10-2021

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Abstract

Individual investors are more likely to sell stocks with nominal gains and losses that are large relative to their brokerage portfolio value. The salience of nominal gains and losses affects stock sales in both taxable and tax-deferred accounts and across investor groups, but the effect of nominal losses is weaker for stocks with high valuation uncertainty. The effect has a time dimension: at short holding periods, individuals are more likely to sell stocks with large nominal losses than gains of the same size, mitigating the disposition effect. Investors may be compelled to revisit their beliefs after incurring large losses quickly.

Keywords: Salience; Disposition effect; Reverse disposition effect; Recency; Valuation uncertainty; Volatility; Individual Investors

JEL Classification: G11 · G41

Correspondence: Abhishek Varma, Illinois State University, Normal, IL, USA, 61790-5480; email: avarma@ilstu.edu. We thank the outgoing editor Srinivasan Krishnamurthy, the current editor Michael Goldstein, the anonymous associate editor, the anonymous referee, as well as Anna Agapova, David Hirshleifer, Alok Kumar, Sonya Lim, John Nofsinger, Drew Winters, session participants at the Financial Management Association and the Southern Finance Association annual meetings, and seminar participants at Illinois State University for helpful comments. We thank Illinois State University for financial support.

1. Introduction

How do gains and losses affect investors' decisions to sell stocks? Do reactions to gains and losses change with the passage of time? Researchers have extensively discussed investors' tendency to hold losers and sell winners, known as the disposition effect (Shefrin and Statman, 1985). More recently, Kaustia (2010) shows that the probability of selling a stock jumps at zero return, and Ben-David and Hirshleifer (2012) find that the magnitude of percentage returns affects the sale decision. Lastly, Hartzmark (2015) reports that stocks with extreme (highest or lowest) percentage returns within a portfolio are more likely to be sold.

Researchers mostly use percentage returns (usually since acquisition) to study the effects of gains and losses on investors' trading decisions. We propose that using nominal gains and losses is more appropriate. Nominal value changes, unlike percentage returns, represent direct changes in the investor wealth. In addition, making selling decisions based on individual positions' percentage returns requires investors to engage in an extreme form of narrow framing (Kahneman and Lovallo, 1993; Tversky and Kahneman, 1981) or mental accounting (Thaler, 1985), wherein they look at each position in isolation and ignore the rest of their portfolio. However, investors should reduce the tendency to engage in extreme narrow framing when they simultaneously observe (e.g., on an account statement or snapshot) values, gains, and losses for the entire portfolio in addition to individual positions. Viewing this information together primes investors to consider their total brokerage portfolio value in addition to or instead of percentage returns on individual positions.[1] Thus, we hypothesize that nominal gains and losses can more robustly explain stock sales than percentage returns. We construct measures of nominal gains and losses scaled by an investor's portfolio value that we label the scaled nominal gain (SNG) and the scaled nominal loss (SNL).

[1] People often make different decisions when considering information together rather than on a stand-alone basis as they start focusing on differences between available alternatives (Bazerman, Loewenstein, and White, 1992; Hsee 1996; Kahneman, 2003; List, 2002).

We establish two new stylized facts when we employ SNG and SNL as explanatory variables in studying individual investors' stock-selling behavior. *First*, consistent with our hypothesis, stocks with large nominal gains and losses (scaled by the portfolio size) are more likely to be sold. The effects of nominal gains or losses on the probability of a stock sale are more robust than the effects of percentage returns. This is consistent with the experimental finding of Shavit et al. (2010) that people spend more time looking at nominal value changes than percentage returns. An increase in SNG (SNL) of one percent is associated with an increase of 0.33 (0.55) percent in the probability of selling a stock by an investor on a day on which the investor sells at least one stock. The higher propensity to sell positions with larger gains and losses reflects the effect of salience on judgment in general (Taylor and Thompson, 1982) and on stock-selling decisions (Barber and Odean, 2007; Ben-David and Hirshleifer, 2012). Investors likely pay more attention to such positions and research them more.

The impact on SNG and SNL on selling decisions is observed across different account types and investor subsamples and survives several other robustness checks.[2] When we control for ranks of SNGs and SNLs within a portfolio to address the importance of the rank effect in the context of stock selling decisions (Hartzmark, 2015), unlike SNG, SNL remains statistically significant. Thus, the size of a loss relative to the portfolio size affects stock sales beyond the ranking of losses within the portfolio. Finally, the impact of SNL on sales is lower for stocks with high valuation uncertainty, which is consistent with Kumar's (2009a) observation of individuals' preferences for stocks with lottery-like features. The higher perceived probability of price recovery for stocks with high valuation uncertainty may prompt investors to hold on to such stocks even when they accumulate large nominal losses.

[2] For example, one concern about using SNG and SNL is that investors may frame their gains and losses in the context of their total wealth rather than their brokerage account value. To alleviate it, we run our tests for subsamples of investors with different portfolio value ranges, likely representing different levels of wealth. As robustness checks, we use an investor's average brokerage portfolio value throughout the entire sample period or an investor's self-reported net worth instead of the previous day's portfolio value as the base for computing SNG and SNL. The results remain the same: the probability of a stock sale on a day on which a given household sells at least one stock still increases with both SNG and SNL.

Second, for stocks with short holding periods investors are more likely to realize large nominal losses compared to gains of the same magnitude, mitigating the disposition effect. These effects are strong for holding periods ranging from a few days to several months and monotonically taper off as the holding period lengthens. They extend to about 15 months in taxable accounts and up to three months in tax-deferred accounts. For example, for holding periods below 0.5 months, 0.5-1 months, and 3-6 months the probability of selling losers is higher than that of selling winners (i.e., the disposition effect is eliminated) when SNL and SNG are above 2.68%, 3.90%, and 21.50%, respectively. While tax-loss selling is important, it does not fully explain the elimination of the disposition effect for large nominal gains/losses at short holding periods as a less pronounced pattern is also present in tax-deferred accounts. While our observed effects for SNL and SNG over different holding periods are impervious to the valuation uncertainty of stocks, consistent with our prior findings, the impact of SNL is notably lower for stocks with high valuation uncertainty.

The impact of holding periods on individual investors' selling decision has also been considered in recent studies. Specifically, Ben-David and Hirshleifer (2012) find that at short holding periods, investors are more likely to sell big (percentage) losers than small ones. Kaustia (2010) finds that not only is the propensity to sell approximately constant in the loss domain (i.e., across various buckets for percentage losses), it is also similar across various holding periods. Based on this and other evidence, Kaustia (2010) concludes that the prospect theory is unlikely to explain the disposition effect. In contrast, while studying the impact of nominal gains/losses, we highlight circumstances under which the disposition effect is mitigated. Specifically, at short holding periods, the impact of nominal losses is the strongest, so much so that investors are also more likely to realize large nominal losses compared to gains of the same size. We hypothesize that when investors face large nominal losses on recently acquired positions, they are compelled to revisit their original beliefs, unlike for positions that quickly incur large gains.

In sum, our findings have two important implications for research on individual investor trading. *First*, investors appear to focus more on nominal changes in value of positions than percentage returns. *Second*, while salience and holding periods separately affect individuals' stock sales, their interaction does, too, and its effect is not symmetric for gains and losses.

2. Data and methodology

We use a data set containing stock trading activity of 77,995 households at a large discount brokerage from January 1991 through November 1996. This data set, described in detail in Barber and Odean (2000), contains about 1.9 million trades.[3] We look at portfolios of stocks held by investors on any date on which they sell at least one stock (a household-sell date).[4] Similar to other researchers, we exclude portfolios with positions acquired prior to January 1, 1991, as we do not have any purchase information for these positions. The data set is rich as it covers a large cross-section of investors and provides demographic information. We require a portfolio to have at least two positions on any sale date to ensure there are different positions to choose from. This filter results in a loss of 28,609 observations out of more than 1.9 million, as our sample is dominated by individuals holding multiple stocks on a given household-sell date.

[3] While this data set is not recent, it has been used in recent literature, including, e.g., Frydman, Hartzmark, and Solomon (2018), as well as two key studies this study builds on – Ben-David and Hirshleifer (2012) and Hartzmark (2015). Though behavioral phenomena tend to transcend time, it would be useful to verify our finding with more recent data. Online account design tabs that allow for sorting by total gains and losses, alongside reduced trading costs could make our findings regarding the effects of salience even more relevant today. We leave this for future research to explore.

[4] Sale refers to either a complete or partial sale of a position. We combine multiple sales of the same stock on the same day using the weighted average price. Only stocks with information in the CRSP database on a sell date are included in our analysis. Gains and losses for positions with multiple acquisition dates are computed using the first-in, first-out method (FIFO). The results are not sensitive to the method of computing gains and losses. We make appropriate adjustments for stock splits. We exclude short sales, which account for a miniscule portion of the total transactions, and aggregate positions across multiple accounts under the same household identifier. The transaction data show some unsold stocks that were acquired during the sample period but failed to appear on successive monthly portfolio statements. We include these positions as part of the portfolio only on household-sell dates that are prior to the last date these positions appear on the monthly position statement. For positions with multiple acquisition dates, we compute holding periods weighted by the number of shares acquired on each date.

The key variables in our analysis are absolute scaled nominal gain (*SNG*) and absolute scaled nominal loss (*SNL*), calculated as follows:

$$SNL_{i,j,t}\ (or\ SNG_{i,j,t}) = \frac{Absolute\ Nominal\ Loss(or\ Gain)\ since\ Purchase_{i,j,t}}{Current\ Portfolio\ Value_{it}} \times 100$$
$$= \frac{Absolute\ Return\ since\ Purchase_{i,j,t} \times Purchase\ value_{i,j}}{Current\ Portfolio\ Value_{i,t}} \times 100$$

where *i,j,t* refers to investor *i* holding stock *j* at time *t*. If a position has accumulated a loss (gain), SNG (SNL) is set to zero. SNL and SNG are changes in a position's value since acquisition relative to the current value of an investor's portfolio, expressed in percent.[5] These measures allow for comparing the scale of nominal losses or gains across households. We use absolute values to facilitate interpretation. Our SNG and SNL measures capture salience beyond percentage returns for positions. An investor can accumulate large nominal gains (SNG) or losses (SNL) due to large initial investments and/or high absolute returns. Separation of nominal gains (SNG) and losses (SNL) allows us to measure the differential effects of gains and losses on the probability of stock sales. That is, we can compare if a gain on a stock equal to a given percentage of the portfolio value effects the probability of selling to the same extent as a loss of the same magnitude. Table 1 summarizes our sample, which consists of approximately 1.94 million positions held by 28,096 households on 198,687 unique household-sell dates. Panel A of Table 1 provides an overview of our data set at the household-sell date level. In Panel A of Table 1 we present the distribution of the mean values of variables calculated on all household-sell dates, except for the numbers of positions. Across all household-sell dates, the median number of positions with gains or losses is six, the median number of positions with gains is three, the same as the median number of positions with losses. The median for the mean SNG (SNL) is 2.72% (1.86%) of the portfolio value, and the median for the mean holding period is 7.72 months for positions with gains and 7.13 months for positions with losses.

[5] As a robustness check, in unreported results we use the average portfolio value across all sell dates for our investors as opposed to the portfolio value on a given day, and our key findings remain unchanged.

Panel B of Table 1 presents the correlations between gain- and loss-related variables across all our household-sell dates (at the household-position-date level).

[Insert Table 1 about here]

When reviewing a brokerage portfolio, an investor observes accumulated gains and losses on open positions. Similar to Grinblatt and Keloharju (2001), Hartzmark (2015), and Kaustia (2010), we study the determinants of households' decisions to sell stocks on days with stock sales. This approach allows us to model sale decisions that could be driven by various factors and makes no assumptions regarding the investor's trading frequency. We employ the following logistic regression:

$$Ln\left[\rho_{i,j,t}/(1-\rho_{i,j,t})\right] = \alpha_0 + \alpha_1 Loss_{i,j,t} + \beta_1 SNG_{i,j,t} + \beta_2 SNL_{i,j,t} + \delta_1 HPGain_{i,j,t} + \delta_2 HPLoss_{i,j,t} + \textstyle\sum_{j=1}^{N} \omega_j\, Control_{j,t} \qquad (1),$$

where ρ is the probability of investor *i* selling stock *j* by on day *t* on which at least one stock is sold by the investor (household); *SNG* and *SNL* are as defined above; *Loss* is a dummy variable equal to one if a position has accumulated a loss and zero otherwise[6]. *HPGain* (*HPLoss*) is the holding period, in months, for stocks sold for a gain (loss). None of the correlation among our key variables are large. The highest correlation of SNG or SNL with another variable is 0.19, between SNG and HPGain (Panel B of Table 1).

The controls are at the stock level and include the following: *RetPrevDay_High*, *RetPrevDay_Low*, *Cap_Decile*, *High_Vlty*, *Div_Stk* and *Tech_Stk*. The first two, *RetPrevDay_High* and *RetPrevDay_Low*, are indicator variables for stocks that had a previous day return in the top and the bottom decile of all CRSP stocks, respectively.[7] Stocks with extreme previous day returns attract more

[6] The Loss dummy captures the general propensity to sell losing positions relative to gaining ones – the disposition effect. This approach has been used in the literature: e.g., Ivković, Poterba, and Weisbenner (2005) use it; Harzmark (2015) interacts Gain and Loss dummies with percentage returns to study differential effects of losses vs. gains on selling decisions.

[7] Other studies cited in this section use similar key variables, e.g., Loss or Gain indicators and measures of a holding period. Our stock-level controls are more extensive than in these papers. Some of the prior studies, e.g., Grinblatt and Keloharju (2001) and Kaustia (2010), include controls for market-level returns over various time horizons and other

attention from investors observing daily changes in values, as well as the media, which influences their trading.[8] *Cap_Decile* is the market capitalization decile based on all CRSP stocks on the previous trading day, with one denoting the smallest decile. *High_Vlty* is an indicator for stocks in the highest volatility decile of all CRPS stocks over the previous six calendar months. Small cap stocks and highly volatile stocks may be associated with a lower probability of selling because they may be harder to value (Kumar 2009a). In our later tests, we present additional evidence of the effects of valuation uncertainty on stock sales in the context of nominal gains or losses. *Div_Stk* is an indicator variable for stocks that paid dividends any time during the previous 12 months. Dividend stocks may be bought for income and may represent more established companies, which may result in a lower probability of sale. *Tech_Stk* is an indicator variable for technology company stocks. These stocks garner more investor attention during our sample period and thus may be sold more frequently.[9] For all our regression results, we present marginal effects, in percent, calculated at the mean values of other variables, alongside the coefficient estimates. We cluster standard errors at the household level.

Consistent with greater salience of larger (absolute) gains and losses, we expect our key variables, *SNG* and *SNL,* to have positive coefficients.[10] We expect a negative coefficient for the *Loss* dummy, implying that investors are generally less likely to sell losers than winners, consistent with the disposition effect. We also expect negative parameters for *HPGain* and *HPLoss,* implying that individuals are more likely to sell stocks they purchased more recently, a manifestation of the recency

control variables. As a robustness check, we estimate regressions with these controls and obtain similar results (available upon request).

[8] Barber and Odean (2007) report that individual investors buy more attention-grabbing stocks (e.g., stocks with high absolute previous day returns) than they sell them. They argue that the buying is affected more than selling for attention-grabbing stocks, since investors can choose from thousands of stocks to buy while only a few stocks to sell. While we agree, we hypothesize that, in a set of stocks held by an individual, stocks with extreme one-day returns are likely to attract more attention and be sold.

[9] We require at least one month of non-missing data for our calculation of volatility. Changing this requirement to one year of non-missing data does not impact our results.

[10] We compute the nominal gains and losses and (in subsequent tests) other measures of return based on capital gain/loss returns. Using total returns instead, which account for both capital gains/losses and dividends, does not affect the results. The realized gains and losses are after commissions.

effect (Nofsinger and Varma, 2013; Chakrabarty, Moulton, and Trzcinka, 2017) or the interference effect (Baddeley and Hitch, 1977). We create separate holding period variables for gains and losses to compare how holding periods impact the probability of selling winners versus losers.

3. Salience of nominal gains and losses

3.1. The effects of nominal gains and losses on stock sales

We draw on Taylor and Thompson (1982) to define salience as possession of an attention-grabbing attribute or attributes. In the context of stock gains or losses, their large size (relative to the portfolio value) is one such attribute. Table 2 reports the first of the two main results of this study. This table presents the output (coefficients, marginal effects, and *t*-values) of four variations of Equation 1. Regression 1 employs only the *Loss* dummy and our scaled nominal gains (*SNG*) and losses (*SNL*) variables, while Regression 2 includes the controls (this is Equation 1). In Regression 3, we use percentage returns since acquisition for gains (*Ret%Gain)* and losses (*Ret%Loss*) in place of SNG and SNL to compare the impact on selling decisions of SNG and SNL to that of percentage returns. In Regression 4, we have both the scaled nominal gains and losses and the percentage returns for gains and losses on the right-hand side (all expressed in absolute terms). The *Loss* dummy has a negative coefficient in all four regressions, indicating that stocks with accumulated losses are less likely to be sold, consistent with the disposition effect. The marginal effect for the Loss dummy in Regression 2 implies that, holding all other variables at their mean levels, a losing stock position is about 5.45% less likely to be sold than other stock positions on a day when at least one stock sale within the portfolio.

[Insert Table 2 about here]

Consistent with our main hypothesis, we find that the estimated parameters for nominal gains and losses scaled by the brokerage portfolio value (i.e., SNG and SNL) are positive and significant, regardless of other explanatory variables included in the regressions. Also, the coefficient for SNL is statistically higher than its SNG counterpart. The marginal effects in Regression 2 indicate that a 1% increase in the scaled nominal gain (SNG) and loss (SNL) increases the likelihood of sale by 0.33% and 0.55% , respectively. Interpreting the results in the context of the odds ratios yields an even stronger economic significance: a 1% increase in SNL and SNG is associated with the increase in the odds of a sale by 4.50%% , respectively. Thus, individuals are more likely to sell their relatively more salient positions that are associated with larger nominal gains and losses. Also, after controlling for a general disposition for realizing gains, increasing nominal losses has a stronger effect on the probability of sale than increasing nominal gains. Explaining this asymmetric pattern would be premature without gaining an insight into its dynamics over different holding periods. In section 4, we investigate the interaction of salience of losses (SNL) and gains (SNG) with holding periods and find that the strong impact of SNL vis-à-vis SNG is primarily driven by stock sales on recently acquired stocks (i.e., positions with shorter holding periods, roughly up to one year).

The percentage return variables' coefficients in Regression 3 are statistically and economically insignificant, and the explanatory power of that regression is much lower than that of Regression 2. The difference in the explanatory power suggests that SNG and SNL are more relevant for retail investors' stock selling decisions than percentage returns. When we include both the scaled nominal gains and losses and the percentage returns in Regression 4, the former retains significance, while the percentage returns become statistically significant but lose their economic significance and have negative signs, which is inconsistent with higher percentage returns being more salient. These results are consistent with experimental findings of Shavit et al. (2010) that subjects fixate their views longer on nominal value changes than on percentage changes. Having established that nominal gains and losses are better predictors of selling decisions than percentage returns, we focus our discussion on Regression 2 (specified in equation 1) hereafter.

The coefficients for HPGain and HPLoss are negative, supporting the recency effect. Individuals are more likely to sell more recently acquired stocks (Ben-David and Hirshleifer, 2012), and to repurchase more recently sold stocks (Nofsinger and Varma, 2013). Such stocks may be more available for recall, consistent with the effects of recency on revival of thought (James, 1892) and on memory/recall (Ebbinghaus, 1913), as well as with the availability heuristic of Tversky and Kahneman (1973). Holding all other variables at their mean levels, an increase in the holding period of one month is associated with a decrease in the probability of sale of 0.36% for winners and 0.26% for losers. We devote section 4 to studying the effects of holding periods on sales of winners and losers. Technology company stocks and stocks with extreme previous day returns are more likely to be sold, while dividend stocks, small cap stocks, and high-volatility stocks are less likely to be sold. Our findings regarding small cap and high-volatility stocks are consistent with Kumar (2009a). We explore the impact of SNG and SNL on sales of hard-to-value stocks in more detail in subsection 3.4. The presence or absence of any of the control variables does not affect the main result.[11, 12]

3.2. Account types and tax considerations

The results for nominal gains and losses may be driven by non-retirement accounts, where investors may be taking a shorter-term view of their investments or taking more risk. In Table 3, we report the output of equation 1 estimations for retirement (tax-deferred) and non-retirement (taxable) accounts in columns 1 and 2, respectively. The marginal effects of a one-percent increase in SNG and

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[11] To ensure that our results are not driven by the current portfolio weight of the position being sold, another measure of salience, we create sub-samples of various portfolio weight buckets and repeat our tests. This analysis is not ideal, given a high (low) current portfolio weight on a position may be consistent with a higher absolute nominal gain (loss) since acquisition, SNG (SNL). It affects the distribution of gain and loss observations across the buckets. Also, higher portfolio weight buckets may be dominated by undiversified households. Nevertheless, the SNG and SNL remain significant for most of our sample classified across various portfolio weight buckets. In particular, the impact of SNL is consistent across all weight buckets. These unreported results hold for both taxable and tax-deferred accounts.

[12] Our approach differs from that of Ben-David and Hirshleifer (2012), who estimate the probability of selling a stock on any day with an open position, an approach suited to analyzing investors who monitor their brokerage accounts daily. Due to the nature of their methods, they only look at a random sample of accounts.

SNL for non-retirement (retirement) accounts is 0.56% (0.48%) and 0.33% (0.42%), respectively. As before, the results hold consistently, with a higher propensity for selling positions with larger nominal gains and losses. In taxable accounts, the probability of sale goes up more with a 1% increase in SNL than in SNG: the difference in the coefficients of SNG and SNL is negative and significant. In tax-deferred accounts, this difference is insignificant. That is, keeping the holding period constant, the probability of a stock sale is equally sensitive to the magnitudes of gains and losses in tax-deferred accounts, but more sensitive to the magnitude of losses than gains in taxable accounts. Tax considerations likely play a role here: in taxable accounts, realizing large gains (losses) may notably increase (reduce) taxable income.

For taxable accounts, we test if the propensity to realize large nominal losses is driven by tax-loss selling at the end of the year. Regression 3 in Table 3 restricts the sample to stock sales in taxable accounts for the months January through November, while Regression 4 only includes December sales. We find a much lower impact of the *Loss* dummy for December because tax-loss selling dampens the disposition effect (Odean, 1998). Also consistent with tax-loss selling, we find a much stronger propensity to realize large nominal losses than gains in December: the marginal effects for SNG and SNL in Regression 4 are 0.26% and 0.83%, respectively, with the difference being statistically significant. For sales during January through November (Regression 3), the propensity to realize large nominal gains and losses remains strong, with marginal effects of SNG and SNL of 0.34% and 0.51%, respectively, and the difference being statistically significant. While tax-loss selling peaks in December, it is observed throughout the year (Ivković, Poterba, and Weisbenner, 2005).[13]

[Insert Table 3 about here]

3.3. Investor characteristics

[13] In unreported results (available upon request), we exclude margin accounts, where selling may be driven by margin calls. The results for nominal gains and losses do not change.

Not all investors may react to gains and losses similarly. Feng and Seasholes (2005) conclude that sophistication and trading experience eliminate the tendency to hold on to losses and reduce the propensity to realize gains. Barber and Odean (2001) find that men, who tend to be more overconfident investors than women, trade excessively and realize poorer net returns as a result. Dhar and Zhu (2006) report that higher investor sophistication (measured by income and professional occupation) as well as trading frequency are associated with a weaker disposition effect. Therefore, as the next step, we re-estimate Equation 1 for various sub-samples based on different investor characteristics. We report the results in Table 4. While we use all the variables from Equation 1 in the estimation, we report the estimates for only our three key variables of interest − SNG, SNL, and the Loss dummy.

Panel A of Table 4 classifies investors by gender and age. Men tend to trade more frequently than women (Barber and Odean, 2001). Our results suggest that men show a stronger "sign realization" preference: the marginal effect of the Loss dummy is larger for males than females (-7.03% vs. -4.81%). However, men are more sensitive to the magnitude of accumulated losses than women: an increase of 1% in the scaled nominal loss (gain) is associated with a 0.55% (0.32%) percent increase in the likelihood of sale by men, with the difference being significant. For women, larger nominal gains and losses are also associated with higher probabilities of sale – by 0.31% and 0.38% for a 1% increase in SNG and SNL, respectively – but the difference between the effects of nominal gains and losses is not significant. Thus, salience of gains and losses matters to both male and female investors. Because men dominate the sample with ten times more sales than women, the men's higher sensitivity to nominal losses drives the results for the entire sample. Older investors (50 years and older) show a reaction to nominal gains and losses that is similar to that of their younger counterparts, but in general appear to be less hesitant to realize losses. They display a lower marginal effect for the

Loss dummy, -5.17%, compared to -9.37% for younger investors.[14] A weaker disposition effect among older investors is consistent with Dhar and Zhu (2006).

[Insert Table 4 about here]

Panel B of Table 4 reports the results for the sample split based on the portfolio turnover and diversification. Investors with low (below median) and high (above median) portfolio turnover, measured as the average portfolio turnover over the 71-month period (similarly to Barber and Odean, 2000), exhibit similar reactions to nominal gains and losses. While the general disposition effect (measured by the Loss dummy) is stronger for high-turnover investors, both high- and low-turnovers investors are more likely to sell a big loser than a big winner.

Next, we consider the level of portfolio diversification, which may partially reflect investor sophistication. In our restricted sample of households that hold at least two stocks on a sale date, the median (mean) number of stocks on a household-sell date is 6 (9.74).[15] Goetzmann and Kumar (2008) report that the median (mean) number of stocks owned by the unrestricted sample of households at the same brokerage house is three (four). We classify a household as undiversified if its portfolio's median number of stocks throughout the entire 71-month data period is three or fewer and diversified if the median is four or more. We find that the general reluctance to sell losers (i.e., the disposition effect) is stronger (p-value <0.01) for undiversified investors: the marginal effect of the Loss dummy is -8.81% for them and -5.11% for the more diversified investors.

For both undiversified and more diversified investor groups, the probability of sale increases when either nominal gains (SNG) or losses (SNL) increase. However, while undiversified investors show somewhat similar sensitivities to both SNG and SNL, their more diversified counterparts are

[14] In regressions with interaction effects (not reported) this difference is statistically significant at the 1% level.
[15] Our sample's means and medians are computed across household-sell dates rather than just households (if a household sells any number of stocks on a given date, it is counted as one household-sell date), and households with more stocks in their portfolios tend to trade more and thus account for the majority of household-sell dates.

more sensitive to SNL rather than SNG. This suggests that undiversified investors exhibit a stable disposition effect across gains and losses of different sizes, while more diversified investors exhibit a diminishing disposition effect (they are more likely to realize large losses compared to large gains). Since more diversified investors expectedly account for most of the observations across all investors, our overall results, displayed in section 3.1, are driven by these potentially more sophisticated investors.

Panel C of Table 4 presents the results for different portfolio value ranges (measured as the average portfolio value prior to the date of sale). Investors with larger portfolios (over $100,000) represent only 11%of accounts but 62% of stock sales. Compared to investors with portfolio values below $100,000, they show a lower disposition effect (the marginal effect of the Loss dummy becomes less negative as the average portfolio value goes up) and lower sensitivity to nominal gains (the marginal effect of SNG declines as the portfolio value goes up). The latter may be consistent with large investors being more tax savvy (and/or more tax-sensitive) and delaying realization of large capital gains (Ivković, Poterba, and Weisbenner, 2005). The coefficients of SNL are positive across the four portfolio size classifications; they are statistically larger than their SNG counterparts for the largest three portfolio size ranges.[16]

Overall, the probability of sale increases with nominal gains and losses for investors with all the different characteristics examined in this section. The higher sensitivity to changes in nominal losses than gains is exhibited by investors who are male, more diversified, and have portfolios with higher values; these groups also dominate the trading activity in the sample.[17]

[16] Knowing investors' net worth in addition to the brokerage portfolio values would be ideal. However, while net worth figures are available for many accountholders, we use the portfolio values. The reported net worth figures may not be very clean measures of wealth because they are (1) self-reported, and thus may be computed differently by different investors, (2) reported once and not updated, and (3) not reported by all investors, and thus are subject to self-selection. Our baseline regressions for investors classified across various net worth ranges yield similar results.

[17] In unreported tests (available upon request), we find that investors who tend to realize larger SNLs underperform (on a risk-adjusted basis) as a group. Being greatly affected by salience of losses may indicate naive behaviors that may contribute to investor underperformance.

3.4. Stock valuation uncertainty

So far, we have established that individuals' stock selling decisions are influenced by SNG and SNL. However, uncertainty associated with a stock price may also affect investor selling decisions. For example, investors with the prospect theory utility function may feel they have little to lose if the stock price continues to go down after accumulating a large nominal loss but would like to avoid regret if the price recovers after the stock is sold. The possibility of a price recovery for a volatile stock may prompt an investor to hold it longer than a less volatile stock. To examine the effects of valuation uncertainty on selling decisions, we use various measures of uncertainty in separate regressions. We label this set of measures *VAR*. It includes the following four indicator variables: (1) *High_Vlty* equals one for stocks in the highest standard deviation decile; (2) *High_Idiosyn* equals one for stocks in the highest idiosyncratic volatility decile; (3) *Low_Cap* equals one for stocks in the lowest market cap decile at the end of the previous day; (4) *Lottery_Stock* equals one for lottery-type stocks, classified as such following Kumar (2009b).[18] We calculate measures of total and idiosyncratic volatility over the last six calendar months for all stocks in the CRSP database with at least one month of non-missing data. Idiosyncratic volatility is the standard deviation of the residuals from the Carhart (1997) four-factor model.

We include in our regressions the interactions of a measure of valuation uncertainty with the *Loss* dummy (*Loss*VAR*) as well as with the scaled nominal gain and loss (*SNG*VAR* and *SNL*VAR*). These interactions allow us to detect if the presence of losses and the salience of gains and losses impact the probability of sale differently for stocks with high valuation uncertainty than for other stocks. We report the results in Table 5. While we use the holding period variables and the

[18] We obtain similar results for alternate specifications of our first three measures of valuation uncertainty that use actual decile rankings instead of extreme decile dummies. Related to our fourth measure, at the end of each month, Kumar (2009b) identifies stocks on the major exchanges (NYSE/NASDAQ/AMEX) with prices in the bottom 50th percentile, idiosyncratic volatility in the top 50th percentile, and idiosyncratic skewness in the top 50th percentile as lottery type stocks. To check the robustness of our results, we also use the 33rd percentile benchmark, which results in fewer stocks classified as lottery stocks. Our results are insensitive to this alternative definition of lottery-type stocks.

control variables in the estimation (see Equation 1), we do not report their parameters in the interests of brevity.[19]

The effects of losses in general (*Loss* dummy) and of the magnitudes of scaled nominal gains and losses (*SNG* and *SNL*) are similar to those we report in earlier tests. In Regression 1, where we use past return volatility (*VAR*=*High_Vlty*) to measure valuation uncertainty, we observe that uncertainty impacts investors' responses to the size of scaled nominal losses but not scaled nominal gains. The marginal effect of the interaction *SNL*High_Vlty* indicates that increasing a scaled nominal loss by one percent for a highly volatile stock reduces the probability of sale by 0.33%compared to an otherwise similar stock with lower valuation uncertainty. This cuts by about a half the marginal effect of 0.62%associated with the SNL variable itself. Perhaps the greater prospects of recovering losses in volatile stocks dampen individual investors' propensity to sell positions with large nominal losses. This explanation is also supported by observing the marginal effect of -5.95% for the interaction of *High_Vlty* with *Loss*, which indicates that the general disposition to avoid selling losing positions is stronger in the presence of greater uncertainty. It is consistent with Kumar (2009a), who shows that individual investors exhibit a stronger disposition effect for hard-to-value stocks. The disposition effect may be stronger for high-volatility stocks due to investors' overconfidence, belief in mean reversion of stock prices, gambling tendencies such as the desire to break even, or reference points being affected by valuation uncertainty. Our results in column 2 of Table 5, with valuation uncertainty measured by idiosyncratic volatility (*High_Idiosyn*), mirror the results in column 1 of Table 5. Column 3 of Table 5 considers low market capitalization (*Low_Cap*) as another proxy for valuation uncertainty: smaller companies may be younger, less established businesses with greater idiosyncratic risk and relatively little media and analyst coverage. Similar to high volatility and high idiosyncratic volatility

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[19] We drop control variables that are similar to the measures of uncertainty being considered in the regression. For example, in Regression 3, we drop the *Cap_Decile* variable because we use *Cap_Low* as a measure of uncertainty.

(columns 1 and 2 of Table 5), low capitalization is associated with a reduced propensity to realize large nominal losses: the marginal effect of the interaction term *SNL*Low_Cap* is -0.33%, offsetting more than a half of the marginal effect of *SNL* of 0.57%. At the same time, small-cap stock sales are very sensitive to the size of gains: the marginal effect of *SNG*Low_Cap* is 1.23%.

A perceived shot at very large gains may tempt people to invest in stocks with lottery-like payoffs. Kumar (2009b) studied retail investors' preference for lottery stocks. In specification 4, we employ the lottery stock dummy (defined in footnote 18) as a proxy for valuation uncertainty. Investors may expect losses on such stocks and may, therefore, react less to the presence and the magnitude of losses. Consistent with this hypothesis, the disposition effect is stronger for lottery-type stocks than other stocks: the marginal effect of the *Loss*Lottery_Stock* interaction is -4.97%. The sensitivities to changes in nominal gains and losses are also lower for lottery-type stocks: the marginal effects of the interactions *SNG* Lottery_Stock* and *SNL* Lottery_Stock* are -0.24% and -0.28%, respectively. They represent reductions of the impact of SNG (SNL) on the probability of sale of two-thirds, or 0.24% out of 0.36% (slightly less than a half, or 0.28% out of 0.65%). Overall, valuation uncertainty reduces the impact of nominal losses on stock sales. As for nominal gains, the relation is not consistent across different measures of stock valuation uncertainty.

[Insert Table 5 about here]

3.5. Salience and the rank effect

Hartzmark (2015) studies stock selling decisions in the context of the overall brokerage portfolio. Using the same data set, it uncovers the rank effect – stocks with highest and lowest value changes within a portfolio are more likely to be sold than other stocks. Gains and losses with extreme ranks (the best and the worst) are more salient than the rest of gains and losses. This subsection tests whether the impact of larger nominal gains and losses on the probability of sale is due to the extreme rankings of such gains and losses within the portfolio. To have meaningful rankings, we restrict our sample to portfolios with at least five positions on a sale day, similar to Hartzmark (2015).

Table 6 presents the results for four alternative regressions. Regression 1 is a rerun of Equation 1 restricted to our constrained sample used in this section. We observe similar results as in Table 2, except the marginal effect of the nominal gains is lower. In Regression 2, we add four dummy variables for the highest, second highest, second lowest, and lowest nominal changes in position values since acquisition: *$Best, $Best2, $Worst2, and $Worst*, respectively.

[Insert Table 6 about here]

In Regression 2, the marginal effects of the highest and lowest (best and worst) nominal value changes on the probability of sale are 12.50% and 7.26% , respectively. They are 4.70% and 3.12% for the second best and second worst position ranks, respectively. Adding the four dummies for the extremely ranked nominal returns results in the coefficient of *SNG* becoming negative and the coefficient of *SNL* remaining positive albeit smaller than in Regression 1. This is a natural consequence of the high influence of rankings because positions with the four extreme nominal value changes are also salient and thus are more likely to be sold. The fact that the impact of SNL on the probability of sale remains positive and significant even after controlling for extremely ranked value changes suggests that the magnitude of nominal losses affects selling decisions beyond the rank effect.

In Regression 3, we follow Hartzmark (2015) by introducing four dummy variables for the best two and the worst two percentage returns instead of the nominal gains or losses normalized by portfolio values. The results are similar to those of Regression 2. Finally, we combine the dummies for the best two and the worst two nominal value changes and percentage returns in Regression 4. While both sets of rank-related dummy variables retain their significance, the extremely ranked nominal value changes have a somewhat higher impact on the likelihood of sale. The correlations between rankings based on percentage returns and those based on nominal value changes are positive but not close to perfect.[20] Thus, the results suggest separate rank effects for nominal value changes and percentage returns within a given portfolio.

4. Holding periods and the disposition effect

4.1. Salience across holding periods

Investors may react differently to gains and losses depending on how long they have held their positions. Prior studies of investors' stock selling behaviors control for holding periods (e.g., Kaustia, 2010; Ben-David and Hirshleifer, 2012). To examine whether and how the effects of salience of gains and losses (measured by SNG and SNL) change with the holding period, we estimate Equation 1 on our full sample with additional interactions between the scaled nominal value changes and the holding period, SNG*HPGain and SNL*HPLoss. Column 1 of Table 7 presents the results for all account, irrespective of their tax status, while columns 2 and 3 of Table 7 display results for taxable and tax-deferred accounts, respectively. We suppress coefficient estimates for our control variables in the interest of brevity. The results across all estimations are similar. As before, we observe the general tendency to avoid realization of losses (the coefficient of Loss dummy is negative and significant) and the effects of salience on stock sales (the coefficients of SNG and SNL are positive and significant), with a stronger effect of nominal losses than gains. The recency effect is also evident: both HPGain and HPLoss variables have negative parameters, and the probability of loss sales declines more slowly than that of gain sales: the marginal effect of HPLoss is smaller in absolute terms than that of HPGain. However, the estimated coefficients of the interaction SNG*HPGain is positive, while that of

[20] For household-sell dates with at least five positions, the correlation between *$Best* and *%Best*, *$Best2* and *%Best2*, *$Worst2* and *%Worst2* and *$Worst* and *%Worst* are 0.68, 0.48, 0.40 and 0.55, respectively. While these correlations weaken further when we require households to have more positions on a given sell date, our key findings remain unchanged. For example, for household-sell dates with at least ten positions, the correlations are 0.63, 0.39, 0.31, and 0.46, respectively.

SNL*HPLoss is negative. That is, the probability of realizing nominal losses falls faster than that of realizing nominal gains of the same size as the holding period lengthens.

[Insert Table 7 about here]

To visualize the dynamic effects of salience on stock selling decisions over different holding periods, we plot in Figure 1 the differences in the predicted probabilities of sale based on the estimates presented in column 1 of Table 7 (all accounts).[21] Positive differences in the sale probabilities are consistent with the disposition effect, while negative differences indicate the reverse disposition effect. We observe that when SNG and SNL are large and holding periods are short, losses are more likely to be realized than gains (the surface of the plot is below zero), indicating that the generally prevalent disposition effect is mitigated. For example, when SNG and SNL are both 20% of the portfolio value (the value 20 on the x-axis) and the holding period is one month, the probability of a gain sale is 4.2% lower than that of a loss sale. When SNG and SNL are small and/or holding periods are long, the surface of the plot is above the zero line, indicating higher probabilities of gain sales compared to sales of losses of the same size, consistent with the disposition effect.

Figure 1 should be interpreted with caution for two reasons. First, loss sales may be driven by tax considerations. Second, reactions to changes in the holding period may be different at short holding periods versus longer ones: e.g., the probability of selling a stock with a given SNG or SNL may change notably if the holding period lengthens from one to two months, but not by much if it lengthens from 24 to 25 months. Meanwhile, the plot in Figure 1 is by construction smooth because it is generated by plotting the differences in sale probabilities for the same given levels of SNG and SNL taken in increments of one percent from a single regression's estimation output.

[Insert Figure 1 about here]

[21] When computing sale probabilities to generate Figure 1, we use SGN/SNL increments of one percent, assume the fifth market capitalization decile (Cap_Decile = 5), and set the rest of control variables to zero.

To address these concerns, we re-estimate our baseline regression (i.e., Equation 1) for different holding period ranges.[22] In Table 8, we present the coefficients and marginal effects of the three key variables – Loss, SNG, and SNL – from the regressions estimated separately for taxable and tax-deferred accounts in Panels A and B of Table 7, respectively. Unlike the rest of the tables, we present marginal effects in curly brackets below the coefficients and do not report standard errors to conserve space. We also present the differences between the marginal effects of SNG and SNL for each holding period range; the indicated significance levels are for the respective coefficients or the differences between coefficients.

The results in Table 8 show that at short holding periods investors are more likely to realize large nominal losses than gains of the same size, even in tax-deferred accounts. The effect is more persistent in taxable accounts (Panel A of Table 8), as the differences between the coefficients of SNG and SNL are negative and statistically significant for holding periods of up to 18 months. For example, the marginal effects of SNL and SNG for holding periods below 0.5 months are 3.993% and 0.075%, respectively. It means that the disposition effect in the 0-0.5 months holding period range is reversed out at the absolute scaled nominal gain or loss level above 2.68% of the portfolio value: the marginal effect of the Loss dummy of -9.00% is completely offset when the difference between the marginal effects of SNL and SNG (3.36%) is multiplied by 2.68. For the 0.5-1 months holding period interval, the disposition effect is reversed out at SNGs/SNLs above 3.90% (found as 7.859/2.015). Overall, as the holding period lengthens the cut-offs for reversal increase significantly. In the 1-3 months interval, the reversal occurs at SNG and SNL levels above 7.52% (found as 6.704/0.891), and in the 3-6 months interval it happens when SNL and SNG exceed 21.50% (found as 8.319/0.387).[23]

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[22] The interactions of the holding period with SNL and SNG are redundant in regressions estimated for fairly narrow holding period ranges. Thus, we do not include them in these estimations. We are now able to observe the variation in the coefficients for SNL and SNG over time and observe non-linearities, if any.

[23] Occurrences of SNL and SNG above the cutoffs are not rare and are more common at shorter holding periods. SNL (SNG) exceeds the cutoffs (the disposition effect reversal levels) of 2.68%, 3.90% and 21.50% for 10.7% (15%), 9.5%

Disposing of large losses may be driven by tax-loss selling in taxable accounts. However, the effect is also quite strong in tax-deferred accounts (Panel B of Table 8), where it persists for holding periods up to six months. The SNG/SNL cutoffs for the reversal of the disposition effect in tax-deferred accounts are: 1.58% for the 0-0.5 months holding period interval (6.189/3.917), 8.48% for the 0.5-1 months interval (13.329/1.572), and 9.30% for the 1-3 months interval (7.167/0.771). For longer holding period intervals, the differences between the effects of SNL and SNG are either insignificant or positive.

As is clear from the results we report in Table 8, as the holding period lengthens, both the difference between relative importance of gains and losses (i.e., between the marginal effects of SNL and SNG) and the propensity to realize larger nominal losses (the marginal effect of SNL) fall. In contrast, the propensity to realize larger nominal gains (SNG) is low at very short holding periods and increases for longer holding periods. The marginal effect of SNG in the shortest holding period range of 0-0.5 months is insignificant in the regression for taxable accounts (Panel A of Table 8), while it is small and marginally significant for tax-deferred accounts (Panel B of Table 8). It is notably higher for longer holding period ranges in both types of accounts.

[Insert Table 8 about here]

4.2. Interaction of salience and valuation uncertainty across holding periods

Next, we test whether our finding about the interaction of time and salience is potentially influenced by a stock's valuation uncertainty. Similar to section 3.4 (refer to regression 1 in Table 5), we use past return volatility (High_Vlty) as a measure of valuation uncertainty. High_Vlty stocks are those in the highest standard deviation decile. We re-estimate regressions for different holding periods for sales of stocks, similar to Table 8, but with the stocks split into high valuation uncertainty and

(13.6%), and 2.1% (2.9%) of positions with the holding periods below 0.5 months, 0.5-1 months, and 3-6 months, respectively.

other stock categories. In Figure 2 we plot the coefficients of SNL and SNG for high-volatility stocks and other stocks from these regressions. Confirming our results from section 3.4, we find that the magnitude of losses (SNL) has a lower impact on sales of stocks with high valuation uncertainty in relation to other stocks across all holding period intervals. The differences between the SNL coefficients for high valuation uncertainty stocks and other stocks are greatest at very short holding periods (under a month). However, the coefficients of SNL are greater than their SNG counterparts even for high valuation uncertainty stocks. This is consistent with our main result discussed in this subsection – investors display a higher propensity to realize larger nominal losses compared to gains on their recently acquired stocks (i.e., those with short holding periods).

[Insert Figure 2 about here]

In sum, investors do *not* hesitate to realize large nominal losses soon after acquisition when compared to gains of the same size. At the same time, investors are not in a hurry to realize large gains that accumulate very quickly (i.e., at very short holding periods). The combination of these behaviors results in the mitigation of the disposition effect at short holding periods when gains and losses are relatively large in the context of the portfolio. While the results are stronger for taxable accounts, they also hold for tax-deferred ones, ruling out tax-related incentives as the sole explanation. As time passes, both propensities weaken, giving way to the disposition effect.[24, 25] Thus, we conclude that the greater impact of salient losses versus gains (i.e., the higher coefficient for SNL in relation to SNG in our baseline results for the entire sample - section 3.1) is primarily driven by the greater propensity to realize large losses in relation to gains at short holding periods.

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[24] Realization of losses may be affected by being slow to close positions of trivial value that had experienced catastrophic losses. In unreported tests, we exclude positions whose values are below 1% of the portfolio value (in another variant – below 5%) and obtain similar results.

[25] Chakrabarty, Moulton, and Trzcinka (2017) find that when professional investment managers face a sharp fall in a stock price shortly after buying the stock, they tend to overreact and close out the position. Our results for individuals are similar: retail investors are more likely to abandon their large nominal losers in the short term, eliminating the disposition effect.

The most common explanations of the disposition effect (DE) are: (1) *Prospect theory* (Kahneman and Tversky, 1979) – investors may be risk averse in the gain domain and risk-seeking in the loss domain; (2) *Regret theory* (Fogel and Berry, 2006; Shefrin and Statman, 1985) – investors want to avoid regret if the investments they sell at a loss recover after the sale; (3) *Realization preferences* (Barberis and Xiong, 2012) – investors may derive utility (disutility) from realizing gains (losses); (4) *Cognitive dissonance* (Festinger, 1957; Chang, Solomon, and Westerfield, 2016; Zuchel, 2001) – investors experience psychological discomfort when their beliefs (e.g., "I am a good investor") are countered by facts (e.g., a loss incurred) and avoid admitting mistakes by holding on to losers. While these are valuable contributions to the explanation of DE, they appear silent about salience and its interaction with the time dimension. Recency has been known to be a factor in judgment and decision making at least since James (1892). Therefore, studies of investor selling decisions (including ours) use the holding period as an explanatory variable. However, to the best of our knowledge, no theories or experiments examine how DE is affected by the interplay of salience (size of gains and losses) and time/recency (holding periods), or even if and how recency and salience interact in general.

Our finding of reversal of DE for large nominal gains and losses at short holding periods, gradually fading and eventually giving way to DE as the holding period lengthens, identifies a potential gap in the existing explanations of DE. Perhaps for large nominal losses on recently acquired positions investors are compelled to revisit their original beliefs, unlike their positions with gains. Also, a large loss soon after acquisition may cause such a high degree of discomfort that it may break the general resistance to realize losses driven by cognitive dissonance or regret. Indeed, if an investor buys a stock on a conviction that it is a good investment and thereafter quickly experiences a large loss in it, it may cause the investor more pain/discomfort than a gradual build-up of losses or a large loss after holding the stock for a while. As suggested by Festinger (1957) in his original work on cognitive dissonance, the level of discomfort may become so strong as to break the resistance to admit a mistake and lead to a reversal of the original decision (which in our setting constitutes the sale of a losing stock). We leave the tests of this and other potential explanations of investors' relatively high propensity to realize larger short-term losses, as well as detailed examinations of the interaction of salience and time/recency in general, to future research.[26]

5. Conclusion

Why do individual investors sell the stocks they sell? The literature suggests that investors' behavior may depend on accumulated gains and losses. The studies that examine investors' reactions to gains and losses (e.g., Ben-David and Hirshleifer, 2012; Grinblatt and Keloharju, 2001; Hartzmar, 2015; Kaustia, 2010) measure gains and losses with percentage returns on positions since acquisition. We hypothesize that nominal gains and losses are more important than percentage returns for two reasons: (1) nominal value changes represent direct changes in investors' wealth, and (2) focusing on percentage returns implicitly assumes extreme narrow framing, which is likely mitigated when investors observe values and value changes for different positions and the entire portfolio at the same time.

Our first main finding is that nominal gains and losses on stocks indeed influence the probability of sale more than percentage returns since acquisition. To compare the effects of gains and losses across investors and time periods, we scale absolute values of nominal gains and losses by the investor's brokerage portfolio value as of the end of the previous trading day. We find that larger absolute scaled nominal gains (SNG) and absolute scaled nominal losses (SNL), but not higher

[26] Fischbacher, Hoffmann, and Schudy (2017) show experimentally that an automatic selling device treatment (i.e., stop-loss orders) significantly reduces the disposition effect, but a reminder treatment does not. For relatively sophisticated investors, setting initial stop-loss orders on newly acquired large stock positions and subsequently not renewing them may result in the pattern we observe – the reverse disposition effect for large nominal value changes at short holding periods, giving way to the disposition effect at longer holding periods. Nevertheless, investors setting stop-loss orders on newly acquired large positions and then failing to renew them (which we cannot test with the data we have) is a manifestation rather than an explanation of investors' greater concern about short-term losses.

absolute percentage returns, are associated with higher probabilities of stock sales by households. This result holds consistently across different account types, holding periods, and investor characteristics. Using various measures of a stock's valuation uncertainty, such as stock volatility and lottery type stock features, we find that the higher probability of sale associated with a large SNL is partially offset for stocks with high valuation uncertainty. This is consistent with the finding of Kumar (2009a) that such stocks are subject to a stronger disposition effect. The effect of SNL (but not SNG) on the probability of sale remains significant after controlling for the rank effect detected by Hartzmark (2015), indicating that the size of a loss influences selling decisions beyond the rank effect.

Our second major finding is that at short holding periods (up to about a year), investors are more likely to realize large nominal losses compared to gains of the same magnitude, mitigating the disposition effect. While the probability of a stock sale is in general inversely related to the holding period for both gains and losses (a manifestation of the recency effect), large nominal losses are more likely to be realized than nominal gains of the same size at holding periods up to one year. This effect cannot be explained by tax incentives because we also observe it in tax-deferred accounts. Also, our findings hold across stocks with different levels of valuation uncertainty. For holding periods longer than a year, large scaled nominal gains (SNGs) are more likely to be realized than SNL's of the same size, consistent with the disposition effect. Small gains are more likely to be realized than losses of the same size across the entire spectrum of holding periods, also consistent with the disposition effect. We conjecture that when investors suffer large nominal losses on recently acquired positions, they are compelled to confront their original beliefs. Perhaps the degree of pain/discomfort suffered helps them confront the reluctance to realize losses rooted in cognitive dissonance or regret theory. More research is needed to evaluate this and other potential explanations. Overall, our findings on salience of nominal gains and losses, recency, and their interaction, contribute to the understanding of the disposition effect.

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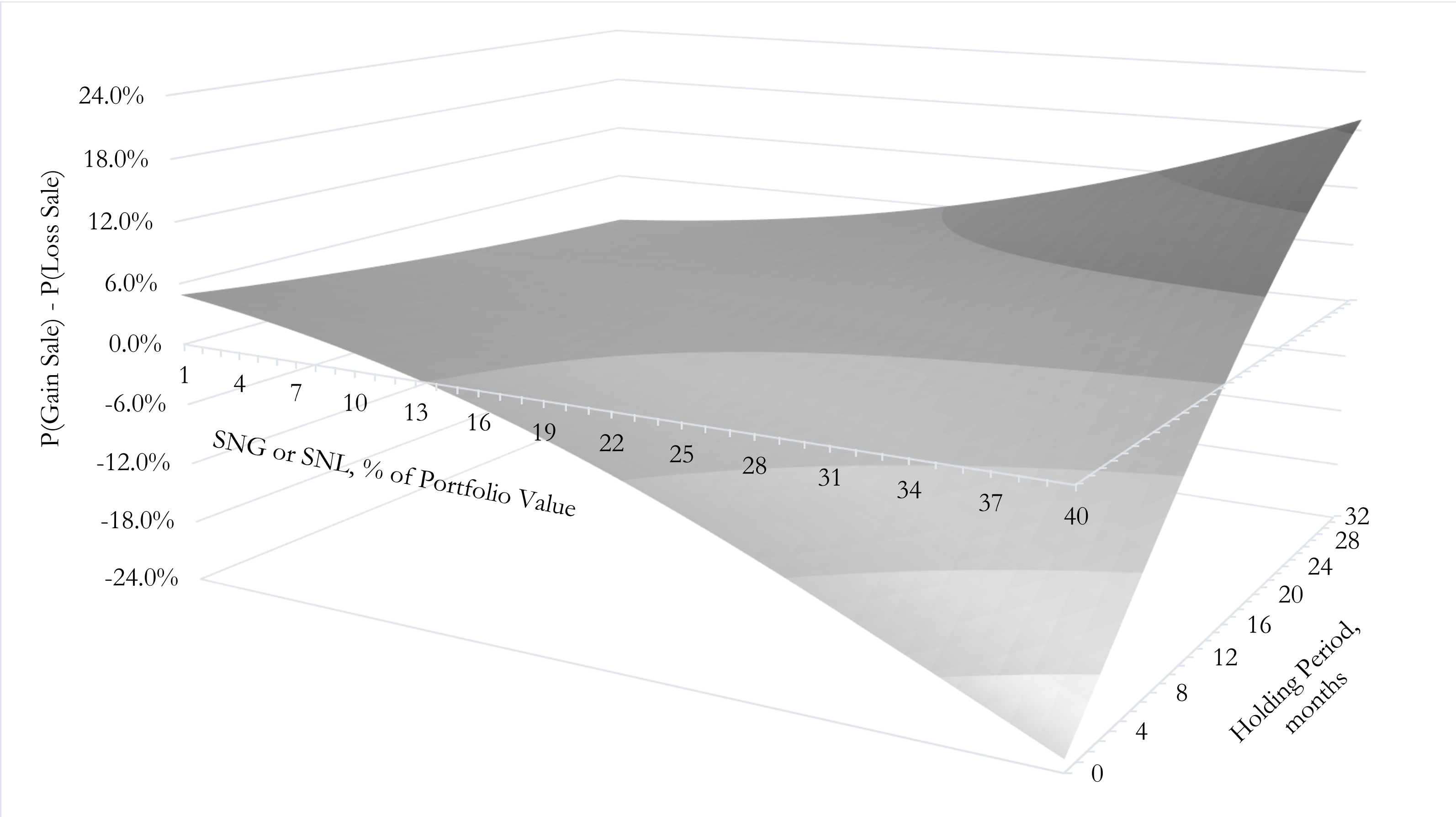

Figure 1: Differences in the impact of SNG and SNL across holding periods

Note: This figure plots the differences in the probabilities of a stock sale on a date on which an investor (household) sells at least one stock for stocks with the same scaled nominal gains (SNG) and scaled nominal losses (SNL), computed for SNG/SNL increments of 1% of the portfolio value. To generate the plot, we estimate Equation 1 on our full sample with additional interactions between the scaled nominal value changes and the holding period, SNG*HPGain and SNL*HPLoss. The variables are defined following Equation 1. To compute the probabilities for the plot, we set all the control variable values to zero, except for the market capitalization decile, which we set to five.

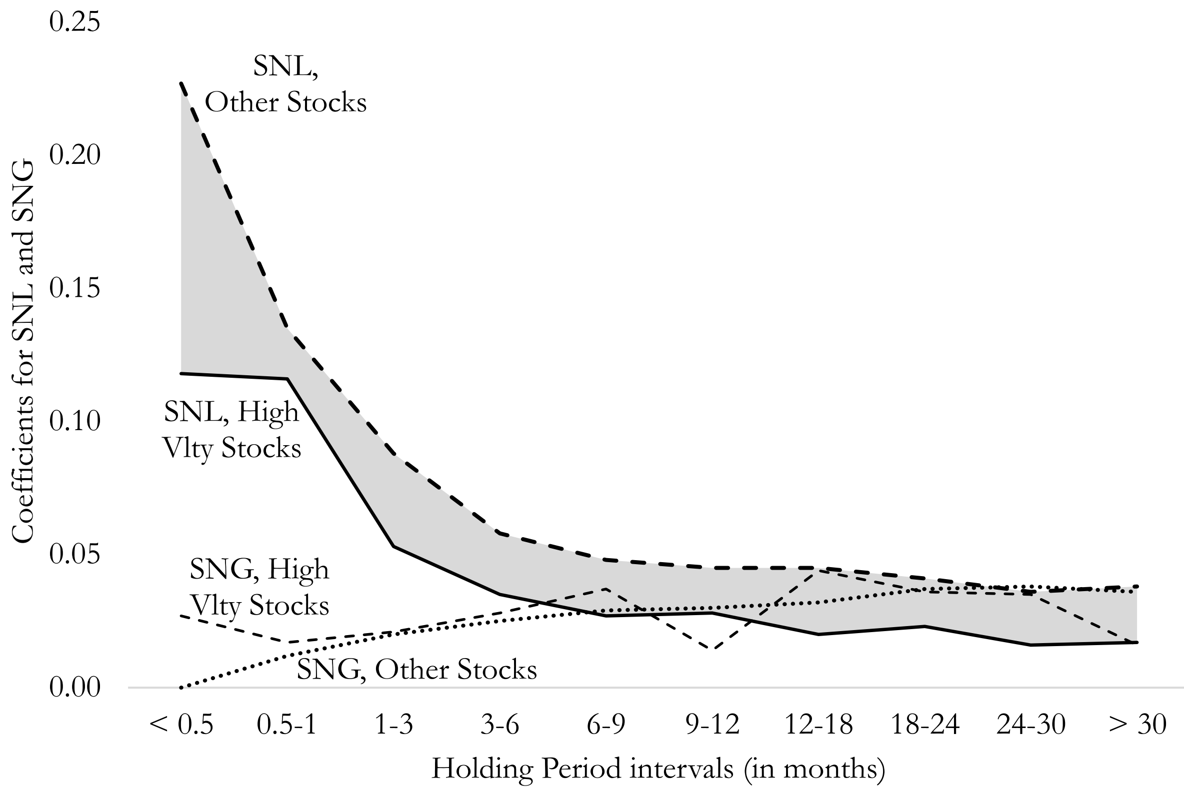

Figure 2: Valuation uncertainty, holding periods, and the effects of SNL and SNG on sales

Note: This figure plots the coefficients of SNL and SNG for high valuation uncertainty stock sales and all other stock sales from regressions estimated separately for different holding period ranges. High stock valuation uncertainty is proxied by the indicator variable *High Vlty*, which labels stocks in the highest volatility decile in the last six calendar months prior to the stock sale. *Other Stocks* refers to all stocks except for those classified as *High Vlty Stocks*.

Table 1: Descriptive statistics

Variable	# HH-Sell Dates	Min	P1	P25	P50	P75	P99	Max	Mean	Std Dev
# of Positions										
# of Gains	198,687	0	0	1	3	6	31	262	5.01	9.64
# of Losses	198,687	0	0	1	3	6	29	209	4.72	7.77
(Mean) Absolute SNG and SNL										
SNG *for gain positions*	183,792	0.00	0.13	1.25	2.72	6.03	39.65	99.99	5.33	7.97
SNL *for loss positions*	183,380	0.00	0.07	0.80	1.86	4.41	40.01	110.54	4.30	7.95
(Mean) Absolute Returns										
Ret%Gain *for gain positions*	183,792	0.00	0.82	11.55	23.76	48.95	490.61	3998.03	50.65	113.62
Ret%Loss *for loss positions*	183,380	0.00	0.89	10.50	18.35	28.01	66.83	100.00	20.79	13.99
(Mean) Holding Period (months)										
HPGain *for gain positions*	183,792	0.03	0.18	3.32	7.72	15.09	44.69	70.80	10.66	9.86
HPLoss *for loss positions*	183,380	0.03	0.15	3.10	7.13	13.58	43.55	70.47	9.84	9.31

Panel B: Correlations between Portfolio-specific Variables

Variables	Loss Dummy	SNG	SNL	Ret%Gain	Ret%Loss	HPGain
SNG	-0.27					
SNL	0.08	-0.02				
Ret%Gain	-0.01	0.18	0.00			
Ret%Loss	0.61	-0.16	0.14	-0.01		
HPGain	-0.54	0.19	-0.04	0.02	-0.33	
HPLoss	0.54	-0.14	0.07	-0.01	0.57	-0.29

Note: Panel A summarizes all positions (sold or unsold) held by investors on various household-sell dates with at least two open positions at the beginning of the trading day. Any day on which a household makes at least one stock sale is referred to as a *household-sell* (HH-sell) date. The sample consists of positions acquired during the 71-month data period (January 1991 to November 1996) at a discount brokerage house. This table summarizes household positions at the household-sell date level. Except for the statistics on the # of positions, we begin by calculating the mean value for each variable on each household-sell date. Thereafter, we present summary statistics for these mean values across all household-sell dates. *SNG (SNL)* is the absolute nominal gain (loss) for positions with gains (losses) only. Ret%Gain (Ret%Loss) is the absolute percentage return on a position since acquisition, computed for gain (loss) stocks only. HPGain (HPLoss) is the holding period, in months, for gain (loss) stocks only. The numbers of HH-sell dates with gains and losses are slightly lower than the overall number of HH-sell dates because not all such dates have both gain and loss positions. Panel B presents correlations between the variables related to gains or losses for all observations at the household-position-date level (used for regression analysis in Table 2).

Table 2: Salience of nominal gains and losses.

	Reg [1]		Reg [2]		Reg [3]		Reg [4]	
Variable	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
SNG (β_1)	0.025***	0.317	0.026***	0.331			0.078***	0.674
	[14.409]		[16.092]				[5.505]	
SNL (β_2)	0.040***	0.506	0.044***	0.549			0.054***	0.466
	[16.940]		[17.221]				[19.465]	
Loss	-0.339***	-4.254	-0.437***	-5.454	-0.438***	-5.355	-0.331***	-2.857
	[14.951]		[21.622]		[21.608]		[15.524]	
Ret%Gain (γ_1)					-0.001	-0.007	-0.005**	-0.041
					[1.421]		[2.450]	
Ret%Loss (γ_2)					-0.001	-0.011	-0.011***	-0.092
					[1.432]		[16.422]	
HPGain (δ_1)			-0.029***	-0.360	-0.026***	-0.315	-0.026***	-0.220
			[10.586]		[7.591]		[8.008]	
HPLoss (δ_2)			-0.021***	-0.259	-0.016***	-0.190	-0.014***	-0.125
			[9.196]		[5.820]		[5.944]	
RetPrevDay_High			0.513***	6.403	0.529***	6.460	0.512***	4.426
			[46.293]		[48.477]		[47.388]	
RetPrevDay_Low			0.388***	4.849	0.430***	5.255	0.424***	3.666
			[31.840]		[36.976]		[35.739]	
Cap_Decile			0.068***	0.852	0.066***	0.803	0.058***	0.499
			[12.513]		[11.033]		[11.492]	
Dividend_Stk			-0.142***	-1.772	-0.185***	-2.265	-0.189***	-1.631
			[6.876]		[8.120]		[8.712]	
High_Vlty			-0.065**	-0.816	0.051	0.624	0.028	0.239
			[2.031]		[1.580]		[0.977]	
Tech_Stk			0.116***	1.446	0.139***	1.697	0.125***	1.078
			[7.780]		[8.565]		[8.628]	
Intercept	-1.841***		-2.144***		-2.022***		-2.024***	
	[31.657]		[33.635]		[27.471]		[29.541]	
# Obs	1,934,558		1,934,558		1,934,558		1,934,558	
# Households	28,096		28,096		28,096		28,096	
Pseudo-R^2	0.020		0.050		0.034		0.067	

Note: This table presents the output for logit regressions that model the probability of a stock sale by a household on a date on which the household sells at least one stock. *SNG (SNL)* is the absolute dollar amount of gain (loss) for a position divided by the total brokerage portfolio value at the end of the previous day, in percent. *Loss* is an indicator variable for positions with a loss. *HPGain (HPLoss)* is the holding period, in months, for a position with gain (loss). Regression 1 does not include control variables. Regression 2 through 4 include control variable. Regression 3 uses absolute percentage returns for stocks sold at a gain *(Ret%Gain)* and loss *(Ret%Loss)* in place of scaled nominal gains and losses. Regression 4 is estimated with both scaled nominal gains and losses and percentage returns as independent variables. The control variables are defined as follows: *RetPrevDay_High* and *RetPrevDay_Low* are indicator variables for stocks with a previous day return in the top and bottom deciles of all CRSP stocks, respectively; *Cap_Decile* is the market capitalization decile based on all CRSP stocks on the previous trading day, with 1 and 10 denoting the smallest and the largest deciles, respectively; *High_Vlty* is an indicator for stocks in the top volatility decile of all CRPS stocks over the previous six calendar months; *Div_Stk* is an indicator variable for stocks that paid dividends any time during the previous 12 month; *Tech_Stk* is an indicator for technology company stocks. The *t*-statistics are in brackets below the coefficients, with standard errors clustered at the household level. The ME columns display marginal effects, in percent, calculated at the mean levels of other variables. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Salience of nominal gains and losses across account types

	Taxable		Tax-deferred		Taxable (Jan-Nov)		Taxable (Dec)	
	Reg [1]		Reg [2]		Reg [3]		Reg [4]	
Variable	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
SNG (β_1)	0.026***	0.332	0.026***	0.421	0.027***	0.337	0.020***	0.257
	[11.920]		[16.941]		[11.821]		[9.584]	
SNL (β_2)	0.044***	0.560	0.030***	0.478	0.040***	0.506	0.066***	0.825
	[13.128]		[13.739]		[12.319]		[13.203]	
Loss	-0.428***	-5.399	-0.427***	-6.790	-0.443***	-5.536	-0.153***	-1.920
	[17.941]		[10.747]		[17.849]		[3.940]	
HPGain	-0.034***	-0.425	-0.011***	-0.179	-0.033***	-0.417	-0.038***	-0.483
	[8.922]		[9.354]		[8.512]		[13.765]	
HPLoss	-0.022***	-0.282	-0.008***	-0.133	-0.027***	-0.334	0.000	0.005
	[6.867]		[6.641]		[7.904]		[0.164]	
RetPrevDay_High	0.507***	6.404	0.509***	8.100	0.519***	6.486	0.395***	4.965
	[37.882]		[25.379]		[37.070]		[12.014]	
RetPrevDay_Low	0.388***	4.898	0.399***	6.344	0.394***	4.932	0.323***	4.054
	[26.094]		[18.237]		[25.788]		[8.595]	
Cap_Decile	0.069***	0.873	0.060***	0.946	0.072***	0.894	0.052***	0.658
	[10.130]		[6.545]		[10.113]		[7.057]	
Dividend_Stk	-0.136***	-1.720	-0.100***	-1.592	-0.133***	-1.668	-0.193***	-2.422
	[5.036]		[2.749]		[4.776]		[6.378]	
High_Vlty	-0.045	-0.573	-0.141***	-2.243	-0.038	-0.478	-0.065	-0.817
	[1.078]		[3.301]		[0.891]		[0.955]	
Tech_Stk	0.116***	1.461	0.092***	1.469	0.112***	1.398	0.148***	1.857
	[6.011]		[4.179]		[5.657]		[5.161]	
Intercept	-2.099***		-1.925***		-2.110***		-2.084***	
	[24.406]		[25.969]		[23.726]		[25.568]	
Test: β_1 - β_2	-0.018***	-0.228	-0.004	-0.057	-0.014***	-0.169	-0.046***	0.568
# Obs	1,319,220		384,612		1,208,819		110,401	
# Households	21,107		10,560		20,304		7,354	
Pseudo-R^2	0.055		0.038		0.057		0.080	

Note: This table presents the output for our baseline (refer Equation 1) logit regression specification, which models the probability of a stock sale, estimated for different account types and calendar months. *SNG (SNL)* is the absolute dollar amount of gain (loss) for a position divided by the total brokerage portfolio value at the end of the previous day, in percent. *Loss* is an indicator variable for positions with a loss. *HPGain (HPLoss)* is a holding period, in months, for a position with a gain (loss). Regression 1 is estimated for taxable (non-retirement) accounts, while Regression 2 is estimated for tax-deferred (retirement) accounts. Regression 3 (4) is estimated for stock sales in taxable accounts made in January through November (December). The control variables, namely *RetPrevDay_High*, *RetPrevDay_Low*, *Cap_Decile*, *High_Vlty, Div_Stk* and *Tech_Stk* are defined in the caption for table 2. The t-statistics are in brackets below the coefficients, with standard errors clustered at the household level. The ME columns display marginal effects, in percent, calculated at the mean levels of other variables. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Salience and investor characteristics

Panel A: Gender and Age

	Gender				Age			
	Male		Female		Low (< 50 yrs)		High (≥ 50 yrs)	
Variable	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
SNG (β_1)	0.022***	0.316	0.022***	0.306	0.020***	0.328	0.021***	0.279
	[16.125]		[6.439]		[10.574]		[12.049]	
SNL (β_2)	0.038***	0.550	0.027***	0.380	0.034***	0.550	0.039***	0.516
	[20.409]		[4.891]		[15.832]		[11.929]	
Loss	-0.483***	-7.026	-0.344***	-4.807	-0.582***	-9.366	-0.389***	-5.168
	[16.592]		[3.309]		[15.163]		[9.264]	
Test: β_1 - β_2	-0.016***	-0.234	-0.005	-0.073	-0.014***	-0.222	-0.018***	-0.237
# Obs	778,352		77,771		373,902		445,616	
# Households	13,991		1,557		7,996		6,945	

Panel B: Portfolio Characteristics

	Monthly Turnover Group				Diversification (# of Stks)			
	Low Turnover		High Turnover		Low (≤ 3 stks)		High (> 3 stks)	
Variable	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
SNG (β_1)	0.033***	0.403	0.024***	0.278	0.015***	0.322	0.024***	0.259
	[24.215]		[11.806]		[7.207]		[13.374]	
SNL (β_2)	0.047***	0.575	0.045***	0.535	0.018***	0.397	0.048***	0.527
	[20.457]		[14.476]		[15.333]		[13.297]	
Loss	-0.365***	-4.437	-0.470***	-5.569	-0.406***	-8.809	-0.465***	-5.109
	[12.112]		[19.247]		[9.483]		[19.658]	
Test: β_1 - β_2	-0.014***	-0.173	-0.022***	-0.256	-0.003	-0.075	-0.024***	-0.268
# Obs	474,192		1,395,065		225,041		1,698,657	
# Households	12,387		12,387		11,757		15,855	

Panel C: Average Portfolio Value Prior to Sale

	<$50,000		$50,000 to $100,000		$100,000 to $500,000		≥$500,000	
Variable	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
SNG (β_1)	0.022***	0.450	0.010***	0.142	0.011***	0.102	0.013***	0.051
	[20.012]		[6.401]		[7.548]		[4.202]	
SNL (β_2)	0.024***	0.483	0.035***	0.494	0.047***	0.442	0.081**	0.319
	[18.472]		[13.429]		[14.341]		[2.549]	
Loss	-0.590***	-12.003	-0.490***	-6.966	-0.399***	-3.782	-0.237***	-0.936
	[29.478]		[12.955]		[10.404]		[2.909]	
Test: β_1 - β_2	-0.002	-0.033	-0.025***	-0.353	-0.025***	-0.353	-0.068**	-0.267
# Obs	468,681		354,181		756,428		355,268	
# Households	20,081		4,163		3,454		398	

Note: This table presents the output for our baseline (refer to Equation 1) logit regression specification, which models the probability of a stock sale, estimated for investors with different demographic and portfolio characteristics. In Panel B, we classify investors into high- and low-turnover groups split across the median monthly turnover of 4.68%. we present only the key variables of interest namely, *SNL*, *SNG* and *Loss* dummy variables, while all other variables (*HPGain, HPLoss,* and numerous controls) have been suppressed to conserve space. Refer to caption for table 2 for variable definitions. The *t*-statistics are in brackets below the coefficients, and the standard errors are clustered at the household level. The ME columns display marginal effects, in percent, calculated at the mean levels of other variables. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Salience and valuation uncertainty

	VAR = High_Vlty		VAR = High_Idiosyn		VAR = Low_Cap		VAR = Lottery_Stock	
	Reg [1]		Reg [2]		Reg [3]		Reg [4]	
Variable	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
SNG (β_1)	0.026***	0.328	0.026***	0.328	0.027***	0.340	0.029***	0.362
	[15.872]		[15.866]		[16.109]		[17.134]	
SNL (β_2)	0.050***	0.619	0.050***	0.619	0.045***	0.569	0.052***	0.648
	[17.299]		[17.323]		[16.875]		[18.691]	
Loss	-0.434***	-5.405	-0.435***	-5.418	-0.472***	-5.979	-0.411***	-5.070
	[21.276]		[21.325]		[23.072]		[19.888]	
VAR	0.370***	4.609	0.365***	4.542	-0.579***	-7.333	0.348***	4.297
	[8.826]		[8.540]		[5.161]		[9.807]	
Loss * VAR	-0.478***	-5.948	-0.470***	-5.850	0.006	0.071	-0.402***	-4.969
	[11.022]		[10.823]		[0.048]		[10.578]	
SNG * VAR (γ_1)	-0.001	-0.011	-0.000	-0.001	0.097***	1.226	-0.020***	-0.242
	[0.248]		[0.018]		[3.408]		[11.455]	
SNL * VAR (γ_2)	-0.027***	-0.331	-0.027***	-0.336	-0.026***	-0.326	-0.023***	-0.279
	[9.732]		[9.873]		[7.660]		[9.338]	
Test: β_1 - β_2	-0.023***	-0.291	-0.023***	-0.291	-0.018***	-0.229	-0.023***	-0.286
Test: γ_1 - γ_2	0.026***	0.320	0.027***	0.335	0.123***	1.552	0.003	0.038
# Obs	1,934,558		1,934,558		1,934,558		1,934,558	
# Households	28,096		28,096		28,096		28,096	
Pseudo-R^2	0.051		0.051		0.048		0.052	

Note: This table presents the output for logit regressions that model the probability of a stock sale by a household on a date on which the household sells at least one stock, with an emphasis on stock valuation uncertainty. Our key variables namely, *SNL*, *SNG* and *Loss* dummy have been defined earlier. *VAR* refers to various indicator variables that may capture a stock's valuation uncertainty: *High_Vlty, High_Idiosyn, Low_Cap,* and *Lotter_Stock*. We further interact these measures of valuation uncertainty with the variables *Loss* dummy*, SNG, and SNL* in each regression. *High_Vlty* (used in Regression 1) is an indicator variable for stocks in the top volatility decile of all CRPS stocks over the previous six calendar months. *High_Idiosyn* (used in Regression 2) is an indicator for stocks in the highest idiosyncratic volatility decile of all stocks in the CRSP database over the last six calendar months. Idiosyncratic volatility is the standard deviation of the residual from the Carhart (1997) four-factor model. *Low_Cap* (used in Regression 3) is an indicator variable for stocks in the lowest market cap decile at the end of the previous day. *Lottery_Stock* (used in Regression 4) is an indicator variable for lottery-type stocks, defined using the methodology of Kumar (2009b): at the end of each month, stocks on the major exchanges (NYSE/NASDAQ/AMEX) with prices in the bottom 50th percentile, idiosyncratic volatility in the top 50th percentile, and idiosyncratic skewness in the top 50th percentile are classified as lottery-type stocks (Regression 4). The variables *HPGain, HPLoss,* and controls, are defined in the caption for Table 2 and have been suppressed to conserve space. The t-statistics are in brackets below the coefficients, and the standard errors are clustered at the household level. The ME columns display marginal effects, in percent, calculated at the mean levels of other variables. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Salience and the rank effect

	Reg [1]		Reg [2]		Reg [3]		Reg [4]	
Variable	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
SNG (β_1)	0.012***	0.121	-0.031***	-0.273	-0.021***	-0.188	-0.034***	-0.299
	[6.241]		[18.508]		[15.776]		[21.412]	
SNL (β_2)	0.049***	0.481	0.018***	0.157	0.027***	0.238	0.017***	0.149
	[11.003]		[7.711]		[10.860]		[7.896]	
Loss	-0.416***	-4.101	-0.313***	-2.786	-0.322***	-2.890	-0.309***	-2.723
	[17.469]		[13.110]		[13.527]		[13.043]	
$Best			1.405***	12.523			0.958***	8.446
			[27.853]				[33.444]	
$Best2			0.528***	4.700			0.350***	3.087
			[19.862]				[21.508]	
$Worst2			0.351***	3.124			0.225***	1.982
			[14.763]				[15.569]	
$Worst			0.814***	7.256			0.488***	4.304
			[18.053]				[19.690]	
%Best					1.259***	11.308	0.594***	5.242
					[23.333]		[17.061]	
%Best2					0.515***	4.625	0.278***	2.451
					[19.255]		[16.512]	
%Worst2					0.343***	3.078	0.212***	1.873
					[14.287]		[12.508]	
%Worst					0.804***	7.221	0.485***	4.281
					[15.878]		[12.797]	
# Obs	1,718,798		1,718,798		1,718,798		1,718,798	
# Households	15,176		15,176		15,176		15,176	
Likelihood	25006***		58308***		55284***		63013***	
Pseudo-R^2	0.030		0.070		0.067		0.076	

Note: This table presents the output for logit regressions that model the probability of a stock sale by a household on a date on which the household sells at least one stock, with an emphasis on the effect of rankings. To have meaningful rankings, we restrict our sample to portfolios with at least five open positions on a sale day. Regression 1 is a rerun of Equation 1 for the sample with at least five open positions on a sale day. Our key variables namely, *SNL*, *SNG* and *Loss* dummy have been defined earlier. In Regression 2, we add four dummy variables for the highest *($Best)*, second highest ($Best2), second lowest *($Worst2)*, and lowest *($Worst)* nominal changes in position values since acquisition normalized by the brokerage portfolio value at the end of the previous day. In Regression 3, we use the rankings of percentage returns in place of the rankings of nominal value changes normalized by the brokerage account value. *%Best, %Best2, %Worst,* and *%Worst2* are the indicators for the highest, second highest, second lowest, and lowest percentage returns on a position since acquisition, respectively, without regard to the brokerage portfolio value. In Regression 4, we use both the normalized nominal change ranking dummies and the percentage return ranking dummies. The variables *HPGain, HPLoss,* and controls, are defined in the caption for Table 2 and have been suppressed to conserve space. The t-statistics are in brackets below the coefficients, and the standard errors are clustered at the household level. The ME columns display marginal effects, in percent, calculated at the mean levels of other variables. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Holding periods and the disposition effect

	All		Taxable		Tax-deferred	
	Reg [1]		Reg [2]		Reg [3]	
Variables	Coeff	ME	Coeff	ME	Coeff	ME
SNG	0.020***	0.250	0.019***	0.247	0.023***	0.366
	[14.405]		[10.297]		[11.718]	
SNL	0.057***	0.720	0.055***	0.706	0.040***	0.646
	[22.036]		[17.198]		[11.940]	
Loss	-0.497***	-6.319	-0.486***	-6.248	-0.477***	-7.680
	[23.583]		[19.377]		[11.458]	
HPGain	-0.032***	-0.403	-0.037***	-0.472	-0.013***	-0.214
	[11.515]		[9.754]		[9.228]	
HPLoss	-0.018***	-0.229	-0.020***	-0.255	-0.006***	-0.095
	[7.366]		[5.634]		[4.233]	
SNG * HPGain	0.001***	0.007	0.001***	0.008	0.000***	0.005
	[7.864]		[6.171]		[3.990]	
SNL * HPLoss	-0.001***	-0.010	-0.001***	-0.009	-0.001***	-0.009
	[8.460]		[6.513]		[5.251]	
Other variables suppressed						
# Obs	1,934,558		1,319,220		384,612	
# Households	28,096		21,107		10,560	
Pseudo-R^2	0.051		0.056		0.038	

Note: This table presents the output for logit regressions that model the probability of a stock sale by a household on a date on which the household sells at least one stock, estimated for different account types. *SNG, SNL, Loss* dummy, *HPGain* and *HPLoss* are defined in caption for Table 2. Regression 1 is estimated for all accounts, Regression 2 – for taxable (non-retirement) accounts, and Regression 3 – for tax-deferred (retirement) accounts. The control variables have been defined in the caption for Table 2 and have been suppressed to conserve space. The *t*-statistics are in brackets below the coefficients, and the standard errors are clustered at the household level. The ME columns display marginal effects, in percent, calculated at the mean levels of other variables. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Holding period intervals and the disposition effect

Panel A: Taxable Accounts										
	Holding Period Ranges (in months)									
Variable	< 0.5 mn	0.5-1 mn	1-3 mn	3-6 mn	6-9 mn	9-12 mn	12-18 mn	18-24 mn	24-30 mn	> 30 mn
SNG	0.001	0.012***	0.019***	0.027***	0.029***	0.030***	0.033***	0.036***	0.039***	0.034***
	{0.010}	{0.204}	{0.302}	{0.388}	{0.425}	{0.354}	{0.409}	{0.416}	{0.368}	{0.179}
SNL	0.183***	0.132***	0.077***	0.053***	0.044***	0.042***	0.041***	0.035***	0.031***	0.036***
	{3.369}	{2.219}	{1.193}	{0.776}	{0.637}	{0.489}	{0.503}	{0.400}	{0.286}	{0.187}
Loss	-0.488***	-0.468***	-0.431***	-0.570***	-0.812***	-0.326	-0.668***	-0.777***	-0.487	0.408***
	{-9.005}	{-7.859}	{-6.704}	{-8.319}	{-11.852}	{-3.786}	{-8.159}	{-8.961}	{-4.543}	{2.119}
Diff: SNG - SNL	-0.182***	-0.120***	-0.057***	-0.027***	-0.015***	-0.012***	-0.008**	0.001	0.009	-0.002
	{-3.359}	{-2.015}	{-0.891}	{-0.387}	{-0.212}	{-0.135}	{-0.094}	{0.016}	{0.082}	{-0.008}
# Obs	88,892	73,733	224,050	219,316	150,958	112,204	147,284	98,507	67,578	136,698
Pseudo-R^2	0.068	0.052	0.040	0.037	0.035	0.036	0.039	0.037	0.041	0.052

Table 8: Holding periods ranges and the disposition effect

(Continued)

Panel B: Tax-deferred Accounts										
	Holding Period Ranges (in months)									
Variable	< 0.5 mn	0.5-1 mn	1-3 mn	3-6 mn	6-9 mn	9-12 mn	12-18 mn	18-24 mn	24-30 mn	> 30 mn
SNG	0.004*	0.015***	0.022***	0.026***	0.031***	0.027***	0.032***	0.035***	0.033***	0.029***
	{0.075}	{0.283}	{0.372}	{0.416}	{0.502}	{0.385}	{0.485}	{0.587}	{0.547}	{0.327}
SNL	0.230***	0.099***	0.069***	0.036***	0.031***	0.031***	0.023***	0.026***	0.022***	0.022***
	{3.993}	{1.855}	{1.143}	{0.582}	{0.509}	{0.438}	{0.354}	{0.432}	{0.356}	{0.254}
Loss	-0.357***	-0.708***	-0.430***	-0.442***	-0.590**	-0.149	-0.418	-0.904**	-0.795	0.161
	{-6.189}	{-13.329}	{-7.167}	{-7.144}	{-9.609}	{-2.129}	{-6.377}	{-15.15}	{-13.14}	{1.810}
Diff: SNG - SNL	-0.226***	-0.084***	-0.046***	-0.010*	-0.000	-0.004	0.009*	0.009**	0.012*	0.007*
	{-3.917}	{-1.572}	{-0.771}	{-0.166}	{-0.007}	{-0.053}	{0.131}	{0.154}	{0.191}	{0.074}
# Obs	27,299	23,309	70,547	70,693	45,941	32,634	42,123	25,168	16,204	30,694
Pseudo-R^2	0.073	0.043	0.038	0.036	0.037	0.040	0.038	0.051	0.044	0.052

Note: This table presents the output for logit regressions that model probability of a stock sale by a household on a date on which the household sells at least one stock, estimated for various intervals of holding periods (in months). The key dependent variables summarized are SNG, SNL and Loss dummy. The control variables have been defined in the caption for Table 2 and have been suppressed to conserve space. Below the coefficient estimates, in curly brackets, we present the marginal effects (MEs), in percent, calculated at the mean levels of other variables. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively