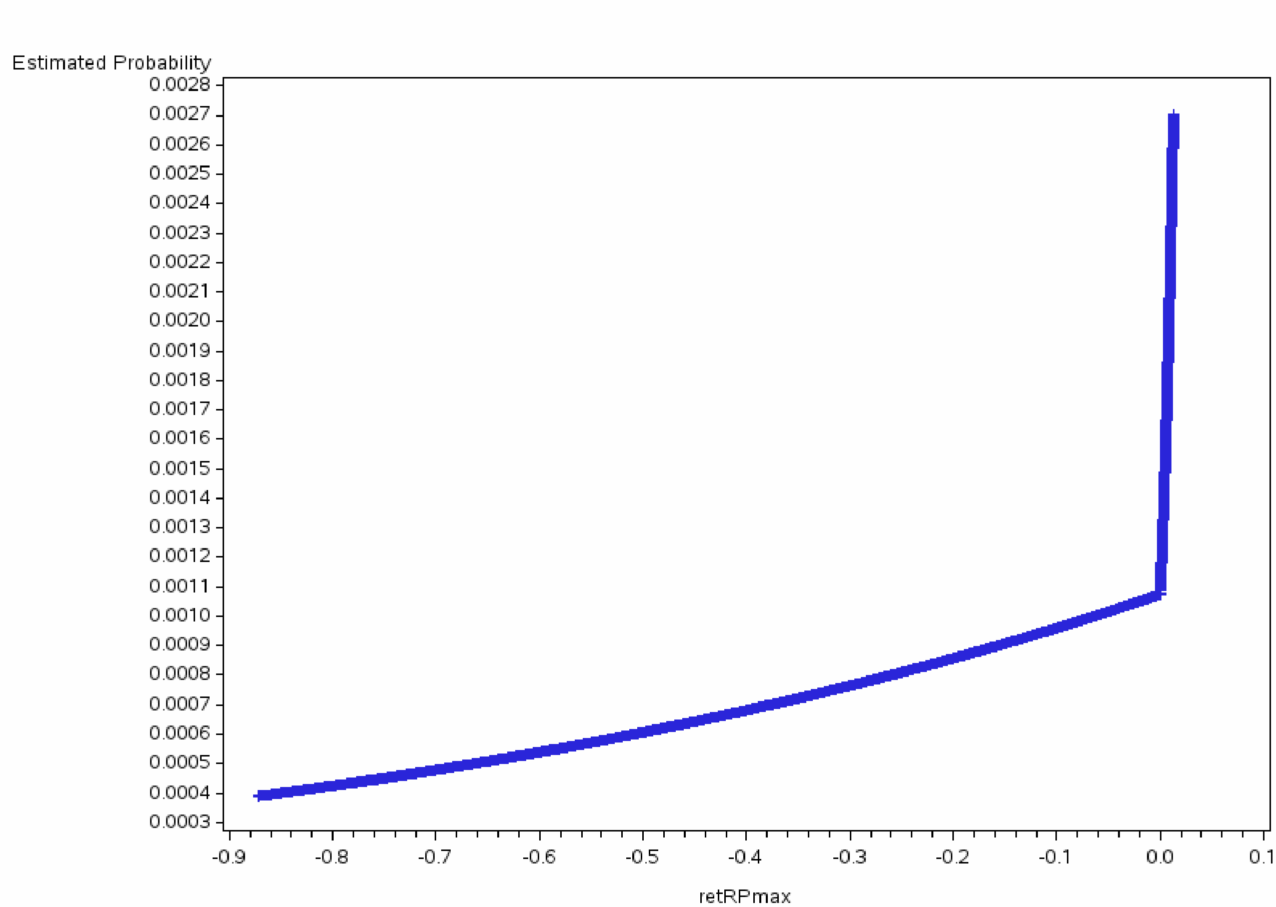

Figure 3. Probability of Selling Schedule across Holding Periods over 250 Days since Purchase

The probability of selling schedule is monotonically increasing from perceived loss region to perceived gain region. There is a kink at zero perceived return and the probability of selling increases dramatically high with magnitude of perceived profits in perceived gain region. The estimated probability is calculated based on a simple logistic regression of Sell indicator on loss and gain side for Ret(RP=max $_{t-1}$), which are defined as Ret- (RP=max $_{t-1}$) and Ret+ (RP=max $_{t-1}$).The variable definitions are listed in the Appendix.

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BIOGRAPHICAL SKETCH

Hope Han was born on July 26, 1988 at College Station, Texas, United States. She grew up in Seoul, Korea for 24 years. She finished her undergraduate study at Korea University in Seoul and earned her B.S. degree in Computer and Communication Engineering and Financial Engineering as a double major in 2011. She obtained her M.S. degree in Statistics at the University of Illinois at Urbana-Champaign in 2013. She was admitted to the doctoral program in Finance at Florida State University in 2014. While a Ph.D. student, Hope participated in the FMA Annual Meeting in 2016 and 2018, the AFA Annual Meeting in 2015 – 2019, and the AEA Continuing Education in 2015 – 2019, which covered topics in Time Series Econometrics, Machine Learning, and Behavioral Finance. She joined the Beta Gamma Sigma International Honor Society at FSU in 2015.

Hope is excited to be starting as an Assistant Professor at UNIST in the Republic of Korea in September 2019.